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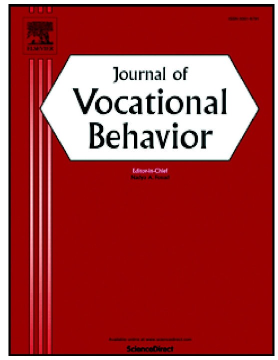

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Person-centered methods in vocational research

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Abstract

The vast majority of vocational research adopts a variable-centered approach. Implicit in this approach is the assumption that the population under study is homogeneous, and that therefore we can use a set of "averaged" parameters to describe it. Person-centered methods are a family of methods that relax this assumption of population homogeneity, viewing the individual as holistic and paying more attention to how specific configurations of variables, present in different subgroups of the population, act in concert to shape behavior. Despite the potential advantages of person-centered research, the adoption of this approach by vocational researchers has been relatively slow for both conceptual (e.g., What exactly is person-centered research?) and methodological (e.g., Which methods?) reasons. In response to these issues, the goal of the present article is to showcase the role and relevance of person-centered methods for vocational research. Having discussed different conceptualizations of the term "person-centered" we present a structured overview of the most relevant person-centered techniques. This overview includes a description of the formal characteristics of each technique, as well as an overview of existing applications of these techniques in the literature. Finally, we provide a balanced discussion of both the advantages *and* challenges associated with the person-centered approach.

In vocational research, the vast majority of studies examines relationships among variables across individuals. Such studies have, for example, shown that charismatic personality relates positively to career outcomes 15 years later (Vergauwe, Wille, Hofmans, & De Fruyt, 2017), or that employment self-efficacy is positively related to job search intensity at the between-person level, while the relation is negative at the within-person level (da Motta Veiga & Turban, 2018). Implicit in such studies is the assumption that the population can be described by a single set of “averaged” parameters (Morin, Bujacz, & Gagné, 2018).

Despite the prevalence of this assumption, career theories suggest that describing an entire population using a single set of parameter estimates most likely oversimplifies reality. For example, vocational researchers are increasingly recognizing that contemporary careers and career orientations cannot simply be categorized as either boundaryless or protean, but that people differ in the extent to which they hold unique combinations of different career orientations. As a result, there have been repeated calls for the integration rather than the separation of different career orientations (Kuron, Schweitzer, Lyons, & Ng, 2016). Also in the counseling field the idea of population homogeneity is called into question by for example research that shows that problems associated with career indecision are manifested in very different ways for different groups of people (e.g., Cohen, Chartrand, & Jowdy, 1995). Such findings have led to the awareness in the counseling literature that phenomena can only rarely be explained by a universal relationship between a small number of variables (Frankfurt, Frazier, Syed, & Jung, 2016). Although variable-centered methods do allow studying the interplay of variables through the inclusion of interaction terms, this quickly becomes impractical when the number of interacting variables increases. Because of the awareness that a single set of parameter estimates cannot be assumed to hold for a whole population and because of the limitations of variable-centered methods to capture complex patterns of interactions, researchers called for supplementing the body of variable-centered research with person-centered research (e.g., Morin et al., 2018).

In person-centered research, the focus is no longer (exclusively) on relations between variables, but (also) on relations among people (Zyphur, 2009). To fulfill this task, person-centered methods do not assume population homogeneity, but model unobserved heterogeneity within the population (Woo, Jebb, Tay, & Parrigon, 2018). Thus, person-centered methods shift the attention away from a focus on variables to a focus on individuals by allowing the study population to be heterogeneous (Weiss & Rupp, 2011). By doing so, person-centered methods pay more attention to how specific configurations of variables act in concert to shape behavior (Bergman & Trost, 2006).

Despite the potential advantages of person-centered research, vocational behavior and counseling researchers have been rather slow in adopting this approach due to conceptual (e.g., What exactly is person-centered research?) and methodological reasons (e.g., Which methods can be used when performing person-centered research?). In response to these issues, the goal of the present article is to showcase the role and relevance of person-centered research for vocational behavior and career counseling (hereafter referred to as vocational research). More specifically, the aims of this article are fourfold. First, we aim to improve the understanding of person-centered research and how it is applied in vocational research. To this end, we first discuss different conceptualizations of the term “person-centered” and differentiate it from related, yet different approaches. Based on this outline, we then present an overview of the most relevant techniques within this approach, including k-means and hierarchical clustering, latent profile and latent class analysis, factor mixture analysis, mixture regression analysis, configural frequency analysis, Davison and Davenport’s (2002) criterion-based method, latent class growth modeling (and growth mixture modeling), and latent transition analysis. As a second contribution, we describe the state-of-the art of person-centered approaches to vocational research by taking stock of the literature in this area. Our literature review covers seven of the most well-established international peer-reviewed journals listed in Web of Science that in their objectives specifically focus on careers, career counseling, and vocational behavior: *Journal of Vocational Behavior*, *Career Development International*, *Career Development Quarterly*, *Journal of Career Development*, *Journal of Career Assessment*, *Journal of Counseling Psychology*, and *The Counseling Psychologist*. The results of this literature search are presented alongside the formal description of each technique, highlighting the most important trends in vocational research using those methods. Third, apart from describing the methods themselves and from summarizing existing research with those methods, we highlight how those person-centered techniques can potentially be used for advancing vocational research. Finally, a fourth objective of this article is to provide a balanced discussion of both the advantages *and* challenges associated with person-centered research.

Person-Centered Methods: Different Conceptualizations and Approaches

Although the ability of person-centered methods to account for unobserved population heterogeneity is a key feature that distinguishes them from variable-centered methods, it is important to note that traditional variable-centered techniques can also deal with observed heterogeneity. Observed heterogeneity occurs when different subpopulations can be differentiated based on an observed variable (e.g., age, occupational category). In this case, the subpopulations are referred to as groups and traditional multi-group analytic techniques such as t-tests, ANOVA, MANOVA and multi-group SEM can be used to test between-group differences (or heterogeneity) on the outcomes of interest. Often, however, the variables that cause population heterogeneity are not known beforehand and/or not observed. If this happens, heterogeneity is due to unknown reasons, which is why this type of heterogeneity is referred to as unobserved heterogeneity and why we speak about latent classes rather than groups. Because in this scenario it not possible to a priori divide the sample into groups, traditional analytic techniques are of little use. It is in this particular situation that person-centered methods, with their ability to infer subpopulation membership from the data, are particularly useful.

Although the differentiation of variable- and person-centered methods in terms of their treatment of observed versus unobserved heterogeneity is relatively straightforward, the term "person-centered" has led to some confusion in previous writings (see Woo et al., 2018 for an excellent treatment of these issues). According to Woo and colleagues (2018), three conceptualizations of the term "person-centered" can be discerned in the scientific literature. First, some researchers refer to person-centered studies as research on the characteristics of individuals (as opposed to research on the characteristics of situations). According to this perspective, a study is person-centered when it focuses on characteristics of people, such as personality, skills, or ability. Second, others have used the term person-centered to refer to research that focuses on the subjectivity of worker experiences, as opposed to research that focuses on more objective characteristics of individuals (Weiss & Rupp, 2011). Finally, according to the third conceptualization, the term person-centered is used to refer to a collection of methods that classify individuals on the basis of the similarity in their scores on a set of variables (Howard & Hoffman, 2018). The approach aligns well with the idea of studying persons based on certain *profiles* across multiple variables or characteristics (see further). This third conceptualization is the one that "maximizes the level of precision in *methodological* discussions …" (Woo et al., 2018; p. 816). Because of this reason, we delve a bit deeper into this conceptualization.

Using the conceptualization of person-centered research as research that clusters individuals, such methods have been argued to be characterized by three features (Morin et al., 2018). The first feature is that they are *typological* in the sense that they use a classification system that categorizes individuals into qualitatively and quantitatively distinct subpopulations, with each of the subpopulations being characterized by different sets of model parameters. The typological nature of such methods is very appealing to vocational researchers since the classification system implied by person-centered models corresponds to a way of thinking often used by managers (i.e., thinking about employees by categorizing them in types of employees) (Morin et al., 2018) and by counseling psychologists, who tailor their treatment based on the type of employee they have in front of them (Cohen et al., 1995).

Second, person-centered research is often said to be *prototypical*. This means that each individual in the sample belongs to each of the estimated profiles with a certain probability. This probability is based on the extent to which the individual's unique configuration of scores on the study variables resembles the profile's specific configuration of scores. In such probabilistic scenario, individuals are not assigned to one of the profiles, but are assessed as being more or less similar to each of the prototypical profiles. Accounting for the uncertainty in assignment by using probabilistic memberships offers a way to account for the fact that the classification of individuals into unobserved subpopulations is not without error. Although prototypicality is undisputedly a key feature of most person-centered methods, some methods use 'definite' (or hard) assignment, implying that each individual is assigned to one and only one profile. Such 'hard clustering' happens in the large majority of the cluster analytic models, some of which will be discussed below.

