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Person-centered Approaches in the Study of Personality Disorders

Brian M. Hicks[1], **D. Angus Clark**[2], and **C. Emily Durbin**[2]

[1]Department of Psychiatry, University of Michigan

[2]Department of Psychology, Michigan State University

Abstract

Existing categorical models of personality disorder diagnoses capture heterogeneous populations in terms of symptom presentation and etiological influences on personality pathology. Though several well-validated alternative dimensional trait models (i.e., variable-centered approaches) of personality disorders have been developed, person-centered approaches can provide important additional information on both the phenotypic expression and etiology of personality pathology. We discuss the utility and necessary attributes of person-centered or subtype models of personality disorders and briefly review statistical approaches and other methodological considerations, drawing specific examples from the psychopathy literature. We conclude by advocating a utilitarian approach whereby person-centered and variable-centered methods complement each other to better understand personality disorders.

Heterogeneity in Personality Disorders

The DSM-5 classifies personality disorders with lists of 7 to 9 symptoms that are characteristic of an enduring pattern of inner experience and behavior that deviate markedly from the expectations of an individual's culture (APA, 2013). A diagnosis is met if a person exhibits a minimum number of disorder-specific symptoms (3 to 5) as well as criteria applicable to all personality disorders. Specifically, the pattern of symptoms is inflexible and pervasive, stable over time, and leads to significant distress or impairment. This categorical diagnostic approach should ideally capture patterns of affective, behavioral, cognitive, and interpersonal characteristics that are internally coherent and distinct.

In practice, however, the DSM-5 approach yields diagnostic groups of relatively high heterogeneity. This is partially because there are dozens to hundreds of different symptom profiles that are sufficient to qualify for a given disorder (e.g., 256 ways to meet a diagnosis of borderline personality disorder [BPD]). Also, the DSM-5 personality disorder symptoms are a mix of features that differ in conceptual breath ranging from relatively enduring temperament characteristics to episodic and acute symptoms (e.g., suicide attempts) (Skodol et al., 2005). There is also substantial comorbidity across personality disorders—particularly among disorders in the same cluster—that further diminishes the scientific utility of DSM

Correspondence: Address correspondence to Brian M. Hicks, Department of Psychiatry, University of Michigan, 4250 Plymouth Rd, Ann Arbor, MI 48109. Electronic mail may be sent to brianhic@umich.edu.

diagnostic categories (Clark, 2007; Zimmerman et al., 2005). Collectively, these sources of heterogeneity represent an ‘overinclusiveness’ problem in that diagnostic categories may capture a mix of individuals that differ in both symptom presentation and the etiological basis of their personality pathology.

Personality disorder diagnoses may also suffer from an ‘underinclusiveness’ problem that occurs when criteria sets identify a group of people who share some personality disorder features, but there are also subgroups within that group that exhibit relatively large differences on a set of important features that are not represented in the criteria sets. This situation is especially important to recognize if the distinguishing features of subgroups not included in the symptom criteria have etiological significance for the common features shared by all groups. Such cases would be indicative of multiple etiological paths that lead to the same phenotypic outcome, which could have implications for intervention and prevention.

As an example of this phenomenon, consider psychopathy and the distinguishing feature of trait anxiety. Though not included in DSM-5, psychopathy is a near-neighbor construct to antisocial personality disorder (ASPD) and has an extensive research literature that supports its validity as a form of personality pathology (Hare & Neumann, 2008). Psychopathy is defined by a number of interpersonal (deceitfulness, superficial charm, glibness, grandiosity, egocentricity), affective (callousness, lack of emotional responsiveness and close attachments), and behavioral (impulsivity, irresponsibility, parasitic lifestyle) features and has a strong association with antisocial and criminal behavior. Among groups that have a high base rate of psychopathy such as adult prisoners and juvenile delinquents, investigators have consistently found that the most psychopathic individuals can be segregated into high and low anxiety subgroups (Hicks et al., 2004, 2010; Kimonis et al., 2012a; Poythress et al., 2010; Skeem et al., 2007; Swogger et al., 2007; Swogger & Kosson, 2008). These findings are consistent with longstanding clinical conceptualizations of primary (low anxious) and secondary (high anxious) psychopathy subtypes (Skeem et al., 2003), and may indicate the presence of different etiological influences (Hicks & Drislane, in press; Skeem et al., 2003; Yildirim & Derksen, 2015).

Person-Centered and Variable-Centered Approaches to Parsing Heterogeneity

Given the limitations of the DSM diagnostic model, a variety of analytic approaches have been used to try and better organize the various forms of personality pathology. Variable-centered approaches seek to define narrower trait constructs consisting of specific maladaptive personality features. Alternatively, person-centered approaches seek to identify more homogenous groups of pathological individuals.

Variable-Centered Approaches

Variable-centered approaches reduce heterogeneity by eliminating the concept of diagnostic groups entirely. Instead, the goal is to make quantitative distinctions among people by identifying dimensional personality trait constructs along which persons can vary. Typically, models that follow this approach are hierarchical in nature. A smaller number of broad and relatively independent higher-order trait constructs capture psychological processes that contribute to the manifestation of multiple, specific lower-order trait constructs. The associations among these lower-order and higher-order trait constructs constitute the structure of maladaptive traits that have been identified as most relevant to personality pathology.

