Annual Review of Organizational Psychology and Organizational Behavior

Person-Centered Modeling: Techniques for Studying Associations Between People Rather than Variables

Sang Eun Woo,[1,*] Joeri Hofmans,[2,*] Bart Wille,[3] and Louis Tay[1]

[1]Department of Psychological Sciences, Purdue University, West Lafayette, Indiana, USA; email: sewoo@purdue.edu

[2]Department of Psychology, Vrije Universiteit Brussel, Brussels, Belgium

[3]Faculty of Psychology and Educational Sciences, Ghent University, Ghent, Belgium

ANNUAL REVIEWS CONNECT

www.annualreviews.org

- Download figures
- Navigate cited references
- Keyword search
- Explore related articles
- Share via email or social media

Annu. Rev. Organ. Psychol. Organ. Behav. 2024. 11:453–80

First published as a Review in Advance on November 14, 2023

The *Annual Review of Organizational Psychology and Organizational Behavior* is online at orgpsych.annualreviews.org

https://doi.org/10.1146/annurev-orgpsych-110721-045646

Copyright © 2024 by the author(s). This work is licensed under a Creative Commons Attribution 4.0 International License, which permits unrestricted use, distribution, and reproduction in any medium, provided the original author and source are credited. See credit lines of images or other third-party material in this article for license information.

*These authors contributed equally to this article

Keywords

latent class, latent profile, cluster analysis, mixture modeling, person-centered, growth mixture model

Abstract

The goal of person-centered methods is to identify subpopulations of individuals based on within-group similarity of data relative to between-group variability. In this article, we provide an overview of specific person-centered methods, thus shifting the attention from studying relations between variables to studying relations between people or entities of interest. Next, we present a selective and critical review of recent research utilizing person-centered modeling approaches, highlighting key trends in the organizational psychology and organizational behavior literature from both the methodological and the conceptual perspectives. Lastly, we conclude with reflections and recommendations, highlighting several areas that need careful consideration when conducting person-centered research.

OPEN ACCESS (cc) BY

INTRODUCTION

Person-centered modeling has had historical roots in the early twentieth century. Within psychology, this was motivated by identifying groups of "like-minded" individuals (Zubin 1938), which led to the development of clustering (Cattell 1944) and latent class methodologies (Lazarsfeld 1950). The interest in identifying similarities among individuals has not only remained but also extended to groups, organizations, and societies. Given its applicability to organizational phenomena, person-centered modeling is widely adopted in organizational research and has grown in sophistication (Hofmans et al. 2020, Woo et al. 2018).

Because of the liberal use of the term "person-centered" in previous writings (e.g., person-centric, person-focused), there is often confusion about what it means. First, some researchers have used person-centered research to refer to research on the characteristics of individuals (versus research on the characteristics of situations). A second usage of the term refers to research on the subjectivity of worker experiences (versus research on objective characteristics of individuals) (Weiss & Rupp 2011). Finally, the third conceptualization uses the term to refer to a set of methods that aim to classify individuals based on the similarity in their scores on a set of variables (Howard & Hoffman 2018). This latter conceptualization is the one we use in the present article because it "maximizes the level of precision in *methodological* discussions" (Woo et al. 2018, p. 816; emphasis in original). Therefore, past work has sought to clarify that person-centered modeling refers to an analytic approach rather than a theoretical focus (Woo et al. 2018).

Our review seeks to provide more clarity by contrasting person-centered modeling with two analytic traditions: variable-centered modeling and person-specific modeling (see also Howard & Hoffman 2018, Morin et al. 2018). We present person-centered modeling in light of these two modeling traditions so that readers can better delineate and understand the unique characteristics of person-centered modeling. To this end, we extend Cattell's (1946) data box to highlight these different modeling approaches in **Figure 1**.

Contrasts with Variable-Centered Modeling

As seen on the left side of **Figure 1*a*,*c***, variable-centered modeling focuses on describing variables and their associations across individuals. The underlying assumption is that the variables function in the same way across all individuals because they are believed to all come from a single population (Morin et al. 2018). Variable-centered modeling can, therefore, be understood through the broader lens of a nomothetic research tradition, where the emphasis is on identifying generalizable laws or parameters in a single population. This includes commonly used analyses in organizational research, such as descriptive statistics to estimate population-level parameters. It also encompasses analyses that capture relationships among variables, such as regression analysis, growth curve modeling, and structural equation modeling (SEM). An illustration of nomothetic variable-centered modeling is in personality research, where variables are analyzed using factor analysis to determine personality structure. By contrast, and as shown on the right side of **Figure 1*a*,*c***, person-centered modeling assumes that variables do not necessarily function in the same way across individuals because there may be multiple subpopulations; there is a change in analytic mindset whereby the focus shifts to individuals (rows of data) rather than variables (columns of data) because we are interested in how variables are configured to identify different subpopulations (Zyphur 2009). Along these lines, variable-centered modeling in personality research has been referred to as differential psychology, emphasizing how individuals vary along a variable or a trait (Revelle et al. 2011). In contrast, person-centered research has been termed "integral psychology," emphasizing how variables vary or are configured among subgroups of individuals (Zubin 1938).

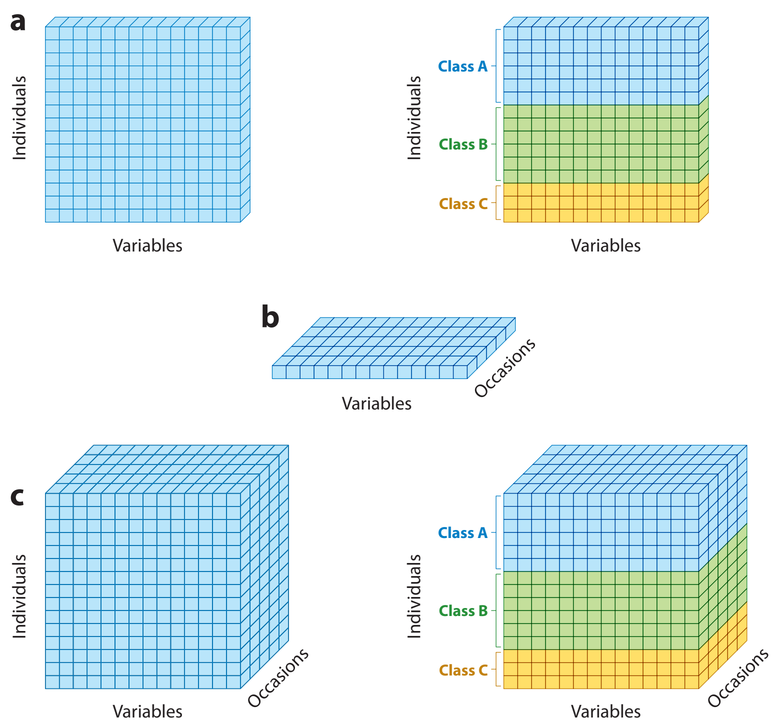

Figure 1

Illustration of data structures for individuals × variables × occasions data. One set of parameters is estimated for all individuals with the same color. (*a*) Examples of a variable-centered approach (*left*) and a person-centered approach (*right*) to individuals × variables data. (*b*) Example of a person-specific approach to variables × occasions data. (*c*) Examples of a variable-centered approach (*left*) and a person-centered approach (*right*) to individuals × variables × occasions data.

Contrasts with Person-Specific Modeling

As displayed in **Figure 1*b***, person-specific modeling focuses on analyzing single individuals or, more generally, individual entities (e.g., firms, countries). The underlying assumption is that each individual is unique, and the phenomena might be distinct for each individual. Therefore, unlike a nomothetic approach in which researchers seek generalizable laws or parameters in a population, the population of interest for person-specific modeling is the particular individual, with the goal of using relevant information to describe them sufficiently (Howard & Hoffman 2018). Person-specific modeling is aligned with an idiographic research tradition, emphasizing an in-depth individual description (Allport 1921). This often entails using qualitative methods but, from a quantitative perspective, can also involve assessing multiple relevant variables within an individual rather than between individuals. In recent times, it has been thought that data collection approaches such as experience sampling can enable person-specific modeling (Conner et al. 2009, Hofmans et al. 2019). Through intensive data collection, commonly used quantitative person-specific methods for analyzing within-individual phenomena include dynamic factor analysis, state-space modeling, and P-technique factor analysis (Molenaar 2004, Nesselroade et al. 2007, Zevon & Tellegen 1982; see also Renner et al. 2020). In contrast, person-centered modeling focuses on identifying groups of similar individuals (i.e., subpopulations), which necessitates going beyond single cases (see the right side of **Figure 1*a*,*c***); that is, even with experience sampling, the goal of person-centered modeling would be to identify subgroups of individuals who share similar within-person associations or trajectories (e.g., Rodríguez-Muñoz et al. 2020).

Person-Centered Modeling

Although these contrasts help delineate person-centered modeling, we need to elaborate more formally on what person-centered modeling is: It aims to reveal unobserved heterogeneity (i.e., latent heterogeneity) within a population by identifying subgroups of individuals for whom variable relationships hold within their subgroup but not across subgroups (Hofmans et al. 2020). In other words, person-centered methods identify subpopulations based on both within-group similarity and between-group variability (Woo et al. 2018). Because they are focused on revealing subgroup differences, person-centered methods are said to focus not only on relations between variables—which is what the variable-centered methods typically do—but also on relations among individuals, which is the reason they are labeled "person-centered" (Zyphur 2009).

Although focusing on population heterogeneity by identifying subgroup differences is a defining characteristic of person-centered methods, traditional variable-centered methods such as t-tests, ANOVA, MANOVA, and multigroup SEM also allow modeling population heterogeneity. Those more traditional variable-centered methods do this by differentiating observed subgroups based on an observed variable such as age, gender, or occupational category. In other words, they capture observed heterogeneity using a multigroup approach in which the groups are defined a priori. However, in person-centered methods, there is no need to measure or even define the variables that cause population heterogeneity beforehand. Population heterogeneity is inferred from the data and modeled using latent rather than observed subpopulations, which are then referred to as latent classes rather than groups.

By looking for unobserved or latent subpopulations characterized by both within-group similarity and between-group variability, person-centered analyses offer a useful compromise between the simplicity or parsimony of the variable-centered approach, which results in a single set of parameters that are assumed to hold for the whole population, and the specificity of the person-specific approach, yielding a unique set of parameters for each individual. Conceptually speaking, this implies that person-centered methods are situated between the purely nomothetic and the idiographic extremes (Howard & Hoffman 2018).

Person-centered research can be conducted in various ways (see **Table 1** for an overview of person-centered methods discussed in this article). The existence of subpopulations within a broader population of interest can be theorized from prior knowledge, empirically tested via hypothetico-deductive processes, and/or discovered and established through inductive/abductive processes. Also, person-centered methods can be used for modeling different types of data. Some analytic methods are used to model variations across individuals as well as variables, identifying similarities among people in terms of how they differ on variables of interest. Examples of such methods include cluster analysis, latent class/profile analysis, factor mixture analysis, and mixture regression analysis. These methods differ in the specific ways in which variable relationships are modeled within groups, as elaborated below.

Adding another layer of complexity, some person-centered methods can model variations across occasions (e.g., temporal fluctuations, developmental/longitudinal trajectories) while focusing on modeling between-person similarities in how variables of interest relate to one another. Two key examples of such methods are growth mixture modeling and latent transition analysis. These two methods differ in terms of how temporal dynamics are modeled: The former takes into account temporal variations at the time of modeling variable relations, whereas the latter considers how the group membership, indicating subpopulations (i.e., similarities among individuals in variable relations), changes over time.

