Person-Centered Methodologies in the Organizational Sciences:

Introduction to the Feature Topic

Alexandre J.S. Morin, Substantive Methodological Synergy Research Laboratory, Department of Psychology, Concordia University, Canada

Aleksandra Bujacz, Department of Psychology, Karolinska Institutet, Sweden

Marylène Gagné, Management and Organisations Discipline, Business School, University of Western Australia, Australia

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Corresponding author:
Alexandre J.S. Morin, Substantive-Methodological Synergy Research Laboratory
Department of Psychology, Concordia University
7141 Sherbrooke W, Montreal, QC, Canada, H3B 1R6
Email: alexandre.morin@concordia.ca

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Authors' Bio:
Alexandre J. S. Morin PhD, is Professor in the Department of Psychology of Concordia University (Montreal, Canada) where he heads the Substantive-Methodological Synergy Research Laboratory. He defines himself as a lifespan developmental psychologist with broad research interests anchored in the exploration of the social and organizational determinants of psychological well-being, self-concept, and commitments at various life stages. His research interests are centered on substantive-methodological synergies aimed at illustrating the usefulness of powerful new statistical methods (including exploratory structural equation models, mixture models, longitudinal models, and multilevel models). Alexandre has published over 175 publications, some of which appear in leading journals such as *Journal of Management*, *Organizational Research Methods*, *Structural Equation Modeling*, *Annual Review of Clinical Psychology*, *Child Development*, *Journal of Educational Psychology,* and *Developmental Psychology*.

Aleksandra Bujacz, PhD, works as a Project Manager at Karolinska Institutet in Stockholm, Sweden. Her research focuses on health and well-being of workers. She is primarily interested in the application of advanced methodological techniques to answer novel research questions in organizational and psychological sciences. Her work has been published in journals such *as Journal of Occupational Health Psychology, Career Development International*, *Journal of Happiness Studies* and *Thinking Skills and Creativity*.

Marylène Gagné, PhD, is Professor of Management and Organizations in the University of Western Australia's Business School. Her research focuses on examining factors, such as job design, compensation systems and leadership, which affect work motivation. She also examines outcomes of work motivation, including performance, wellbeing, retention and knowledge sharing. Her work has been published in journals such as *Journal of Management*, *Journal of Organizational Behavior*, and *Psychological Bulletin*. She also recently edited the *Oxford Handbook of Employee Engagement, Motivation, and Self-determination Theory*.

Abstract

The 2011 *Organizational Research Methods* Feature Topic on latent class procedures has helped to establish person-centered analyses as a method of choice in the organizational sciences. This establishment has contributed to the generation of substantive-methodological synergies leading to a better understanding of a variety of organizational phenomena and to an improvement of research methodology. The present Feature Topic aims to provide a user-friendly introduction to these new methodological developments to applied organizational researchers. Organized around a presentation of the typological, prototypical, and methodologically exploratory nature of person-centered analyses, this introductory article introduce seven contributions aiming to: (a) clarify the meaning, advantages, and application of person-centered analyses; (b) illustrate emerging prototypical and longitudinal cluster analytic approaches; (c) introduce researchers to multilevel person-centered analyses, as well as to auxiliary approaches that will drastically increase the scope of application of these methods; and (d) describe the application of these methods for confirmatory purposes.

Key Words. Person-centered analyses, mixture models, cluster analyses, organizational sciences, research methods.

Variable-centered approaches (e.g., multiple regression, CFA, SEM) assume that all individuals from a sample are drawn from a single population for which a single set of “averaged” parameters can be estimated. In contrast, person-centered approaches (e.g., cluster analyses, latent profile analyses, latent class analyses) relax this assumption and considers the possibility that the sample might include multiple subpopulations characterized by different sets of parameters. Person-centered approaches thus provide a rich complement to traditional variable-centered methods, allowing researchers to model complex processes in a more heuristic way (Wang & Hanges, 2011).