Third, person-centered models are *exploratory*. Because of a lack of goodness-of-fit information that allows for a direct assessment of the adequacy of the tested model(s), the 'final' model is typically obtained by comparing solutions with different numbers of profiles or clusters. Moreover, and similar to what happens in exploratory factor analysis, in person-centered methods the relations between the profiles and indicators are typically freely estimated (Morin, McLarnon, & Litalien, in press). It is important to note that these methodological peculiarities do not imply that person-centered models cannot be used for confirmatory purposes, an issue that will be elaborated on in the Discussion section.

It is important to note that there are a number of methods that, while they are strictly speaking not encompassed by this definition, fit the goal of person-centered approaches because they are aimed at studying profiles or patterns of scores (e.g., Asendorpf, 2006; Davison & Davenport, 2002; von Eye, 2002). That is, whereas these methods are not classification-based, they do focus on the pattern of scores of individuals and therefore they do consider the person as an “organized whole” (Bergman & Magnusson, 1997, p. 291). Because of this reason, some authors consider them to be person-centered (e.g., Asendorpf, 2006). Because the goal of non-typological methods closely relates to the central goal of the “typical” person-centered approaches (i.e., moving the focus away from studying relations between variables to studying relations between people on the study variables), we will include two of such methods in our overview (i.e., configural frequency analysis and Davison and Davenport’s (2002) criterion-based method).

As we mentioned above, person-centered methods relax the assumption of population homogeneity by clustering individuals in subgroups or subpopulations. One might relax this assumption even further, in which case inferences are made for each individual separately. Such an approach, which in the context of Cattell’s (1952) data box has been described as the P-technique, is referred to as an idiographic or person-specific approach. In person-specific analyses, the goal is to build a model for each individual separately, drawing on the idea that each individual can best be described and understood using an individualized model (Howard & Hoffman, 2018). The philosophical differences underlying the person-specific and the person-centered approach clearly show in the data they use as input. Unlike person-specific methods, which operate on occasions × variables matrices, person-centered methods operate on persons × variables matrices (except for longitudinal person-centered methods, which use the full persons × variables × occasions data box). In other words, whereas person-specific methods by definition analyze intra-individual variation[1], person-centered methods can work with both inter-individual and/or intra-individual variation (Woo et al., 2018). In that sense, person-centered analyses offer a compromise between the parsimony of the variable-centered approach, yielding a single set of parameters, and the person-specific approach, yielding a set of parameters for each individual in the sample.

Following this discussion of definitional issues, in the next section, we offer an overview of several methods that move the focus away from studying relations between variables to studying relations between people. Three types of methods are discussed. First, we review methods that seek to identify subpopulations based on their profile of scores (i.e., cluster analysis, latent class and latent profile analysis, and factor mixture analysis). In all of those methods the profiles are based on scores on a set of variables, without taking into account potential outcome variable(s). The second category of models addresses the issue of a lack of criterion variables by making explicit reference to such variable. That is, in this category of models, subpopulations are either made based on differential relationships between a set of predictors and an outcome variable (i.e., mixture regression analysis), or the models identify specific patterns of predictors that are associated with the criterion variable (e.g., Davison & Davenport, 2002). Finally, and in line with recent calls for more longitudinal studies in organizational research in general (e.g., Vantilborgh, Hofmans, & Judge, 2018), and vocational research in particular (e.g., Zacher, Rudolph, Todorovic, & Ammann, 2019), we also pay attention to longitudinal person-centered models, being growth mixture modeling and latent transition analysis. This last category of models is particularly interesting as such methods allow studying interindividual differences in intraindividual change processes (Ram & Grimm, 2007).

[1] Some person-specific techniques, such as dynamic factor analysis (Molenaar, 1985) and dynamic structural equation modeling (Asparouhov, Hamaker, & Muthén, 2018) allow for the consideration of between-person variation. Those techniques thus also operate on the full persons × variables × occasions data box.

From Studying Variables to Studying People: An Overview of Person-Centered Methods

Modeling profiles of scores

We will review four internal person-centered methods (i.e., cluster analysis, latent class analysis, latent profile analysis, and factor mixture analysis). The preposition "internal" refers to the fact that in those analyses, only "internal variables" matter for profile estimation. "External variables"—including predictors, outcomes and/or covariates of the profiles—can be included in the analysis, but those variables do not directly contribute to the definition of the profiles. They are instead used to provide validity evidence for the profiles obtained[2].

Cluster Analysis. Cluster analysis pertains to a family of methods aimed at dividing objects into a limited number of mutually exclusive groups (or clusters), in such way that objects belonging to one cluster are more similar to each other than objects belonging to another cluster[3]. In general, there are two broad cluster analytic approaches: hierarchical clustering and nonhierarchical clustering.

In hierarchical clustering, one seeks to build a hierarchy of clusters, and this hierarchy can be either built bottom-up (the agglomerative approach) or top-down (the divisive approach). In the bottom-up approach, one starts from a cluster solution in which each object has its own cluster, after which pairs of clusters are merged when moving up the hierarchy. In the top-down approach, the initial cluster solution is one in which all objects are grouped into one cluster, after which splits are performed while moving down the hierarchy. Thus, the idea in the bottom-up approach is to merge pairs of clusters that are most similar to one another, while in the top-down approach one splits those clusters that are most dissimilar to one another. An important question in hierarchical clustering pertains to the measurement of (dis)similarity of clusters. There are several ways to measure (dis)similarity, including the

[2] Note that for LCA and LPA, direct inclusion of predictors, outcomes and/or covariates of profile membership can be done within the Generalized Structural Equations Modeling framework (GSEM) (see Morin et al., 2019).
[3] Note that cluster analysis can also cluster variables into groups based on their values on a set of objects.

nearest neighbor (or single linkage) method, the furthest neighbor (or complete linkage) method, and the average linkage method.

Nonhierarchical clustering, as opposed to hierarchical clustering, is not aimed at building a hierarchy of clusters. Instead, its aim is to cluster objects into a pre-defined number of clusters by maximizing or minimizing some criterion. Arguably the most popular type of nonhierarchical clustering is the K-means method (Hofmans, Ceulemans, Steinley, & Van Mechelen, 2015). In K-means clustering, the algorithm searches for a combination of a binary partitioning matrix $\boldsymbol{P}_{I\times K}$ (containing the memberships of the *I* objects to the *K* clusters) and a centroids matrix $\boldsymbol{C}_{K\times J}$ (containing the centroids for the *K* clusters) that minimizes the following least squares loss function (with $\boldsymbol{X}_{I\times J}$ being the data matrix in which *I* objects are measured on *J* variables):

$$\min_{P,C} \|\mathbf{X} - \mathbf{PC}\|^2. \tag{1}$$

Formula 1 implies that the K-means algorithm assigns objects to the cluster for which the distance to the cluster centroid (i.e., the center of the cluster) is minimal. Readers interested in learning more about K-means clustering can consult the overview paper of Steinley (2006), while Kaufman and Rousseeuw (2005) provide an excellent treatment of cluster analysis in general.

Our literature review reveals that cluster analysis has a relatively long history in vocational research, with the first studies using this technique already dating back more than half of a century (e.g., Matthews & Tiedeman, 1964). Today, the technique is still commonly used to group individuals and/or career events based on shared/similar features (see Table A1 for an overview) .

Latent Class Analysis (LCA) and Latent Profile Analysis (LPA). The goal of LCA and LPA is to identify subpopulations of people, with those subpopulations being characterized by distinct configurations of scores on a set of variables (see Figure 1). In that sense, LCA and LPA are similar to cluster analysis. However, unlike cluster analysis, LCA and LPA (1) are model-based (i.e., they are based on a formal model instead of (dis)similarity measures) and (2) are prototypical, which means that they yield probabilistic, rather than hard, assignment [note that some clustering methods, such as fuzzy clustering (see Tan, Steinbach, Karpatne, & Kumar, 2019) also yield probabilistic memberships].

Although the terms LCA and LPA are often used interchangeably, the difference is that LCA uses categorical indicators, while in LPA the indicators are continuous. More formally, the traditional latent class analysis (LCA) model can be expressed as follows:

$$P(Y = y) = \sum_{k=1}^{K} \pi_k \prod_{j=1}^{J} \prod_{r_j=1}^{R_j} \rho_{j,r_j|k}^{I(y_j = r_j)} \quad (2)$$

In this formula, y represents a specific response pattern (or a pattern of scores on *J* categorical variables). The chance of observing this particular response profile is a function of the probability of membership to the *k* latent classes (the π's), and the probability of observing each response conditional on latent class membership (the ρ's). The indicator function $I(y_j = r_j)$ equals 1 when the response to variable j equals r_j. If not, this indicator function is 0 (see Collins & Lanza, 2010 for an in-depth overview of the technicalities of LCA).

