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INVITED COMMENTARY

CATEGORIES OR DIMENSIONS: LESSONS LEARNED FROM A TAXOMETRIC ANALYSIS OF ADULT ATTACHMENT INTERVIEW DATA

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ABSTRACT Booth-LaForce and Roisman's monograph on the Adult Attachment Interview (AAI) featured a taxometric analysis to determine whether variation along two components, dismissing and preoccupied states of mind, was categorical or dimensional. Empirically evaluating the latent structure of these constructs helps to avoid spurious categories or dimensions. This benefits researchers working with measures of adult attachment to maintain as much predictive validity and statistical power as possible, and it benefits researchers who build or test theories of adult attachment by steering the search for causal factors in fruitful directions. Fraley and Roisman (Chapter 3, this volume) performed their taxometric performed their taxometric analyses in an exemplary fashion, adhering carefully to empirically supported, practical guidelines. They adopted an appropriate inferential framework for their taxometric results that pits two competing structural models against one another. They were willing to accept that the taxometric results for preoccupied states of mind were ambiguous and they tentatively advocated a dimensional measure on the grounds that, even if this was not the best representation, using a spurious dimension might do less harm than using spurious categories. Rather than embracing a general preference for categories or for dimensions, researchers should evaluate the pros and cons of each potential structure-measurement mismatch on a case-by-case basis.

Together with the many collaborators who contributed to one or more of the chapters in their monograph, Booth-LaForce and Roisman presented a broad range of analyses of a large sample of data ($N = 857$) from the Adult

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Attachment Interview (AAI). Part 1 included two chapters that examined fundamental psychometric issues. First, Haltigan, Roisman, and Haydon (Chapter 2) addressed the question of whether adult attachment is best represented as a unitary construct, with individuals classified into one of three mutually exclusive categories (secure-autonomous, dismissing, or preoccupied), or whether it is best represented using two components, with individuals varying relatively independently along these components (dismissing and preoccupied states of mind). They performed factor analyses of AAI data and obtained evidence favoring the latter model. Second, Fraley and Roisman (Chapter 3) pursued the follow-up question of whether variation along these components is categorical or dimensional in nature. They employed Meehl's (1995) taxometric method and obtained evidence suggesting that both components are best represented dimensionally.

In this comment, I focus on Fraley and Roisman's (Chapter 3) exemplary application of taxometric analysis, which helped pave the way for the many subsequent explorations of the stability, change, and developmental origins of adult attachment in Part 2 of the monograph. The fact that Fraley and Roisman were willing and able to perform taxometric analyses to tease apart categorical and dimensional structural models, the effectiveness with which they applied taxometric methodology, and the reasonableness of the conclusions that they drew from the taxometric results are all laudable aspects of their investigation. In what follows, I review these three areas of strength and expand on some of the points that the authors raised along the way.

ADDRESSING LATENT STRUCTURE EMPIRICALLY

Incorporating a taxometric analysis into the program of research on the AAI is a model to follow. The taxometric method is neither the beginning nor the end of a research endeavor. Rather, it complements other data-analytic tools in a program of research on the latent structure of a target construct (Ruscio & Ruscio, 2004), which in turn lays the groundwork for subsequent theoretical and empirical research. Fraley and Roisman (Chapter 3) astutely noted that the factor-analytic findings of Haltigan et al. (Chapter 2) were ambiguous with regard to the categorical versus dimensional nature of variation along the two components of dismissing and preoccupied states of mind. The taxometric method was a well-chosen follow-up technique to help determine whether individuals differ in categorical or dimensional ways. More investigators would be wise to examine this issue empirically rather than take for granted that their preferred conceptualization, whether categorical or dimensional, is appropriate. An inappropriate presumption can carry substantial costs.

As Fraley and Roisman argue, using categorical measures of dimensional constructs can reduce predictive validity, underestimate stability, and weaken statistical power. Their arguments draw from and extend the earlier cases made by Fraley and Waller (1998) and Fraley and Spieker (2003). Both of these sources spoke specifically to issues in the domain of infant and adult attachment research, though the important points they make are more broadly applicable. It's worth adding that the mistake of using a categorical measure of a dimensional construct might also reify a spurious classification, lead to improperly specified theoretical models, or prompt searches for the wrong kinds of causal factors (Meehl, 1992; Ruscio, Haslam, & Ruscio, 2006). For example, adopting a categorical framework for adult attachment patterns despite their apparently dimensional variation might mislead readers into assuming that these categories exist in some theoretically meaningful sense, rather than merely serving as shorthand for endpoints along one or more latent dimensions. Likewise, investigators might undertake a search for the causes of bifurcation into categories when no such causes exist because individuals do not in fact divide themselves into categories. The types of causal models most consistent with dimensional structure tend to involve the sum of many small influences (e.g., additive genetic or environmental factors).

