Chapter 34. Person-Centered Research Strategies in Commitment Research

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Online Supplements for this chapter can be accessed at statmodel.com/MixtureModeling.shtml, or upon request from the author.

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Abstract

This chapter provides a broad introduction to a person-centered perspective of commitment research more generally, and to the various possibilities provided by mixture models more specifically. Thus, after introducing the person-centered approach to commitment research, key elements of its implementation in research are addressed. A Generalized Structural Equation Modeling framework of broad relevance to all forms of person-centered analyses is then introduced, together with user-friendly descriptions of the various types of models that can be estimated using this framework (latent profile analyses, latent profile analyses with covariates, factor mixture analysis, similarity testing for profile solutions, latent transition analyses, mixture regression analyses, growth mixture analyses). For each model, a non-technical description of the model and of its implementation is provided, and followed by a brief illustration of the model through a short description of previously published applications.

Commitment is a vibrant field of research, encompassing multidimensional (Allen, this volume), unidimensional (Klein & Park, this volume), and multifocal (Becker, this volume) theories. Although a person-centered approach can inform all of these frameworks, Meyer and Allen (1991) three component model (TCM) is arguably the model that has been the most extensively investigated from a person-centered perspective and the focus of this chapter. The TCM defines commitment as a “force that binds an individual to a target and to a course of action of relevance to that target” (Meyer, Becker, & Van Dick, 2006, p. 666). This attachment is proposed to be maintained through three distinct mindsets: affective (AC), normative (NC) and continuance (CC). Employees are assumed to experience each mindset to varying degrees in relation to multiple targets (e.g., organization, colleagues, supervisors, occupation; Morin, Madore, Morizot, Boudrias, & Tremblay, 2009), so that individual profiles reflect a combination of AC, NC and CC directed at various constituencies. Specific mindset-target combinations are hereafter referred to as a commitment component.

Variable-centered studies looking at interactions among commitment components showed that the relations involving specific components differed as a function of the strength of the other components (Gellatly, Meyer, & Luchak, 2006). However, these studies are limited in their power to detect and interpret complex interactions among multiple components. A *person-centered* approach aiming to identify distinct, and relatively homogenous, subgroups presenting qualitatively and quantitatively distinct profiles on a set of commitment components, has been advocated as more appropriate for investigations of complex relations among multiple commitment components (Meyer, Stanley, & Vandenberg, 2013). A person-centered approach views individuals in a more holistic fashion, and affords the opportunity to address complex interactions among commitment components that would be difficult to detect using traditional variable-centered analyses (Meyer et al., 2013; Morin, Morizot, Boudrias, & Madore, 2011). However, person-centered approaches also require a paradigmatic shift in the way research questions are framed, moving away from a correlational approach centered on variables to a configurational approach centered on persons (Delbridge & Fiss, 2013).

This chapter aims to provide a broad introduction to a person-centered perspective of commitment research more generally, and to the analytical possibilities provided by mixture models more specifically. This chapter first briefly presents the underpinnings of the person-centered perspective, before proposing a user-friendly description of the various types of mixture models available to person-centered commitment researchers.

A person-centered approach to commitment research

In the original formulation of the TCM, Meyer and Allen (1991) proposed that employees would present commitment profiles reflecting their relative levels of AC, NC and CC to the organization. Building on this, Meyer and Herscovitch (2001) offered a set of propositions concerning eight hypothetical profiles of commitments reflecting distinct combinations of high or low scores on each mindset. Essentially, the logic of these propositions is that commitment mindsets can combine and be experienced in different ways so that how any one is experienced or relates to other variables will depend on the context created by the other mindsets. For example, Gellatly et al. (2006) proposed that NC might be experienced as a *moral imperative* when combined with strong AC, but as an *indebted obligation* when combined with weak AC and strong CC. When multiple targets are considered, the notion that commitment to a specific target can contextualize commitment to the other targets has been addressed through the ideas that commitment to different targets may conflict with one another (Reichers, 1985) or that compatible commitments may reinforce one another (Meyer & Allen, 1997). When multiple targets and mindsets are combined, Meyer and Allen (1997) proposed that dependencies, or nesting, can develop among commitment targets, which may have implications for mindsets pertaining to each target. To illustrate, consider two groups of employees, both of whom have a strong desire to continue working with their colleagues (strong group AC). The first group also enjoys working in their organization (strong organizational AC), evidencing compatibility. However, the second group has little desire to remain with the organization (weak organizational AC), suggesting conflict. The first group would be expected to stay in the organization and workgroup, and to perform up to or beyond the standards of both. The second group could be expected to develop a high level of CC to the organization as this employment tie is their only way to remain working with their colleagues. This scenario illustrates how nested commitments can generate compatibility or conflict.

So far, studies have attempted to verify these propositions through the identification of profiles of employees' AC, NC, and CC to their organizations (for reviews, see Meyer et al., 2013; Meyer & Morin, 2016), AC to two or more targets (e.g., Morin, Morizot et al., 2011), or AC, NC and CC to more than one target (e.g., Meyer, Morin, & Vandenberg, 2015; Morin, Meyer, McInerney, Marsh, & Ganotice, 2015; Tsoumbris & Xenikou, 2010). This research has supported the idea that commitment components create a context for other commitment components, and that both compatibility and conflicts among commitments is possible. However, the use of different idiosyncratic reporting and labeling approaches makes it difficult to integrate results from multiple studies.