Table 1 Overview of person-centered modeling methods

Method(s)	Description/purpose	Recommended reading(s)
Modeling individuals × variables data		
Cluster analysis	For grouping (or clustering) individuals into mutually exclusive groups (or clusters) based on their profile of scores on a set of variables, maximizing within-cluster homogeneity as well as between-cluster heterogeneity.	Arabie et al. (1996), Clatworthy et al. (2005)
Latent class analysis (LCA) and latent profile analysis (LPA)	For identifying latent subpopulations characterized by distinct configurations of scores on a set of indicator variables; indicator variables are categorical in LCA and continuous in LPA.	Vermunt & Magidson (2002)
Factor mixture analysis	A model using both categorical and continuous latent variables; the categorical latent variable allows for the classification of individuals into subpopulations, while the continuous latent variable(s) allow for the modeling of heterogeneity within those subpopulations.	Clark et al. (2013), Lubke & Muthén (2005)
Mixture regression analysis	For identifying latent subpopulations of individuals that are characterized by differential relations between a set of predictor variables and an outcome variable.	Wedel & DeSarbo (1994, 1995)
Modeling individuals × variables × occasions data		
Growth mixture modeling	A person-centered extension of the latent growth curve model for identifying subpopulations of individuals who follow different growth trajectories over time.	Ram & Grimm (2009), Wang (2007)
Latent transition analysis	A longitudinal extension of LCA/LPA in which individuals' membership to the latent classes can change over time.	Bray et al. (2010), Jung & Wickrama (2008), Nylund-Gibson et al. (2023)
Newer/underutilized approaches		
Multilevel mixture models	A multilevel extension of mixture models (e.g., multilevel latent profile analysis or multilevel mixture regression) to take into account the nested nature of organizational data, capturing between-unit differences contributing to subgrouping results.	Tay et al. (2011), Vermunt (2003)
Machine learning and Big Data	Algorithms for clustering can range from more traditional clustering approaches (e.g., k-means) to newer and less-known approaches such as density-based clustering and deep clustering.	Ezugwu et al. (2022)
Group iterative multiple model estimation	A network analysis approach for intensive longitudinal data that builds person-specific networks, after which the clustering algorithm clusters individuals based on their person-specific network patterns.	Gates et al. (2017)

The rest of this article is structured into three parts. First, we provide an overview of specific person-centered methods that shift the attention from studying relations between variables to studying relations between people or entities of interest (see **Table 1**). The overview is structured along the different cross-sections one can draw from Cattell's data box (**Figure 1**). That is, we first discuss methods that allow modeling individuals × variables data, and then we review methods for modeling individuals × variables × occasions data. Next, we present a selective and critical review of recent research utilizing person-centered modeling approaches, highlighting key trends in the organizational psychology and organizational behavior (OP/OB) literature from both the methodological and the conceptual perspectives. Lastly, we conclude with reflections and recommendations, highlighting several areas that need careful consideration when conducting person-centered research.

PART 1: A BRIEF OVERVIEW OF PERSON-CENTERED METHODS

Person-Centered Methods for Modeling Individuals × Variables Data

There are multiple ways to model individuals × variables data from a person-centered perspective. In this review, we focus on four methods that are most commonly known: cluster analysis, latent class analysis (LCA) and latent profile analysis (LPA), factor mixture analysis (FMA), and mixture regression analysis (MRA). We briefly describe each of them below.

Cluster analysis. Cluster analysis is undoubtedly the most well-known person-centered method (for a review of its application in health psychology, see Clatworthy et al. 2005). The goal of cluster analysis is to group (or cluster) individuals into mutually exclusive groups (or clusters) based on their profile of scores on a set of variables. This is done in such a way that the homogeneity of individuals within clusters is maximized while the heterogeneity between clusters is maximized. In other words, one seeks to cluster objects in such a way that individuals belonging to one cluster are more similar to each other than to individuals belonging to the other cluster(s).

Cluster analysis can take two forms: hierarchical clustering or nonhierarchical clustering (Arabie et al. 1996, Clatworthy et al. 2005). In hierarchical clustering, a hierarchy of cluster solutions is built in either a bottom-up (agglomerative approach) or top-down (divisive approach) manner. In the bottom-up approach, the initial cluster solution is one in which each individual belongs to a different cluster, after which, in each step, pairs of clusters that are most similar to one another are merged. In the top-down approach, all individuals are initially grouped into one cluster, after which one repeatedly splits those clusters that are most dissimilar to one another. Well-known hierarchical clustering methods are single linkage clustering, complete linkage clustering, average linkage clustering, and Ward's minimum variance method. Nonhierarchical clustering, in contrast, does not result in a hierarchy of cluster solutions but clusters individuals into a predefined number of clusters. Probably the best known nonhierarchical clustering methods are k-means and k-medoids clustering.

Latent class analysis and latent profile analysis. The goal of LCA and LPA is similar to that of cluster analysis in that these methods aim to identify latent subpopulations characterized by distinct configurations of scores on a set of indicator variables. In the LCA model, those indicator variables are categorical, while in the LPA model, they are continuous. Despite having similar goals, cluster analysis and LCA/LPA differ in the sense that cluster analysis deals with grouping observed data using an index of similarity, whereas LCA and LPA deal with uncovering latent subpopulations. This implies that—unlike cluster analysis—LCA and LPA (*a*) postulate a formal probabilistic model for the population from which the sample is obtained, assuming that the data are generated from a mixture of underlying multivariate distributions (Vermunt & Magidson 2002); and (*b*) assign objects to all latent classes/profiles in a probabilistic way, rather than assigning each individual to one, and only one, cluster (i.e., hard assignment).[1]

Factor mixture analysis. FMA is often applied when researchers are interested in understanding not only the latent classes but also how individuals within a given latent class may differ on a latent continuous variable or variables—for example, assessing diagnostic classes and the range of severity (Clark et al. 2013). This extends LPA by adding one or more latent continuous variables

[1] Some clustering methods, such as fuzzy clustering (see Tan et al. 2019), also yield probabilistic memberships.

to the categorical latent variable postulated by the LPA model. The latent categorical variable in the FMA captures distinct subpopulations that exhibit different response patterns on the indicator variables by classifying individuals in latent classes. The latent dimensional variable(s) in FMA explain covariation between observed indicators within each class, thereby capturing the underlying dimensions or constructs contributing to the observed variables. This simultaneous modeling of continuous and categorical latent variables allows us to relax the conditional independence assumption of classical LPA analyses (i.e., the assumption that the indicator variables are unrelated within each latent profile; Lubke & Muthén 2005) while also informing us about the underlying continuous and categorical nature of psychological constructs (Clark et al. 2013). FMA is particularly useful when one suspects that the population consists of multiple subgroups that may differ in both their response patterns (which in FMA is captured by the latent categorical variable) and the underlying constructs explaining these patterns [which in FMA is captured by the latent continuous variable(s)].

Mixture regression analysis. The goal of MRA, which is also referred to as clusterwise regression, is different from that of the preceding techniques in the sense that MRA aims to identify latent subpopulations of individuals that are characterized by differential relations between a set of predictor variables and an outcome variable (Wedel & DeSarbo 1994, 1995). This means that the latent subpopulations can differ in terms of the regression intercepts, slopes, and residuals. In that sense, the latent categorical variable in MRA functions as an unobserved moderator of the relation between the predictor variable(s) and the criterion variable. This enables researchers to identify ways that unobserved groups of individuals may differ in how predictor variables are related to outcomes (e.g., Poirier et al. 2017).

Person-Centered Methods for Modeling Individuals × Variables × Occasions Data

Although most of the aforementioned methods have in recent years been extended to data with a multilevel structure (including repeated measures of individuals × variables × occasions data), there are person-centered methods that have explicitly been developed from the start to model stability and change over time in individuals × variables × occasions data. Because their focus is on examining interindividual differences in intraindividual processes, these models are particularly aimed at longitudinal, within-person research.

Growth mixture modeling. Growth mixture modeling (GMM) is a person-centered extension of the latent growth curve model to identify subpopulations of individuals who follow different growth trajectories over time. For example, it has been used to identify different patterns of psychological well-being in retirees over time (Wang 2007). In this sense, GMM resembles multigroup growth curve modeling, with the important difference that in GMM, the grouping variable is not observed but latent (Ram & Grimm 2009). A wide range of GMM specifications exist. The most basic one, referred to as the latent class growth model, is one in which the latent subpopulations only differ in their average level of growth factors but there is no within-class variation. However, more complex GMMs can also be estimated, with the subpopulations differing not only in the intercept and slope(s) averages but also in the intercept and slope(s) variances and covariances, and even the time-specific residuals (Ram & Grimm 2009).

Latent transition analysis. Latent transition analysis (LTA) is a longitudinal extension of LCA/LPA in which individuals' membership to the latent classes can change over time (Bray et al. 2010, Jung & Wickrama 2008, Nylund-Gibson et al. 2023). In other words, LTA conceptualizes class membership as being dynamic (which is why the term "latent statuses" rather than "latent classes" is used) and answers the question of whether individuals remain in the same latent class over time or they transition to a different latent class at a later time point. In that sense, LTA is particularly well suited for testing stage-sequential developmental or change theories. For example, it has been used to identify classes of employees who share similar transition patterns in their work-family interface before and after the pandemic (Vaziri et al. 2020).

PART 2: REVIEW OF RECENT PERSON-CENTERED RESEARCH

To take stock of what is currently available and to identify recent trends in the applications of person-centered modeling within the field of OP/OB research, we present a selective and critical review of empirical research articles published in nine major journals over the past four years (i.e., since 2019)—namely, *Academy of Management Journal*, *Journal of Applied Psychology*, *Journal of Business and Psychology*, *Journal of Management*, *Journal of Organizational Behavior*, *Journal of Occupational Health Psychology*, *Journal of Vocational Behavior*, *Leadership Quarterly*, and *Personnel Psychology*. These journals were selected based on impact and content coverage, as we sought to cover a variety of topic areas in our review.

Although it was not our goal to conduct a comprehensive and exhaustive review of all person-centered modeling studies in the entire OP/OB field, we sought to be as systematic as possible in how our article searches and reviews were conducted. First, we searched for articles that mentioned any of the following terms associated with person-centered modeling in the full text: cluster, latent class, latent profile, latent transition, growth mixture, mixed measurement, mixture regression, factor mixture, mixture-SEM, and clusterwise regression. This search yielded 167 articles published in the aforementioned nine journals between 2019 and 2023. Based on a closer look at each of these articles, we identified a total of 47 articles that were indeed based on empirical studies using a person-centered modeling method to identify underlying or latent subpopulations (**Table 2**). We organize the review by (*a*) statistical/analytic methods used (i.e., the methodological landscape), which are closely intertwined with the prototypical research questions addressed (e.g., different configurations/profiles, differential predictions, different measurement models, different longitudinal trajectories) (see Woo et al. 2018); and (*b*) general content/topic domains (e.g., leadership, commitment) that are covered by each study (i.e., the thematic landscape).