The variable-centered approach has been successful at identifying important trait constructs (e.g., stress reactivity), and delineating their interrelationships and associations with important outcomes (Clark, 2007; Widiger & Trull, 2007). The strength of the variable-centered approach is that the trait constructs are relatively narrow and unidimensional, that is, they refer to one thing and one thing only, which minimizes their complexity and facilitates several psychometric properties such as precision, stability, and discriminant validity. However, variable-centered approaches are less useful for integrating information about a person's personality profile across a variety of traits.

Though the variable-centered approach excels at pulling apart the most recognizable pieces of individual differences in personality pathology, it does a poor job of representing the holistic arrangement of these pieces, and the mechanisms driving pathology. The processes of interest in theories of personality pathology are necessarily processes *within* persons, not between persons. Moreover, while it may be possible to describe all people on all traits in dimensional terms, there may be certain 'natural types' or particular combinations of traits that are more commonly observed than others, or are present at rates higher than would be expected given random variation in trait levels. Specific combinations of traits may be especially predictive of certain outcomes as well, suggesting distinctive subgroups in terms of risk factors, course, or treatment response. Thus, the variable-centered approach elegantly resolves some problems by simplification, but also introduces other problems when it is called upon to support causal models of the etiology of personality pathology.

Person-centered Approaches

The shortcomings of variable-centered approaches call for person-centered analytic approaches. Person-centered methods aim to detect latent subgroups in the population that are defined by distinctive patterns of personality features. That is, these different subgroups are defined by characteristic response patterns for a set of observed variables that accounts for the interrelationships among the set of trait measures. The different response patterns or subtypes should then be associated with differences on other variables that are of etiological significance for personality pathology.

At the most basic level, person-centered approaches reduce heterogeneity by sorting members of a large group into smaller, more homogenous subgroups. Subtype classifications should ideally provide additional information relative to a trait taxonomy regarding (1) a description of important phenotypic characteristics and distinguishing features across subgroups, (2) prediction of important outcomes such as risk factors, course, and treatment response, and (3) information on etiological processes underlying personality pathology and membership in both the larger and smaller groups. Person-centered approaches should also identify personality subtypes that provide greater explanatory power than the sum of their constituent traits. In all, subtypes should help to provide insights into personality dynamics that emerge from certain combinations of traits, some of which may even seem contradictory (e.g., vulnerable narcissism, successful psychopathy).

Analytic Approaches to Identifying Subtypes

If subtypes exist, they should be present in existing datasets, and readily identifiable when using appropriate methods to detect them. The most common analytic methods used for this purpose are cluster analysis and finite mixture modeling, the latter of which tests the hypothesis that given a particular density function or distribution (e.g., multivariate normal), the observed data can best be accounted for by a mixture of populations (i.e., latent subgroups) that each account for a certain proportion of cases in the sample (Lubke & Miller, 2015; Steinley & Brusco, 2011). Notably, reducing heterogeneity by subgrouping is not the same as detecting naturally occurring clusters or latent subgroups. Simply setting a diagnostic threshold on a measure of personality pathology will reduce within-sample heterogeneity, but it does not typically result in clearly separated groups. Rather, naturally occurring clusters or latent subgroups should be both internally cohesive and externally isolated (Conrad, 1971).

Cluster Analysis

Traditional cluster analysis includes a wide variety of algorithmic methods that subgroup objects by calculating a similarity or distance metric (e.g., squared Euclidean distance) for each object in the data set (i.e., persons) and applying a computational procedure that is guided by a minimization criterion (e.g., to minimize the within-cluster variance). Cluster analyses will always subgroup objects when applied to a dataset, and objects are either members or non-members of a given cluster. In the strict sense, cluster analytic algorithms are computational rather than statistical methods; that is, they do not utilize distributional theory and so do not use likelihood based methods for hypothesis testing or assessing model fit. For this reason, traditional cluster analytic methods have declined in popularity in recent years.

Instead, researchers have increasingly turned to finite mixture modeling in the form of either model-based cluster analysis (MCA; Fraley & Raftery, 2002), or structural equation modeling approaches such as latent class analysis (LCA) and factor mixture modeling (FacMM). Most MCA models specify that the set of clustering variables have a multivariate normal distribution, though other distributions can be specified (e.g., binomial, Poisson; Fraley & Raftery, 2002). If latent subgroups are present, each subgroup will have its own distribution including a unique mean vector and covariance matrix. Properties of the covariance matrix (variances, eigen values, and eigen vectors) determine the size, the shape, and the orientation of the clusters in the multivariate space created by the clustering variables (see Figure 1 for examples). MCA studies usually entail fitting a series of models that differ in the number of clusters, and the structure of the within-cluster covariance matrix. MCA studies thus tend to take an exploratory approach, whereby a variety of models are tested and then compared on a statistic of model fit, with cluster assignment from the best fitting model used in further analysis.

MCA has a number of elegant statistical features, such as objective fit statistics and flexibility in defining the shapes of clusters. Few studies, however, have systematically demonstrated the superiority of MCA relative to traditional cluster analytic approaches. Steinley and Brusco (2011) found that although MCA outperformed traditional cluster analysis under some conditions, it underperformed under a number of other conditions. In fact, the most general MCA models performed particularly poorly, likely due to these more complex models capitalizing on chance variation. Results such as these illustrate that the use of a more complex statistical model does not guarantee better results in terms identifying the latent structure of a data set, and emphasizes the importance of other aspects of validating a subtyping scheme (e.g., criterion validity and consistency with theory) in addition to model fit.