On the other hand, Fraley and Roisman also noted that for categorical constructs, the taxometric method can help to estimate base rates (i.e., relative group sizes) and improve assessment. Here, too, it's worth adding that there may be implications of a structural mismatch for building and testing theoretical models. Using a dimensional measure of a categorical construct may throw investigators off the trail of causes of bifurcation into categories. The types of causal models most consistent with categorical structure tend to involve dichotomous causal factors (e.g., a single gene or environmental influence necessary and sufficient to produce category membership), cumulative or interactive effects (e.g., neither a genetic predisposition nor an environmental influence is necessary to produce category membership, but they are jointly sufficient to do so), or threshold effects (e.g., an environmental factor has little influence up to a point, but beyond this level it bumps individuals into a new category).

Because either type of mismatch can have serious consequences for theory, research, or practice, investigators would be well-advised to evaluate the latent structure of target constructs empirically (Ruscio & Ruscio, 2002). Though there are many data-analytic procedures that relate observable, measured variables to unobservable, latent constructs, relatively few of these are useful as tests of whether a construct is best represented categorically or dimensionally. As Fraley and Roisman state, there is an important difference between structure-imposing techniques and structure-uncovering techniques. For example, cluster-analytic algorithms will always identify categories because the methodology presumes categorical variation. Though this can be useful for any number of other research purposes, cluster analysis does not afford very useful tests between categorical and dimensional structural models. This is an obvious case of a structure-imposing technique.

On the other hand, some techniques are misunderstood as imposing structure when in fact they do no such thing. Factor analysis, as Fraley and Roisman correctly note, can be used to determine the number of latent factors along which individuals differ, but it is a mistake to equate these factors with dimensions. Rather, variation along any specific factor can be categorical or dimensional in nature (Waller & Meehl, 1998).

Paul Meehl developed his taxometric method expressly to make the distinction between categories and dimensions (Meehl, 1995), and a wealth of research supports its utility under a wide range of data conditions (for an overview, see Ruscio, Ruscio, & Carney, 2011). McGrath and Walters (2012) described Meehl's taxometric method as a general-purpose tool for differentiating between categorical and dimensional structural models. Though there are other latent variable modeling techniques designed to achieve the same goal (e.g., factor mixture models), it is presently unknown whether any of these methods performs as well or better under comparable data conditions. Likewise, it is unknown whether other methods might perform well under data conditions unsuitable for taxometric analysis. Thus, it would be premature to conclude that Meehl's taxometric method is the only reasonable data-analytic choice one could make when attempting to tease apart categorical and dimensional structural models. It can, however, be considered a strong contender, backed by substantial theoretical and empirical support when its data requirements are satisfied (Ruscio et al., 2011).

Given the strong track record of taxometric analyses in simulation studies, it remains disappointing to observe how few important constructs in the social and behavioral sciences have been studied using this method. Nick Haslam and his colleagues have reviewed taxometric studies a number of times (e.g., Haslam, 2003, 2007, 2011; Haslam & Kim, 2002), including a quantitative review which showed that how the taxometric method is implemented can affect the conclusions researchers draw from the results (Haslam, Holland, & Kuppens, 2012), a subject that will be revisited shortly. Each of these reviews of taxometric research sheds light on the constructs that have been studied, the methods that have been used to do so, and trends in the conclusions that researchers have reached. Perhaps most striking of all is what is missing from these reviews: the large number of constructs that have not (yet) been studied taxometrically.

Even with the understanding that taxometric analysis is by no means the only way to differentiate between categorical and dimensional structures, theory and research in many, perhaps most, realms of social and behavioral science appears to operate on the presumption that important constructs are structured one way or the other without subjecting these presumptions to rigorous tests. Thus, an unusual and salient strength of the Booth-LaForce and Roisman monograph is that they included a taxometric analysis in the psychometric stage of the research. Providing empirical support for the dimensional structure of measures constructed using AAI data places all the subsequent chapters, and their data analyses in particular, on a more solid psychometric foundation.