Methodological Landscape

LPA/LCA was by far the most widely used person-centered method in the reviewed articles (in 35, or 74%, of the articles reviewed). In addition, LTA was used in 10 studies, and variations of GMM were used in 9 studies. Cluster analysis was used in 4 studies. The observation that LPA/LCA methods represent a much higher percentage compared to cluster analytic methods is consistent with what was noted by Woo et al. (2018) in their review article. We think that this is because the model-based, probabilistic approach of LPA/LCA is considered more methodologically sophisticated than the algorithmic approach used in cluster analysis, as it takes into account more nuanced variations among individuals with differing degrees (or probabilities) of belonging to the specified latent subpopulations. By contrast, a heavy reliance on typological thinking runs the risk of being overly simplistic and unrealistic if it fails to consider meaningful variations across individuals within the identified types.

Comparisons with variable-centered approaches. Many of the studies using LPA/LCA methods have combined LPA with variable-centered analysis. For example, Chawla et al. (2020) first utilized person-centered methods to identify profiles of daily recovery experiences and examine how such profiles might vary daily. The authors also examined how these profiles were associated with various work and well-being outcomes (e.g., sleep quality in the morning,

Table 2 Articles reviewed ($k = 47$)

Authors (year)	Title	Journal	Content/topic domain(s)	Method(s)
Achnak & Vantilborgh (2021)	Do individuals combine different coping strategies?	*Journal of Vocational Behavior*	Psychological contract breach, stress trajectories, coping profiles, time dynamics	Latent profile analysis
Auvinen et al. (2020)	Leader motivation as a building block	*Journal of Vocational Behavior*	Motivation to lead, resources, sustainable career, occupational well-being, career intentions, follower-rated leader behaviors, leader–member exchange	Latent profile analysis
Blustein et al. (2020)	The uncertain state of work in the US	*Journal of Vocational Behavior*	Decent work, precarious work, psychology of working, work volition, well-being	Latent profile analysis
Bouckenooghe et al. (2022)	A latent transition analysis examining the nature of and movement between career adaptability profiles	*Journal of Vocational Behavior*	Career adaptability	Latent transition analysis
Bramble et al. (2020)	Finding the nuance in eldercare measurement	*Journal of Business and Psychology*	Eldercare, work-family, well-being	Latent profile analysis
Campion & Csillag (2022)	Multiple jobholding motivations and experiences	*Journal of Applied Psychology*	Multiple jobholders, enrichment and depletion, alternative work arrangements	Latent profile analysis
Chawla et al. (2020)	Unplugging or staying connected?	*Journal of Applied Psychology*	Discretionary behaviors, recovery, well-being	(Multilevel) latent profile analysis
Chawla et al. (2021)	A person-centered view of impression management, inauthenticity, and employee behavior	*Personnel Psychology*	Impression management, performance, social hierarchies, well-being, work withdrawal	Latent profile analysis
Cruz & Nagy (2022)	Profiles in persistence	*Journal of Organizational Behavior*	Chronic stereotype threat, coping strategies, persistence, stereotype threat in the workplace, women in STEM	Latent profile analysis
Diefendorff et al. (2019)	Emotion regulation in the context of customer mistreatment and felt affect	*Journal of Applied Psychology*	Affect, emotional labor, emotion regulation	(Multilivel) latent profile analysis
Duffy et al. (2022)	A latent profile analysis of perceiving and living a calling	*Journal of Vocational Behavior*	Calling, job satisfaction, life satisfaction	Latent profile analysis
Fan et al. (2019)	Job strain, time strain, and well-being	*Journal of Vocational Behavior*	Job demands-resources model, job strain, work hours, schedule control, working conditions, job satisfaction, emotional exhaustion, work-family conflict, subjective well-being	Group-based multi-trajectory modeling

(*Continued*)

Table 2 (*Continued*)

Authors (year)	Title	Journal	Content/topic domain(s)	Method(s)
Fernet et al. (2020)	Self-determination trajectories at work	*Journal of Vocational Behavior*	Work motivation, self-determination theory, leadership, socialization, commitment, turnover intentions	Growth mixture analysis
French et al. (2020)	Faculty time allocation in relation to work-family balance	*Journal of Vocational Behavior*	Time allocation, faculty, gender, job attitudes, work-family balance	Latent profile analysis
Gabriel et al. (2019)	Examining recovery experiences among working college students	*Journal of Vocational Behavior*	Recovery, working college students, well-being, job demands	Latent profile analysis
Gagnon et al. (2019)	Developmental trajectories of vocational exploration from adolescence to early adulthood	*Journal of Vocational Behavior*	Vocational exploration, parental need, supporting behaviors	Growth mixture analysis
Garfield & Hagen (2020)	Investigating evolutionary models of leadership among recently settled Ethiopian hunter-gatherers	*The Leadership Quarterly*	Leadership traits, evolutionary psychology, prestige, dominance	Hierarchical cluster analysis
Grosemans & De Cuyper (2021)	Career competencies in the transition from higher education to the labor market	*Journal of Vocational Behavior*	Career competencies, transition to the labor market, conservation of resources, stalled resources	Latent growth class analysis
Hancock et al. (2021)	Good, bad, and ugly leadership patterns	*Journal of Management*	Leadership, well-being, commitment	Latent profile analysis
He et al. (2023)	Error disclosure climate and safety climate trajectories	*Journal of Business and Psychology*	Safety climate, error disclosure climate, counterfactual	Latent growth mixture modeling
Hirschi et al. (2020)	A whole-life perspective of sustainable careers	*Journal of Vocational Behavior*	Nonwork orientations, personality, work values, work commitment, work-nonwork interface	Latent profile analysis
Houle et al. (2020)	A latent transition analysis investigating the nature, stability, antecedents, and outcomes of occupational commitment profiles for school principals	*Journal of Vocational Behavior*	Occupational commitment, leadership, relationships, involvement, turnover intentions, job satisfaction, work-life imbalance	Latent profile analysis, latent transition analysis
Huyghebaert-Zouaghi et al. (2022)	Longitudinal profiles of work-family interface	*Journal of Vocational Behavior*	Work-family interface, conflict and enrichment, work passion, job demands, work engagement, performance	Latent profile analysis, latent transition analysis
Klug et al. (2019)	Trajectories of insecurity	*Journal of Vocational Behavior*	Employment insecurity during the first six years of the career, employment insecurity, self-rated health, well-being, young adults, early career	Latent class growth analysis

(*Continued*)

Table 2 ***(Continued)***

Authors (year)	Title	Journal	Content/topic domain(s)	Method(s)
Liu et al. (2023)	Behavior change versus stability during the college-to-work transition	*Personnel Psychology*	Alcohol use, behavior change, cohort drinking norms, life course, mentoring	Latent transition analysis
Mäkikangas & Schaufeli (2021)	A person-centered investigation of two dominant job crafting theoretical frameworks and their work-related implications	*Journal of Vocational Behavior*	(Managers') job crafting and well-being, job crafting, work engagement, person-job fit	Latent profile analysis
McKay et al. (2020)	Types of union participators over time	*Personnel Psychology*	Unions, union commitment and participation	Latent transition analysis
Meyer et al. (2021)	Profiles of global and target-specific work commitments	*Journal of Vocational Behavior*	Multiple commitments, organizational support, values fit, well-being, turnover intention, organizational citizenship behaviors	Latent profile analysis
Mühlenmeier et al. (2022)	The ups and downs of the week	*Journal of Occupational Health Psychology*	Time pressure, well-being, diary study, temporal dynamics	Latent class growth analysis
Naranjo et al. (2021)	When minor insecurities project large shadows	*Journal of Occupational Health Psychology*	Cognitive job insecurity, affective job insecurity, work strain	Latent profile analysis
Parker et al. (2021)	Employee motivation profiles, energy levels, and approaches to sustaining energy	*Journal of Vocational Behavior*	Human energy, well-being, motivation, energy management, recovery, motivation profiles at work, relations with specific indicators of work-related energy (vigor, exhaustion, need for recovery)	Latent profile analysis
Parmentier et al. (2021)	Anticipatory emotions at the prospect of the transition to higher education	*Journal of Vocational Behavior*	Anticipatory emotions, mixed emotions, transition to higher education	Latent profile analysis/factor mixture model, latent transition analysis
Qi et al. (2022)	The influence of identitiy faultlines on employees' team commitment	*Journal of Business and Psychology*	Identity faultlines, team commitment, inclusive leadership, team identification	Cluster analysis
Reknes et al. (2021)	The influence of target personality in the development of workplace bullying	*Journal of Occupational Health Psychology*	Workplace bullying, trait-anxiety, trait-anger, transitions in bullying exposure	Latent class transition analysis
Rodríguez-Muñoz et al. (2020)	Short-term trajectories of workplace bullying and its impact on strain	*Journal of Occupational Health Psychology*	Trajectories, workplace bullying, insomnia, anxiety/depression, time	Latent class growth modeling

(*Continued*)

Table 2 (*Continued*)

Authors (year)	Title	Journal	Content/topic domain(s)	Method(s)
Salter et al. (2021)	How does intersectionality impact work attitudes?	*Journal of Business and Psychology*	Intersectionality, gender, race, sexual orientation, age, disability, workplace	Latent profile analysis
Shimizu et al. (2019)	Conceptualizing calling: cluster and taxometric analyses	*Journal of Vocational Behavior*	Meaningful work, calling, vocation	Cluster analysis (hierarchical and k-means)
Shipp et al. (2022)	Profiles in time	*Journal of Applied Psychology*	Temporal focus, time, individual differences	Latent profile analysis
Shockley et al. (2021)	Work-family strategies during COVID-19	*Journal of Applied Psychology*	Work-family, dual-earner couples, division of childcare, gender, remote work	Latent class analysis
Shockley et al. (2022)	Profiles of attribution for work-family conflict episodes and their relation to negative emotions	*Journal of Organizational Behavior*	Work-family conflict attributions, emotions	Multilevel latent profile analysis
Slaughter et al. (2021)	Getting worse or getting better?	*Journal of Applied Psychology*	Emotions, organizational crisis, well-being, performance	Latent transition analysis
Takeuchi et al. (2019)	Expatriates' performance profiles	*Journal of Management*	Expatriate performance profiles, international job and organizational experiences, trajectory/change patterns	Latent class growth analysis
Tordera et al. (2020)	The lagged influence of organizations' human resources practices on employees' career sustainability	*Journal of Vocational Behavior*	Sustainable careers, human resources practices, well-being, performance, lifespan	Cluster analysis (hierarchical and k–means), latent profile analysis
van de Brake & Berger (2023)	Can I leave my hat on?	*Personnel Psychology*	Multiple team membership, role theory, teamwork quality	Latent profile analysis
Vaziri et al. (2020)	Changes to the work-family interface during the COVID-19 pandemic	*Journal of Applied Psychology*	COVID-19, work-family conflict and enrichment, technostress, supervisor support and compassion, changes in work and family roles	Latent profile analysis, latent transition analysis
Zhao et al. (2020)	Justice, support, commitment, and time are intertwined	*Journal of Vocational Behavior*	Organizational justice, perceived organizational support, commitment profile, change	Latent profile analysis, latent transition analysis
Zhong et al. (2021)	Hot, cold, or both? A person-centered perspective on death awareness during the COVID-19 pandemic	*Journal of Applied Psychology*	Death awareness, well-being, prosocial behavior, COVID-19, health, mortality	Latent profile analysis

emotional exhaustion in the morning and the afternoon). After that, they also did a series of supplemental analyses using a variable-centered approach (i.e., six multiple regression analyses, each predicting one of the six outcome variables from four predictor variables representing the daily recovery experiences that were used as LPA indicators). They found limited support for the independent effects of the four predictor variables. Comparing the two analytic approaches, the authors concluded that a person-centered analysis offers unique insights into the configurations of daily recovery experiences that may be detrimental when considered simultaneously. Other studies, such as the one by Diefendorff et al. (2019), have taken similar approaches to comparing and contrasting the informational value of person-centered versus variable-centered approaches.

