Chapter 14

Profiles of engagement dimensions and targets: Applications and opportunities for person-centered analytic techniques

Order of authorship and contact information:

Matthew J. W. McLarnon
Bissett School of Business
Mount Royal University
4825 Mount Royal Gate SW
Calgary, AB, Canada, T3E 6K6
Phone: (+1) 403-440-6991
Email: mmclarnon@mtroyal.ca

Alexandre J. S. Morin
Substantive-Methodological Synergy Research Laboratory
Department of Psychology, Concordia University
7141 Sherbrooke W,
Montreal, QC, Canada, H4B 1R6
Phone: (+1) 514-848-2424 ext. 3533
Email: alexandre.morin@concordia.ca
https://smslabstats.weebly.com/

David Litalien
Département des fondements et pratiques en éducation
Faculté des sciences de l'éducation, Université Laval
2320, rue des Bibliothèques, Office 938
Québec, QC, Canada, G1V 0A6
Phone: (+1) 418-656-3131 ext. 408699
Email: david.litalien@fse.ulaval.ca

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Abstract

This chapter introduces person-centered analytic techniques and their applications to the study of employee engagement within and across multiple targets. We provide a brief background on several common person-centered methods, which fall within the family of mixture models, and include latent profile analysis, mixture regression analysis, latent transition analysis, and growth mixture analysis. We then summarize past engagement research that has used person-centered analyses. Although potentially unfamiliar to some researchers, person-centered approaches can afford numerous data analytic possibilities that can be leveraged to investigate a wide-range of questions associated with the structure, function, and similarity (and dissimilarity) of patterns of employee engagement within and across multiple targets. As such, we then provide a gentle introduction to person-centered analyses which could be applied to the study of employee engagement. Finally, we discuss the importance of thoroughly investigating optimal measurement models (using advanced forms of factor analyses) that capture the underlying multidimensionality of employee engagement as it may be represented within and across targets. A proper measurement model will form the foundation of insightful person-centered contributions to the study of employee engagement. We intend for this chapter to be a springboard for future research and hope that scholars may use it to further develop their repertoire of advanced methods.

Keywords: employee engagement, multiple targets, mixture modeling, person-centered analyses, latent profile analyses

Engagement plays a central role in employee commitment, well-being, and performance (e.g., Crawford et al., 2010; Harter et al., 2002). It is therefore not surprising that employee engagement is among the most widely researched workplace attitudes (see Macey & Schneider, 2008; Meyer & Gagné, 2008). Although employee engagement has been primarily used in reference to focal work or job-relevant tasks, engagement can also be represented by multi-target conceptualizations. Saks (this volume) noted that engagement might be experienced differently across distinct work-related targets, such as tasks, occupation, organization, team, as well as across targets external to work, like family and leisure activities. Moreover, within targets, engagement is often conceptualized as having multiple facets, or dimensions (see Xanthopoulou & Bakker, this volume). The adoption of multi-dimensional and multi-target conceptualizations clearly provides many novel theoretical and empirical opportunities for engagement scholars. In this regard, the present chapter was guided by three potential research questions which might be worth considering when exploring the nature of employee engagement within and across targets. First, do employees differ in the extent to which they experience engagement to different targets (e.g., job, team, organization, occupation, family)? Put differently, this question asks whether there are distinct subpopulations, or profiles, of employees characterized by distinct configurations of engagement within and across targets. Second, do these different profiles of employees differ in terms of outcomes (e.g., job satisfaction, commitment, turnover intention), and can membership in these profiles be predicted, or explained, by theoretically important antecedents (e.g., tenure, work demands, leadership)? Third, do these profiles demonstrate change over time? In other words, how stable are these distinct configurations, and which shape best characterizes change over time.

We believe these research questions are crucially important, and provide a guide and foundation for a person-centered research agenda into employee engagement. However, little guidance is available on the data analytic techniques that are able to leverage the advantages of multi-target data. Thus, a major goal of this chapter is to introduce person-centered analyses to highlight how they may be applied to the study of engagement within and across targets. Importantly, person-centered approaches can be applied in multi-dimensional and/or multi-target research studies. We begin by briefly outlining engagement, providing background detail on multi-target approaches. Next, we introduce person-centered analyses, which are specifically designed to help researchers identifying employees characterized by distinct configurations, or patterns, of engagement. The use of person-centered analyses may afford researchers unique insights into the structure and function of employee engagement within and across multiple targets. When considering the approaches outlined here, it is however important to keep in mind that person-centered analyses represent only one potential means for examining employee engagement, which is likely to be relevant for some research questions, but not for all. Then, we briefly review past person-centered engagement research before discussing person-centered methods that can be used in single- or multi-target engagement investigations. Finally, we highlight potential measurement issues surrounding the multi-dimensional nature of engagement when multiple targets are considered.