As opposed to LCA, in LPA the latent variable indicators are continuous. Assuming that these indicators are normally distributed within each latent profile, that the indicators are unrelated within each latent profile (i.e., local independence), and that the indicator variances are equivalent across the latent profiles (i.e., homogeneity), LPA models the distribution of observed scores on a set of indicators ($x_i = 1, 2, \dots, n$) as a function of the probability of membership to the K latent classes (the π's) and each class' normal density $f_k(x_i|\theta_k)$ (with each class having a class-specific mean vector and covariance matrix $\theta_k = (\mu_k, \Sigma_k)$):

$$f(x_i|\theta) = \sum_{k=1}^{K} \pi_k f_k(x_i|\theta_k) \quad (3)$$

In a more generic form, the LPA model decomposes the variance of each indicator *i* into two components (see Formula 4): a between-profile component that captures how far the profile-specific means μ_{ik} are from the general mean μ_i (i.e., $\sum_{k=1}^{K} \pi_k (\mu_{ik} - \mu_i)^2$) and a within-profile component containing the profile-specific variances σ_{ik}^2 (i.e., $\sum_{k=1}^{K} \pi_k \sigma_{ik}^2$). In both the between- and the within-profile component, π_k denotes the density parameter, or the probability of membership to profile *k*.

$$\sigma_i^2 = \sum_{k=1}^{K} \pi_k (\mu_{ik} - \mu_i)^2 + \sum_{k=1}^{K} \pi_k \sigma_{ik}^2 \quad (4)$$

Although LPA can thus be used to estimate profiles differing in both means and variances, more constrained versions in which only the means are profile-specific can also be tested (i.e., $\sigma_{ik}^2 = \sigma_i^2$; Peugh & Fan, 2013). This assumption of homogeneity of variances is shared with methods such as K-means clustering and is the default parameterization in some statistical packages, such as M*plus* (Muthén, & Muthén, 2017). Readers interested in a more in-depth discussion of LPA can consult the book chapter by Masyn (2013) or the paper by Sterba (2013).

Our review indicates that the application of LCA and LPA in vocational research took off around 2012-2013, with the first studies using these techniques to identify subgroups of people based on their commitment profiles (e.g., Meyer, Stanley, & Parfyonova, 2012). Since then, LCA and LPA have been adopted widely with the aim to study among other things interest profiles, motivation profiles, and profiles of work characteristics (see tables A2 and A3 for LCA and LPA, respectively).

Factor Mixture Analysis (FMA). Whereas in LCA and LPA unobserved heterogeneity is modeled through the inclusion of a categorical latent variable, FMA simultaneously includes a latent categorical and one or multiple latent continuous variables within the same model (see Figure 2). The latent categorical variable allows for the classification of individuals in groups, whereas the latent dimensional variable(s) allow for heterogeneity within groups by modeling covariation between observed variables within each class. Hence, FMA relaxes the conditional independence assumption of classical LPA analyses (Lubke & Muthén, 2005). This is of particular importance to vocational research, where the assumption of conditional independence is often unlikely due to a global factor underlying the different indicators (e.g., in commitment research; Morin, Morizot, Boudrias, & Madore, 2011). Moreover, because in FMA the continuous latent variable controls for variance shared across all indicators when estimating latent profiles, FMA may result in profiles with clearer shape differences (Morin & Marsh, 2015). Finally, by combining latent continuous and latent categorical variables within the same model, FMA can tell us something about the underlying continuous *and* categorical nature of psychological constructs (Clark et al., 2013). Formally, the FMA model is expressed as follows (see Lubke & Muthén, 2005 for a thorough treatment of FMA):

$$y_{ik} = v_k + \Lambda_{yk}\eta_{ik} + \varepsilon_{ik} \tag{5}$$

$$\eta_{ik} = Ac_i + \zeta_{ik} \tag{6}$$

Scores on indicator variable y_{ik} are expressed as a function of the regression intercept v_k, the regression slope or factor loading Λ_{yk} and the residual ε_{ik}. Factor scores are denoted as η_{ik}. All parameters in Formula 5 have subscript *k*, implying that they may vary across classes. Formula 6 shows that the factor scores are a function of the latent class variable c_i, an intercept vector A, and the residual factor scores ζ_{ik}.

Our review demonstrates that FMA has been applied scarcely in careers research. The studies that were identified adopted FMA for the categorization of reward patterns, or for creating subgroups based on stereotype sensitivity, or vocational interests (see Table A4).

The potential of modeling profiles of scores for vocational research. Cluster analysis, LPA, LCA and FMA can be used to address a wide variety of questions in vocational research. First of all, many of the constructs being studied in this domain are multidimensional. This for example holds true for predictor variables such as personality and interests, but also for outcomes such as performance, career success or commitment. Person-centered techniques such as cluster analysis, LPA, LCA or FMA allow studying how those different characteristics combine into profiles. Such insight is important because, by showing which profiles emerge and how frequent those profiles are, these methods contribute to a better understanding of the psychological makeup of individuals. This is crucial for vocational research, where a basic principle is that vocational behavior and attitudes result from the unique interplay or patterning of a broad set of different characteristics. Moreover, it aligns well with the increasing individualization of career development (Vondracek & Porfeli, 2002) and the person-focused approach used in career counseling.

An important remark is that the techniques that allow for the modeling of scores do not require the different scores to tap into one overall dimension (Morin et al., 2019). They can also be used when studying profiles across a collection of variables of interest. For example, Haines, Doray-Demers, and Martin (2018) performed LCA with the goal to develop a typology of part-time employment on the basis of work characteristics and role occupancy. To this end, they included a wide range of variables into their LCA, including having a partner or not, having children or not, household income distribution, educational requirements of the part-time position and work hours. Or in the counseling domain, Hirschi and Valero (2017) used LPA to identify five differing profiles according to levels of perceived chance events and career decidedness.

Such endeavors have the potential to advance the career and counseling field in various ways (Borgen & Barnett, 1987). First, they allow exploring the identification and structure of subgroups, which might help in understanding the research problem better. For example, drawing on the idea that the traditional career is declining, Gerber, Wittekind, Grote, and Staffelbach (2009) used LCA to explore the nature and prevalence of different types of career orientation. Second, these techniques can be used to challenge or confirm existing classifications. For example, the four-class solution by Haines and colleagues (2018) revealed that qualifying part-time work in good and bad is too reductionist, and that a more complex classification is warranted. Third, these techniques allow simplifying complex datasets. For example, Ferguson and Hull (2019) identified profiles of science career interests based on scores on science motivation, attitude, interest, and academic experiences.

Modeling predictor-outcome profiles

The methods we have reviewed up until now are all ‘internal techniques’, meaning that the profiles are derived without taking into consideration their predictive value for outcome variable(s) (Davison & Davenport, 2002). The second category of models addresses this issue. That is, in this category, some models use subpopulations to capture differential relations between a set of predictors and an outcome variable (i.e., mixture regression analysis), while others look for specific patterns of predictors that are uniquely associated to the criterion variable [i.e., configural frequency analysis and Davison and Davenport’s (2002) criterion-based method].

Mixture Regression Analysis (MRM). The subpopulations in mixture regression analysis (MRM) differ from each other in the relationships between the constructs of interest. Similar to traditional multiple regression, in MRM a criterion variable is regressed on a set of predictors. The major difference, however, is that subpopulations are identified for whom the predictor(s)–criterion relationship is different (Brusco, Cradit, Steinley, & Fox, 2008). In that sense, the latent categorical variable in MRM can be thought of as an unobserved moderator of the relation between the predictor and the criterion (see Figure 3). For example, in their study on reward satisfaction, Hofmans, De Gieter, and Pepermans (2013) found two subpopulations with a different pattern of job reward–job satisfaction relationships. For the first type, job satisfaction related to financial and psychological reward satisfaction, whereas for the second type it related to psychological reward satisfaction only. Formally, the MRM model can be expressed as follows:

$$y_{ik} = \beta_{0k} + \beta_k x_i + \varepsilon_{ik} \tag{7}$$

In Formula 7, the latent subpopulations are represented by a latent categorical variable C, where $C = 1,2,3,\ldots K$. Hence, β_{0k} represents the intercept for subpopulation (or class) k, while β_k and ε_{ik} represent the regression coefficient and error term for this subpopulation. Similar to the traditional regression model, more than one predictor variable can be included, in which case each of the predictor variables has a class-specific regression coefficient. Moreover, as in traditional regression models, the errors are assumed to be multivariate normal with a mean of zero and a class-specific variance (i.e., $\varepsilon_{ik} \sim N(0, \sigma_k^2)$). Readers interested in a more technical treatment of MRM can consult Wedel and DeSarbo (1995).