Latent Class Analysis

Latent variable modeling approaches have also produced forms of finite mixture modeling, the original being LCA, which accounts for the covariance among categorical observed variables (e.g., responses to test or survey items) by identifying latent subgroups (Lazarsfeld, 1950). In LCA, the latent variable is an unobserved category or class, and the distinctive response pattern associated with each class accounts for individual differences in response patterns in the sample. Interpretation of the resulting classes is easiest when each class has a high response probability on only a subset of items and low response probability for all other items. For example, if a subgroup of persons in a sample assessed for all personality disorder criteria endorses only BPD symptoms with high probability and another group endorses only ASPD symptoms with high probability, the interpretation would be that the pattern of responses to the personality disorder criteria is due in part to distinct BPD and ASPD latent classes. The latent class model was later extended for continuous observed variables in the form of latent profile analysis (LPA; Lazarsfeld & Henry, 1968).

The key parameters of the LCA model are the class size (or proportion of the sample in each latent class), and the conditional response probabilities of each class, that is, the probability of item endorsement given a person's class membership (or the variable means for the latent subgroups in LPA). The number of classes is not a parameter of the model; rather the appropriate number of classes needed to best account for the observed data is determined by comparing the fit of alternative models, similar to MCA. A strength of LCA relative to MCA, however, is that covariates can be added to the model to predict class membership. Covariates such as demographic (age, gender) and substantive variables help define the latent subgroups analytically, as well as inform their psychological interpretation. Compared to MCA, LCA requires a larger sample ($N > 100$) to obtain good solutions and avoid various model fitting problems (Lo, Mendell, & Rubin, 2001; Ning & Finch, 2004), though including a covariate with a large effect size and a greater number of high quality indicator variables (i.e., have a high probability of endorsement in one class and low probability of endorsement in other classes) helps to mitigate these problems, at least for 2- and 3-class solutions (Wurpts & Geiser, 2014).

Importantly, LCA and LPA models assume local independence among the observed variables. In practical terms, this means that observed variables are uncorrelated within each class (i.e., each class has a diagonal covariance matrix). Originally, the assumption of local independence was the primary distinction between LCA/LPA and MCA, the latter of which did not include the local independence assumption, at least for its general models. The distinction is less relevant today, however, and LCA/LPA can be conceptualized as equivalent to certain MCA models, and more restrictive submodels of FacMM (see below; Steinley & Brusco, 2011).

Factor Mixture Modeling

More recently, hybrid models called FacMM have been developed that eliminate the assumption of local independence and effectively integrate LCA/LPA and Confirmatory Factor Analysis (CFA; Lubke & Muthen, 2005). This can be better appreciated by briefly reviewing the key elements of the CFA model (see Figure 2) wherein a latent trait or common factor (F) is hypothesized to account for the covariance among a set of observed variables (Y_1 to Y_n). Factors have a mean (α) and variance (σ or covariance matrix ψ in multifactor models) and are usually assumed to follow a normal distribution. Parameters called factor loadings (λ_1 to λ_n) index the strength of the associations between the latent trait and the observed variables. Mean-level information of the observed variables is represented by a set of intercept terms (τ_1 to τ_n , which are the mean values for each variable at a latent trait level of zero. Variation in the observed variables not accounted for by the latent factor is attributed to a set of residual terms (ε_1 to ε_n).

CFA is called a measurement model because it specifies the properties of the observed variables in terms of how well each measures the latent trait. Multiple-group CFA is a technique that has been used to test whether the measurement properties of the indicator variables differ across known groups (e.g., men and women; different racial, cultural, or nationality groups). These tests are called tests of *metric invariance*, and entail testing the equality of factor loadings, intercepts, and residual terms across groups (Meredith, 1993). If the observed variables function differently across groups in terms of their measurement of the latent trait, the factor scores have a different meaning (i.e., are on a different scale) across groups. For example, differences in factor loadings would indicate a particular symptom is a better measure of the latent trait in one group relative to another. Consequently, some degree of invariance in at least the factor loadings and intercepts across groups must be present to directly compare groups on factor means and variances (Widaman & Reise, 1997).

FacMM has been described as a multi-group CFA where group membership is unknown (Hallquist & Wright, 2014); rather, group membership is detected based on subgroup differences in the latent trait model, e.g., latent subgroups may differ in their factor means. In Figure 2 the latent subgroups or classes are represented by C, and a model can include 1 to K classes. Unlike LCA/LPA models, FacMM allow for within-class variability (i.e., members of the same class may differ on levels of the latent trait) that can be modeled using a CFA model, depicted by the second factor model in the figure. Therefore, FacMM provides a general model that can account for the interrelationships among observed variables as a function of both latent traits and latent classes, wherein CFA (latent trait model and no latent subgroups) and LCA/LPA (multiple latent subgroups with no latent trait model) are more restrictive submodels.

Which Analytic Model?

One challenge that comes with the flexibility of FacMM is that there are a multitude of potential models to fit, and so there is a danger of overfitting the model to the idiosyncrasies of the sample (Hallquist & Wright, 2014). If a researcher wants to identify a best fitting FacMM, their efforts should be driven by a strong theoretical rationale to test only a subset of models. MCA deals with this problem by taking a relatively atheoretical or empirical approach to model fitting by selecting the best fitting model and then examining cluster differences on validation variables not used in the MCA. This difference in approach is somewhat attributable to the different intellectual traditions of the two analytic methods. FacMM evolved from the latent variable and psychometric approach that emphasizes testing specific hypotheses about the link between the latent and indicator variables. Such models are most appropriate when there are relatively strong correlations among observed variables that are all indicators of a common latent trait. In contrast, MCA evolved from the statistical approach of attempting to identify subgroups, often using clustering variables that have small to medium correlations. In such cases there is less of a need to model the covariance structure because it is unlikely to be accounted for by a common factor.