Nature of employee engagement

Engagement has been defined in a number of ways (e.g., Mäkikangas et al., 2012). One common conceptualization is that engagement reflects "a positive, fulfilling, work-related state of mind that is characterized by vigor, dedication, and absorption" (Schaufeli et al., 2002, p. 74). This framework is reflected in the Utrecht Work Engagement Scale (UWES; Schaufeli & Bakker, 2010), which assesses the three-dimensional structure of vigor, dedication, and absorption. These can be characterized as experiencing the target of engagement as stimulating and energizing (vigor), personally significant and meaningful (dedication), and emotionally, physically, and mentally engrossing (absorption).

An alternative conceptualization stems from Rich et al. (2010; based on Kahn, 1990) representation of job engagement as encompassing physical, cognitive, and affective dimensions seen as important for optimal performance. Physical engagement reflects behavioral involvement with one's tasks, cognitive engagement reflects attention on one's tasks, and affective engagement denotes emotional connection to one's work and to others. Although we use the UWES framework in our examples, we do not necessarily advocate for this specific definition of engagement, nor do we prefer a specific set of engagement targets. Relevance of particular definitions, dimensions, and targets should be informed by appropriate theory and specific research questions.

Multi-target approaches. A major tenet of multi-target approaches is that engagement can be experienced dissimilarly across different targets in an employee's environment. Saks (this volume) provides insight into the different engagement targets of work tasks, profession and occupation, work team, and to external targets such as the family. Within multi-target approaches, the nature of engagement can correspond to any of the above definitions or conceptualizations and can be applied to any target present in an employee's environment. For instance, the vigor, dedication, and absorption employees' feel towards their work may be different from the vigor, dedication, and absorption they simultaneously feel towards their colleagues and occupation.

Emphasizing multi-target approaches, Rich et al. (2010) noted that engagement reflected multiple involvements, operating in a connected, holistic manner in an employee's life. Recently, a multi-target approach was proposed by Newton et al. (2020), who developed a task-level theory of engagement to suggest that engagement demonstrated dynamicity across tasks (see Sonnentag et al., this volume, for further discussion on dynamic issues). Using NASA astronaut trainees, they provided evidence for how engagement in a previous task influenced performance and engagement in a subsequent task. Their results broadly underscored the need to consider stability and change in the study of engagement across targets. This perspective also highlighted the importance of adopting a multi-target (e.g., multi-task) perspective because not all engagements are equal, and different engagements may have differential antecedents and/or outcomes, and may influence each other.

Introduction to person-centered analyses

Person-centered analyses are designed to classify cases (individuals, teams, etc.) based on the assumption that a sample includes a *mixture* of unobserved subpopulations presenting distinct configurations of scores on a set of focal variables. In other words, person-centered analyses assume that observed data reflect a 'mix' of parameters (e.g., means, variances, and even relations among variables) that stem from the presence of discrete subpopulations of cases. Person-centered analyses are part of the mixture modeling framework, and offer insight into how multiple variables simultaneously and holistically co-occur within subpopulations. For instance, it may be possible for a subpopulation of employees to have very strong task and team engagement, but weak organizational engagement, whereas another subpopulation of employees might present weak task engagement, coupled with strong organizational and team engagement. These subpopulations could have distinct relations with antecedents and outcomes, leading to different interpretations, and importantly, different practical implications. It is important to emphasize that the purpose of mixture models is to explore the presence and nature of these discrete subpopulations across a set of focal variables, rather than focusing on the variables themselves (at least until predictors and/or outcomes are included).

In this way, and in contrast to factor analyses, which estimate continuous latent variables (i.e., the factors), mixture models rely on the estimation of a categorical latent variable (i.e., the profiles) with the categories reflecting reflect discrete subpopulations. Mixture modeling also differs from factor analyses in that the latter are variable-centered. Variable-centered analyses assume population homogeneity (i.e., all cases drawn from a single population) and result in single set of quantitative estimates (i.e., means, regression coefficients, factor loadings) that apply equally to all population members. Mixture models relax this homogeneity assumption, potentially allowing for any model parameters to differ across discrete subpopulations.

In mixture models, these unobserved subpopulations are called *latent profiles* or *latent classes*. Although the terms latent profile analysis (LPA) and latent class analysis (LCA) are often used interchangeably, the former seeks to identify subpopulations presenting distinct configurations of a set of continuous variables, whereas the latter relies on binary or categorical variables. Given that modern mixture modeling can incorporate many types of ratings (i.e., ordinal, nominal, continuous, count, etc.) we hereafter use *LPA* to summarize both approaches.