Our literature review demonstrated that MRM has only seldom been used in vocational behavior research (see Table A5).

Configural Frequency Analysis (CFA). The aim of Configural Frequency Analysis (CFA) is to identify whether specific configurations or response patterns are more likely to be associated with specific criterion groups (von Eye, 1990). This method is developed for the analysis of categorical predictors and outcomes and draws on an analysis of frequencies in multi-way contingency tables. In such multi-way contingency tables, individuals are categorized in disjunct categories based on their unique profile (or configuration of scores) on the study variables. For example, when one has two dichotomous predictor variables and one trichotomous outcome, participants can belong to one of 2 × 2 × 3 = 12 unique profiles. After having tabulated those unique profiles and their frequencies, the crucial test is in the comparison of the observed with the expected frequencies of those configurations. In case n individuals are being measured on $i = 1, 2, \ldots, m$ dichotomous variables, and assuming that all variables are independent, the expected frequencies of a specific configuration c can be calculated as follows:

$$e(c) = \left(\prod_{i=1}^{m} p_i(c_i)\right) n \tag{8}$$

with $p_i(0)$ being the probability for a member of the population to have a value of 0 on variable i, and $p_i(1)$ being the probability for a member of the population to have a value of 1 on variable *i*. To test whether these expected frequencies (assuming independence of all variables) differ significantly from the observed frequencies (denoted by $o(c)$), the following χ^2-statistic can be calculated:

$$\chi^2 = \frac{(e(c)-o(c))^2}{e(c)} \tag{9}$$

In case a configuration is significantly more often observed than expected, it is referred to as a type, whereas an antitype refers to the case where a configuration is significantly less often observed than expected. Although we have presented the default version of CFA, the χ^2-test can be replaced by other tests (e.g., von Eye, 2002) and the expected frequencies can be calculated using another model than the independence model (e.g., von Eye, 1990). Finally, because in CFA one performs a (χ^2-)test to each profile or configuration, a Bonferroni-correction is often used to control for Type I error inflation. An in-depth discussion of the technicalities of CFA can be found in the books by von Eye (1990; 2002).

Our literature review revealed two empirical studies which used CFA in the context of vocational research (see Table A6). First, Reitzle and Vondracek (2000) illustrated the usefulness of this technique by identifying patterns of (categorical) career and family characteristics, including marital status, completion of training, history of unemployment, etc. More recently, Moeller and colleagues (2018) investigated the relationship between demands-resources profiles and engagement-burnout profiles. For this purpose, they compared the proportions of three demands-resources profiles in one of four engagement-burnout profiles, testing whether each profile combination was more (or less) frequent than would be expected if the types of profiles were unrelated.

Davison and Davenport's (2002) criterion-based method. Similar to mixture regression analysis (MRM), Davison and Davenport's (2002) criterion-based method draws on a multiple regression-based model. Unlike MRM, however, it does not look for subpopulations with different predictor–criterion relationships but tries to capture profile similarity as a continuous measure. Moreover, the method has an even stronger focus on the criterion variable as its explicit goal is to maximize the predictive value of the profile.

When performing Davison and Davenport's (2002) criterion-based method, four steps are taken. First, for each individual, a level score, or an average score across the predictor variables, is calculated. Second, the criterion-related profile is identified. This is done by (1) predicting the criterion variable from the predictor variables using multiple regression analysis, (2) calculating the average unstandardized regression coefficient across all predictors, and (3) ipsatizing each regression coefficient around the average unstandardized regression coefficient. This yields the criterion-related profile, or a set of deviations around the average unstandardized regression coefficient. After having calculated this criterion-related profile, one can calculate the profile fit score for each individual as the average covariance between the individual's predictor profile and the criterion-related profile. Thus, rather than identifying different subgroups of profile scores, Davison and Davenport's (2002) criterion-based method treats the different profiles in a continuous manner, ranging from fit (i.e., high average covariance with the criterion-related profile) to misfit (i.e., low average covariance with the criterion-related profile). Third, the level and (mis)fit scores are related to the criterion variable using multiple regression analysis. This allows testing what percentage of the variance in the criterion can be accounted for by level and profile effects. Finally, because the criterion-related profile is obtained using multiple regression, and because the regression weights tend to capitalize on the characteristics of the sample at hand, a crucial test is evaluating whether the level and profile effects cross-validate. This can be done by splitting the data in half, after which one can estimate the criterion-related profile using the first half of the data after which the level and (mis)fit scores can be related to the criterion variable in the second half. Note that, although Davison and Davenport's (2002) criterion-based method is explicitly criterion-focused, it does not explain additional variance in the criterion above and beyond a traditional multiple regression analysis. Instead, it separates the predictor variance into level and profile effects, thereby providing insight into the usefulness of using profiles or patterns in applied prediction.

Our literature review identified two articles using criterion profile/pattern analysis in the context of vocational research (see Table A7). In a first application of this technique, Perry (2008) investigated the effects of vocational exploration and racial identity on behavioral (attendance, attention, time spent on class work) and psychological (identification with school) factors of school engagement among urban youth of color. The criterion-based method revealed a predictive profile marked by high levels of positive racial internalization and career planning combined with low levels of racial dissonance. As a second application, Wiernik (2016) identified patterns in the predictive relationships between personality traits and Realistic vocational interests. In two studies, he demonstrated that one's personality profile pattern, rather than the absolute levels of those traits, drove the validity of personality traits in explaining Realistic vocational interest.

The potential of modeling predictor-outcome profiles for vocational research. The usefulness of MRM for vocational research lies in the fact that in this domain people's behaviors and attitudes are thought to result from the unique interplay of a broad set of characteristics. For example, in their overview of 100 years of research on career management and retirement, Wang and Wanberg (2017) noted that career choices are impacted by among other things ability, personality characteristics and biographical data such as socioeconomic status and parental involvement. Similarly, De Vos, Van der Heijden, and Akkermans (in press) note that "careers form a complex mosaic of objective experiences and subjective evaluations, resulting in an enormous diversity in terms of how careers can take shape" and that "different levels of influential factors have to be taken into account" to understand the nature of contemporary careers. Importantly, those factors are not only assumed to have unique effects, but they interact in complicated manners. For example, Chlosta, Patzelt, Klein, and Dormann (2012) demonstrated that the likelihood to become self-employed depends on the unique interplay of the presence of parental role models and the person's score on trait openness. In such situation, where behaviors and attitudes are believed to result from the unique interplay of multiple determinants, assuming that predictors relate to outcomes in the same way for everyone is counterintuitive at best. Considering this complexity, methods for modeling predictor-outcome profiles are very useful, particularly because those predictor-outcome relations are likely to be affected by not one variable, but by a wide range of variables (and their unique interplay), some of which are not known a priori.

The goal of configural frequency analysis and Davison and Davenport's (2002) criterion-based method are somewhat different from that of MRM in the sense that the former focuses on capturing unobserved heterogeneity in predictor-outcome relations, whereas the latter techniques are explicitly designed to test the predictive validity of patterns or profiles of predictor variables. Hence, CFA and Davison and Davenport's (2002) criterion-based method are well suited to test the idea that people develop interests for jobs that align with their relative strengths (i.e., the peaks in their profile of trait scores), rather than their absolute trait levels (Weirnik, 2016), or the hypothesis that it is the particular patterning of specific job demands and resources that is predictive of burnout and engagement, rather than the demands and resources as such (Moeller et al., 2018). In sum, those techniques can be particularly helpful in expanding our knowledge on how specific patterns of variables matter for vocational outcomes.

Modeling profiles of intraindividual change processes

In this last category of models, we review two longitudinal person-centered models, being growth mixture modeling and latent transition analysis. Those models are well suited to model stability and change over time, allowing for example for an assessment of the impact of important transitions in employees' lives (e.g., starting a job, promotion, retirement; see Solinger, van Olffen, Roe, & Hofmans, 2013), or for analyzing the impact of the occurrence of critical events in organizations (e.g., organizational change). Because of their ability to examine inter-individual differences in intra-individual processes, these models are ideally placed as the analytical solution to calls for more longitudinal, within-person research in vocational research (e.g., Zacher et al., 2019).