Underutilized methods. Notably, our review detected no OP/OB studies that used FMA and MRA. These methods are relatively less known in the fields of organizational psychology and management, although there are many possibilities for using such modeling approaches to further advance the understanding of workplace psychological phenomena. For example, FMA may be used to investigate whether there are multiple subgroups in which one's overall attitudes toward their job are influenced by different aspects of the job (e.g., pay, work itself, promotion opportunities, coworkers, supervisors). As another example, MRA may be used to explore the presence of subpopulations within which there is a unique and shared pattern of predictive relationships between various decision factors (e.g., socioemotional versus economic reasons) and one's ultimate decision to leave their job. While OP/OB scholars have often conducted differential prediction analyses based on known group membership information (such as gender and race), research implementing more model-based approaches to identifying those subgroups inductively is much less common and represents a potentially fruitful exploratory approach to prediction.

Indicators of latent profiles. We observed some notable differences regarding the domain coverage and treatment of the profile indicators. Regarding domain coverage, some studies used subscale scores of measures that are intended to assess specific facets that are subsumed under an overall construct of interest. For example, Mäkikangas & Schaufeli (2021) used scores drawn from two separate scales, collectively representing seven job crafting strategies, which yielded four distinct profiles of job crafting. Similarly, Hancock et al. (2021) started with six commonly studied leadership styles (e.g., transformational leadership, laissez-faire, contingent reward) as LPA indicators and identified three leadership patterns (i.e., optimal, passive, and passive-abusive). Using a more open-ended approach, Campion & Csillag (2022) began by identifying eight distinct motivations for holding multiple jobs (e.g., personal interest, financial need) via qualitative content analysis, which was then turned into quantitative indicators measured with questionnaire items adapted from the existing literature. In all of these three cases, indicators come from a well-defined, homogenous content domain (e.g., job crafting, leadership, multiple job holding motivations). Research on commitment profiles also tends to be this way, although recent person-centered studies have broadened the content domain by considering commitments to various entities such as organizations, supervisors, and work groups (Meyer et al. 2021). Others have taken a more expansive approach by selecting the indicators and their underlying content domains from multiple topic areas. For example, Hirschi et al. (2020) sought to identify sustainable career profiles from variables representing nonwork orientation (e.g., family, community, personal life) together with work role commitment. Tordera et al. (2020) considered profiles of sustainable careers by considering both well-being and performance variables as indicators. However, such studies are rare in organizational research; most person-centered research tends to stay within a relatively well-defined (and somewhat distinct) content domain of interest.

Regarding the treatment of profile indicators, most studies included in our review used raw scale scores. One consideration regarding this dominant approach is that raw scale scores are not corrected for measurement error variance (Meyer & Morin 2016). The latter—thanks to the blending of mixture models and the SEM framework (which is referred to as generalized SEM; Muthén 2002)—can be done by implementing an entirely latent approach in which the item scores are used in combination as indicators of the latent factors; then, the latent factors serve as indicators of the latent categorical variable as part of the mixture model. A caveat here, however, is that fully latent models are computationally demanding and may result in nonconvergence or inadmissible solutions. Because of this, a reasonable alternative is to adopt a two-step approach in which one first tests the measurement model(s) and retrieves the factor scores, which can then be saved and used in a second step as profile indicators of the mixture model (Zyphur et al. 2023). Apart from the fact that factor scores partially control for measurement error variance by differentially weighting the items based on their reliability, this approach allows researchers to extract factor scores based on alternative measurement models, such as a bifactor model or an exploratory SEM (ESEM). Finally, in the context of longitudinal or cross-cultural person-centered research, this approach also allows for performing tests of measurement invariance, after which the scores of the most invariant model can be used (Meyer & Morin 2016).

Level versus shape. Liu et al.'s (2023) study found three profiles of drinking (i.e., alcohol consumption) during college-to-work transition that were largely differentiated by levels—i.e., minimal, moderate, and high-risk drinkers, differentiated by the probability of daily drinking and the average number of drinks. Similarly, Bouckenooghe et al. (2022) found three profiles of career adaptability (indicated by four resource dimensions, i.e., concern, control, confidence, and curiosity) that were characterized as low, average, and high adaptability. A study by Achnak & Vantilborgh (2021) is another example: The authors found three individual profiles of coping strategies in response to a psychological contract breach, characterized as low copers, average-problem-focused copers, and high-problem-and-emotion-focused copers. In cases like these, in which profiles are defined mainly by (quantitative) levels without much configurational (qualitative) difference, one might question the unique value of person-centered approaches (Chen et al. 2015, De Boeck et al. 2005). We further discuss this point below.

In contrast, many studies identified profiles differentiated by both levels and shapes. For example, in Cruz & Nagy's (2022) research, three distinct profiles of women in STEM occupations emerged based on how they engaged nine coping strategies for managing stereotype threat (i.e., preservationists, protectors, and protagonists). These profiles were uniquely configured: Two of the three were characterized as consistently high versus low engagement across all strategies (protagonists versus preservationists, respectively), whereas the third profile (protectors) showed particularly high engagement with strategies focused on group-level concerns (e.g., advocacy, changing the field). More interestingly, these qualitatively different profiles were also differentially linked to person-related and work-related factors such as gender centrality, science identity, perceived organizational support, and exit due to gender bias. Such research serves as an example of how the value of person-centered modeling can be fully capitalized.

Overall rigor. Our review identified a dozen studies ($k = 12$) that took a more rigorous approach by investigating some form of replication within their study. In eight cases, this involved a replication study with at least one more sample. In the four remaining cases, the approach consisted in investigating subsamples within the original sample or replicating the results of the original sample at two different points in time (i.e., Duffy et al. 2022). In addition, we also found some variabilities among the 10 LTA studies we reviewed in the way that temporal invariance/similarity of profiles was explicitly tested versus being simply assumed/imposed. Three out of 10 studies assumed/imposed the invariance, whereas the other 7 studies included some sort of empirical verification or a (more open-ended) test of it.

Thematic Landscape

To get a general sense of the substantive topics covered in these person-centered studies, we coded each article for the following 14 topics commonly studied in OP/OB research: careers (e.g., mentoring, newcomer socialization/onboarding, retirement), commitment, work-life, emotion, leadership, attitudes (e.g., satisfaction, justice, perceived organizational support), well-being (e.g., stress, occupational health and safety), motivation, culture and climate, performance (e.g., task performance, organizational citizenship behavior, counterproductive work behavior), diversity and inclusion, teams, individual differences (e.g., abilities, personality), and training and development. Three coauthors of the current article went through 18 topics listed on the *Journal of Applied Psychology* website and 31 content areas listed in the 2023 conference program of the Society for Industrial and Organizational Psychology, and they collectively decided on the 14 topics that we thought covered the overall OP/OB research landscape sufficiently while also capturing specific domains within the field in a meaningful way.

As shown in **Figure 2**, the most commonly studied topic was well-being ($k = 20$), followed by careers ($k = 13$). Work attitudes ($k = 10$), work-life/work-family interface ($k = 9$), and commitment ($k = 8$) were also identified as frequently researched topics using a person-centered modeling approach. Without going into too much detail, our general sense is that such topical/thematic trends are at least partly attributable to a productive subset of scholars in certain content domains (e.g., well-being, work-life interface, socialization) who particularly favor person-centered modeling approaches.

We also evaluated each study on one additional aspect that speaks to the nature of scientific contributions: the exploratory–confirmatory continuum, that is, the degree to which a priori knowledge and theoretical insights were incorporated [e.g., whether the study aimed to test the existence of a specific cluster(s) of interest or the specific number/content of clusters based on theory, or whether the paper reported any preparatory steps taken on theoretical development

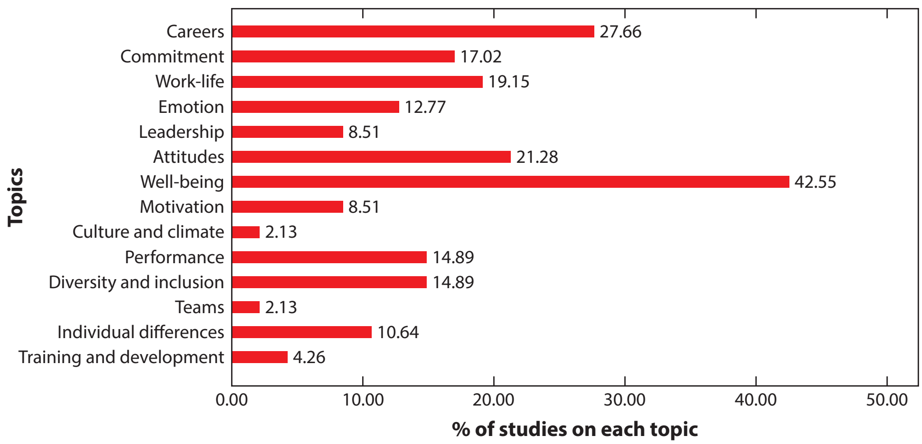

Figure 2

Thematic landscape. The figure shows the proportion of person-centered studies out of the 47 articles included in our review (expressed as percentages) covering each of the 14 topics commonly studied in organizational psychology/organizational behavior research.

around the phenomenon of interest via qualitative and/or quantitative investigations]. Our evaluations of studies based on this aspect are less readily quantifiable and thus are not included in the summary table. However, these considerations were a critical component of our review of the empirical articles, further described in Part 3.

Exploratory–Confirmatory Continuum

Person-centered techniques are typically used to model unobserved heterogeneity within the population, using multiple indicators simultaneously. The focus thus lies on identifying (potentially complex) configurations of variables that typically have not been identified before, although in other cases, there might be some empirical and/or theoretical guidance about their existence. The inductive nature of this approach has been argued to foster theory development, for instance, by "generating comprehensive typologies" (e.g., Campion & Csillag 2022) or by allowing a more "comprehensive" (e.g., Chawla et al. 2021) or "holistic" (e.g., Hancock et al. 2021) understanding of how complex and multifaceted constructs impact on people's functioning at work. However, to some extent, this approach may be at odds with the still dominant focus on hypothesis development and testing in OP/OB research, which could potentially explain the relative underuse of these methods in our discipline.

The majority of the studies included in our review were largely exploratory in the sense that no formal expectations were formulated about the results of the person-centered method. In contrast, 7 out of 48 were identified as at least somewhat confirmatory.[2] It is also important to note that we did not consider research that simply hypothesized the presence of profiles as truly confirmatory. Instead, we looked for the extent to which prior knowledge informed the authors' specific hypotheses about the substantive meanings of cluster(s) expected to exist.