Since the publication of the 2011 *Organizational Research Methods* Feature Topic on latent class procedures (Wang & Hanges, 2011), person-centered analyses methodologies, including classical latent profile analyses (LPA) and latent class analyses (LCA), have become relatively well-established in the organizational sciences. This is illustrated by the appearance of review papers summarizing person-centered knowledge accumulated in some specific substantive areas (e.g., Mäkikangas & Kinnunen, 2016; Mäkikangas, Kinnunen, Feldt, & Schaufeli, 2016; Meyer & Morin, 2016), as well as of introductory papers aiming to review best practices in the estimation of person-centered models (e.g., Masyn, 2013; Meyer & Morin, 2016; Morin, 2016).

As noted by Marsh and Hau (2007; also see Borsboom, 2006) more than a decade ago, quantitative researchers live in very exciting times. Methodological developments are fast paced, and backed up by exponentially increasing levels of computing power and flexible statistical packages. However, this “excitement” comes at a cost for applied researchers: that of having to keep up with new developments. The lack of appropriate or sufficient technical training, coupled with the technical language used by the statistical experts involved in these new developments, pose major challenges to applied researchers. Marsh and Hau (2007) suggest substantive-methodological synergies as a way to re-instate communications between applied researchers and statistical experts. Substantive-methodological synergies essentially involve a collaborative work of knowledge translation, through which new methodological developments are applied to substantively important research areas either to address previously unresolved issues, or to reveal unexplored facets of the research object. Through this collaborative process, applied researchers become aware of the benefits of these new developments, which are presented to them in a user-friendly manner grounded in their research field, whereas methodological experts are challenged to find ways through which existing methods could be used, or refined, to address substantively important issues. The current Feature Topic was built as an attempt to help in the generation of such substantive-methodological synergies. This Feature Topic does not develop new methodologies, but rather was designed, written, reviewed, and fine-tuned in order to provide user-friendly introductions to, and illustrations of, new and evolving person-centered methodologies to applied organizational researchers.

We believe that the 2011 *Organizational Research Methods* ground-breaking Feature Topic on latent class procedures (Wang & Hanges, 2011) succeeded in achieving this objective. To illustrate this impact, let us consider the example of the Morin, Morizot, Boudrias, and Madore (2011) study of employees’ profiles of workplace affective commitment. In their study, Morin et al. (2011) included a continuous latent factor to their model (i.e., a factor mixture approach) in order to control for the covariance shared among all foci of workplace affective commitment included in their study, later referred to as employees’ global tendency to commit affectively to any foci. Although the meaning and role of this factor remained underdeveloped in the original study, it planted the seed for future developments. A few years later, Morin and Marsh (2015) noted that the identification of profiles differing only quantitatively from one another, which they referred to as presenting “level” differences, should be taken as evidence against the added-value of a person-centered solution. However, they noted that the failure to control for global tendencies shared among profile indicators could artificially inflate “level” differences and hide meaningful “shape-related” qualitative differences. They proposed Morin et al.’s (2011) factor-mixture approach as a solution.

Unfortunately, Morin, Boudrias et al. (2016, 2017) realized that this approach relied on the very strict, and unrealistic, assumption that each profile had to present the same level on this global factor. They further noted that this approach only provided a post hoc correction for the multidimensionality of the profile indicators which should have been identified, and taken into account, well-before the estimation of the profiles. As a result, they recommended relying on factors extracted from preliminary bifactor measurement models as a better way to control for global tendencies shared among profile indicators, and to identify profiles differing on both the global and specific nature of the indicators.

Interestingly, Perreira et al. (2018) recently applied bifactor measurement models to the study of workplace affective commitment, which led them to propose a new hierarchical model of commitment, in which the organization itself is positioned on an equal footing with the other foci, thus providing a way to make sense of some previously inconsistent research results identified in this field.