Growth Mixture Modeling (GMM). Growth Mixture Modeling (GMM) aims at identifying subpopulations that follow different longitudinal growth trajectories over time, thereby being a mixture extension of latent growth or latent curve models (see Bollen & Curran, 2006)[4]. In such latent growth models, one or more variables is measured repeatedly and growth in the level of these variables across time is estimated via random intercept and slope(s) factors. The random intercept factor(s) capture each individual's initial level on the repeated measures, while the random slope factor(s) capture each individual's change in those repeated measures as a function of time. At its simplest, growth is characterized by a random intercept and a random linear slope factor, although more complicated growth trajectories can be modeled by adding additional, higher-order slope factors (e.g., quadratic, cubic, ….).

GMM, being a mixture extension of the latent growth model, aims to identify subpopulations following different growth trajectories over time (see Figure 4). In this sense, GMM is similar to multi-group growth curve modeling, where different growth models are tested for each group. However, unlike in multi-group growth curve modeling, where the

[4] Latent Class Growth Analysis (LCGA) is a special case of GMM in which the variances and covariances of the growth factors in each latent class are fixed to zero (see e.g., Jung & Wickrama, 2008).

groups are observed, in GMM the grouping variable is latent or unobserved (Ram & Grimm, 2009). In its simplest form, the latent subpopulations are only allowed to differ regarding their average level on the growth factors. However, more complex GMMs can also be estimated, with the subpopulations being allowed to vary not only on intercept and slope(s) averages, but also intercept and slope(s) variances and covariances, and even time-specific residuals. Moreover, the subpopulations can also be allowed to follow a different functional form. Formally, a general linear GMM can be expressed as:

$$y_{it} = \sum_{k=1}^{K} p_k \left[\alpha_{iyk} + \beta_{iyk}\lambda_t + \varepsilon_{yitk}\right] \tag{10}$$

$$\alpha_{iyk} = \mu_{\alpha yk} + \zeta_{\alpha ik} \tag{11}$$

$$\beta_{iyk} = \mu_{\beta yk} + \zeta_{\beta ik} \tag{12}$$

In Formula 10, y_{it}—or the level of variable *y* for person *i* at time *t*— is a function of (1) the profile-specific random intercepts α_{iyk}, linear slopes β_{iyk}, and error terms ε_{yitk} (with *k* = 1, 2, …, *K* being the latent profiles), and (2) the probability of belonging to each of the latent subpopulation or profiles, p_k (with all $p_k > 0$ and $\sum_{k=1}^{K} p_k$=1). In other words, the raw repeated measures data for each individual are conceived of as a mixture (i.e., a weighted sum) of the *K* different latent growth profiles. Time in formula 10 is represented by λ_t, being the factor loading matrix relating the repeated measures of *y* to the slope factor. In GMM, λ_t should be coded in such way that it reflects the interval between measurement occasions (for example $\lambda_1 = 0$, $\lambda_2 = 1$, $\lambda_3 = 2$, $\lambda_4 = 3$ with four equally spaced measures or $\lambda_1 = 0$, $\lambda_2 = 1$, $\lambda_3 = 1.5$, $\lambda_4 = 2$ in case the measurement one and two are separated by a period double the period separating measurement two and three and three and four). More information on the technicalities involved in defining the time codes can be found in Biesanz, Deeb-Sossa, Papadakis, Bollen, and Curran (2004). The random intercepts α_{iyk} in Formula 10 can further be decomposed into $\mu_{\alpha yk}$, or the average intercept for each profile, and $\zeta_{\alpha ik}$, or the deviation of each person's profile intercept from this average intercept (see Formula 11). Similarly, the random linear slope β_{iyk} is decomposed into $\mu_{\beta yk}$, or the average slope for each profile and $\zeta_{\beta ik}$, or the deviation from this average slope for each person *I* (see Formula 12). Interestingly, because $\zeta_{\alpha ik}$ and $\zeta_{\beta ik}$ capture deviations from the average intercept and slope, respectively, they represent the variability of the intercepts and slopes across cases within profiles. Of particular importance is that, because all terms in formulas 11 and 12 have a subscript *k*, each of the profiles can have a unique growth function. Although the GMM in formulas 10-12 is a linear GMM, other functional forms can be tested as well, such as a quadratic or cubic GMM. Readers interested in a more thorough treatment of GMM can consult the papers by Jung and Wickrama (2009) or Ram and Grimm (2009).

Our literature review revealed a modest number of studies applying this longitudinal person-centered technique in vocational research, with the first studies using this technique being published around the year 2010 (see Table A8). For instance, Hirschi (2011c) used LCGA to identify different developmental trajectories of career-choice readiness: (1) "high increasing" describes a class of people with high initial readiness and a linear increase of readiness over time; (2) "high decreasing" is characterized by a very high initial level of readiness followed by a decline in readiness over time; (3) "moderate increasing" showed a moderate initial level of readiness and a linear subsequent increase in readiness; and finally (4) "low stable" showed a low initial level of readiness and almost no increase in readiness over time.

Latent Transition Analysis (LTA). Latent Transition Analysis (LTA) is a longitudinal extension of LCA/LPA (Collins & Lanza, 2010). That is, in LTA people can transition from one latent class to another over time (see Figure 5). Because the latent classes in LTA refer to subgroup memberships at that particular point in time, they are referred to as latent statuses, rather than latent classes. A good illustration of this technique comes from research conducted by Mäkikangas (2018), who studied latent profiles of job crafting strategies across time. Using latent profile analysis, she first demonstrated that in a sample of Finnish rehabilitation center employees a distinction can be made between ‘active’ and ‘passive’ job crafters, with the latter only trying to decrease their hindering job demands to some extent, without trying to increase their job resources or challenging job demands. In a next step, she used LTA to investigate the stayer-mover patterns across job crafting profiles over time. In this specific example, the latent transition probabilities were zero, indicating that no transitions occurred across a one-week interval.

In a LTA for categorical indicators, three sets of parameters are estimated. First, at each time point the proportion of individuals that is expected to belong to each latent status is estimated. This is referred to as the latent status membership probabilities (π in Formula 13). Second, the transition probabilities capture the probability of transitioning from a specific latent status at time *t* to another latent status at time *t+1* (τ in Formula 13). Third, item-response probabilities tap into the connection between latent status membership and the observed categorical indicators at each time point (the ρ’s in Formula 13). By doing so, item-response probabilities provide information on the differentiation of the latent statuses. Formally, a LTA model for two measurement occasions (i.e., *t* and *t+1*), $a, b = 1, \dots S$ latent statuses (with *a* denoting a latent status at measurement occasion *t*, and *b* denoting a latent status at measurement occasion *t+1*), and four indicators at each measurement occasion (i.e., $i_t, i_{t+1} = 1, \dots I$, $j_t, j_{t+1} = 1, \dots J$, $k_t, k_{t+1} = 1, \dots K$, $l_t, l_{t+1} = 1, \dots L$) can be expressed as follows:

$$\mathrm{P}(Y = y) = \sum_{a=1}^{S} \sum_{b}^{S} \pi_a \, \rho_{i_t|a} \, \rho_{j_t|a} \, \rho_{k_t|a} \, \rho_{l_t|a} \, \tau_{b|a} \, \rho_{i_{t+1}|a} \, \rho_{j_{t+1}|a} \, \rho_{k_{t+1}|a} \, \rho_{l_{t+1}|a} \quad (13)$$

In Formula 13, *y* represents a specific response pattern on the categorical indicators across both measurement occasions (i.e., $y = \{i_t, j_t, k_t, l_t, i_{t+1}, j_{t+1}, k_{t+1}, l_{t+1}\}$), π_a represents the proportion of individuals in latent status *a* at time *t*, and $\tau_{b|a}$ is the probability of membership in latent status *b* at measurement occasion *t+1*, conditional on membership in latent status *a* at measurement occasion *t*. Finally, $\rho_{i_t|a}$ is the probability of response *i* to the first item at measurement occasion *t*, conditional on membership in latent status *a* at measurement occasion *t*. Readers interested in a more thorough treatment of LTA can consult the book by Collins and Lanza (2010).

Our literature review identified only three studies that used LTA in vocational research so far (see Table A9). In addition to Mäkikangas (2018; see above), Kunst, van Woerkom, van Kollenburg and Poell (2018) used LTA to identify trajectories of goal orientation profiles in a teacher sample. Although the majority of teachers remained in the same goal orientation profile over the one-year interval (i.e., success-oriented, diffuse, low-performance, or high-avoidance), a small percentage of teachers shifted towards a different profile, and this shift was supported by a specific type of managerial coaching. Rice, Ray, Davis, DeBlaere and Ashby (2015) used LTA to study the stress trajectories of different types of perfectionists, showing that maladaptive perfectionists never transitioned to low stress whereas only 4% of the adaptive perfectionists transitioned to high stress.