Therefore, FacMM is most appropriate when indicator variables have relatively high correlations consistent with a latent trait(s) (e.g., item or symptom-level data), but with the possibility that latent subgroups may account for additional heterogeneity, perhaps due to differences in latent trait levels (i.e., factor means) or a lack of metric invariance across subgroups. MCA and LCA/LPA are more appropriate when the cluster variables have relatively low correlations and measure different constructs (e.g., different lower-order trait constructs) indicative of distinct configural patterns of personality pathology. In some circumstances, LCA/LPA will identify latent classes that differ quantitatively (e.g., low, medium, and high groups) rather than qualitatively in terms of personality structure. This is likely to be the case when the clustering variables have relatively high correlations, similar content, and the assumption of local independence is violated, which can lead to an overextraction of latent classes to improve model fit (Hallquist & Wright, 2014). In such cases, it is most appropriate to compare model fit with alternatives that include a latent trait model either a dimensional CFA or a hybrid FacMM.

When using latent variable approaches to identify subtypes, Hallquist and Wright (2014) recommend first fitting a dimensional CFA model, followed by a categorical LCA/LPA model. If there is evidence for potential latent subgroups either due to the nonnormal distribution of a latent trait or qualitatively distinct response patterns, then one should proceed to fit a limited number of *theoretically driven* FacMMs. For MCA, a researcher may simply follow an empirical approach to identify the best fitting model. If the best fitting includes an orientation parameter then they may follow-up with a limited number of theoretically informed FacMMs to attempt to gain a greater understanding of the psychological interpretations of the resulting clusters.

Other Methodological Considerations as Illustrated with Psychopathy Subtypes

In addition to the choice of analytic approach, there are several other methodological considerations when attempting to identify subtypes or latent subgroups of personality pathology. These considerations will be strongly driven by the theory and content domain, that is, the symptoms and other important features of the specific construct. To help illustrate these points, we refer to the example of psychopathy subtypes.

First proposed by Karpman (1941) and since elaborated on by others (Hicks & Drislane, in press; Lykken, 1995; Skeem et al., 2003; Yildirim & Derksen, 2015), the primary and secondary psychopathy classification attempts to distinguish among persons who engage in high-levels of antisocial behavior. Primary psychopathy was conceptualized as a predominately inherited affective deficit that precludes the development of close attachments and social emotions such as empathy and guilt, as well as diminished internally focused negative emotions such as anxiety. Consequently, their antisocial behavior was viewed as predatory and calculating with a fundamental callousness towards others. In contrast, secondary psychopathy was conceptualized as the result of an affective disturbance; that is, though they may have inherited the ability to form emotional attachments with others, this ability has been compromised, for example, as a result of environmental deprivation such as child maltreatment (Porter, 1996). Rather than being cold and calculating, antisocial behavior associated with secondary psychopathy is a function of a failure to appropriately modulate intense negative emotional reactions. In personality trait terms, secondary psychopathy is characterized by high levels of anger, aggression, anxiety, and impulsivity.

Empirical studies on psychopathy subtypes have steadily accumulated over the past 20 years. Hicks and Drislane (in press) recently reviewed this literature and found that 20 out of 24 germane studies identified psychopathy subgroups consistent with conceptualizations of primary and secondary subtypes. Importantly, these subgroups were identified with a variety of different analytic approaches (traditional cluster analytic methods, MCA, LCA, LPA), clustering variables, sampling strategies (community, prisoner samples), and participant characteristics (nationality, age, and sex). In terms of their basic validity for identifying subgroups of highly psychopathic individuals, meta-analytic results found that relative to non-psychopathic control groups, the primary and secondary psychopathy subtypes identified in these studies scored more than 2.5 SDs higher on global measures of psychopathy. That is, these studies identified groups of people that could be reasonably classified as psychopaths. Below, we discuss how lessons learned from investigations on psychopathy subtypes might inform future person-centered research on personality pathology.

How Many Subtypes?

While an empirically driven approach to identifying subtypes of personality pathology can be justified, the process is greatly aided by a sound theory by which to interpret resulting clusters or latent subgroups. Clinical conceptualizations can serve as an initial step in theory building as keen observers can often recognize patterns indicative of different personality structure and correlates that are of potential etiological significance. A more systematic approach, however, is to review the empirical literature on the psychometric structure of the content domain for the construct of interest. *Content domain* refers to not only the symptoms for a certain personality disorder, but also other affiliated attributes associated with a domain of personality pathology more broadly defined. Given that the goal of both variable-centered and person-centered approaches is to parse heterogeneity and identify the major dimensions of systematic covariation, evidence of multiple latent traits within the content domain of the construct suggests the possibility of latent subgroups.

Psychopathy provides an especially illustrative example. The Psychopathy Checklist-Revised (PCL-R; Hare, 2002) is an interview and file review designed to assess psychopathy in prisoner and forensic samples, and is the most widely used instrument for that purpose. Though its authors originally conceptualized psychopathy as a unitary construct (Hare, 1980), factor analyses consistently found that the PCL-R items cohere around two broad factors (Harpur et al., 1988) that can be further bifurcated into four facet scales. Factor 1 encompasses the interpersonal and affective facets, and Factor 2 includes the impulsive and chronically unstable lifestyle and antisocial behavior facets (Hare & Neumann, 2006).