LPA makes it possible to examine the combined effects of a set of variables that would be challenging to examine within typical variable-centered approaches like multiple regression and factor analysis (e.g., Morin et al., 2011). Although moderated multiple regression can assess how effects of one variable change according to another variable, thus potentially providing insight into the combined influence of different engagement dimensions and targets, the nature of interactions can be difficult to interpret when three or more interaction terms are considered, especially in the presence of nonlinearity. Instead, mixture modeling, provides a holistic perspective on the combined influence of a set of variables within and between cases. It is also important to recognize that mixture modeling is not the only person-centered framework. For instance, modern cluster analysis techniques (Brusco et al., 2011; Hofmans et al., 2018) may provide alternatives for addressing person-centered research questions. However, mixture modeling provides a more flexible approach to the integration of latent subpopulations in models that contain predictors, outcomes, and complex chains of relations (i.e., mediation, moderation; see McLarnon & O'Neill, 2018), as well as longitudinal or multilevel components. Readers interested in gaining further background on LPA may find the following resources useful: Morin et al. (2020), Morin and Litalien (2019), and Morin and Wang (2016).

Employee engagement through a mixture modeling lens

Though focused on a single target of engagement (work in general), one of the most cutting-edge examples of person-centered analyses as applied to employee engagement (using the UWES) comes from Gillet et al. (2019). Using LPA across two time points, Gillet et al. (2019) identified five subpopulations of employees: (a) engaged, yet distant, corresponding to employees with moderate levels of overall engagement, vigor, and dedication, coupled with very low levels of absorption (we discuss how overall and specific dimension scores can be included in the same model in the Multidimensional issues section); (b) normatively engaged, corresponding to individuals with average levels of engagement across dimensions; (c) vigorously absorbed, corresponding to individuals with high levels of vigor and absorption, (d) disengaged-vigorous, corresponding to individuals with low levels of dedication, absorption, and overall engagement, but high levels of vigor; (e) totally disengaged, corresponding to individuals with low levels across all engagement facets. Notably, these profiles demonstrated differential relations with stress, turnover intentions, and satisfaction. Specifically, engaged, yet distant individuals had the highest job satisfaction, and the lowest stress and turnover intentions. More recently, Gillet et al. (2020) applied a similar method to the job engagement measures of Rich et al. (2010) and identified globally disengaged, globally engaged, globally but not emotionally engaged, and moderately engaged profiles.

Several other studies have applied person-centered analyses to employee engagement. However, much of this work has explored profiles based on combinations of engagement with other variables (e.g., burnout; Mäkikangas et al., 2017; workaholism; Gillet et al., 2018). Thus, despite their importance, these studies remain limited in their ability to provide a direct interpretation of the unique effects of engagement. Accordingly, future studies on multi-target conceptualizations may wish to solely focus on indicators of engagement when conducting LPA. This will allow researchers to concentrate on the structure and function of engagement configurations within and across targets, without needing to interpret the resulting subpopulations in relation to other constructs. With that said, researchers should of course use their theoretically-informed judgment when determining the set of variables to include, and inclusion of other constructs may indeed be worthwhile in many studies.

Typical person-centered approaches

We now present key person-centered approaches, illustrated in Figure 1, that are suitable to the analysis of cross-sectional and longitudinal data. For cross-sectional data, we highlight LPA and mixture regression analyses (MRA). For longitudinal data, we discuss latent transition analyses (LTA) and growth mixture analyses (GMA). We also highlight multiple-group and longitudinal tests of profile similarity, multilevel models, and methods to examine covariate effects (e.g., predictors, outcomes). Extensive M*plus* syntax for these models is provided in Morin et al. (2020) and Morin and Litalien (2019).

Latent profile analysis. LPA is designed to identify subpopulations characterized by quantitatively and qualitatively distinct configurations of scores on a set of focal variables. For example, LPA can be used to identify subpopulations of employees who demonstrate different configurations of the engagement dimensions (e.g., vigor, dedication, absorption) within and across targets. The LPA model is shown in Figure 1A, where the octagon represents the latent profile variable, C, with *k* latent profiles (i.e., $C_1 \ldots C_k$) derived from a series of indicators ($X_1 \ldots X_i$; e.g., vigor, dedication, absorption). In a basic formulation, LPA is expressed as (see Masyn, 2013 for technical details):

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

LPA decomposes the variance, σ^2_i, of each *i* indicator into between-profile (the first term) and within-profile (the second term) components. Profile-specific means, μ_{ik}, and variances, σ^2_{ik}, operate as a function of π_k, which reflects the proportion of cases assigned to each profile. Despite this relatively straightforward decomposition, the complexity of LPA and other mixture models can increase the chance of converging on improper models (e.g., with negative variances) or models that fail to converge, which may occur when a model is overparameterized (e.g., too many profiles or free parameters estimated). Should this occur, more parsimonious models with profile-invariant variances ($\sigma^2_{ik}=\sigma^2_i$) can be explored. We recommend starting with "optimal" models (i.e., use σ^2_{ik}) and then reduce complexity as needed.