The potential of modeling profiles of intraindividual change processes for vocational research. Methods for detecting profiles of intraindividual change have direct relevance to vocational research because careers by definition develop and evolve over time (De Vos et al., in press; Hall, 2002). Traditional longitudinal models, such as the latent growth model, however, make the strong assumption that change can be described using the same functional form (e.g., linear or quadratic) for everyone. Whereas this might be true in very specific circumstances, the awareness that careers and career choices are driven by the complex interplay of a wide set of person characteristics, as well as the situations one encounters, suggests that heterogeneity in change might be the rule rather than the exception. In response to this awareness, GMM is particularly interesting because it allows the change over time to be qualitatively different for different groups of individuals. Using GMM, Hirschi (2011) for example identified distinct developmental trajectories of career-choice readiness in adolescents and demonstrated that students in those trajectories differed on core-self evaluations, occupational knowledge and barriers. Also for the counseling field GMM shows a lot of promise because it for example allows studying patterns of responses to treatment, showing "what works or does not work for whom?" (Frankfurt et al., 2016; p. 624). Such insights gained through GMM might help counseling psychologists tailoring their treatments and intervene more effectively.

LTA, being a longitudinal extension of LCA/LPA, is a method holding a lot of promise for the careers field because it aligns well with the definition of careers as "the individually perceived sequence of work-related experiences and activities over the span of a person's life" (Hall, 2002, p. 12). In LTA—and LPA and LCA more broadly—those work-related experiences are not studied in isolation, rather the combined profile states of those work-related experiences are the unit of analysis. Moreover, because of its ability to model transitions between those profile states, the treatment of careers in LTA closely resembles our theoretical conceptualization of it. This is not only important from a substantive-methodological fit perspective, but studying careers in this way might also provide novel and unique information. For example, Xu and Payne (2018) used LTA for studying changes (or transitions) in organizational commitment profiles over time, and they demonstrated that those transitions themselves (e.g., from a value-based commitment profile to a weak commitment profile) were predictive of turnover hazards. Future studies could for example use LTA to investigate transitions in career profiles (e.g., from "protean career architects" to "solid citizen", Briscoe & Hall, 2006) or in work versus family commitment profiles (e.g., from "work profile" to "family profile", Cinamon & Rich, 2002).

Important issues in person-centered research

There are a number of issues that are fundamental and practical to many contemporary person-centered analyses, including class enumeration, profile labeling, inclusion of covariates, and multi-group invariance testing. Because these issues apply to most methods discussed above, we review them in a separate section.

Class enumeration

Selecting the optimal number of latent profiles is a thorny issue. Typically, models with an increasing number of latent profiles are tested after which the most optimal one is selected based on interpretability and theoretical conformity of the solution, statistical adequacy (e.g., no negative residual variances), and statistical indicators. Regarding the latter, several indicators are available, with simulation research showing that the Bayesian Information Criterion (BIC), the sample-adjusted BIC (SABIC), the Consistent Akaike Information Criterion (CAIC), and the Bootstrap Likelihood Ratio Test (BLRT) are among the most effective ones (e.g., Henson, Reise, & Kim, 2007; Nylund, Asparouhov, & Muthén, 2007). However, because of the sample size dependency of those indicators, they might suggest keeping on adding profiles in case one's sample size is large. If this happens, Morin and colleagues (2011) suggest looking at additional gains in fit when adding more latent profiles using so-called "elbow plots".

Labeling of profiles

The latent profiles in a profile solution can differ in many ways, including differences in the unique pattern of high and low mean scores on the indicators (i.e., shape differences), differences in the mean score across all indicators (i.e., level differences), and differences in the degree of differentiation among indicators within a profile (i.e., scatter differences) (Meyer & Morin, 2016). When it comes to labeling of the profiles, any of these differences can be referred to, with different labeling schemes being used in different research fields. For example, in the commitment literature, researchers have predominantly focused on shape differences, with the most common labeling scheme being one in which the commitment component with the highest score is referred to as “dominant” (e.g., affective commitment dominant or continuance commitment dominant). The advantage of focusing on only one of the differences is simplicity. The downside, however, is that it comes with decreased accuracy because other between-profile differences are not taken into account. One solution adopted by Meyer and Morin (2016) is to add level and scatter information whenever relevant (i.e., whenever level or scatter are either high or low).

Incorporating covariates

When engaging in person-centered research, one is often interested in learning how profile membership relates to covariates. Research generally shows that covariates should only be included once the optimal unconditional profile solution (i.e., the profile solution based on only those variables making up the profile) is selected (Morin et al., 2019; Nylund-Gibson & Masyn, 2016). Moreover, inclusion of covariates in the model should not change the nature of the profiles as this causes the latent categorical variable to “lose its meaning” (Asparouhov & Muthén, 2014; p. 329).

Looking at different ways in which covariates can be included in the analysis, a first way to test predictors and/or outcomes is to directly include them in the final solution. For example, one might include profile outcomes by specifying them as additional profile indicators. Whereas direct inclusion of covariates might help to reduce biases in the estimation of the profile-covariate relations and although this helps limiting Type 1 errors (Diallo & Lu, 2017), one needs to make sure that including the covariates does not change the optimal unconditional profile solution (see above). In case the profile solution is modified by the inclusion of the covariates, a different approach can be taken. This approach, referred to as the automated auxiliary approach, is specifically designed to prevent this from happening. In fact, there is not one but different automated auxiliary approaches, with Morin and colleagues

(2019) suggesting that the preferred automated auxiliary approach depends on whether you look at predictors, outcomes or correlates of profile membership. In case one is interested in predictors, the "three-step" approach seems to perform well (see Asparouhov & Muthén, 2014 for more information). For outcomes, either the three-step approach, the approach by Lanza, Tan, and Bray (2013), or the BCH approach (see Asparouhov & Muthén, 2014 for more information) can be used. According to Meyer and Morin (2016), correlates can best be tested using the E function in Mplus because this approach does not assume directionality of the associations. Finally, McLarnon and O'Neill (2018) discuss how one can manually implement the BCH and three-step approach when one wants to test more complex mediation and moderation models or models that look at the effect on an outcome after accounting for control variables.

Multi-group invariance testing

An important issue in person-centered research is whether profiles found in one sample generalize across known subpopulations (Morin, Meyer, Creusier, & Biétry, 2016). For LCA, multi-group invariance has typically been tested using a three-step approach in which one tests whether (1) the same numbers of latent classes are extracted within each group, (2) the response probabilities are the same across groups, and (3) the relative size of the profiles is the same across groups (see Eid, Langeheine, & Diener, 2003).

Recently, Morin and colleagues (2016) extended this approach by revising the second step for LPA rather than LCA and by including tests of similarity between the profiles, antecedents and outcomes across subpopulations. This approach consists of six steps that test (1) whether the same number of latent profiles is found in each group (i.e., configural similarity), (2) whether the indicator's levels are equal across groups (i.e., structural similarity), (3) whether the indicator's variability is equal across groups (i.e., dispersion similarity), (4) whether the relative size of the profiles is the same across groups (i.e., distributional similarity), (5) whether the predictor-profile relations are the same across groups (i.e., predictive similarity), and (6) whether the profile-outcome relations are the same across groups (i.e., explanatory similarity). Morin and Wang (2016) extended this approach to MRM, which essentially requires one additional step between the first and second one in which the invariance of regression coefficients is tested across groups. Readers interested in learning more about multi-group invariance testing in the context of LPA can consult the paper and accompanying Mplus code by Morin and colleagues (2016), while the chapter by Morin and Wang (2016) shows how to perform multi-group invariance testing for MRM.

Finally, as argued by Morin and colleagues (2019), the six-step multi-group profile similarity framework can also be used to test for longitudinal invariance in LTA, although in the presence of distributional similarity (i.e., the profiles account for equal proportions of the sample over time) one cannot directly impose equality constraints on the relative size of the profiles over time. In this case, the approach described by Morin and Litalien (2017) is needed.

Discussion: Critical Reflections on the Use of Person-Centered Methods

Despite their promise to vocational research, as evidenced by our literature review, some researchers remain reluctant to adopt person-centered methods because of their exploratory nature and their choice for a categorical rather than a continuous latent variable. In what follows, we aim to offer a balanced discussion of these issues, hoping that this helps researchers to take a stance and make informed decisions when designing their studies and plans of analysis.

The exploratory nature of person-centered methods

As mentioned earlier, person-centered models are exploratory in the sense that a ‘final’ model is typically obtained by comparing solutions with different numbers of profiles (or subpopulations) after which the ‘optimal’ one is selected. One concern is that such an exploratory procedure is highly sample-dependent, thus limiting the generalizability of one's findings.