The arguments underlying specific hypotheses could be derived from insights from qualitative research, prior results from quantitative studies, theoretical claims, or a combination of all these factors. It is difficult to evaluate when such arguments are sufficiently strong to be categorized as truly confirmatory, a concern equally applicable to variable-centered approaches (Zyphur et al. 2023). One caveat is that researchers should avoid overreliance on specific prior findings or the stretching of theoretical arguments to generate a formal hypothesis to be tested for its own sake. Regarding the conceptual underpinning of hypotheses, in particular, it can even be questioned whether much of the theory commonly used in our discipline is even sufficiently developed to allow such predictions. As an analogy, theory in psychology has struggled to adequately describe and explain temporal dynamics in many phenomena of interest (Hopwood et al. 2022). It has actually been the accumulation of (largely exploratory) empirical findings in this area that has pushed forward our understanding of the role of time. Similarly, there are limited person-centered theories that provide explicit operational and testable depictions of subpopulations for confirmatory approaches.

Nevertheless, our review did identify several studies taking a relatively strict confirmatory approach. In some of these cases, the goal of the study was to replicate a specific cluster or profile solution in a different population (e.g., across cultures; Shimizu et al. 2019), which may inform the generalizability of the phenomenon of interest (e.g., calling). Other studies have formulated hypotheses about profiles by combining all possible combinations (high or low) of a set of dichotomized indicator variables (e.g., high conflict and high enrichment, low conflict

[2] van de Brake & Berger (2023) and Qi et al. (2022) used latent profile analysis not as a primary element of their substantive inquiry but mostly as a methodological exploration. We considered these cases as somewhat unique and difficult to characterize as exploratory or confirmatory for the purpose of the current review.

and low enrichment, low conflict and high enrichment, and high conflict and low enrichment; Huyghebaert-Zouaghi et al. 2022). Finally, some studies successfully built hypotheses based on a combination of prior empirical findings and theoretical insights. For instance, the research by Hancock et al. (2021) drew on transformational leadership theory to predict the co-occurrence of specific leadership behaviors according to patterns that had already been (partially) found in prior work.

PART 3: CRITICAL REFLECTIONS AND RECOMMENDATIONS

In this concluding section, we highlight key areas of deficiency, ambiguity, or inconsistency that require critical reflection. These are somewhat open-ended recommendations for future person-centered research, as they speak to methodological, conceptual, and practical issues that require special care and attention. When feasible, we provide some guidance on tackling these important challenges. At the same time, we do not mean to provide precise solutions for every concern we raise here, but instead we hope these discussions will spark more methodological investigations and critical conversations that will move forward research in this field.

Methodological Issues

When conducting a person-centered study, researchers encounter many methodological decision points and challenges that can affect the substantive quality and/or informational value of their results. These issues include: (*a*) determining an appropriate sample size for the method of choice, (*b*) deciding on model constraints, (*c*) selecting an optimal number of classes, (*d*) deciding whether and how to include covariates in the analysis, and (*e*) testing (versus assuming) invariance of latent classes across samples or time points. We elaborate on each of these issues below and also highlight some of the newer and/or underutilized person-centered methods that may be valuable for OP/OB research.

Sample size. Many person-centered techniques are latent variable models, and those models require larger sample sizes than methods that do not specify latent variables. Although developing rules of thumb that apply across the different person-centered techniques is challenging, most simulation studies suggest that proper estimation of different mixture models requires at least a few hundred participants (e.g., Nylund et al. 2007) and even more than 500 (Nylund-Gibson & Choi 2018). Inadequate sample size can result in convergence issues, low power to detect classes, and unstable solutions. Moreover, a small sample size complicates the detection of small latent classes; thus researchers should be wary about selecting such classes, particularly when the sample size is small (Nylund-Gibson & Choi 2018). Even though simulation research can help decide on the required sample size for a particular model, such simulation research requires the specification of the "true model," and parameters such as the proportion of individuals within a latent class can substantially change sample size requirements (e.g., Dziak et al. 2014). As person-centered models are often used in an exploratory fashion, this true model is often unknown, which means that simulations become tricky or even impossible (Nylund-Gibson & Choi 2018).

Apart from a larger sample size, Monte Carlo simulation research[3] demonstrates that more indicators, a higher quality of indicators (i.e., indicators that better differentiate between the different classes and more reliable indicators), a higher degree of class separation, more equal class sizes, and larger covariance effects result in more converged solutions and less parameter bias

[3]The **Supplemental Appendix** provides a list of recommended readings for Monte Carlo studies organized by specific person-centered modeling techniques.

Supplemental Material >

(Dziak et al. 2014, Wurpts & Geiser 2014). Simulation research also shows that when sample size decreases, other characteristics such as higher separation between the classes (Tein et al. 2013), the relative size of the profiles (Lubke & Neale 2006), and the number and quality of indicators (Wurpts & Geiser 2014) become more critical in the sense that these characteristics might to some extent compensate for the negative effects of small sample size. These findings suggest that the careful choice of the indicators that are expected to separate classes well is very important and even more so when the sample size is small. As Nylund-Gibson & Choi (2018) argue, this is a substantive issue and is ideally guided by theory and previous research.

Model constraints. Deciding on model constraints is a tricky yet important topic in person-centered analyses, because simulation research has shown that imposing or freeing model constraints can affect the accuracy of the solution and the number of retained classes. For example, a common model constraint in the context of LCA and LPA is that indicators are assumed to be independent within each latent profile conditional on the latent class/profile solution (i.e., local independence). In many applications, however, this constraint is too restrictive (Vermunt & Magidson 2004), with the violation of local independence assumption generally resulting in biased model parameters and overestimation of the true number of latent classes (Swanson et al. 2012). The same goes for the homogeneity assumption in LPA, or the assumption that the indicator variances are equivalent across the latent profiles. Violating this assumption can result in inaccurate parameter estimates (Peugh & Fan 2013). Similar findings are obtained for other person-centered analyses. For GMM, misspecification of the latent variance-covariance matrix and the residual structure affects the model's accuracy in detecting the correct number of classes (Diallo et al. 2016), while imposing equality constraints on the residual variances of the class-specific regressions in MRA tends to result in less accurate estimates (Choi & Hong 2022).

Awareness of this issue is critical because some constraints are implemented as default settings in popular software packages. When there is no strong theoretical reason to implement certain constraints, it is crucial to systematically compare alternative models that differ in the constraints they impose (Masyn 2013). In the context of GMM, for example, Diallo et al. (2016) suggest starting with a model that includes as few constraints as possible, after which model complexity can be reduced when needed.[4]

Model constraints not only are relevant for obtaining unbiased parameter estimates but also can provide an inroad to using person-centered analyses in a more confirmatory way, testing theoretical ideas, or replicating previous work (Schmiege et al. 2018). For example, Schmiege et al. (2018) describe how the placement of model constraints in LCA generates a confirmatory latent class structure in which specific hypotheses can be tested.

Class enumeration. A key issue when performing person-centered analyses is selecting the optimal number of latent classes, or class enumeration. This is typically done by testing models with an increasing number of latent classes, after which the optimal solution is selected based on statistical and substantive grounds. The latter pertains to interpretability and fit with one's theoretical expectations, whereas the former boils down to the inspection of statistical indicators as well as the statistical admissibility of the solution. For mixture models, a wide range of indicators can be used to compare models with different numbers of latent profiles.

The first class of indicators are relative fit indices, such as the Akaike information criterion (AIC), the consistent AIC (CAIC), the Bayesian information criterion (BIC), and the sample-adjusted BIC (SABIC). All these indices balance goodness of fit and model complexity but differ

[4]In many cases, a fully unconstrained model will result in convergence issues or it will show convergence on improper solutions. In such case, imposing constraints is necessary.

in the penalty function they apply to the likelihood. For AIC, the penalty function accounts for the number of model parameters, while for CAIC, BIC, and SABIC, both the number of model parameters and the sample size are considered. For each of those indices, lower values indicate a better-fitting model.

A second class of indicators tests whether the fit of a model with k latent profiles significantly differs from that of a model with $k - 1$ latent profiles. Classical likelihood ratio tests (LRTs) cannot be used because models with a different number of profiles are not necessarily nested. Given this, two approximations of the LRT have been developed: the Lo et al.'s (2001) LRT and the bootstrap LRT (BLRT; McLachlan & Peel 2000). For both tests, a statistically significant result implies that the more complex model fits the data significantly better than the simpler model.

Simulation research suggests that for the relative fit indices, AIC performs poorly, while CAIC, BIC, and SABIC perform well in case the sample size is large. With a smaller sample size, SABIC seems to be preferred because it is least sensitive to a reduction in sample size (Nylund et al. 2007, Peugh & Fan 2013, Tein et al. 2013, Tofighi & Enders 2008). In terms of LRTs, the BLRT seems to be the preferred option (Nylund et al. 2007, Peugh & Fan 2013). Finally, although mixture models also yield an index of entropy, or an index that reflects the level of certainty with which objects are assigned to the latent profiles, simulation research shows that entropy performs poorly as a method for class enumeration (Tein et al. 2013).

In general, the issue of class enumeration is developing along with the growth of newer or more complex person-centered methods. More research points to the importance of assessing the performance of indicators, or fit indices, based on the different types of person-centered methods used. We encourage researchers to look into using established research to justify and select the number of classes for the specific type of person-centered method used—e.g., for LCA (Morgan 2014, Nylund-Gibson & Choi 2018), GMM (Nylund et al. 2007, Peugh & Fan 2012, Tofighi & Enders 2008), and LTA (Edelsbrunner et al. 2023, Nylund-Gibson et al. 2023).

Inclusion of covariates in the analysis. Because person-centered analyses are often exploratory, a vital question pertains to the interpretation and validity of the obtained profile/class solution. One common way to examine this is by assessing how the latent classes are related to different variables. In other words, researchers include covariates as part of the latent class model or post-hoc analyses (e.g., Achnak & Vantilborgh 2021, Cruz & Nagy 2022, Salter et al. 2021). This allows them to test whether the profiles relate to covariates in a theoretically meaningful way.

In person-centered analyses, different types of covariates can be distinguished: predictors (i.e., covariates that have an impact on profile membership), outcomes (i.e., covariates that are affected by profile membership), and correlates (i.e., covariates that relate to profile membership without assuming any directionality). Conceptualizing a covariate as a predictor, outcome, or correlate should ideally be done on theoretical grounds, and this choice is not without consequence because it needs to be theoretically aligned. To give one example from our review, Shipp et al. (2022) theorized how temporal focus profiles in employees may influence rumination over past grievances, which may subsequently affect job satisfaction and work withdrawal. Importantly, different conceptualizations of covariates can imply different analytical treatments, as shown in **Figure 3** and further discussed below.

Regardless of whether the covariate is modeled as a predictor, outcome, or correlate, it is important that the inclusion of the covariate in person-centered modeling should not change the number of classes or the nature of those classes.[5] It is therefore recommended to first select

[5]If the profile solution is affected by inclusion of the covariate, the status of the covariate as a predictor, outcome, or correlate rather than a direct profile indicator is doubtful (Morin et al. 2020).