Though Factor 1 and Factor 2 typically have a correlation of 0.5, they exhibit a distinctive pattern of external correlates—sometimes in opposing directions—that are reminiscent of the clinical descriptions of primary and secondary psychopathy, respectively. Factor 2 is positively associated with all facets of negative emotionality (anxiety, distress, depression, anger, aggression), impulsivity, substance use disorders, history of suicide attempts, and environmental risk factors, consistent with descriptions of secondary psychopathy (Blonigen et al., 2010; Harpur et al., 1988; Hicks & Patrick, 2006; Patrick, 1994; Smith & Newman, 1990; Verona et al., 2001, 2005). In contrast, Factor 1 is positively associated with dominance and narcissism, negatively related to most facets of negative emotionality, and exhibits small to negligible associations with impulsivity and anger-aggression, substance use problems, and environmental risk, though many of these associations are only clearly evident after controlling for the variance in Factor 1 that overlaps with Factor 2 (Blonigen et al., 2010; Harpur et al., 1988; Hicks & Patrick, 2006; Patrick, 1994; Smith & Newman, 1990; Verona et al., 2001, 2005). This is because Factor 1 and Factor 2 exhibit co-operative suppressor effects—the situation wherein the association between a predictor and criterion variable increases after adjusting for the variance shared with another predictor variable—though in opposite directions for certain outcomes, especially measure of neuroticism or trait anxiety. The finding of cooperative suppressor effects between correlated measures each designed to assess different features of the same overarching construct suggests the presence of the subgroups high in overall psychopathy (i.e., both Factor 1 and Factor 2) that can be differentiated on the criterion variable. That is, it should be possible to distinguish subgroups of high PCL-R scorers (i.e., psychopaths) on the basis of neuroticism.

A similar approach could be used to develop theories of subtypes for different domains of personality pathology. For example, if a researcher was interested in identifying subgroups across the domain of personality pathology writ large, a reasonable initial hypothesis would be 4 to 5 subtypes consistent with the number of high-order factors identified in several trait taxonomies of personality pathology. Examining the pattern of correlates for the traits especially instances of suppressor or interaction effects could help to refine these hypotheses. Again, this merely provides a starting point for hypothesis generation and a framework for interpreting potential subgroups.

Clustering Variables

Ultimately, however, the results of a person-centered analysis will be dependent upon the sampling strategy and the clustering variables used to characterize and potentially disaggregate the sample. The role of clustering variables is crucial for establishing the boundaries of the clusters or latent subgroups. (For the purpose of the discussion on clustering variables, the term "clusters" and "latent subgroups" are used interchangeably as are the terms "clustering", "observed", and "indicator" variables.) Specifically, the within-cluster means for clustering variables form the center of the cluster, while the variances and covariances of the variables determine the size and shape of the clusters. Therefore, to achieve good cluster separation, the clustering variables should exhibit large mean-level differences across clusters. Further, within-cluster variance should be low, but there should be high variance across the full sample to achieve a high ratio of within-to-between cluster variance.

Because the variance of clustering variables has such a large effect on cluster structure, it has long been recommended that variables should be standardized prior to clustering—most typically using z-scores for continuous variables—so that the final cluster solution is not unduly influenced by spurious factors such as scaling differences. However, standardizations such as z-scores that result in all variables having equal variance are problematic, because they remove between-cluster variance necessary to determine cluster boundaries. This is further complicated by the fact that clustering variables do not contribute equally to defining cluster structure. In fact, variables that contribute little or no clustering information can "mask" or hinder an analytic method's ability to uncover the underlying cluster structure. To avoid these pitfalls, Steinley and Brusco (2008) recommended a scaling procedure that uses the range and variance to put all variables on the same scale while retaining variance information, so that variables are weighted in terms of their relative contributions to cluster structure.

How then does one identify clustering variables that will have large mean-level differences across clusters and a high ratio of within-to-between cluster variance? Theory is again an indispensable aid as putative etiological variables can serve as initial step for theory testing. Researchers can also refer to the correlates of variable-centered measures of the content domain of interest. Specifically, we recommend using variables that exhibit the largest *differences* in their associations with facet measures of the target personality pathology, as differences in external correlates may be a signal for subgroups. We also note that symptom measures will sometimes not serve as the best clustering variables *depending on the base rate of the disorder* in the sample as symptom measures often identify the common features about a form of personality pathology. For example, as part of their meta-analysis, Hicks and Drislane (in press) found that primary psychopathy subtypes had higher PCL-R total and Factor 1 scores and secondary psychopaths had higher Factor 2 scores, but all of these effects were small (all Cohen's $d < 0.30$). Instead, non-symptom measures that index other attributes of the construct's content domain or its broader nomological network may be more sensitive to differences among subgroups. For example, Hicks and Drislane (in press) calculated meta-analytic effects for subtype differences on four personality constructs and found psychopathy subtypes were most consistently distinguished by measures of neuroticism ($d = 1.28$; primary < secondary) followed by anger/aggression ($d = 0.75$; secondary > primary), extraversion ($d = 0.70$; primary > secondary), and disinhibition ($d = 0.60$; secondary > primary).

