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The analysis of bridging constructs with hierarchical clustering methods: An application to identity

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ABSTRACT

When analyzing psychometric surveys, some design and sample size limitations challenge existing approaches. Hierarchical clustering, with its graphics (heat maps, dendrograms, means plots), provides a nonparametric method for analyzing factorially-designed survey data, and small samples data. In the present study, we demonstrated the advantages of using hierarchical clustering (HC) for the analysis of non-higher-order measures, comparing the results of HC against those of exploratory factor analysis. As a factorially-designed survey, we used the Identity Labels and Life Contexts Questionnaire (ILLCQ), a novel measure to assess identity as a bridging construct for the intersection of identity domains and life contexts. Results suggest that, when used to validate factorially-designed measures, HC and its graphics are more stable and consistent compared to EFA.

1. Introduction

The development of new psychometric surveys can be a difficult task, both conceptually and statistically. This is particularly true when a measure is created to assess complex constructs that are not formatted with items grouped into subscales. Indeed, several statistical techniques have been developed to aid researchers in assessing the underlying structure of measures, but these analyses are often based in classical or modern test theories and assume that the measure has a higher-order latent structure – that is, that the measure consists of one or more subscales, each of which consists of some number of items. Classical test theory, as well as commonly-used factor analytic methods, posits that correlations between or among items are related to latent factors in a hierarchical-type relationship, such that measured items on a lower level feed into a higher, latent level of the measurement model (Dimitrov & Atanasov, 2011). Often, exploratory/confirmatory factor analytic (or item response) methods are used to assess the extent to which the estimated factor structure of the measure conforms to the hypothesized structure of the construct being assessed (Dimitrov & Atanasov, 2011).

Bridging (non-hierarchical) constructs involve complex, factorially structured surveys, which challenge existing methods (Floyd, Cornelissen, Wright, & Delios, 2011). By "factorial," we refer to constructs defined by the intersection of sets of elements – such as identity domains with life contexts – rather than defined in terms of higher-order latent constructs giving rise to lower-order manifestations. Indeed, within factorially structured measures, the objective is to compare both means and structural relationships across the row variable, the column variable, and their interaction – rather than examining the extent to which a set of items pattern onto a single higher-order construct.

Given the lack of hypothesized higher-order constructs in a factorial design, the theoretical constructs being measured by this design do not necessary lend themselves to being assessed through a factor analytic approach where sets of items are attached to subscales. When a survey employs a factorial design, in which no higher-order constructs are hypothesized, all variables of interest are directly observed in the dataset.

An example is that of bridging constructs, which have a nomological (theoretical) structure but which consist of several

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components that may or may not be empirically related to one another. One such bridging construct is identity – for example, people possess many different identity domains, such as gender, ethnicity, nationality, sexuality, morality, and career (see Schwartz, Luyckx, & Vignoles, 2011, for a collection of reviews). These various identity domains may or may not be related to one another, and it is possible that their interrelationship may depend on the specific social/relational context in which one finds oneself at any given point in time. Further, different individuals may emphasize different domains of their identity (such as a strong athletic identity for one person and a strong family and religious identity for another person), and these identities may be expressed differently across different social and relational contexts (Ellemers, Spears, & Doosje, 2002; Spears, 2011). Following Sellers, Smith, Shelton, Rowley, and Chavous (1998), we contend that identity domains may have different salience across diverse life contexts (such as family, workplace, leisure contexts and so on), where salience refers to the extent to which a specific identity domain is a relevant part of one's self-concept at a given moment or in a given situation. Thus, a bridging construct such as identity, which does not have a clear higher-order structure, may not be amenable to factor-analytic methods, especially when variations both in identity aspects and in life contexts are considered within a single measurement instrument.

As an example, in the present study we used a new psychometric measure of identity, the Identity Labels and Life Contexts Questionnaire (ILLCQ), to assess identity as a factorial, rather than higher-order, construct. The factorial measurement structure resembles a contingency table, and, in this case, identity domains are listed as rows and contexts are listed as columns. Participants must then enter some sort of rating (such as importance or salience) for each domain-context pairing. Similar measurement structures have been used for substance use, where participants were asked to indicate the likelihood of use of a range of substances in a range of social contexts (Honess, Seymour, & Webster, 2000).