It is our hope that the present Feature Topic will generate similar synergistic developments across the organisational sciences. Indeed, despite the success of the previous Feature Topic, we felt that the number of new developments occurring in this methodological field was sufficient to justify a follow-up aiming to illustrate new and emerging applications of person-centered analyses. In previous publications, person-centered analyses were defined as being typological, ideally prototypical, and methodologically exploratory (Morin, 2016; Morin & Wang, 2016). All of the publications included in this Feature Topic directly or indirectly address one of these components.

Person-Centered Analyses: A Typological Approach

A unique feature of person-centered approaches (e.g., mixture models, latent profile analyses, latent class analyses, cluster analyses, growth mixture analyses) lays in relaxing the assumption that all individuals from a sample are drawn from a single population for which a single set of "averaged" parameters can be estimated. As such, person-centered analyses are typological in nature, considering the possibility that the sample might include multiple subpopulations characterized by different sets of parameters. More precisely, their results provide a classification system that helps categorize individuals into qualitatively and quantitatively distinct profiles. There lies the key heuristic advantage of person-centered analyses: It provides a typological classification system that is well-anchored into the managerial ways of thinking about "types" of employees. Although more advanced mixture regression of growth mixture models might achieve improved predictive accuracy (Morin, Rodriguez, Fallu, & Maïano, 2012), even without necessarily resulting in predictive increases (Marsh, Lüdtke, Trautwein, & Morin, 2009), person-centered analyses provide a uniquely informative perspective to organizational research by focusing on variables configurations. In the first contribution to this Feature Topic, Woo, Jebb, Tay, & Parrigon (2018, this issue) provide a global overview of the various classification methods that have been used in the organizational sciences and a review of the research in which these methodologies have been applied. They also propose a set of practical recommendations to guide users in their selection of an appropriate approach for their research.

A possible source of confusion for applied researchers in the selection of suitable research methodologies comes from the fact that the methodological literature has sometimes used the expression "person-centered" to describe non-typological statistical techniques focusing on "individuals" rather than "samples", but without attempting to classify these individuals (e.g., dynamic factor analysis, time series analysis). Howard and Hoffman (2018, this issue) propose to rely on the label "person-specific" to refer to these alternative statistical models, and provide a comprehensive presentation and illustration of the differences, complementarity, and fields of applications of variable-centered, person-centered, and person-specific approaches for organizational researchers.

Person-Centered Analyses: A Prototypical Approach

Although not all person-centered approaches are prototypical in nature, it has often been argued that this characteristic represents a key advantage of some person-centered approaches (e.g., latent profile analyses) over others (e.g., classical cluster analytic methods). In latent profile analyses, as well as in the overarching mixture modeling framework participants are assigned a probability of membership in all of the profiles based on their degree of "prototypical" similarity with each profile. These profiles are called "latent" because they are represented by a latent categorical variable, within which each category reflects an inferred and unobserved subpopulation. Participants are thus not directly classified, assigned, or allocated to one of the profiles, but rather are assessed as being more or less similar to each of these prototypical profiles. Individual profile membership is thus calculated while taking into account the measurement errors inherent in this classification process. Thus, just like latent continuous factors are corrected for the random measurement errors present at the item level, latent categorical profiles are also corrected for the imprecision of the classification process.

Emerging Cluster Analytic Approaches. The prototypical nature of person-centered analyses is one of the many key differences between mixture models and classical cluster analytic procedures which have been discussed in prior publications (e.g., Morin et al., 2011; Vermunt & Magidson, 2002). Still, despite this difference, research has revealed that when mixture models or classical cluster analytic models are used purely for classification purposes, both types of analyses tend to achieve similar rates of classification accuracy (Steinley & Brusco, 2011). Many of these comparisons have focused on traditional (e.g., *k*-means) approaches to clustering, neglecting the fact that cluster analytic procedures have also evolved considerably (for a review see Brusco, Steinley, Cradit, & Singh, 2011). For example, fuzzy clustering procedures now provide a way to achieve a cluster-based prototypical classification. In the present Feature Topic, Gabriel, Campbell, Djurdjevic, Johnson, and Rosen (2018, this issue) introduce organizational researchers to fuzzy clustering procedures, as well as to the differences and similarities between these clustering procedures and latent profile analytic models.