LPA can be used to explore questions related to engagement as it functions simultaneously across dimensions *and* targets. Consider an example in which a researcher has customized two versions of the UWES: one where the vigor, dedication, and absorption items are tailored to reflect task engagement, and a second version where the items reflect engagement in one's occupation. Such an approach could provide six indicators (three dimensions for each target), allowing for the estimation of profiles reflecting vigor, dedication, and absorption in one's task *and* occupation.

This might reveal highly distinct profiles demonstrating, for example: (a) a configuration mirroring the engaged, yet distant pattern mentioned above for task engagement, but a normatively engaged configuration for occupation engagement, and (b) a configuration corresponding to the vigorous absorption profile described earlier for task engagement, but a totally disengaged configuration for occupation engagement. In this way, a parsimonious, holistic approach to assessing engagement within and between targets can be achieved. Further illustrations of LPA are available for instance in the motivation (Howard et al., 2016), organizational commitment (for a review, see Meyer & Morin, 2016), and team conflict literatures (O'Neill et al., 2018).

LPAs are also flexible enough to accommodate the examination of profile similarity across samples. A comprehensive framework for assessing similarity in multi-group LPA was developed by Morin, Meyer, et al. (2016; see Table 1). Assessing the extent to which a core set of engagement profiles emerge across samples from different organizations, for example, can provide evidence for generalizability and construct validity, but can also enable discussion of the contexts that enable unique, peripheral subpopulations. For an illustration of this framework, see Litalien et al. (2017).

Mixture regression analysis. Whereas LPA identifies subpopulations presenting distinct configurations of a series of indicators, MRA (Figure 1B) identifies subpopulations that differ from one another in the way variables relate to other variables (i.e., on the basis of differing regression relations between variables). MRA freely estimates the regressions relations, as well as the means and variances of the outcome variables, to identify profile-specific regression equations (i.e., differing slopes, intercepts, and residuals across profiles; $y_{ik} = b_{ik} \times x_{ik} + \varepsilon_{ik}$). More precisely, in this classical approach to MRA, the profiles function as moderators of predictor-outcome relations. Unfortunately, we are not aware of any engagement research that has used classical MRA, so we direct readers to other research areas. For instance, Hofmans et al. (2013) used MRA to examine relations between pay satisfaction and job satisfaction. They found two profiles of employees: 80% of employees had a significant positive relation between pay and job satisfaction, whereas 20% of employees had a non-significant relation. Despite the lack of classical MRA applications to the study of engagement, examples can be imagined. Referring back to the previous example of engagement dimensions directed at one's task and occupation, MRA-based analyses could be designed to assess how the six engagement variables can predict burnout and stress. Here, MRA could reveal profiles differing in terms of the relations observed between the six engagement indicators and the two outcomes. For example, a profile could present strong negative relations between engagement and the outcomes, another profile could present null relations, and/or another profile could present negative relations from some predictor-outcome pairs, but not others.

Moving beyond the classical MRA model, Chénard-Poirier et al. (2017) developed a more flexible hybrid MRA-LPA approach that allows for the identification of subpopulations presenting distinct configurations on a set of predictors (as in LPA) but also characterized by distinct predictors-outcomes relations (as in MRA). This approach was applied by Gillet et al. (2018) to study the combined effects of work engagement and workaholism, allowing them to identify a mainly workaholic profile, a mainly engaged profile, and an engaged-workaholic profile, each of which was characterized by a distinct pattern of relations between the predictors (workaholism and engagement) and outcomes (sleeping difficulties and work-family conflict). Importantly, this hybrid framework makes it possible to differentiate outcome relations on the basis of between-profile predictor-outcome associations (i.e., profiles that are characterized by distinct configurations of predictor and outcome levels) from within-profile predictor-outcome associations (i.e., profiles that are each characterized by distinct sets of predictor-outcome relations).

Latent transition analysis. LTA (Figure 1C) combines a series of time-specific LPAs into a single model. For example, a LPA describing Time 1 profiles can combined with a second LPA estimated at Time 2 from repeated measures of the same set of indicators. LTA helps to assess stability and change over time in terms of profile definition (within-sample stability) and membership (within-person stability), enabling consideration of the effects of important time-related events (e.g., organizational changes, promotions). Within-person (in)stability represents individual transitions, or lack thereof, across profiles over time and is specifically assessed via LTA. In contrast, within-sample stability is first assessed within longitudinal LPAs (see Table 1; Morin & Litalien, 2017) to test for temporal consistency in the number, nature, and relative size of profiles, as well as longitudinal equivalence of predictors and outcomes. Ideally, LTAs should be derived from the most *similar* longitudinal LPA to maximize parsimony and comparability (Gillet et al., 2017).