Based on the overarching bridging construct and the design of the measure to assess this construct, it is likely that data from such a survey "live" in a topologically rich space of connected components, where these connections may be of varying strength in either/both hierarchical or non-hierarchical manners. Decomposing these connected components to identify weak and strong connections through a hierarchy of strengths can help facilitate an understanding of the social and psychological processes at work. Technically, this is can be done by tracking the evolution of the 0th Betti numbers, which corresponds with agglomerative hierarchical clustering (Kim et al., 2015; Lee, Kang, Chung, Kim, & Lee, 2012). Thus, clustering provides a way to validate psychometric data that violate the assumptions of factor analytic and other commonly used methods, as well as a tool with a strong topological basis, allowing for interpretation of strength of relationships among bridging concepts. We propose hierarchical clustering as an alternative analytic method where traditional methods such as CFA or EFA cannot be applied, do not match the assumptions of the measures used to collect the data, or are inappropriate because of small sample sizes.

Our objectives in this paper are twofold. Primarily, we set out to evaluate the use of hierarchical cluster analysis as tool for validating factorially structured questionnaire measures (i.e., those designed to assess bridging constructs). Specifically, we sought to compare hierarchical cluster analysis against latent variable modeling (which is traditionally used to validate measures) to determine the advantages – and potential disadvantages – that hierarchical cluster analysis would provide. Because exploratory factor analysis is most often used when the structure of scores generated by a measure is not known, we used exploratory factor analysis as the form of latent variable modeling against which to compare the performance of hierarchical clustering.

Our secondary focus was on studying identity as a bridging construct – that is, examining the ways in which it would manifest itself. More precisely, we were interested in the specific identity profiles that would emerge from analysis. That is, how would identity-context interactions be empirically grouped? Would identity domains take precedence, where ratings for a single identity domain would largely cluster together across life contexts? Alternatively, would life contexts take precedence, where identity processes cluster together within each life context and across domains? Or would we find some combination of the two, where some life contexts – and some identity domains – exert strong effects on the cluster solution that emerges?

2. Analyses for psychometric scale validation

2.1. Existing scale-validation analytic methods

Commonly used methods in developing new scales include two types of factor analysis, namely exploratory factor analysis (EFA) and p-technique. The EFA algorithm essentially examines a covariance or correlation matrix and extracts independent, latent factors that are assumed to underlie the associations among item responses. In this way, measured variables can be grouped together empirically in the absence of a priori assumptions or theoretical notions about how they should be grouped. Typically, the EFA is followed up with confirmatory factor analysis (CFA) on another sample to validate the findings. CFA posits which and how many factors exist and then tests these hypotheses. For measures in which a preexisting theoretical structure exists, CFA may be the first step of the analytic plan (i.e., EFA may not be necessary; Thompson, 2004). A number of variations of CFA have been proposed, including multilevel CFA for hierarchically nested data (Li, Duncan, Harmer, Acock, & Stoolmiller, 1998; Mehta & Neale, 2005) and bifactor modeling for more complex constructs or those for which both substantive and methods factors may exist (Chen, Hayes, Carver, Laurenceau, & Zhang, 2012). All EFA and CFA approaches, however, carry the assumption that a set of higher-order latent factors are responsible for the covariation among the questionnaire items (Brown, 2006).

In more rigorous terms, for EFA, given a vector of observable variables, $\mathbf{X}$, with $E(\mathbf{X}) = \mu$ and $var(\mathbf{X}) = \Sigma$, one can consider elements of X to be generated by a linear combination of unobserved factors, such that:

$$\mathbf{X} = \mathbf{CF} + \boldsymbol{\mu} + \boldsymbol{\varepsilon}$$

where $\mathbf{C}$ is a matrix of coefficients consisting of factor loading scores and $\mathbf{F}$ is a vector of factors (Suhr, 2006). Viewing factor analysis in this manner allows one to see how observable variables can be decomposed into unobservable factors, where the number of unobserved factors is typically much smaller than the number of observed variables. In this way, a large number of variables (items) assessed in the survey can be represented by or grouped into a smaller number of factors. For example, a survey designed to assess depression will likely ask about a range of depressive symptoms and behaviors (i.e. sleeping and eating disorders, sadness, low body energy, suicide attempts, etc.), which serve as indicators of the latent underlying depressive condition.

One of the major drawbacks of exploratory factor analytic methods is the requirement of many observations per variable ($n > p$, or ideally $n \gg p$) for numerical calculation of the factors (Fabrigar, Wegener, MacCallum, & Strahan, 1999; Ford, MacCallum, & Tait, 1986; Henson & Roberts, 2006). For stable factor loading results, it is recommended that minimally 5–10