Person-centered approaches

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Chapter 101: PERSON-CENTERED APPROACHES

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Abstract

The person-centered approach, rather than assuming population homogeneity, explicitly models unobserved population heterogeneity. Person-centered methods thus shift the attention from associations between variables to associations – or similarities – between persons. More precisely, the person-centered approach pays explicit attention to the identification of subpopulations displaying distinct configurations on a set of variables (e.g., Latent Profile Analyses) or different associations among variables (e.g., Mixture Regression Analyses). It also seeks to understand how these profiles, or configurations, differ from one another in terms of outcomes, are differentially influenced by predictors, and remain stable or not over time or across different types of individuals. The person-centered approach thus views individuals as complex beings that are best described in a holistic (i.e., describing individuals by looking at configurations across variables) rather than a reductionist (i.e., describing individuals by looking at differences on one or a limited set of variables) manner.

Keywords: Mixture Modeling; Latent Class Analysis; Growth Mixture Modeling; Latent Profile Analysis; Latent Transition Analysis; Mixture Regression Analysis.

History

The origins of the person-centered approach goes back to the early 20th century, when psychologists started to gain interest in detecting groups of "like-minded" individuals (Zubin, 1938). This led to the development of methods that classify individuals based on the similarity of their scores on a set of variables, or based on similarities in how specific variables relate to one another (Howard & Hoffman, 2018). During the past two decades, person-centered methodologies have become more sophisticated, increasingly popular, and are now well-established in organizational research (Hofmans et al., 2020).

The variable-centered versus the person-centered approach

Research in the field of organizational research has traditionally focused on associations between variables assumed to generalize to the whole sample under study. Prototypical research questions concern the associations between job satisfaction and performance, between autonomy and motivation, or between job demands and burnout. Because of their focus on examining associations among variables, these methodologies are referred to as variable-centered. Underlying the variable-centered approach is the assumption that the relationships between variables are homogenous within the population, which means that they can be described using a single set of "averaged" parameters (Morin et al., 2018). Whereas assuming population homogeneity is helpful in the sense that it reduces complexity, for most phenomena this assumption is highly dubious and overly simplifies the reality. For example, job satisfaction and performance may be positively associated for some employees, but unrelated for others who value more the social interactions that they have at work than their work itself. These variables may even be negatively related for employees trying to maximize their performance to be able to transfer out of a job that they hate. Likewise, experiencing high levels of autonomy at work might lead to a higher level of motivation for some employees, but may be harmful for employees with a high need for structure.

To circumvent the limitations of variable-centered analyses, methods have been developed that do not assume population homogeneity but explicitly seek to identify unobserved heterogeneity within the population (Woo et al., 2018). These person-centered methods seek to capture unobserved heterogeneity within the population by identifying subsamples of “similar” individuals, thereby shifting the attention from studying associations among variables to studying associations – or similarities – between persons.

An overview of popular person-centered models

Hofmans et al. (2020) distinguished between three types of person-centered methods: (1) methods that identify subpopulations based on their configuration (or profile) of scores, (2) methods that identify subpopulations based on differential associations among a set of predictors and outcomes, and (3) methods that identify subpopulations based on differential longitudinal trajectories.

A first set of methods groups people into subpopulations based on their configuration, or profile, of scores on a set of variables. Classical approaches belonging to this category are part of the cluster analytic family of analyses. With the upsurge of model-based mixture analyses and the broader Generalized Structural Equation Modeling (GSEM) framework, however, cluster analysis has been superseded by latent class analysis (LCA – for categorical indicators) and latent profile analysis (LPA – for continuous indicators), although both types of indicators can also be combined into the same model. Like cluster analysis, LPA and LCA seek to identify profiles of individuals characterized by a qualitatively and quantitatively distinctive configuration on a series of indicators. Unlike cluster analysis, however, LPA and LCA are based on a formal statistical model (i.e., the data is assumed to result from a mixture of underlying multivariate distributions) and result in a probabilistic, rather than deterministic, assignment of individuals into each of the latent subpopulations. This probabilistic assignment is important, as it results in the estimation of latent profiles that are corrected for classification errors. A final method in this category is factor mixture analysis (FMA). FMA lies at the border between variable-centered and person-centered methods by extending LPA/LCA through the incorporation of one or more continuous latent variables to the model. FMA thus combines factor analysis and LPA/LCA. In FMA the latent categorical variable allows for the classification of individuals in latent subgroups, whereas the latent continuous variable(s) allow for capturing covariation between the observed indicators within each subgroup.