As noted, Gillet et al. (2019) examined engagement profiles longitudinally, finding that over a four-month period profile membership was stable for more than 90% of employees. Extending this approach to examine multiple targets would also be relatively straightforward. For instance, the measures of task and occupational vigor, dedication, and absorption can be measured at multiple time points, and modeled using a LTA representation incorporating multiple time-specific LPAs (as described previously). This would enable comprehensive investigations into the stability of profiles characterized by multiple engagement dimensions and targets.

Other examples of LTA are available in the area of organizational commitment (Kam et al., 2016), and respondent faking (McLarnon et al., 2019), among others. Though we have discussed LTA as incorporating time-specific LPAs, LTA is sufficiently flexible to estimate transitions between different mixture models (Nylund-Gibson et al., 2014). For example, LTA can be used to explore how a LPA at Time 1 relates to a MRA at Time 2.

Growth mixture analysis. GMA (Figure 1D) extends latent curve models (LCMs; Bollen & Curran, 2006) to identify subpopulations characterized by distinct longitudinal trajectories. LCM uses indicator variables assessed on multiple occasions (i.e., 3 or more), and estimates trajectories via intercept (initial level) and slope factors (change over time). GMAs are highly flexible for modeling different trajectories, and may be useful for investigating dynamic engagement processes (see Sonnentag et al., this volume). The most common trajectory reflects a single, linear slope, though more complex trajectories can also be estimated.

Linear and quadratic models. Linear GMAs estimate profiles with different average intercept and slope factors, such that the profiles reflect different trajectories (e.g., steady increases, decreases, or static levels over time). Quadratic GMA, which requires 4 or more measures, incorporates an additional slope factor, representing a curvilinear trajectory. More complex GMAs can be designed to allow profiles to follow trajectories of higher-order polynomial functions (e.g., cubic, quartic).

Piecewise models. Piecewise GMAs estimate trajectories before and after a transition point (potentially reflecting an intervention or notable life event like a promotion). Piecewise models incorporate two or more slopes, representing the pre- and post-transition trajectories. Linear piecewise models with two slope factors require ≥2 measures before the transition, ≥2 after the transition point, *and* a total of at least five measures. Additional measures can allow for the estimation of curvilinear functions before or after the transition. Piecewise models require knowledge of when the transition occurs (though see Kwok et al., 2010).

Latent basis models. A limitation of typical GMA is that all profiles are assumed to follow a trajectory characterized by the same shape (e.g., linear, quadratic, piecewise). The latent basis model provides a workaround. GMA (and LCM, by association) requires only two time codes (slope factor loadings) to be fixed to identify the model. Commonly, the first measure, X_1 (see Figure 1D), is fixed to 0 to designate the trajectory start, and the final measure, X_t, is fixed to 1. The remaining time codes can be freely estimated (as in typical factor loadings). In this 0,1 coding, the slope represents the total change between the measures coded 0 and 1. In a GMA with this coding, the freely estimated time codes can differ across profiles and reflect the proportion of total change that occurred at each measurement occasion, thus allowing each profile to follow distinctly shaped, non-linear trajectories.

Non-linear models. GMA can also incorporate other non-linear forms (i.e., exponential, logistic, Gompertz, etc.), and descriptions of these trajectories are available in Grimm et al. (2016).

Growth mixture analysis summary. We presented GMA, in many of its different forms, because they could be useful for longitudinal multi-targets engagement studies. However, GMA may be better suited for exploring a limited set of engagement variables in a single model (see e.g., De Wind et al., 2017; Upadyaya & Salmela-Aro, 2015). For instance, GMA may be an option for examining trajectories of vigor across task and occupation targets. Unfortunately, GMA with six constructs (vigor, dedication, and absorption across two targets) would have at the least 12 factors (intercept and slope for each engagement construct), leading to an extremely complex model, which would likely have convergence issues and lengthy computation time. If interest is on the combined experience of vigor, dedication, and absorption within and across targets, then LTA may be better suited. Of course, choice of an analytical model must be guided by theory and relevant research questions. Given our relatively brief survey of analytical options, readers should consider Morin et al. (2020) and Morin and Litalien (2019) for more thorough discussions of GMA.

Auxiliary variables and covariates

Once an optimal person-centered model is determined, the next stage of data analysis often addresses how covariates have an influence on membership (i.e., predictors), or how profile membership influences outcomes. Covariates are considered *auxiliary* variables because they are external to the focal mixture model. These approaches allow exploring whether, for example, tenure is a predictor of a set of engagement profiles, and also whether engagement profile membership results in meaningful differences in performance and burnout.