Sampling Strategy

The impact of the clustering variables on identifying potential subtypes is inherently linked to the sampling strategy. Specifically, it is important to know the base-rate or mean-level of the type of personality pathology that is the focus of study (Lubke & Miller, 2015). This is because person-centered approaches will identify subgroups that are defined by those variables that account for the most variability across the sample.

For example, the base-rate of psychopathy is low in unselected community samples; therefore, differentiating psychopathy subtypes is difficult because the differences between psychopathic and non-psychopathic individuals are much larger than the differences within the group of high psychopathic individuals. Consequently, it might be necessary to use a screening measure to identify a subsample of individuals elevated on psychopathy in order to identify subtypes. Alternatively, samples that have relatively high-base rates of both high and low psychopathy individuals –such as unselected prisoner samples—are likely to identify subgroups in addition to primary and secondary psychopathy (Poythress et al., 2010; Swogger et al., 2008; Swogger & Kosson, 2007; Vassileva et al., 2005). In samples composed entirely of individuals with a high level of psychopathy, the variance of psychopathy facet variables will be somewhat restricted and less useful for defining clusters. Instead, other variables that exhibit large differences in their associations with different psychopathy facet measures will account for more variability and so will be better able to define cluster structure. These key sample characteristics should be considered when deciding on a sampling strategy to investigate a different form of personality pathology to anticipate the number of subgroups and inform their interpretation.

External Validation and Replication

Once clusters have been identified, it is then necessary to validate the clusters in terms of meaningful differences on variables not used to define the cluster structure. Differences should be evident on theoretically relevant criterion variables, for example, measures that index putative etiological processes or variables of clinical importance such as risk for violence or suicide. Interpretations of group differences and defining features are also greatly improved if a control group low on personality pathology or another group representing a theoretically distinct form of psychopathology is available for comparison.

To illustrate, both the primary and secondary psychopathy subtypes exhibit a more severe pattern of antisocial behavior relative to low psychopathic control groups (Drislane et al., 2014; Hicks, et al., 2010; Swogger & Kosson, 2007; Swogger et al., 2008; Vassileva et al., 2005). In terms of personality, Hicks and Drislane (in press) conducted meta-analytic comparisons with control groups, and found that the secondary subtype scored higher on anger/aggression ($d = 1.37$), neuroticism ($d = 0.72$), and disinhibition ($d = 0.49$), and lower on extraversion ($d = -0.30$). In contrast, the primary subtype scored slightly lower on neuroticism ($d = -0.33$), and higher on anger/aggression ($d = 0.54$) and disinhibition ($d = 0.24$) than the control groups. These results indicate that the primary variant had relatively modest deviations on measures of normal range personality traits despite their extreme antisocial deviance and psychopathic traits, while the secondary variant had a personality structure consistent with poor functioning and persistent criminal behavior (Moffitt et al., 1996).

Primary and secondary psychopathy subtypes also exhibit several differences relative to each other. Primary psychopathy is consistently associated with fewer internalizing problems (Drislane et al., 2014; Falkenbach et al., 2014; Hicks et al., 2004; Kahn et al., 2013; Kimonis et al., 2011; Lee & Salekin, 2010; Poythress et al., 2010; Swogger & Kosson, 2007; Swogger et al., 2008). Secondary psychopathy on the other hand is associated with elevated levels of both internalizing (Blackburn et al., 2008; Cox et al., 2013; Hicks et al., 2004; Poythress et al., 2010) and externalizing problems including more severe substance use problems (Claes et al., 2014; Hicks et al., 2004, 2010; Kimonis et al., 2012b; Magyar et al., 2011; Swogger & Kosson, 2007; Swogger et al., 2008; Vassileva et al., 2005; Vaughn et al., 2009). Secondary psychopathy is also associated with having experienced child maltreatment and other traumatic events as well as symptoms of PTSD (Blackburn et al., 2008; Kahn et al., 2013; Kimonis et al., 2011, 2012a; Poythress et al., 2010; Vaughn et al., 2009).

Primary and secondary psychopathy subtypes also differ on important clinical outcomes. Secondary psychopathy is associated with a higher incidence of institutional infractions in incarcerated offenders, particularly involving impulsive or reactive aggression (Cox et al., 2013; Hicks et al., 2010; Kimonis et al., 2011; Poythress et al., 2010). Nevertheless, there is also evidence that the secondary subtype is associated with greater treatment motivation (Poythress et al., 2010) and treatment change (Olvet et al., 2015) than the primary subtype, with higher likelihood of receiving mental health treatment (Hicks et al., 2010; Vaughn et al., 2009).

Finally, replicating the cluster structure identified in a dataset is fundamental to establishing that the clusters are naturally occurring subtypes that represent meaningful patterns of psychological differences. In the context of replication, examination of potential moderating variables such as age, gender, and race/ethnicity can provide further clues to the nature of subtype differences.

Summary and Conclusion

We have reviewed the rationale and utility of person-centered approaches relative to variable centered approaches in the study of personality disorders. In basic terms, person-centered approaches are better suited to identify patterns indicative of configural effects on personality pathology. That is, a particular configuration of maladaptive personality traits may represent a natural type that provides more information relevant to key scientific questions than traits alone. There are several analytic methods available to identify such configurations, the strengths and weaknesses of which were briefly reviewed above.