A second set of person-centered methods identifies subpopulations based on the differential relationships observed between a set of predictors and outcomes variables. To this end, the multiple regression model has been extended with a mixture component (i.e., mixture regression analysis). In mixture regression analysis one or more outcomes are regressed on a set of predictors, and subpopulations characterized by distinct forms of predictor(s)–outcome(s) relations (in terms of the regression intercepts, slopes and residuals) can be identified. In that sense, the latent subpopulations in mixture regression analysis form an unobserved moderator of the predictor(s)–outcome(s) relations. Hybrid approaches to mixture regression also allow the extracted profiles to differ from one another in predictor levels and configuration, providing an even more powerful way to disaggregate complex patterns of associations between variables.

The third set of person-centered methods identifies subpopulations based on their differential longitudinal trajectories. A well-known example of this category is Growth Mixture Modeling (GMM). GMM extends the latent growth curve model by identifying subpopulations that follow different longitudinal growth trajectories over time.

All of these types of models can be extended to multi-group comparisons, longitudinal comparisons, and connections among different types of models. For instance, Morin et al. (2016) have developed a framework to systematically test whether a specific person-centered solution is replicated across groups or time points (i.e., tests of profile similarity, similar to variable-centered tests of measurement invariance). In longitudinal analyses, Latent Transition Analyses (LTA) can be used to model associations or transitions between two or more latent categorical variables (e.g., profiles at Time 1, profiles at Time 2, and their connections). In other words, in LTA membership into one set of profiles is used to predict membership into a second set of profiles. As such, LTA can be seen an extension of the other mixture models by allowing individuals to transition from one latent profile to another over time. Although the basic LTA set up entails longitudinal connections between LCA/LPA solutions estimated at two or more time points based on the same set of indicators, the latent Markov link function that underpins LTA can be used to model connections between any sets of latent categorical variables (e.g., between a LPA and a GMM).

Important consideration for person-centered research

Person-centered analyses often follow an exploratory, or inductive, analytic process in which one typically tests a series of alternative models each including a different number of subpopulations, after which the 'best' model is retained. This methodologically exploratory nature does not mean that these methods cannot be used for confirmatory purposes. It simply means that the 'best' solution will end up being chosen based on a combination of statistical (i.e., statistical model fit indicators such as the Bayesian Information Criterion) and substantive grounds. Because this process is sample-dependent and exploratory in nature, an important concern pertains to the replicability and validity of one's findings. Replicability can be ensured by performing the analysis on separate datasets or on the same dataset but over time, after one can test to what extent the model parameters generalize across datasets or over time using a sequence of profile similarity tests (see Morin et al., 2016). Evidence for the construct validity of the obtained solution can be provided by testing associations with predictors and/or outcomes of the latent profiles to establish the discriminant validity of the profiles. An important caveat is that the nature of the profiles should not be affected by inclusion of the covariates. To guarantee such robustness, one should estimate conditional models (i.e., including covariates) using (or fixing) the starts values obtained in the final unconditional (i.e., excluding covariates) solutions. When this is not enough to preserve the nature of the profiles, a variety of "auxiliary" approaches can be used to achieve stability.

Another important consideration when doing person-centered research—particularly when using mixture modeling—is that the models are very flexible (i.e., various model parameters can be allowed to differ, or not, across profiles). Because of this flexibility, it is important to be wary of imposing or relaxing model constraints because simulation studies have demonstrated that imposing or freeing model constraints might affect the accuracy of the solution. For instance, Diallo et al. (2016) suggest starting with a model that includes as few constraints as possible, after which model complexity can be reduced if needed. A second implication of this flexibility is that mixture models are typically computationally intensive, implying that their estimation requires more computational time than most other types of models. A third consequence of this model complexity is that mixture models require larger samples than similar types of variable-centered models. This not only ensures that the models converge on proper solutions, but also that small but meaningful profiles can be detected. Importantly, this does not mean that mixture models cannot be estimated using smaller samples (e.g., $N = 100$ to 200), simply that with smaller samples, convergence difficulties are more likely and smaller profiles might be harder to detect (although the main dominant profiles may still be identified). Finally, because person-centered methods are exploratory in nature, they require an accumulation of studies to differentiate profiles that systematically emerge from situation-specific profiles and from profiles that reflect random sampling variations. Hence, it is important to keep in mind that—like everything in empirical science—person-centered evidence is cumulative in nature.

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