Recent work on using auxiliary variables has suggested that an optimal, unconditional profile structure should be determined before covariate relations are examined. Of covariate methods available, the approach of directly including the covariates into the optimal model is one of the most straightforward, and can reduce Type 1 errors and limit bias (see Bolck et al., 2004). When covariates are directly included, care should be taken to ensure that the nature of the optimal unconditional model is unchanged. Asparouhov and Muthén (2014) suggested that if covariates change the unconditional model, the latent categorical variable could have lost its meaning. Techniques such as using the starting values from the optimal unconditional model may help remedy this, but caution must still be exercised (see Morin et al., 2020).

Because of the chance that direct inclusion can change the meaning of a profile, several methods have been developed to help circumvent this issue. Best practice recommendations currently suggest using M*plus*' R3STEP procedure for predictors, the DCAT procedure for binary, categorical, and nominal outcomes, and either the DU3STEP, DCON, or BCH procedures for continuous outcomes (for additional details, see Morin et al., 2020).

Whether direct inclusion or R3STEP is used, predictor relations involve multinomial logistic regression, in which k-1 effects for each pairwise comparison of profile membership is estimated (k=number of profiles). The multinomial logistic coefficients, typically transformed into odds ratios (ORs) to assist with interpretation, give the probability of membership in one profile versus another (e.g., an OR=2.00 suggests that for a 1-unit increase in the predictor, a case is twice as likely to be a member of a target profile versus a comparison profile). Outcome relations are somewhat more straightforward. Regardless of direct inclusion or M*plus*' auxiliary procedures, outcome relations are estimated as tests of mean differences across profiles.

LPAs and mixture models can also be used within mediated and/or moderated models. These possibilities can be facilitated with direct inclusion, or through the manual approaches associated with M*plus*' R3STEP/DU3STEP and BCH procedures (McLarnon & O'Neill, 2018; Nylund-Gibson et al., 2014).

Multilevel approaches

LPAs can also be used with multilevel data. Although examples of multilevel mixture models are relatively rare, Mäkikangas et al. (2018) provided an overview of multilevel LPAs, and they are presented as a candidate for use in engagement research. A multilevel LPA of multi-target engagement would allow researchers to account for the nesting of employees in teams, and could allow for estimating distinct employee- and team-level profiles. For example, team engagement can be modeled alongside task engagement, resulting in (individual-level) multi-target profiles, whereas the multilevel framework allows for estimating team-level profiles that represent the relative occurrence of individual-level profiles within each team. Conceivably, teams that comprise individuals with strong team engagement profiles might have more positive team outcomes than teams with members who have different multi-target engagement patterns. Readers should consult González-Romá (this volume) for greater detail on multilevel engagement issues and models.

Multidimensional issues

Gillet et al. (2019, 2020) noted that vigor, dedication, and absorption, just like physical, cognitive, and affective engagement, tend to be quite highly correlated. High correlations can suggest redundancy, multicollinearity, and conceptual overlap between variables, but also unmodelled multidimensionality. High correlations are even more likely for multi-target approaches. For example, two measures of vigor – one assessing task engagement, and another corresponding to occupational engagement would likely be highly correlated. This would stem from the similarity of the constructs, but also from the similarity in contexts in which these forms of engagement would be enacted, as well as from the reliance on similarly worded items across vigor scales.

Unfortunately, highly correlated variables can obscure unique profile configurations, potentially negating the added value of person-centered methods. As a potential solution, a close examination of preliminary measurement models and factor analyses has been advised (Morin, Boudrias et al., 2016, 2017). Specifically, exploratory structural equation modeling (ESEM), integrated with bifactor models, can provide superior variance decomposition for multidimensional measures (Morin, Arens, et al., 2016). ESEM functions similarly to exploratory factor analysis, allowing for measured variables to be indicators of multiple latent factors. ESEM, however, when paired with target rotation, reflects a confirmatory approach, leveraging researcher knowledge of the hypothesized factor structure. In this way, ESEM can better represent the construct-relevant psychometric multidimensionality (Morin, Arens, et al., 2016), reducing factor correlations. As well, integrating a bifactor model, in which a global factor defined by all items included in a measure (e.g., all task engagement items) is estimated in conjunction with a series of specific factors (e.g., task-related vigor, dedication, and absorption) reflecting variance left unexplained by the global factor, has recently been shown to result in a more accurate depiction of employee engagement (Gillet et al., 2020).

After identifying an optimal multidimensional measurement model, factor scores can be exported from this model for use in LPA (Gillet et al., 2019). Factor scores partially control for measurement error by differentially weighting more reliable items (i.e., those with stronger factor loadings). As well, factor scores preserve the underlying measurement model, which can include global and specific factors, and/or longitudinal and multi-group invariance. Together, bifactor-ESEM with target rotation might be strongly advantageous for studying the multidimensional structure of employee engagement within and between targets. The application of this approach to the UWES measure would equip subsequent LPAs with four engagement variables for each target – one global factor, and one each for the vigor, dedication, and absorption specific factors (for illustrations, see Gillet et al., 2019, 2020). Therefore, researchers should view person- and variable-centered analyses as complementary. When paired together, these approaches can enable comprehensive investigations of employee engagement and of many other organizational phenomena.