Similarly, another traditional advantage of mixture models over classical clustering procedures was the ability of mixture models to take into account the within-individual dependencies inherent in longitudinal data analyses (for instance, via growth mixture models). This advantage is no longer true given the availability of cluster analytic methods specifically designed for the analyses of longitudinal data. In the present Feature Topic, Hofmans, Vantilborgh, and Solinger (2018, this issue) introduce one of these approaches, *k*-centres functional clustering, to organizational researchers.

Advantages of Mixture Models. Despite all of these recent developments in cluster analytic methods, mixture models still retain some advantages. One of these advantages is related to the ability to directly incorporate predictors and outcomes to the model while taking into account the prototypical nature of the latent profiles. In addition, mixture models may also be extended to hybrid factor mixture models (Lubke & Muthén, 2005) that can be used to control for underlying global tendencies (Morin et al., 2011; Morin, & Marsh, 2015), to probe the underlying nature of psychological constructs (Clark et al., 2013; Masyn, Henderson, & Greenbaum, 2010), or even to test the invariance of variable-centered measurement models across unobserved (latent) subpopulations of participants (Carter, Dalal, Lake, Lin, & Zickar, 2011; Tay, Newman, & Vermunt, 2011). Moreover, mixture regression (Chénard-Poirier, Morin, & Boudrias, 2017) and mixture structural equation modeling (Morin, Scalas, & Marsh, 2015) makes it possible to extract subgroups of participants differing not only in their configuration on a series of indicators, but also characterized by different relations among these indicators. Similarly, multilevel mixture models (Finch & French, 2014; Henry & Muthén, 2010) provide a way to estimate profiles in data presenting a multilevel structure. Given the importance of taking into account multiple levels of analyses (employee, group, organization) in the field of organizational research, it is surprising that multilevel mixture models have not yet been illustrated to organizational researchers (with the sole exception of a psychometric application of multilevel mixed-measurement item response theory presented in the previous Feature Topic by Tay, Diener, Drasgow & Vermunt, 2011). Multilevel mixture modeling, which is introduced and illustrated in this Feature Topic by Mäkikangas, Tolvanen, Aunola, Feldt, Mauno, & Kinnunen (2018, this issue), is a very flexible data analytic approach in which profiles can be estimated both at the employee (level 1) and group (level 2) level, where the relative frequency of level 1 profiles can be used to estimate level 2 profiles, and where covariates can be added at both levels to predict the likelihood of profile membership at the employee and group level.

Another key advantage of mixture models rests in their ability to integrate covariates of profile membership directly into the model. Still, mixture models present a high level of computational complexity, requiring an estimation process involving random starts that tends to be highly sensitive to the inclusion of covariates to the model. Despite the fact that recent statistical research (Diallo, Morin, & Lu, 2017; Nylund-Gibson & Masyn, 2016) has shown that covariates (predictors, outcomes, or correlates) need to be integrated to a person-centered solution once the most optimal unconditional model (without covariates) has been identified, and should not be allowed to influence the nature of the profiles, the reality is that covariate inclusion often results in a switch in profile definition. This has led to the development of auxiliary approaches, which have been automated in various statistical packages (Asparouhov & Muthen, 2014; Lanza, Tan, & Bray, 2013; Bakk, Tekle, & Vermunt, 2013). However, these automated procedures remain limited in only allowing for the assessment of relations between isolated predictors and profile membership, or between profile membership and isolated correlates or outcomes. Thus, for models involving more complex predictive relations, such as when profile membership is assumed to moderate or mediate the relations among a set of predictors and outcomes, or when one wants to control for the effects of a covariate in outcome levels, then these approaches are not suitable. In this Feature Topic, McLarnon and O'Neill (2018, this issue) demonstrate how to circumvent this limitation by implementing these auxiliary approaches manually. In doing so, they also provide a very informative introduction to the basic principles of the causal effects decomposition approach to mediation (Muthen & Asparouhov, 2015; Van der Weele, 2014).