Our purpose was not to suggest the superiority of one technique over the other or that person-centered approaches should be preferred to variable-centered approaches. Rather, person-centered and variable-centered methods should complement one another to further the understanding of personality pathology. Variable-centered approaches are crucial to mapping out the psychometric space of a content domain that can then be subsequently examined for distinct configural patterns. The kinds of questions one can answer with each approach are different, and therefore they are not competing for the same scientific space. Therefore, we specifically do not emphasize the use and comparison of these different methods to ‘uncover’ the latent structure of personality pathology. We find making strong claims that personality pathology is either dimensional or categorical “in nature” as beyond the scope of the kinds of data that are commonly collected and the appropriate inferences for the models available for evaluating data against hypotheses. Further, these claims represent a level of abstraction that is not especially helpful and is potentially distracting from the more generative goals of furthering our understanding of etiology and improving prediction of important outcomes.

Rather, the models we discuss help to provide a framework for iterative theory building and hypothesis testing, but should not be considered an end unto themselves. Fitting models to data is an important part of investigating many scientific questions, but an exclusive focus on the relative fit of different models ignores the reality that this activity is a small part of the overall scientific agenda. A better understanding of personality pathology will also involve accessing populations of interest, collecting rich data using multiple methods, and clever approaches to study design that allow for a sharper identification of processes of interest, and theoretical work that translates the complexity of clinical presentation into manageable constructs that can be employed in this work. Person-centered approaches can facilitate this process when used alongside variable-centered approaches in datasets and designs that test clearly articulated hypotheses about the causes and outcomes of personality pathology. Diversity of thought and approach to this field will be important to preventing reification that can occur when a limited number of approaches or analytic methods are given undue weight.

We illustrated several points using examples from the psychopathy literature. We note that there is now substantial evidence indicating that especially antisocial individuals can be meaningful subgrouped into primary and secondary variants that differ in their personality structure, and that these variants are associated with several other outcomes (Hicks & Drislane, in press; Yildirim & Derksen, 2015). These patterns of findings cannot be explained by reference to quantity (i.e., levels of traits), but can be accounted for by a configural pattern of traits that is difficult to detect without a person-centered approach.

Consequently, findings generated using the person-centered approach have contributed to theory building and resolving inconsistencies between theory and empirical findings. We think this can serve as a model for future investigations into personality pathology that could benefit from person-centered approaches. Of course, the fact that particular trait configurations are important for understanding heterogeneity in etiology and outcomes in psychopathy does not necessarily indicate that the same configural forms or similar correlates with also be discovered for other forms of personality pathology. Rather, they demonstrate that we cannot predict from the basis of evidence generated yielded from variable-centered approaches what one might find using a person-centered approach. The potential for new observations that could shift the field in creative ways is an important argument for exploring these approaches.

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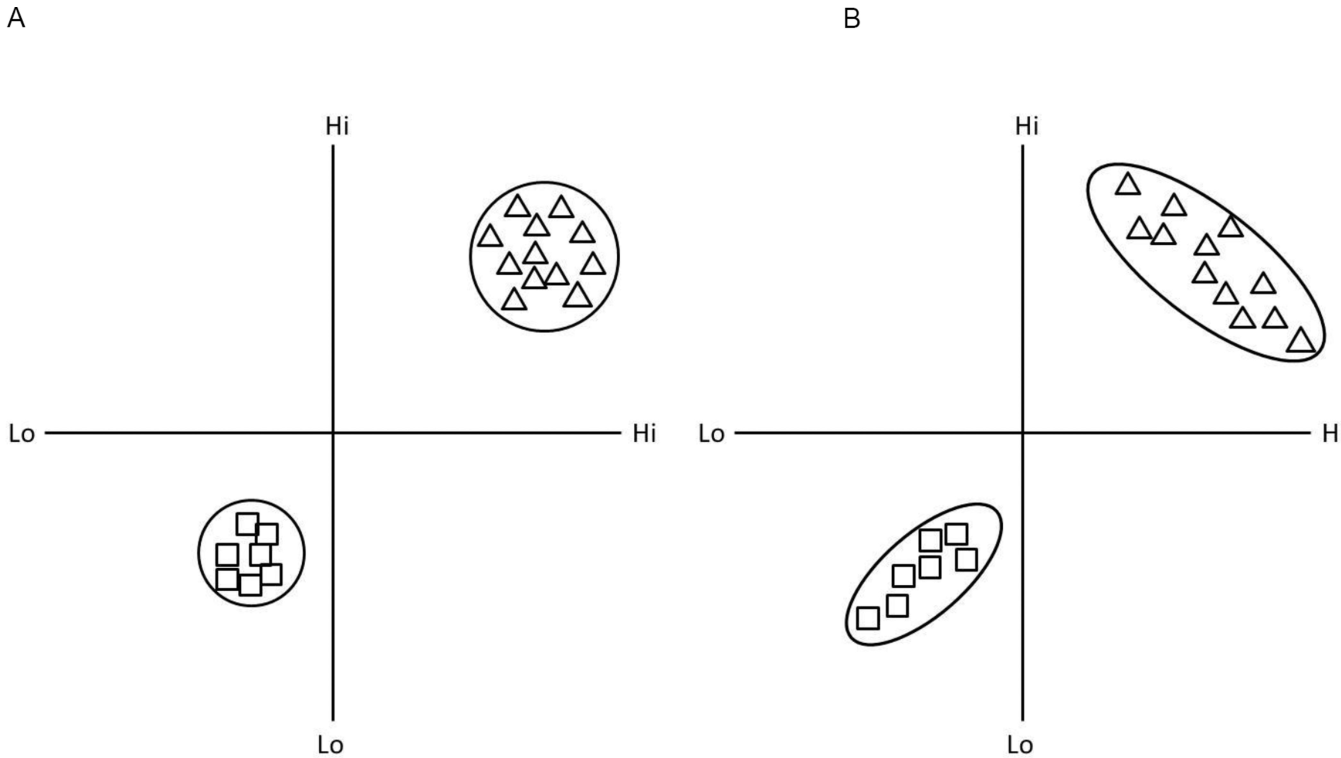