Sample size issues

A final point worthy of consideration concerns sample size requirements for person-centered analyses. The mixture models discussed here are generally best suited to large sample sizes. Large samples of employees not only provide greater statistical power, but more importantly enhance the ability of mixture models to converge on proper numerical solutions that may reveal theoretically important profiles (Meyer & Morin, 2016). However, no clear guidelines are currently available on sample size requirements for the models we have described. To this end, we echo Meyer and Morin (2016) and suggest that researchers be cognizant of two contrasting perspective on sample size. On one hand, although researchers should aim to access large (~500 cases) or very large (~1,000 cases) samples, which enable the application of the more complex models highlighted in this chapter, large samples might reveal statistically significant differences that have weak practical significance, or may identify subpopulations that have low theoretical importance. On the other hand, lower sample sizes (e.g., <300) may only allow researchers to apply mixture models of moderate complexity, thus potentially requiring them to make adjustments to their focal model.

Conclusion

Person-centered analyses, like LPA, may be ideally suited for investigating research questions on employee engagement as it functions within and between targets. We provided readers with a brief overview of person-centered approaches that could be applicable to studying engagement through a multi-dimensional and/or multi-target lens. We are confident these analytical techniques will afford researchers unique opportunities to investigate important questions on the role of employee engagement from single- and/or multi-target perspectives.

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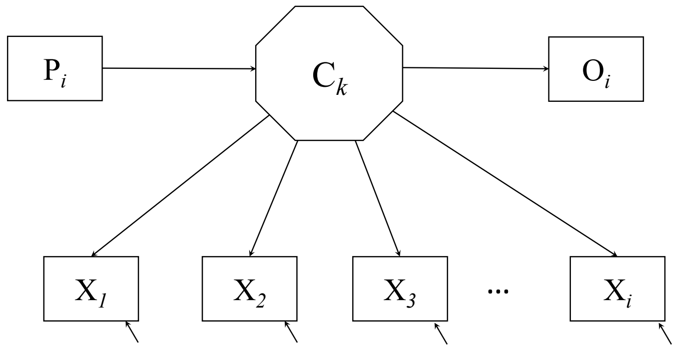

Figure 1A. Latent profile analysis. This model shows *k* latent profiles, C_k, derived on the basis of scores on X_1 to X_i indicators. Predictors, P_i, and outcomes, O_i, can be examined, where the predictors influence likelihood of profile membership, and where profile membership influences mean differences in the outcomes across subgroups.

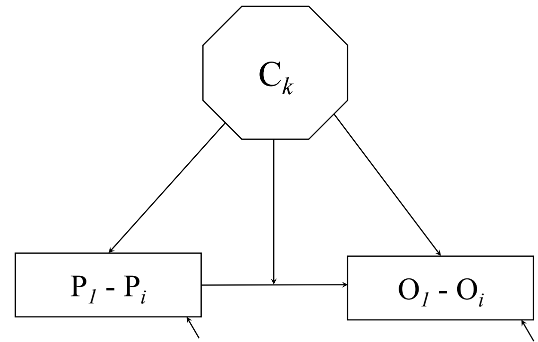

Figure 1B. Mixture regression analysis. MRA estimates *k* latent profiles, C_k, based on differing regression relations between a set of P_1 to P_i predictors and O_1 to O_i outcomes. MRA can also be combined with LPA to identify subgroups that differ on the configuration of indicators, as well as on the strength of relations between indicator variables (see Chénard-Poirier, Morin, & Boudrias, 2017).

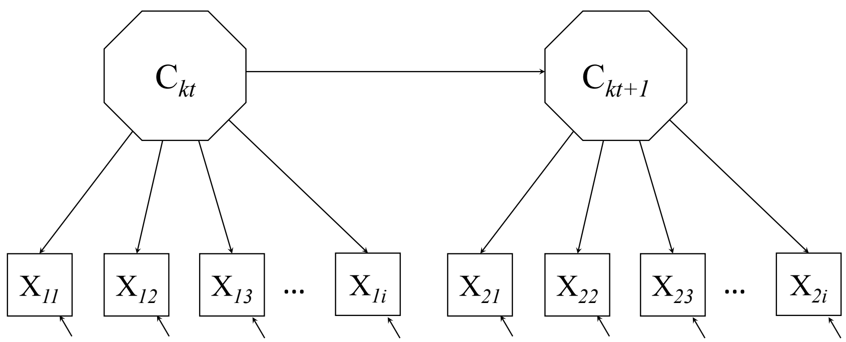

Figure 1C. Latent transition analysis. LTA estimates *k* latent profiles at two time points, C_{kt} and C_{kt+1}, from repeated measures of the same set of X_i items. LTA can assess the probabilities of cases transitioning between C_k and C_{kt+1} profiles over time. LTA can also assess the similarity of a profile solution over time, however, the model at Time *t+1* (i.e., C_{kt+1}) does not need to be equivalent the model at Time *t* (i.e., C_k). In other words, it is not required that C_k and C_{kt+1} have the same structure or number of profiles.