Person-Centered Analyses: Exploratory Methods that can be used for Confirmatory Purposes

Finally, person-centered analyses are exploratory, at least from an analytical perspective (Meyer & Morin, 2016). More precisely, given the lack of conventional goodness-of-fit information allowing one to directly assess the adequacy of an a priori model, solutions including different numbers of profiles need to be contrasted in order to select the optimal solution in a mainly exploratory manner. In addition, just like exploratory factor analytic (EFA) models, "relations" between all profiles and all indicators are typically freely estimated. However, this exploratory nature does not preclude the possibility of generating theory-based expectations regarding the number and structure of the extracted profiles, and confirming or infirming these hypotheses based on the solutions generated. In other words, exploratory or confirmatory *methods* can be used both for exploratory and confirmatory *purposes* (Morin, Myers, & Lee, 2018). Importantly, when dealing with new and emerging research methods allowing for a paradigmatic shift in how we see research questions, it is often simply not possible to devise clear-cut hypotheses regarding expected results, given the lack of any prior theoretical or empirical guidance. In this case, abductive reasoning (Bamberger & Ang, 2016) can be used to "discover" new phenomena in a data-driven manner. Without restricting the use of person-centered methods to abductive research, their exploratory nature suggests that they might be well-suited to accompany such research endeavours. Indeed, repeated calls have been made to encourage organizational research to become more open to exploratory or inductive studies driven by research questions rather than directional hypotheses (e.g., Hambrick, 2007; Jebb, Parrigon, & Woo, 2017; Miller, 2007; Spector, Rogelberg, Ryan, Schmitt, & Zedeck, 2014).

We are not advocating a return to "dustbowl empiricism" where data sets are fed to the ever hungry data analytic machine to see whether anything interesting would come up. However, we also find that equating "theory-driven" with "hypothesis-driven" is overly restrictive. After all, if no valuable research could be conducted without directional hypotheses, we would likely still ignore that hand washing kills germs, that cigarette smoking causes cancer, and that sugar is worse for your health than fat. With this in mind, we prefer to define "theory-driven" as a research in which research questions are investigated based on a strong rationale supporting their importance for a specific field of research. To illustrate this point, let us consider the "fishing expedition" analogy that is often used to illustrate "dustbowl empiricism". From our standpoint, "dustbowl empiricism" corresponds to dynamite fishing, were one throws explosive into a lake and picks up whatever comes up. In contrast, valuable exploratory research is closer to fly fishing, where one carefully picks a place and specific bait in order to catch a specific type of fish (e.g., salmon). Even then, one cannot be sure that salmon will be caught. One cannot be sure about the size of fish that will be caught. One cannot even be sure whether a trout might also be caught. However, one can still come well prepared to that expedition, knowing that something valuable will come out of it. Some examples of such abductive reasoning are already available in the organizational sciences, where person-centered analyses helped to realize that high levels of continuance commitment to the organization were not necessarily harmful to employees as long as they were combined with matching levels of affective and normative commitments (Meyer & Morin, 2016). Similar results have been observed in motivational research regarding the role of more controlled forms of behavioral regulations, which appeared to carry some benefits when coupled with matching levels of more autonomous forms of behavioral regulations (Howard, Gagné, Morin, & Van den Broeck, 2016).