Figure 1.
The two panels illustrate the cluster properties of size, shape, and orientation using simple hypothetical examples of two clusters that are distinguished on two clustering variables. The two clustering variables intersect at their mean values; therefore, one cluster has low scores on both clustering variables while the other cluster has high scores on both. Panel A depicts the scenario of two clusters that differ in size or volume but have the same shape, specifically, a spherical shape. The spherical shape is due to the two clustering variables being uncorrelated within each cluster. Panel B depicts the scenario of two clusters that differ in size and orientation, but have the same shape. Because a correlation is present between the clustering variables within each cluster (negative correlation within the larger cluster, positive correlation within the smaller cluster), these clusters have an elliptical shape and the property of orientation (not present for spherical clusters).

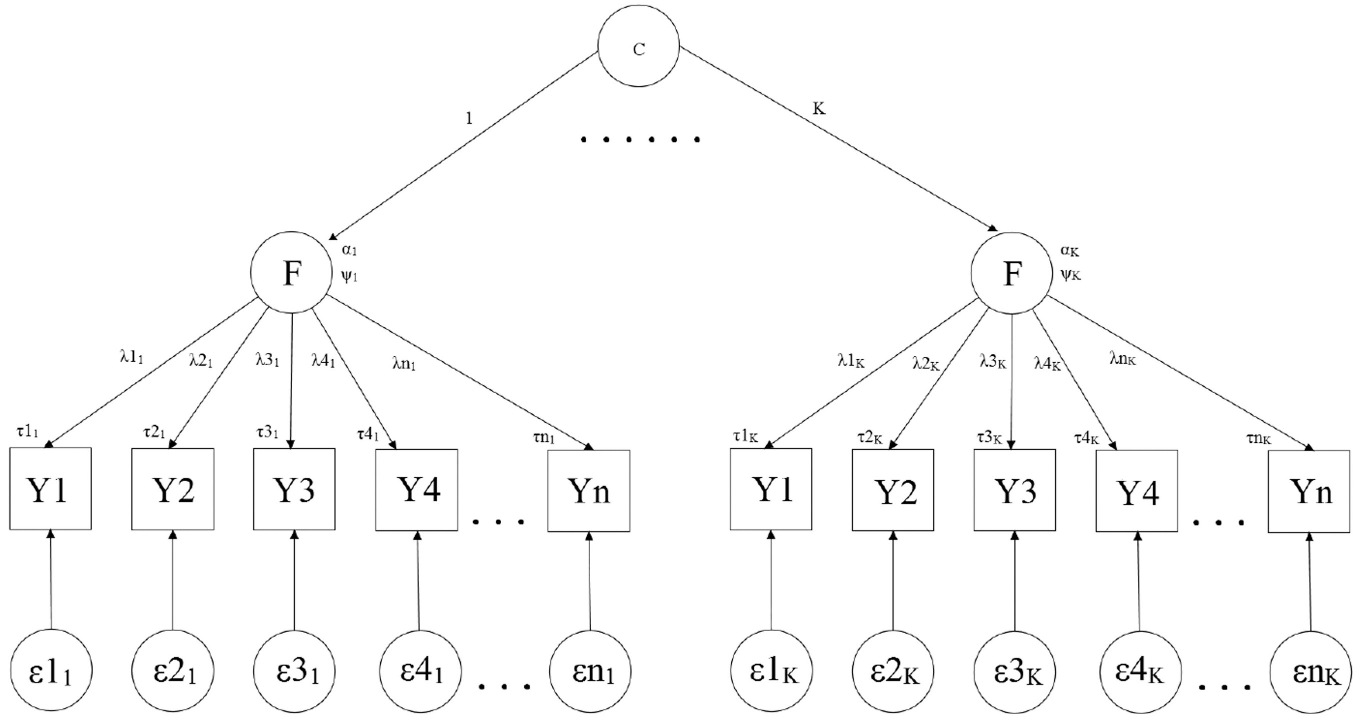

Figure 2.

Path diagram of a factor mixture model. The model includes a standard confirmatory factor model wherein a latent factor (F) accounts for the covariance among a set of observed variables (Y_1 to Y_n). The latent factor has a mean (α) and variance (σ), and in the case of models with multiple latent factors, a covariance with other latent factors (matrix Ψ). Scores on the observed variables are linked to the latent factor by a set of factor loadings (λ_1 to λ_n). A set of intercept terms (τ_1 to τ_n) models the mean structure of the observed variables, and a set of residual terms (ε_1 to ε_n) models the variance in the observed variables not accounted for by the latent factor. The factor mixture models can further model the presence of latent subgroups or classes represented by C, with 1 to K classes in the model (class is represented by the second subscript number for the factor loadings, intercepts, and residual terms). C is not a parameter that is estimated in the model; rather, the number of classes is specified by the user. Each class then has a latent factor structure, and parameters of the latent factor model can either be constrained or allowed to vary across classes.