First, it is important to note that balancing model fit and model parsimony does not preclude the generation of expectations regarding the number and/or the structure of the profiles (Morin et al., 2018). For example, in case one would study how people's job satisfaction develops after starting a new job, it would be good practice to build on previous research that has demonstrated that job satisfaction generally shows a trend of steady decline after entering a new job (e.g., Boswell, Boudreau, & Tichy, 2005). Hence, in that particular case one expects a hypothesis that at least one of the subpopulations follows such a hangover-pattern (see Solinger et al., 2013). Thus, although the exact number of profiles can often not be predicted when performing person-centered analyses, one might still have expectations concerning the nature of some of the profiles. Morin and colleagues (2018) make exactly the same point, using the analogy of fishing. Whereas a fully a-theoretical undertaking (which they refer to as dustbowl empiricism) corresponds to dynamite fishing, in which one throws sticks of dynamite into the water and catches whatever floats to the surface, valuable exploratory research is like fly fishing. In fly fishing, one starts by carefully selecting the appropriate bait and fishing location, anticipating catching a particular type of fish. While in the fly fishing scenario the number of fish, their size and even the type of fish is not known in advance, the difference with dynamite fishing is that one goes well prepared to the expedition, knowing that something valuable will come out of it (Morin et al., 2018).

Even though exploratory research, when well-planned, often leads to interesting findings, the lack of a comprehensive theory that serves as a basis for clear hypotheses makes replication of one's findings increasingly important. This is particularly true provided that in some cases—for example when the model's distributional assumptions are violated—spurious profiles can emerge (Bauer & Curran, 2003). Therefore, construct validation of one's solution is essential (Morin et al., 2018). According to Morin and colleagues (2018), such construct validation involves the following steps: (1) demonstrating that the profiles have theoretical value, (2) demonstrating that the profiles relate in a meaningful way to key covariates, and (3) demonstrating that the profiles generalize to new samples or are (at least somewhat) stable across time.

Finally, we believe that person-centered methods are useful for inductive theorizing (Hofmans, Vantilborgh, & Solinger, 2018). In case suitable theory is scarce or even non-existing, restricting oneself to deductive logic in which one draws on a theory to build a general rule, after which one tests whether the rule also applies to one's data, might be too limiting (Ketokivi & Mantere, 2010). In the scenario where there is little theory, person-centered methods are particularly interesting because they offer a way to discover new aspects of phenomena through inductive thinking. This inductive thinking might take the form of contextual or theoretical induction (Ketokivi & Mantere, 2010). With contextual induction, the reason for existence of (some of) the subpopulations is looked for in the research context. In theory-based induction, the subpopulations are not assumed to be the result of a particular sample setting; instead one tries to achieve a theoretical understanding of the subject matter. Apart from contextual and theoretical induction, researchers can also look for counter-factuals in their findings. Such counter-factuals are findings that are counter to one's set of theoretical assumptions, and typically give rise to imaginative and innovative research because they are followed by a problematization of assumptions from the part of the researcher and the presentation of an alternative (Cornelissen & Durand, 2014).

A categorical versus dimensional approach to latent variables

As we have argued above, person-centered methods are typically classification-based. This means that, in case the method is performed in a latent variable framework, it posits a categorical latent variable. A logical question then is whether the choice for a categorical latent variable, rather than a continuous one, makes sense. This issue is particularly important because, as Molenaar and von Eye (1994) demonstrated, under certain conditions, an m-factor common factor model can be perfectly reproduced with a $K = m + 1$ class latent profile model (see also Bauer & Curran, 2003). This equivalence is important because it places great onus on researchers to argue for the tenability of one representation versus the other. We feel that there are two possible ways to go about this (see also Collins & Lanza, 2010).

First, one may have a strong belief that the latent variable is categorical, and that it therefore should be modeled in a person-centered, categorical way. Although such discussions are not very prominent in vocational research, there are a number of research domains in which the issue of dimensionality versus categoricity is a key question. Psychopathology research is such a domain, with the crucial question being whether a dimensional or categorical classification of personality disorders should be used (Ruscio, Ruscio, & Carney, 2011). An important criterion that is used to argue for the meaningfulness of a categorical (or person-centered) rather than a dimensional (or variable-centered) solution is the presence of qualitative, rather than quantitative differences between profiles (Chen, Morin, Parker, & Marsh, 2015; De Boeck, Wilson, & Acton, 2005). The rationale behind this idea is that quantitative differences, or ordered profiles that differ only in level, can be well accommodated by a model with a continuous latent variable. Qualitative differences, or profiles that differ in shape, instead, support the meaningfulness of a categorical, person-centered approach because such differences cannot be captured well using the traditional, variable centered approach. Although the issue of testing for dimensionality versus categoricity goes beyond the scope of the present article, it is important to know that empirical tests have been developed to evaluate whether a construct is categorical versus dimensional. Readers interested in this issue can consult the taxometric method developed by Meehl (1992) or the article of Ruscio and colleagues (2011).

Second, rather than debating whether a construct is continuous or categorical, one might consider that both the continuous as well as the categorical approach provide separate, but equally useful information (Collins & Lanza, 2010). When such an agnostic perspective on the nature of constructs is adopted, the choice for a continuous or a categorical latent variable is dictated by the research question at hand. For example, although few people would dispute a continuous treatment of personality traits, according to which individual differences in personality traits are expressed as the degree to which the trait is characteristic of those individuals, most people also see value in a categorical, profile-perspective on traits. The reason is that those two approaches to personality traits address different questions. While the dimensional perspective is well suited to study the effect of individual differences in one or more traits, thereby taking those traits as the focal point of analysis, the categorical perspective looks at the effects of specific combinations of trait scores, which implies shifting the focus from the traits to the individual. This example also illustrates a broader point. Despite our plea for more person-centered vocational research, it is important to realize that person- and variable-centered approaches are not conflicting but rather complementary. Ultimately, person- and variable-centered approaches can even be used in tandem to provide a more comprehensive view of the same phenomena (e.g., Morin, Boudrias, Marsh, Madore, & Desrumaux, 2016).

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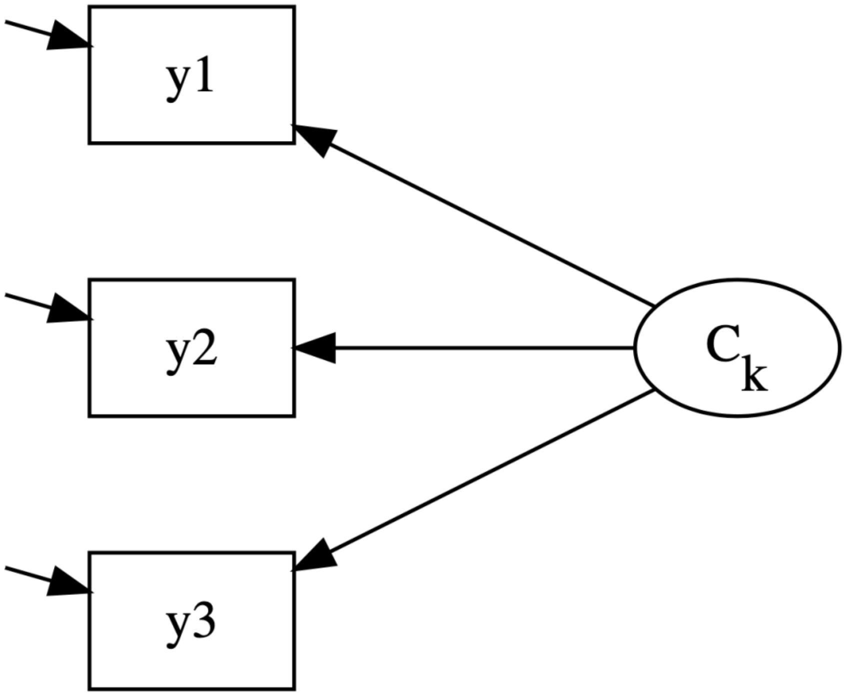

Figure 1: Latent Profile Analysis (LPA). Scores on the continuous (LPA) indicators (y's) are caused by the categorical latent variable C (with k latent classes). In the most constrained model, the latent classes differ in mean scores on the indicators only, but in alternative formulations, indicator variances can be class-specific and correlated residuals can be added. In case the indicators are not continuous but categorical, LPA becomes Latent Class Analysis (LCA).