APPLICATION OF TAXOMETRIC METHODOLOGY

Just as the AAI monograph deserves credit for including a chapter on taxometric analysis, that analysis itself was performed in an exemplary manner by Fraley and Roisman. They described their methodology clearly and concisely, perhaps so much so that readers unfamiliar with taxometric analysis might fail to appreciate that it confronts researchers with many potentially important decision points. Ruscio et al. (2011) spelled these out and summarized the available research that can help researchers make smart choices. Though Fraley and Roisman did not cite this particular source, the fact that they carefully followed empirically supported, practical guidelines for implementing the taxometric method demonstrates their attention to the relevant literature.

Fraley and Roisman performed three taxometric procedures: MAXCOV (MAXimum COVariance; Meehl & Yonce, 1996), MAMBAC (Mean Above Minus Below A Cut; Meehl & Yonce, 1994), and L-Mode (Latent Mode; Waller & Meehl, 1998). These are well chosen as complements to one another because they analyze the data in distinct ways. By doing so, they provide nonredundant checks on the consistency of results. This constitutes a cornerstone of the taxometric method, Meehl's (1995) emphasis on "consistency tests" rather than tests of statistical significance. Fraley and Roisman not only performed three distinct procedures to examine the consistency of the results, they implemented each one in ways supported by the results of simulation studies. For example, whereas earlier taxometric studies often performed the MAXCOV procedure by dividing the sample of cases into ordered subsamples that did not overlap with one another (intervals), research suggests that MAXCOV yields more informative results when cases are divided into ordered subsamples that do in fact overlap substantially with one another (sliding windows). Waller and Meehl (1998) introduced this innovation along with the MAXEIG (MAXimum EIGenvalue) procedure, which is a multivariate generalization of MAXCOV. Sliding windows can be used just as profitably with the MAXCOV procedure (Walters & Ruscio, 2010), and Fraley and Roisman took advantage of this technique.

Perhaps the most important implementation decision that Fraley and Roisman made was to incorporate parallel analyses of categorical and dimensional comparison data. These data are generated in ways that reproduce the observed distributions and correlations of the research data, but starting from two different structural models (categorical and dimensional). Parallel analyses of these comparison data provide a baseline for interpreting the results for the research data that is tailored to these unique data conditions (Ruscio, Ruscio, & Meron, 2007). For example, positively skewed dimensional data can yield taxometric results that are easily misinterpreted as evidence of categorical structure (Ruscio & Marcus, 2007). Because skewed data are common (Micceri, 1989), so are potentially misleading taxometric results. The parallel analysis of comparably skewed comparison data can help to determine whether the results for the research data actually correspond more closely to those for the categorical or the dimensional comparison data (Ruscio & Marcus, 2007).

When parallel analyses of comparison data are performed, this also allows the calculation of the Comparison Curve Fit Index (CCFI; Ruscio et al., 2007). The CCFI quantifies how closely the results for the research data map onto those for the categorical and the dimensional comparison data. CCFI values can range from 0, representing the strongest support for dimensional structure, to 1, representing the strongest support for categorical structure. Values close to .5 are ambiguous. Haslam et al. (2012, p. 911) described "the analysis of simulated comparison data and the use of the CCFI" as "the most important historical development in taxometric practice." They noted that across 177 taxometric studies with 311 distinct structural findings, use of the CCFI is strongly correlated with other indices of methodological quality and reduces the likelihood of reaching categorical conclusions. This is consistent with speculation that, absent the more appropriate interpretational baseline provided by parallel analyses of comparison data, skewed data can easily lead to mistaken inferences of categorical structure.

Fraley and Roisman incorporated comparison data into all taxometric analyses and calculated the CCFI for each taxometric procedure (MAXCOV, MAMBAC, and L-Mode) as an objective decision aid to supplement their visual inspection of the taxometric curves. Each of their figures shows the taxometric results for one set of indicators, with the results for each procedure plotted in a way that affords an easy visual inspection against the baseline results for the comparison data. The CCFI values are presented in the text and summarized in a table. In this way, Fraley and Roisman examined the consistency of results in an open, comprehensive, and rigorous manner.