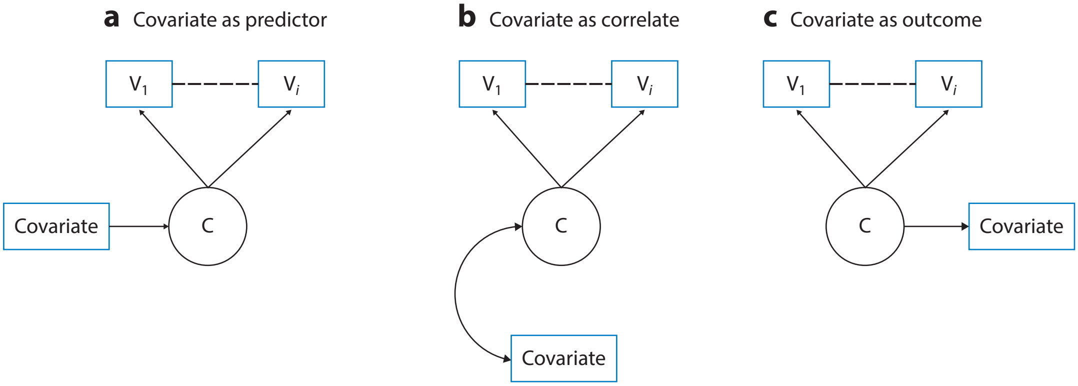

Figure 3

Different conceptualizations of covariates that imply different analytical treatments within person-centered research.

the unconditional class solution, after which covariates can be simultaneously included in the modeling (Diallo et al. 2016, Nylund-Gibson & Masyn 2016). Generally speaking, there are two ways to model covariates: direct inclusion and auxiliary approaches. Direct inclusion means that the covariates (predictors or outcomes) are directly included in the final solution by, for example, including the covariate as a profile indicator when modeling a profile outcome or testing multinomial logistic regressions between the covariate and the membership likelihoods for each profile when modeling a profile predictor. Because direct inclusion sometimes changes the unconditional class solution, auxiliary approaches have been developed with the explicit goal of minimizing the occurrence of such changes (Morin et al. 2020). Several auxiliary approaches have been developed, with research showing that all of those methods perform reasonably well and that one method might be more suited than another depending on one's goals. Morin et al. (2020) provide an excellent overview of these methods and the circumstances under which they perform optimally.

Invariance tests for latent classes. As person-centered analyses are often done in an exploratory fashion, a critical question pertains to the validity and replicability of the obtained solution. In other words, Do the classes found replicate? One way to demonstrate the generalizability and meaningfulness of one's solution is to test whether the obtained classes hold across different samples and contexts (e.g., Hirschi et al. 2020, Shipp et al. 2022). Such exercise is informative because it shows which profiles regularly emerge across studies and contexts and it can identify profiles that might only exist in specific contexts or under specific conditions (Morin et al. 2020).

To guide systematic tests of profile similarity, and inspired by the literature on measurement invariance, a sequence of invariance tests was proposed by Morin et al. (2016) for LPA, by Morin & Wang (2016) for MRA, and by Morin & Litalien (2017) for LTA. For LPA, the following six-step sequence is proposed: First, one tests whether the same number of profiles is identified in each sample and/or at each time point (i.e., configural similarity). Second, one tests whether the profile structure, or the levels on the indicators within each profile, is similar (i.e., structural similarity). Third, the similarity of the within-profile variability or dispersion is tested across samples/time points (i.e., dispersional similarity). Fourth, one assesses whether the relative size of the profiles is similar across samples or time (i.e., distributional similarity). Fifth, if predictors of the profile solutions are included, one can test whether the effect of those predictors on profile membership is the same (i.e., predictive similarity). Sixth, the fifth step is repeated for outcomes, testing whether the effect of profile membership on the outcome is similar across samples/time (i.e., explanatory similarity). For MRA, a seventh step is added between the first and the second steps, in which the similarity of the regression parameters defining the profiles across samples or time is tested (i.e., regression similarity). For LTA, the framework developed for LPA applies (see Morin et al. 2016), with the exception that in the fourth step (i.e., distributional similarity), equality constraints cannot straightforwardly be imposed on the relative size of the profiles. A workaround for this issue has been developed by Morin & Litalien (2017).

Like measurement invariance tests, configural and structural similarity are prerequisites to proceed with subsequent tests for LPA. On the other hand, configural, regression, and structural similarity are required to proceed with subsequent steps for MRA. Also, paralleling measurement invariance tests, from the second step onward one can proceed with tests of partial similarity when full similarity is not obtained.

Novel and/or underutilized methods. In OP/OB research, data are often multilevel in nature: Employees are nested within teams, teams are nested within organizations, and organizations can be nested within sectors or countries. In such a situation, the clustering of employees within specific latent subgroups may (partially) be driven by differences between the teams, organizations, or countries they belong to. To reveal such variability in employee profiles across teams, organizations, and/or countries, multilevel mixture models—such as multilevel latent profile analysis or multilevel mixture regression—can be used. This enables researchers to derive different latent classes at the individual level and also at the higher level. For instance, one application (not included in our review) used multilevel mixed-measurement item response theory on 100,000 individuals across 116 nations to estimate classes of individuals with similar emotion models and classes of countries that share similar proportions of individual classes (Tay et al. 2011).

Similar to the traditional multilevel model, in multilevel mixture models, variability in employee profiles across teams, organizations, and/or countries is captured by random effects at the team, organization, and/or country levels (Vermunt 2003). Random effects can be either continuous (i.e., specification of one or more continuous latent variables) or discrete (i.e., specification of a categorical latent variable, leading to yet another clustering at the team/organization/country level), with the simulation study by Finch & French (2014) showing that both approaches perform reasonably well. Additionally, one can include covariates at the employee and team/organization/country levels, with the latter being used to tell whether higher-level characteristics influence the profile of the employees.

Apart from multilevel extensions of the traditional person-centered techniques, techniques that originate from different fields, such as biostatistics or machine learning, and are therefore less well-known to OP/OB researchers, can be used for person-centered modeling. For example, in the domain of machine learning, clustering of individuals into unobserved subgroups is done with unsupervised learning algorithms, that is, the algorithm is not supervised or trained using a labeled training data set (i.e., a data set that contains cluster labels and is used to train the algorithm). Although unsupervised learning algorithms include well-known algorithms such as k-means clustering and mixture modeling, they also include less-known techniques such as density-based or deep clustering. Several of those algorithms can be used in the context of person-centered research.

Another example is cluster algorithms developed in the context of network models. Network models are gaining popularity in psychological science because of their ability to describe the organization of a system by observing the associations between the system components (Borsboom et al. 2021). In industrial-organizational psychology, Carter et al. (2020) recently used network analysis to study the structure and operation of job satisfaction, demonstrating that features more central to one's job satisfaction network are more likely to affect change throughout the network. Relevant to our review is the fact that clustering can also be performed in the context of network modeling, which then allows researchers to identify subgroups of individuals with a similar network structure. Of particular interest might be the clustering extension of the Group Iterative Multiple Model Estimation model (GIMME; Gates & Molenaar 2012). GIMME is a network analysis approach for intensive longitudinal data that builds person-specific networks, after which the clustering algorithm (called subgrouping GIMME; Gates et al. 2017) clusters individuals based on their person-specific network patterns. In this sense, subgrouping GIMME bridges the divide between idiographic and nomothetic science by looking for regularities in idiographic networks.

Conceptual and Practical Issues

An appealing feature of person-centered methods is the possibility to classify individuals into groups, which corresponds well with the often-used way of thinking about types of employees (Morin et al. 2018). Even though the conceptual resemblance is clear, caution is needed. A key characteristic of most (but not all) person-centered analyses is their prototypicality, meaning that individuals are not associated with a single latent profile but rather are assessed in terms of their similarity with each profile (Morin et al. 2018). The methodological consequence is that most person-centered models yield latent profiles corrected for classification errors (exceptions are several cluster analytic techniques resulting in a deterministic assignment). The conceptual implication of prototypicality is at least as important. Because individuals are assigned to the latent class in a probabilistic way, each latent class is an imperfect descriptor of the individual profiles, implying that individual profiles and latent classes should not be confused. It is important to remember that person-centered methods aim to capture population heterogeneity in a parsimonious way rather than capturing the profile of every individual in full detail.

A second point of conceptual and practical concern pertains to the conditions under which person-centered methods are appropriate or useful. A criterion that is sometimes used to argue for the appropriateness or usefulness of a person-centered approach is that the profiles are distinguished by shape rather than by level (Chen et al. 2015, De Boeck et al. 2005). The rationale is that profiles that are distinguished only by level can be well represented by a model with a continuous latent variable, whereas this is not true for profiles that are distinguished by shape. To complicate matters further, methods exist that disentangle level from shape differences (see Morin & Marsh 2015). For example, because the continuous latent variable(s) in FMA absorb(s) the level differences, the categorical latent variable in FMA may yield profiles with clearer shape differences than LPA would. While navigating this complexity, it is important to remember that the choice of a continuous or categorical latent variable, or a combination of both, should be dictated by one's theoretical expectations and one's substantive research questions rather than by the results obtained. The question of whether showing unique predictive validity above and beyond variable-centered analysis is needed for person-centered analyses to be useful can be approached in the same manner. What matters most is not whether unique predictive validity is found but whether methodological fit—or the alignment of theory, measurement, and analytical methods—is maximized (Edmondson & McManus 2007). Taking this perspective implies that neither variable-centered nor person-centered methods are superior, but both can coexist and can even be used in tandem to provide a more profound and complete understanding of the phenomena at hand (e.g., Chawla et al. 2020).

DISCLOSURE STATEMENT

The authors are not aware of any affiliations, memberships, funding, or financial holdings that might be perceived as affecting the objectivity of this review.

LITERATURE CITED

Achnak S, Vantilborgh T. 2021. Do individuals combine different coping strategies to manage their stress in the aftermath of psychological contract breach over time? A longitudinal study. *J. Vocat. Behav.* 131:103651

Allport GW. 1921. Personality and character. *Psychol. Bull.* 18(9):441–55

Arabie P, Hubert L, De Soete G, eds. 1996. *Clustering and Classification*. Singapore: World Sci.

Auvinen E, Huhtala M, Kinnunen U, Tsupari H, Feldt T. 2020. Leader motivation as a building block for sustainable leader careers: the relationship between leadership motivation profiles and leader and follower outcomes. *J. Vocat. Behav.* 120:103428

Blustein DL, Perera HN, Diamonti AJ, Gutowski E, Meerkins T, et al. 2020. The uncertain state of work in the U.S.: profiles of decent work and precarious work. *J. Vocat. Behav.* 122:103481

Borsboom D, Deserno MK, Rhemtulla M, Epskamp S, Fried EI, et al. 2021. Network analysis of multivariate data in psychological science. *Nat. Rev. Methods Prim.* 1(1):58

Bouckenooghe D, Kanar A, Klehe U-C. 2022. A latent transition analysis examining the nature of and movement between career adaptability profiles. *J. Vocat. Behav.* 136:103728

Bramble RJ, Duerk EK, Baltes BB. 2020. Finding the nuance in eldercare measurement: latent profiles of eldercare characteristics. *J. Bus. Psychol.* 35(1):29–43

Bray BC, Lanza ST, Collins LM. 2010. Modeling relations among discrete developmental processes: a general approach to associative latent transition analysis. *Struct. Equ. Model.* 17(4):541–69

Campion ED, Csillag B. 2022. Multiple jobholding motivations and experiences: a typology and latent profile analysis. *J. Appl. Psychol.* 107(8):1261–87. **https://doi.org/10.1037/apl0000920**

Carter NT, Lowery MR, Williamson Smith R, Conley KM, Harris AM, et al. 2020. Understanding job satisfaction in the causal attitude network (CAN) model. *J. Appl. Psychol.* 105(9):959–93