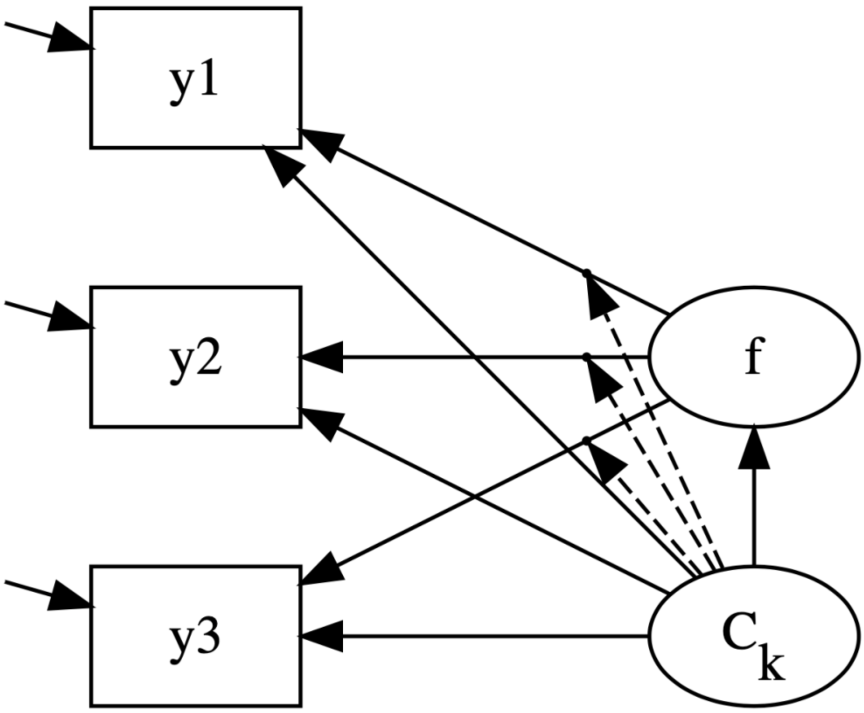

Figure 2: Factor Mixture Analysis (FMA). The indicators (y's) are caused by both a continuous latent variable f and a categorical latent variable C (with k latent classes). The dashed lines indicate that the factor structure can be different in each latent class. In FMA, factor loadings, factor means, the factor covariance matrix and item intercepts/thresholds can be class-specific.

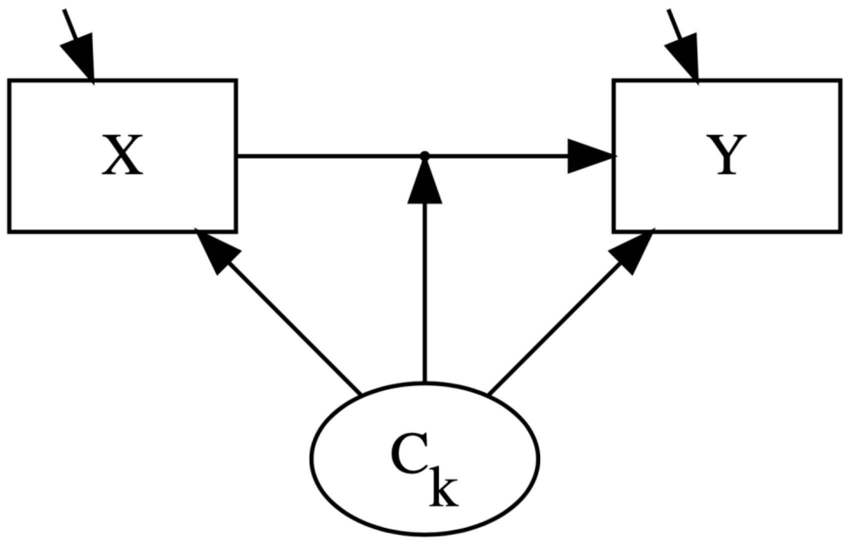

Figure 3: Mixture Regression Analysis (MRM). The latent variable C (with k latent classes) moderates the relation between X and Y. In the basic MRM, the means and variances of the outcome(s) are class-specific, while in a more flexible representation the means and variances of the predictor(s) can also be class-specific.

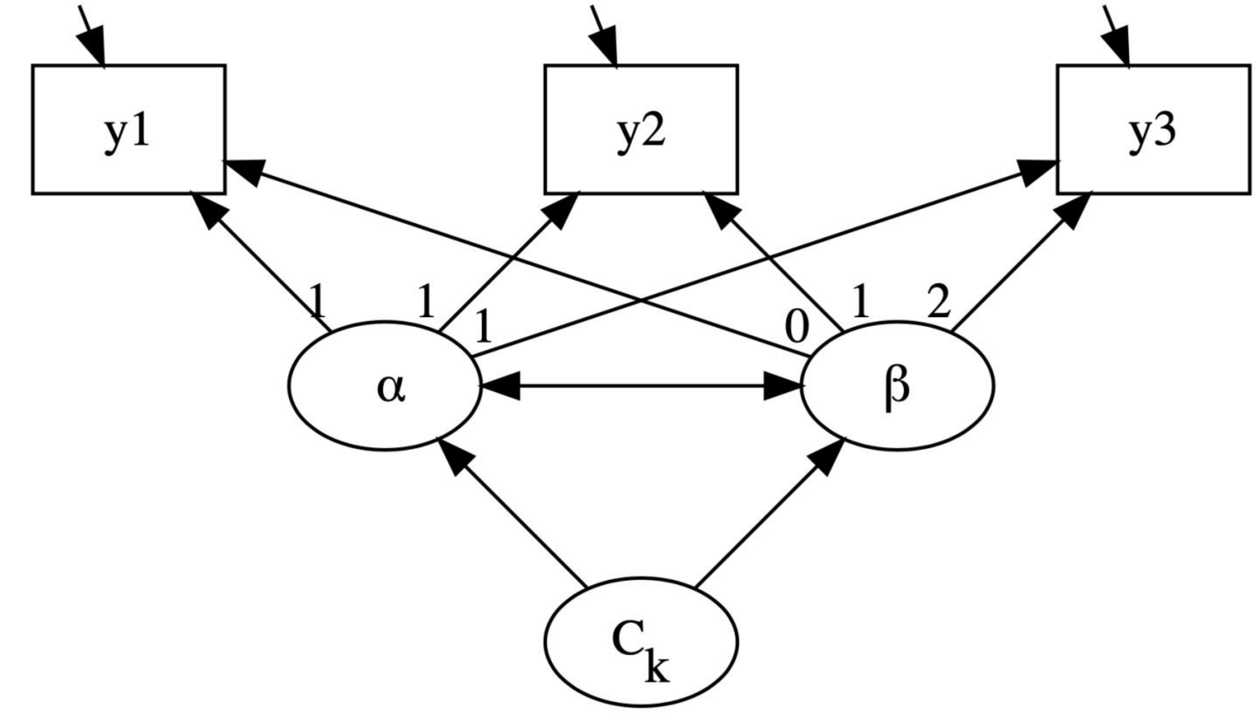

Figure 4: Growth Mixture Modeling (GMM). k latent classes are estimated, each having class-specific growth parameters. In GMM, any part of the model can be class-specific (including the means and variances of the latent growth parameters, the indicator variances, etc.).

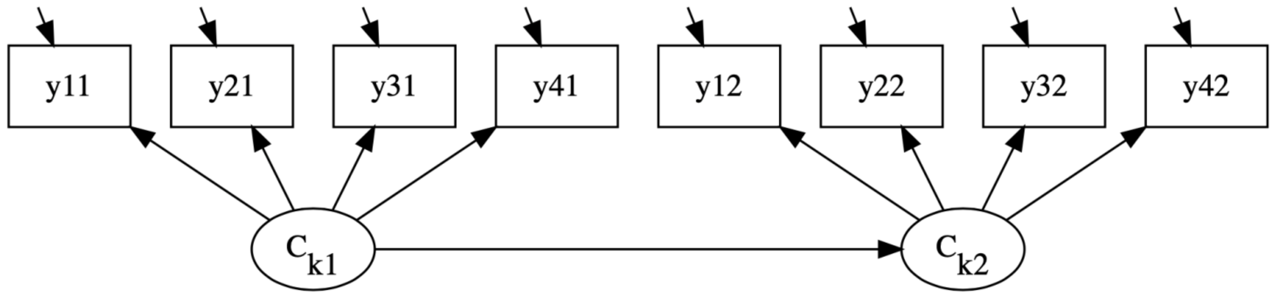

Figure 5: Latent Transition Analysis (LTA). The LTA model estimates on both measurement occasions k latent classes (from repeated measures of the same four items at t_1 and t_2), as well as the probabilities to transition from classes in C_{k1} to classes in C_{k2} over time. The number and structure of profiles can be different on both measurement occasions, and indicators can be categorical (implying that the latent transition model is an extension of Latent Class Analysis) or continuous (implying that the latent transition model is an extension of Latent Profile Analysis).

Highlights

- We showcase the relevance of person-centered research for vocational research
- We discuss different conceptualizations of the term “person-centered”
- We performed a review of these methods in the vocational research domain
- We provide a discussion of the advantages *and* challenges of person-centered research