Before closing this section, one very minor criticism of Fraley and Roisman's taxometric analysis should be noted: They provided estimates of the taxon base rate, or the size of the higher-scoring of the two putative groups in a categorical model. These estimates would have been informative if the authors had concluded that one or more of the AAI factors was in fact categorical. These estimates do not correspond to any parameters in a dimensional structural model, though, so it's not clear why they were presented. There has been considerable speculation in the taxometric literature that taxon base rate estimates might be helpful as a kind of consistency test (e.g., Meehl, 1995). The idea is that these estimates should cohere around a single value if in fact a taxon exists, but not otherwise (i.e., not if the structure is dimensional rather than categorical). Plausible as this may seem, simulation studies have not supported the utility of such a base-rate consistency test (Ruscio, 2007; Ruscio et al., 2006). No particular threshold has been supported for differentiating the degree of consistency of taxon base rate estimates one would expect for categorical as opposed to dimensional data. The fundamental problem is that under many data conditions, taxon base rate estimates can be extremely consistent even for dimensional data. Providing taxon base rate estimates for constructs judged to be dimensional, though not a serious flaw in any event, is arguably the most questionable choice that Fraley and Roisman made when implementing the taxometric method and reporting the results.

DRAWING CONCLUSIONS FROM TAXOMETRIC RESULTS

The inferential framework for taxometric analysis has been a subject of some dispute in the literature. Ruscio (2007) considered three inferential frameworks that had been advanced—detection of categorical structure, dimensional structure as a null hypothesis, and two competing structural hypotheses—and reviewed the advantages and disadvantages of each. The recommended approach, that of two competing structural hypotheses, is consistent with Meehl's (2004) conceptualization of his taxometric method as providing one of three kinds of evidence: support for categorical structure, support for dimensional structure, or ambiguous results. Fraley and Roisman implicitly adopted this inferential framework by being willing to withhold judgment when the CCFI fell within an ambiguous range of intermediate values. Specifically, their results for preoccupied state of mind indicators yielded a mean CCFI value of .46, which they characterized as ambiguous because it fell between the dual thresholds of .45 and .55 that Ruscio, Walters, Marcus, and Kaczetow (2010) recommended as defining the ambiguous range of mean CCFIs. Whereas the mean CCFI for every other series of analyses fell outside this range—in each case, it was below .45, supporting dimensional structure—this exception was cautiously interpreted as uninformative. It is arguably a feature, and not a bug, that the taxometric method is capable of identifying ambiguous results to prevent potential misinterpretations. Particularly in light of the temptation to draw some affirmative conclusion from every data-analytic result, it is significant that Fraley and Roisman were willing to exercise restraint and acknowledge that the results from one series of analyses were inconclusive.

Having chosen not to reach a conclusion of categorical or dimensional structure with respect to the preoccupied states of mind indicators, Fraley and Roisman explained why they tentatively preferred to use a dimensional measure of this construct. They contrasted the costs of both kinds of structure-measurement mismatches that were possible, a dimensional measure of a categorical construct or a categorical measure of a dimensional construct, and argued that the former mistake would be less harmful than the latter. Fraley and Roisman emphasized the assessment implications, noting that if later evidence lent support to categorical structure, one could always use the dimensional measure to reassign cases to categories, whereas if later evidence lent support to dimensional structure, it would not be possible to use a categorical measure to relocate cases along a dimension.

In this instance, Fraley and Roisman's argument is reasonable, but a reader should not leave with the impression that this same argument would necessarily be as persuasive in other contexts. It is conceivable that a consideration of the two types of structure-measurement mismatches might tip the other way in a different context. For example, if a practical decision needs to be made (e.g., determination of legal status such as competency to stand trial), a compelling case might be made that a categorical measure might be helpful even if the categorical distinction is spurious with respect to the latent structure of the target construct. A dimensional measure may be less helpful to real-world decision makers, perhaps leading to more arbitrary, subjective, or inconsistent judgments as different people interpret scores along a dimension in different ways by implicitly or explicitly applying their own thresholds. A categorical measure is less prone to this particular form of idiosyncratic interpretation.

This is not to suggest that spurious categories are, in general, more or less acceptable than spurious dimensions. The point is that the costs and benefits of each type of mismatch, or even each type of match, should be considered on a case-by-case basis. Researchers may have the luxury of focusing on the R^2 values in their statistical models, in which case even spurious dimensions can compete favorably with categories, be they real or spurious (Grove, 1991). But in the high-stakes realm of real-world decision making, other considerations can be more important, and the clarity and consistency afforded by categories may become compelling virtues. This is by no means a criticism of Fraley and Roisman's argument in favor of a tentative acceptance of a dimensional model for preoccupied states of mind. Rather, it is simply a reminder that there should be no general preference for categories or dimensions, that their relative merits depend on the context and should be carefully considered in each new application.

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