Cattell R. 1944. A note on correlation clusters and cluster search methods. *Psychometrika* 9:169–84

Cattell RB. 1946. Personality structure and measurement. I. The operational determination of trait unities. *Br. J. Psychol.* 36:88–102

Chawla N, Gabriel AS, Rosen CC, Evans JB, Koopman J, et al. 2021. A person-centered view of impression management, inauthenticity, and employee behavior. *Pers. Psychol.* 74(4):657–91

Chawla N, MacGowan RL, Gabriel AS, Podsakoff NP. 2020. Unplugging or staying connected? Examining the nature, antecedents, and consequences of profiles of daily recovery experiences. *J. Appl. Psychol.* 105(1):19–39

Chen X, Morin AJ, Parker PD, Marsh HW. 2015. Developmental investigation of the domain-specific nature of the life satisfaction construct across the post-school transition. *Dev. Psychol.* 51(8):1074–85

Choi J, Hong S. 2022. The impact of imposing equality constraints on residual variances across classes in regression mixture models. *Front. Psychol.* 12:736132

Clark SL, Muthén B, Kaprio J, D'Onofrio BM, Viken R, Rose RJ. 2013. Models and strategies for factor mixture analysis: an example concerning the structure underlying psychological disorders. *Struct. Equ. Model.* 20:681–703

Clatworthy J, Buick D, Hankins M, Weinman J, Horne R. 2005. The use and reporting of cluster analysis in health psychology: a review. *Br. J. Health Psychol.* 10(Pt. 3):329–58

Conner TS, Tennen H, Fleeson W, Barrett LF. 2009. Experience sampling methods: a modern idiographic approach to personality research. *Soc. Pers. Psychol. Compass* 3:292–313

Cruz M, Nagy N. 2022. Profiles in persistence: a latent profile analysis of multilevel coping strategies enacted among women in the sciences. *J. Organ. Behav.* In press. **https://doi.org/10.1002/job.2657**

De Boeck P, Wilson M, Acton GS. 2005. A conceptual and psychometric framework for distinguishing categories and dimensions. *Psychol. Rev.* 112(1):129–58

Diallo TM, Morin AJ, Lu H. 2016. Impact of misspecifications of the latent variance-covariance and residual matrices on the class enumeration accuracy of growth mixture models. *Struct. Equ. Model.* 23(4):507–31

Diefendorff JM, Gabriel AS, Nolan MT, Yang J. 2019. Emotion regulation in the context of customer mistreatment and felt affect: an event-based profile approach. *J. Appl. Psychol.* 104(7):965–83

Duffy RD, Spurk D, Perez G, Kim HJ, Rosa AD. 2022. A latent profile analysis of perceiving and living a calling. *J. Vocat. Behav.* 134:103694

Dziak JJ, Lanza ST, Tan X. 2014. Effect size, statistical power and sample size requirements for the bootstrap likelihood ratio test in latent class analysis. *Struct. Equ. Model.* 21(4):534–52

Edelsbrunner PA, Flaig M, Schneider M. 2023. A simulation study on latent transition analysis for examining profiles and trajectories in education: recommendations for fit statistics. *J. Res. Educ. Eff.* 16(2):350–75

Edmondson AC, McManus SE. 2007. Methodological fit in management field research. *Acad. Manag. Rev.* 32(4):1246–64

Ezugwu AE, Ikotun AM, Oyelade OO, Abualigah L, Agushaka JO, et al. 2022. A comprehensive survey of clustering algorithms: state-of-the-art machine learning applications, taxonomy, challenges, and future research prospects. *Eng. Appl. Artif. Intell.* 110:104743

Fan W, Moen P, Kelly EL, Hammer LB, Berkman LF. 2019. Job strain, time strain, and well-being: a longitudinal, person-centered approach in two industries. *J. Vocat. Behav.* 110:102–16

Fernet C, Morin AJS, Austin S, Gagné M, Litalien D, et al. 2020. Self-determination trajectories at work: a growth mixture analysis. *J. Vocat. Behav.* 121:103473

Finch WH, French BF. 2014. Multilevel latent class analysis: parametric and nonparametric models. *J. Exp. Educ.* 82(3):307–33

French KA, Allen TD, Hughes Miller M, Kim ES, Centeno G. 2020. Faculty time allocation in relation to work-family balance, job satisfaction, commitment, and turnover intentions. *J. Vocat. Behav.* 120:103443

Gabriel AS, Calderwood C, Bennett AA, Wong EM, Dahling JJ, Trougakos JP. 2019. Examining recovery experiences among working college students: a person-centered study. *J. Vocat. Behav.* 115:103329

Gagnon É, Ratelle CF, Guay F, Duchesne S. 2019. Developmental trajectories of vocational exploration from adolescence to early adulthood: the role of parental need supporting behaviors. *J. Vocat. Behav.* 115:103338

Garfield ZH, Hagen EH. 2020. Investigating evolutionary models of leadership among recently settled Ethiopian hunter-gatherers. *Leadersh. Q.* 31(2):101290

Gates KM, Lane ST, Varangis E, Giovanello K, Guiskewicz K. 2017. Unsupervised classification during time-series model building. *Multivar. Behav. Res.* 52(2):129–48

Gates KM, Molenaar PC. 2012. Group search algorithm recovers effective connectivity maps for individuals in homogeneous and heterogeneous samples. *NeuroImage* 63(1):310–19

Grosemans I, De Cuyper N. 2021. Career competencies in the transition from higher education to the labor market: examining developmental trajectories. *J. Vocat. Behav.* 128:103602

Hancock AJ, Gellatly AR, Walsh MM, Arnold KA, Connelly CE. 2021. Good, bad, and ugly leadership patterns: implications for followers' work-related and context-free outcomes. *J. Manag.* 49(2):640–76

He Y, Lee J, Huang Y, Yao X, Courtney TK. 2023. Error disclosure climate and safety climate trajectories: the mediating role of counterfactual sharing. *J. Bus. Psychol.* 38:907–24

Hirschi A, Steiner R, Burmeister A, Johnston CS. 2020. A whole-life perspective of sustainable careers: the nature and consequences of nonwork orientations. *J. Vocat. Behav.* 117:103319

Hofmans J, De Clercq B, Kuppens P, Verbeke L, Widiger TA. 2019. Testing the structure and process of personality using ambulatory assessment data: an overview of within-person and person-specific techniques. *Psychol. Assess.* 31(4):432–43

Hofmans J, Wille B, Schreurs B. 2020. Person-centered methods in vocational research. *J. Vocat. Behav.* 118:103398

Hopwood CJ, Bleidorn W, Wright AGC. 2022. Connecting theory to methods in longitudinal research. *Perspect. Psychol. Sci.* 17(3):884–94

Houle SA, Morin AJS, Fernet C, Vandenberghe C, Tóth-Királya I. 2020. A latent transition analysis investigating the nature, stability, antecedents, and outcomes of occupational commitment profiles for school principals. *J. Vocat. Behav.* 121:103460

Howard MC, Hoffman ME. 2018. Variable-centered, person-centered, and person-specific approaches: where theory meets the method. *Organ. Res. Methods* 21(4):846–76

Huyghebaert-Zouaghi T, Morin AJS, Fernet C, Austin S, Gillet N. 2022. Longitudinal profiles of work-family interface: their individual and organizational predictors, personal and work outcomes, and implications for onsite and remote workers. *J. Vocat. Behav.* 134:103695

Jung T, Wickrama KAS. 2008. An introduction to latent class growth analysis and growth mixture modeling. *Soc. Pers. Psychol. Compass* 2(1):302–17

Klug K, Drobnič S, Brockmann H. 2019. Trajectories of insecurity: young adults' employment entry, health and well-being. *J. Vocat. Behav.* 115:103308

Lazarsfeld PF. 1950. The logical and mathematical foundation of latent structure analysis. In *Measurement and Prediction*, ed. SA Stouffer, L Guttman, EA Suchman, PF Lazarsfeld, SA Star, JA Clausen, pp. 362–472. Princeton, NJ: Princeton Univ. Press

Liu S, Bamberger P, Wang M, Nahum-Shani I, Larimer M, Bacharach SB. 2023. Behavior change versus stability during the college-to-work transition: life course and the "stickiness" of alcohol misuse at career entry. *Pers. Psychol.* 76(3):945–75

Lo Y, Mendell NR, Rubin DB. 2001. Testing the number of components in a normal mixture. *Biometrika* 88(3):767–78

Lubke GH, Muthén B. 2005. Investigating population heterogeneity with factor mixture models. *Psychol. Methods* 10:21–39

Lubke GH, Neale MC. 2006. Distinguishing between latent classes and continuous factors: resolution by maximum likelihood? *Multivar. Behav. Res.* 41(4):499–532

Mäkikangas A, Schaufeli W. 2021. A person-centered investigation of two dominant job crafting theoretical frameworks and their work-related implications. *J. Vocat. Behav.* 131:103658

Masyn KE. 2013. Latent class analysis and finite mixture modeling. In *The Oxford Handbook of Quantitative Methods: Statistical Analysis*, ed. TD Little, pp. 551–611. Oxford, UK: Oxford Univ. Press

McKay AS, Grimaldi EM, Sayre GM, Hoffman ME, Reimer RD, Mohammed S. 2020. Types of union participators over time: toward a person-centered and dynamic model of participation. *Pers. Psychol.* 73(2):271–304

McLachlan GJ, Peel D. 2000. *Finite Mixture Models*. Hoboken, NJ: Wiley

Meyer JP, Morin AJS. 2016. A person-centered approach to commitment research: theory, research, and methodology. *J. Organ. Behav.* 37(4):584–612

Meyer JP, Morin AJS, Rousseau V, Boudrias J-S, Brunelle E. 2021. Profiles of global and target-specific work commitments: why compatibility is better and how to achieve it. *J. Vocat. Behav.* 128:103588

Molenaar PCM. 2004. A manifesto on psychology as idiographic science: bringing the person back into scientific psychology, this time forever. *Meas. Interdiscip. Res. Perspect.* 2(4):201–18

Morgan GB. 2014. Mixed mode latent class analysis: an examination of fit index performance for classification. *Struct. Equ. Model.* 22(1):76–86

Morin AJS, Bujacz A, Gagné M. 2018. Person-centered methodologies in the organizational sciences: introduction to the feature topic. *Organ. Res. Methods* 21(4):803–13

Morin AJS, Litalien D. 2017. *Webnote: Longitudinal Tests of Profile Similarity and Latent Transition Analyses.* Montreal, Can.: Subst. Methodol. Synerg. Res. Lab.