Essentially, this example aims to illustrate the fact that valuable research can emerge from the examination of well-supported research questions, even when it is impossible, due to lack of previous theoretical or empirical guidelines, to clearly specify the exact nature of the results that are expected. In this case, replication becomes particularly important. In fact, replication is critical for person-centered research given that it is technically impossible to empirically distinguish a LPA model including k profiles from a common factor model including $k - 1$ factors (e.g., Steinley & McDonald, 2007). Both have identical covariance implications and can be considered 'equivalent' models (e.g., Cudeck & Henly, 2003). It is also hard to rule out the possibility that spurious profiles might emerge due to violations of the model's distributional assumptions (Bauer, 2007). Thus, in order to support a substantive interpretation, construct validation is necessary and involves demonstrating that the profiles: (a) have heuristic and theoretical value, (b) are meaningfully related to key covariates, which we discussed earlier, and (c) generalize to new samples or present some degree of stability over time (Marsh et al., 2009; Meyer & Morin, 2016).

In variable-centered methods, it is possible to analyse the invariance of a variety of measurement (e.g., confirmatory factor analyses – CFA) or predictive (e.g., structural equation modeling – SEM) models across meaningful subgroups of participants or time points (Millsap, 2011). Similarly, recent developments make it possible to analyse the degree of similarity of person-centered solutions across meaningful subgroups of participants (Morin, Meyer, Creusier, &Biétry, 2016) or time points (Morin & Litalien, 2017). However, some research areas might be sufficiently advanced to generate clearer a priori hypotheses regarding the expected nature of profiles (Finch & Bronk, 2011). More importantly, we believe that contexts favorable to purely deductive forms of person-centered analyses are likely to become more frequent as research keeps on evolving. For all of these contexts, we believe that Schmiege, Masyn, and Bryan (2018, this issue) comprehensive introduction to various forms of "confirmatory" applications of latent class analyses is likely to be very informative.

Areas of Upcoming Developments

Obviously, this Feature Topic is far from having covered all of the possibilities offered by person-centered analyses, in addition to leaving open a number of questions for which no responses are yet available. Still, between the time we wrote the call for papers for this Feature Topic underlying a few areas of anticipated upcoming developments and the moment at which we wrote this introduction piece, we were very impressed by the fact that many of the areas that we noted should be more thoroughly explored had indeed progressed over this relatively short period of time. Obviously, many of the advances and recommendations made in this Feature Topic, or referred to in this introduction, still need to be more thoroughly studied in statistical research in order to identify conditions in which these approaches work best or not as well, and ways in which their functioning may be optimized. For example, the optimization of these approaches for small samples is clearly an area where statistical research lags behind. Although it might be easy to simply note that person-centered methodologies are large-sample approaches, the reality is that in some situations, such as when the level 2 sample size is considered in multilevel mixture models or in the context of newly developed mixture time series analyses (Asparouhov, Hamaker, & Muthén, 2017), there will always be some research questions in which small samples will remain the norm. Thus, the ability to optimize current methodologies for these situations would certainly represent a key area for future development.

At the other end of the spectrum, there is a need for recommendations on how to best synthesize person-centred analytic results. For instance, Meyer and Morin (2016) proposed recommendations on how to clarify the reporting of person-centered results to facilitate their integration into a qualitative review paper. However, their recommendations remained focused on commitment research and not straightforward to generalize across the organization sciences. But more importantly, guidelines for the realization of quantitative (meta-analytic) syntheses of person-centered research are clearly lacking. For instance, although Kabins, Xu, Bergman, Berry, & Wilson (2016) conducted a meta-analysis of person-centered commitment studies, the approach taken by these authors required them to access raw data sets from the published studies. Thus, future research is clearly needed in order to consider how to simplify and optimize this process. Finally, both the generalized structural equation modeling (mixture modeling) framework and the ever increasing family of cluster analytic studies provide opportunities that have yet to be more systematically explored in applied research. We hope that the present Feature Topic will give you some ideas in this regard, and stimulate new applied and statistical research in the area of person-centered methodologies.

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