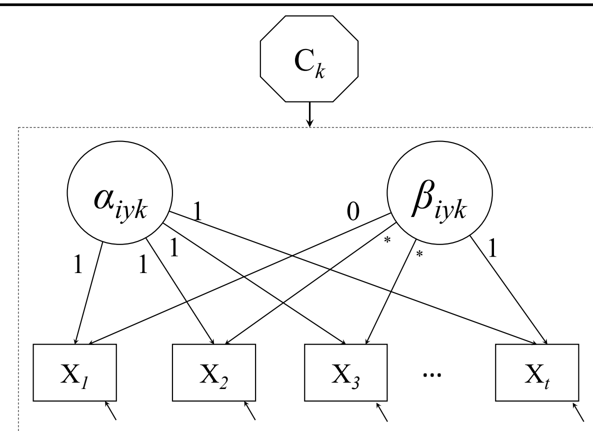

Figure 1D. Growth mixture analyses. C_k profiles of differing longitudinal trajectories (i.e., discrete intercepts/slopes) over time. Trajectories are estimated within a latent curve model, of which any part can vary across profiles (i.e., means/ variances of growth factors, slope factor loadings [as in a latent basis model], etc.), hence the dashed line around the entire model.

Table 1. *Tests of Multi-Group and Longitudinal Profile Similarity*

Test	Description
A – Configural Similarity	• Assesses whether same number of profiles are identified in each group or at each repeated measure. • Is a *prerequisite* for all subsequent similarity tests; if configural similarity cannot be supported the latent profile solutions must be compared through a qualitative process.
B – Structural Similarity	• Assesses within-profile similarity of respective indicator means across each group/repeated measure (i.e., whether profile structure is similar). Requires configural similarity to be assessed. • Configural and structural similarity are prerequisite to all further tests, but partial structural similarity is possible. • Lack of partial structural similarity: The profiles differ across groups and require a qualitative comparison process.
C – Dispersional Similarity	• Assesses within-profile variability of respective indicators are the same in each group/repeated measure. Partial dispersion similarity is possible. Not applicable when indicators are binary or categorical. • Lack of dispersion similarity suggests that within-profile variability varies across groups/repeated measures. • Prerequisite for assessing dispersional similarity: Configural and structural similarity.
D – Distributional Similarity	• Assesses similarity of relative size of the profiles (i.e., % of cases in each profile) across groups/repeated measures. • The size of all profiles needs to be either similar or not across pairs of groups/repeated measures, but partial distributional similarity is possible across different pairs (e.g., Time 1 is similar to Time 2, but different than Time 3). • Lack of distributional similarity: The size of the profiles differs across groups/repeated measures. • Prerequisite for assessing distributional similarity: Configural and structural similarity.
E – Predictive Similarity	• Assesses similarity of the effects of predictors on profile membership across groups/repeated measures. • Prerequisite: Configural and structural similarity; predictors are *directly included* into the *most* similar model (Models A-D, above). • Predictor effects can be similar or not across pairs of profiles, and partial predictive similarity is possible across different pairs of groups/repeated measures, or across different predictors. • Lack of predictive similarity: The effects of predictors on profile membership differ across groups/repeated measures.
F – Explanatory Similarity	• Assesses similarity of effects of profiles on outcomes are the same across all groups/repeated measures. • Prerequisite: Configural and structural similarity; outcomes are directly included into the most similar model (Models A-D, above). • Partial explanatory similarity is possible. • Lack of explanatory similarity: The effects of profile membership on the outcomes differ across groups.
G – Regression Similarity	• Assesses similarity of regressions that define mixture regression profiles across all groups/repeated measures. • Only relevant in mixture regression analysis (MRA), and is the second step of similarity analyses for MRAs. • Partial similarity is possible. • Lack of partial regression similarity: The latent profiles differ across groups and require must be compared through qualitative means. • Prerequisite: Configural similarity.
Recommended order	Steps that are a prerequisite to subsequent steps are bolded: Latent Profile Analysis: **A-B**-C-D-E-F Mixture Regression Analysis: **A-G-B**-C-D-E-F