Morin AJS, Marsh HW. 2015. Disentangling shape from level effects in person-centered analyses: an illustration based on university teachers' multidimensional profiles of effectiveness. *Struct. Equ. Model.* 22(1):39–59

Morin AJS, McLarnon MJ, Litalien D. 2020. Mixture modeling for organizational behavior research. In *Handbook on the Temporal Dynamics of Organizational Behavior*, ed. Y Griep, SD Hansen, pp. 351–79. Lodnon: Edward Elgar Publishing

Morin AJS, Meyer JP, Creusier J, Biétry F. 2016. Multiple-group analysis of similarity in latent profile solutions. *Organ. Res. Methods* 19(2):231–54

Morin AJS, Wang JCK. 2016. A gentle introduction to mixture modeling using physical fitness data. In *An Introduction to Intermediate and Advanced Statistical Analyses for Sport and Exercise Scientists*, ed. N Ntoumanis, N Myers, pp. 183–210. Hoboken, NJ: Wiley

Mühlenmeier M, Rigotti T, Baethge A, Vahle-Hinz T. 2022. The ups and downs of the week: a person-centered approach to the relationship between time pressure trajectories and well-being. *J. Occup. Health Psychol.* 27(3):286–98

Muthén BO. 2002. Beyond SEM: general latent variable modeling. *Behaviormetrika* 29:81–117

Naranjo A, Shoss M, Gebben A, DiStaso M, Su S. 2021. When minor insecurities project large shadows: a profile analysis of cognitive and affective job insecurity. *J. Occup. Health Psychol.* 26(5):421–36

Nesselroade JR, Gerstorf D, Hardy SA, Ram N. 2007. Focus article: idiographic filters for psychological constructs. *Meas. Interdiscip. Res. Perspect.* 5(4):217–35

Nylund KL, Asparouhov T, Muthén BO. 2007. Deciding on the number of classes in latent class analysis and growth mixture modeling: a Monte Carlo simulation study. *Struct. Equ. Model.* 14(4):535–69

Nylund-Gibson K, Choi AY. 2018. Ten frequently asked questions about latent class analysis. *Transl. Issues Psychol. Sci.* 4(4):440–61

Nylund-Gibson K, Garber AC, Carter DB, Chan M, Arch DAN, et al. 2023. Ten frequently asked questions about latent transition analysis. *Psychol. Methods* 28:284–300

Nylund-Gibson K, Masyn KE. 2016. Covariates and mixture modeling: results of a simulation study exploring the impact of misspecified effects on class enumeration. *Struct. Equ. Model.* 23(6):782–97

Parker SL, Dawson N, Van den Broeck A, Sonnentag S, Neal A. 2021. Employee motivation profiles, energy levels, and approaches to sustaining energy: a two-wave latent-profile analysis. *J. Vocat. Behav.* 131:103659

Parmentier M, Dangoisse F, Zacher H, Pirsoul T. 2021. Anticipatory emotions at the prospect of the transition to higher education: a latent transition analysis. *J. Vocat. Behav.* 125:103543

Peugh J, Fan X. 2012. How well does growth mixture modeling identify heterogeneous growth trajectories? A simulation study examining GMM's performance characteristics. *Struct. Equ. Model.* 19(2):204–26

Peugh J, Fan X. 2013. Modeling unobserved heterogeneity using latent profile analysis: a Monte Carlo simulation. *Struct. Equ. Model.* 20(4):616–39

Poirier L-AC, Morin AJS, Boudrias J-S. 2017. On the merits of coherent leadership empowerment behaviors: a mixture regression approach. *J. Vocat. Behav.* 103(Pt. B):66–75

Qi M, Liu Z, Kong Y, Yang Z. 2022. The influence of identity faultlines on employees' team commitment: the moderating role of inclusive leadership and team identification. *J. Bus. Psychol.* 37:1299–311

Ram N, Grimm KJ. 2009. Growth mixture modeling: a method for identifying differences in longitudinal change among unobserved groups. *Int. J. Behav. Dev.* 33(6):565–76

Reknes I, Notelaers G, Iliescu D, Einarsen SV. 2021. The influence of target personality in the development of workplace bullying. *J. Occup. Health Psychol.* 26(4):291–303

Renner K-H, Klee S, von Oertzen T. 2020. Bringing back the person into behavioural personality science using Big Data. *Eur. J. Pers.* 34(5):670–86

Revelle W, Wilt J, Condon DM. 2011. Individual differences and differential psychology: a brief history and prospect. In *The Wiley-Blackwell Handbook of Individual Differences*, ed. T Chamorro-Premuzic, S von Stumm, A Furnham, pp. 3–38. Hoboken, NJ: Wiley-Blackwell

Rodríguez-Muñoz A, Antino M, Ruiz-Zorrilla P, Sanz-Vergel AI, Bakker AB. 2020. Short-term trajectories of workplace bullying and its impact on strain: a latent class growth modeling approach. *J. Occup. Health Psychol.* 25(5):345–56

Salter NP, Sawyer K, Gebhardt ST. 2021. How does intersectionality impact work attitudes? The effect of layered group memberships in a field sample. *J. Bus. Psychol.* 36(6):1035–52

Schmiege SJ, Masyn KE, Bryan AD. 2018. Confirmatory latent class analysis: illustrations of empirically driven and theoretically driven model constraints. *Organ. Res. Methods* 21(4):983–1001

Shimizu AB, Dik BJ, Conner BT. 2019. Conceptualizing calling: cluster and taxometric analyses. *J. Vocat. Behav.* 82(3):176–87

Shipp AJ, Gabriel AS, Lambert LS. 2022. Profiles in time: understanding the nature and outcomes of profiles of temporal focus. *J. Appl. Psychol.* 107(9):1640–54

Shockley KM, Clark MA, Dodd H, King EB. 2021. Work-family strategies during COVID-19: examining gender dynamics among dual-earner couples with young children. *J. Appl. Psychol.* 106:15–28

Shockley KM, Gabriel AS, Yuan Z. 2022. Profiles of attribution for work-family conflict episodes and their relation to negative emotions. *J. Organ. Behav.* 43(4):643–61

Slaughter JE, Gabriel AS, Ganster ML, Vaziri H, MacGowan RL. 2021. Getting worse or getting better? Understanding the antecedents and consequences of emotion profile transitions during COVID-19-induced organizational crisis. *J. Appl. Psychol.* 106(8):1118–36

Swanson SA, Lindenberg K, Bauer S, Crosby RD. 2012. A Monte Carlo investigation of factors influencing latent class analysis: an application to eating disorder research. *Int. J. Eating Disord.* 45(5):677–84

Takeuchi R, Li Y, Wang M. 2019. Expatriates' performance profiles: examining the effects of work experiences on the longitudinal change patterns. *J. Manag.* 45(2):451–75

Tan P-N, Steinbach M, Karpatne A, Kumar V. 2019. *Introduction to Data Mining*. New York: Pearson

Tay L, Diener E, Drasgow F, Vermunt JK. 2011. Multilevel mixed-measurement IRT analysis: an explication and application to self-reported emotions across the world. *Organ. Res. Methods* 14(1):177–207

Tein JY, Coxe S, Cham H. 2013. Statistical power to detect the correct number of classes in latent profile analysis. *Struct. Equ. Model.* 20(4):640–57

Tofighi D, Enders C. 2008. Identifying the correct number of classes in growth mixture models. In *Advances in Latent Variable Mixture Models*, ed. GR Hancock, KM Samuelsen, pp. 317–41. Charlotte, NC: Inf. Age

Tordera N, Peiró JM, Ayala Y, Villajos E, Truxillo D. 2020. The lagged influence of organizations' human resources practices on employees' career sustainability: the moderating role of age. *J. Vocat. Behav.* 120:103444

van de Brake HJ, Berger S. 2023. Can I leave my hat on? A cross-level study of multiple team membership role separation. *Pers. Psychol.* 76(1):221–48

Vaziri H, Casper WJ, Wayne JH, Matthews RA. 2020. Changes to the work-family interface during the COVID-19 pandemic: examining predictors and implications using latent transition analysis. *J. Appl. Psychol.* 105(10):1073–87

Vermunt JK. 2003. Multilevel latent class models. *Sociol. Methodol.* 33(1):213–39

Vermunt JK, Magidson J. 2002. Latent class cluster analysis. In *Applied Latent Class Analysis*, ed. J Hagenaars A McCutcheon, pp. 89–106. Cambridge, UK: Cambridge Univ. Press

Vermunt JK, Magidson J. 2004. Local independence. In *The SAGE Encyclopedia of Social Science Research Methods*, ed. MS Lewis-Beck, A Bryman, TF Liao, pp. 732–33. London: Sage

Wang M. 2007. Profiling retirees in the retirement transition and adjustment process: examining the longitudinal change patterns of retirees' psychological well-being. *J. Appl. Psychol.* 92(2):455–74

Wedel M, DeSarbo WS 1994. A review of recent developments in latent class regression models. In *Advanced Methods of Marketing Research*, ed. RP Bagozzi, pp. 352–88. Cambridge, UK: Blackwell

Wedel M, DeSarbo WS. 1995. A mixture likelihood approach for generalized linear models. *J. Classif.* 12:21–55

Weiss H, Rupp D. 2011. Experiencing work: an essay on a person-centric work psychology. *Ind. Organ. Psychol.* 4(1):83–97

Woo SE, Jebb AT, Tay L, Parrigon S. 2018. Putting the "person" in the center: review and synthesis of person-centered approaches and methods in organizational science. *Organ. Res. Methods* 21(4):814–45

Wurpts IC, Geiser C. 2014. Is adding more indicators to a latent class analysis beneficial or detrimental? Results of a Monte-Carlo study. *Front. Psychol.* 5:920

Zevon MA, Tellegen A. 1982. The structure of mood change: an idiographic/nomothetic analysis. *J. Pers. Soc. Psychol.* 43(1):111–22

Zhao P, Xu X, Peng Y, Matthews RA. 2020. Justice, support, commitment, and time are intertwined: a social exchange perspective. *J. Vocat. Behav.* 120:103432

Zhong R, Paluch RM, Shum V, Zatzick CD, Robinson SL. 2021. Hot, cold, or both? A person-centered perspective on death awareness during the COVID-19 pandemic. *J. Appl. Psychol.* 106(6):839–55

Zubin J. 1938. A technique for measuring like-mindedness. *J. Abnorm. Soc. Psychol.* 33(4):508–16

Zyphur MJ. 2009. When mindsets collide: switching analytical mindsets to advance organization science. *Acad. Manag. Rev.* 34(4):677–88

Zyphur MJ, Bonner CV, Tay L. 2023. Structural equation modeling in organizational research: the state of our science and some proposals for its future. *Annu. Rev. Organ. Psychol. Organ. Behav.* 10:495–517

RELATED RESOURCES: MONTE CARLO SIMULATION STUDIES ON SPECIFIC PERSON-CENTERED TECHNIQUES

Growth mixture modeling

Kim SY. 2014. Determining the number of latent classes in single- and multiphase growth mixture models. *Struct. Equ. Model.* 21(2):263–79

Latent class analysis/latent profile analysis

Dziak JJ, Lanza ST, Tan X. 2014. Effect size, statistical power and sample size requirements for the bootstrap likelihood ratio test in latent class analysis. *Struct. Equ. Model.* 21(4):534–52

Peugh J, Fan X. 2013. Modeling unobserved heterogeneity using latent profile analysis: a Monte Carlo simulation. *Struct. Equ. Model.* 20(4):616–39

Tein JY, Coxe S, Cham H. 2013. Statistical power to detect the correct number of classes in latent profile analysis. *Struct. Equ. Model.* 20(4):640–57

Wurpts IC, Geiser C. 2014. Is adding more indicators to a latent class analysis beneficial or detrimental? Results of a Monte-Carlo study. *Front. Psychol.* 5:920

Multilevel latent class analysis

Park J, Yu HT. 2018. Recommendations on the sample sizes for multilevel latent class models. *Educ. Psychol. Meas.* 78(5):737–61

Regression mixture models

Jaki T, Kim M, Lamont A, George M, Chang C, et al. 2019. The effects of sample size on the estimation of regression mixture models. *Educ. Psychol. Meas.* 79(2):358–84