Reporting and labelling

To facilitate the systematic comparison and integration of results across studies, a common profile labelling scheme and clear reporting guidelines seems to be required. Profiles of any kind can vary along three dimensions (Meyer & Morin, 2016): (i) *shape* (the overall pattern, or configuration, of high and low scores on various indicators), (ii) *elevation* (the average level of commitment across indicators within each profile), and (iii) *scatter* (the degree of differentiation among indicators within each profile). So far, research has mainly used profile *shape* to determine labels, such as through the identification of the mindset(s) with the highest score as being 'dominant' (Meyer et al., 2013). Shape-differentiated profiles are considered to be *qualitatively* differentiated. When all indicators (e.g., mindsets) are at approximately the same level, labels such as 'uncommitted', 'moderately committed', or 'fully committed' are typically used and profiles are said to be *quantitatively* differentiated.

For illustration purposes, prototypical TCM profiles corresponding to these qualitative and quantitative differentiations are illustrated in Figure 1a. With the exception of the moderately committed profile, these profiles correspond to the eight theoretical profiles discussed by Meyer and Herscovitch (2001). A series of descriptive labels (in parentheses in Figure 1a) are also proposed to depict the psychological states reflected in these profiles, which may be more meaningful to practitioners: *emotionally committed* (AC-dominant), *obligated* (NC-dominant), *trapped* (CC-dominant), *morally committed* (AC/NC-dominant), *indebted* (CC/NC-dominant), and *invested* (AC/CC-dominant).

< Insert Figures 1a and 1b about here >

To add precision to the description of the profiles, Meyer and Morin (2016) proposed to add qualifiers to describe profiles where the level of elevation is either high or low, and profiles that show a weak level of differentiation (scatter) across indicators. To reflect elevation, 'high' is used when all indicators are above the average and 'low' when all indicators are below average. To reflect scatter, the term 'weak' is used when there are relatively small differences between indicators within a profile. Note that in cases where elevation is high or low, scatter is naturally restricted so that the qualifier 'weak' is not used in this situation. It is also possible to include indicators of elevation (the average level across indicators in a single profile) and scatter (the standard deviation across indicators in a single profile) to the graphical presentation of the profiles. Figure 1b illustrates variations in elevation and scatter for the AC-dominant and AC/NC-dominant profiles, and incorporates within-profile indicators of elevation and scatter to the graphical representation. These indicators of elevation and scatter were calculated as the mean and standard deviation of the indicators within each profile, and added to the figure (for a similar procedure, see Marsh, Lüdtke, Trautwein, & Morin, 2009). Profiles characterized by the same scatter but in which with all mindsets are located above average (high), below average (low), or both above and below average (weak) are presented.

The application of this profile labelling scheme also involves systematizing the way results are reported. Typically, studies have either reported raw scores (Meyer, Kam, Goldenberg, & Bremner, 2013) or standardized scores (Morin, Morizot, et al., 2011) of commitment components. The second approach is more naturally suited to the proposed profile labeling scheme. In measurement, raw scores can seldom be ascribed any substantive meaning due to the lack of meaningful unit of measurement. Even comparisons across scales from a single instrument are precarious unless one can demonstrate that the implicit unit of measurement is equivalent across these scales. Furthermore, many studies rely on idiosyncratic measures, or modified versions of validated questionnaires, making comparisons based on raw scores simply impossible. Standardized scores not only make scores interpretable as a function of the sample mean and standard deviation, they make the graphical presentation of results (and the identification of high/low scores) clearer, especially when histograms are used. However, standardized scores remain a function of samples' means and standard deviations, which may differ across studies. Thus, a third and stronger alternative is to present scores based on normative data (Kam et al., 2015). Norms are currently available for 54 distinct countries for TCM measures of AC, NC, and CC to the organization (Meyer, Stanley, Jackson, McInnis, Maltin, & Sheppard, 2012). Overall, our recommendation is to graphically represent the profiles using histograms based on standardized scores, or normed scores when available, while reporting raw scores (and sample means and variance) in supplementary tables to help contextualize sample characteristics.

Mixture modelling approaches to person-centered analyses

This chapter focuses on a mixture modeling approach to person-centered analyses (for a brief overview of alternative approaches, see the online supplements). Mixture modeling is a model-based approach to clustering, based on the assumption that a sample includes a mixture of subpopulations, and is part of the Generalized Structural Equation Modeling (GSEM) framework (Muthén, 2002). GSEM allows for the estimation of relations between any type of continuous and categorical observed and latent variables. Traditional latent variable models (e.g., confirmatory factor analyses – CFA, and structural equation models – SEM) assume that all individuals are drawn from a single population and yield *variable-centered* results reflecting a synthesis of the relations observed in the total sample. GSEM relaxes this assumption by allowing all or part of any CFA/SEM model to differ across unobserved subgroups of participants. More precisely, GSEM identifies relatively homogeneous subgroups of participants differing qualitatively and quantitatively from one another in relation to: (a) their configuration of a set of observed and/or latent variable(s), and/or (b) relations among observed and/or latent variables. These subgroups are typically referred to as latent profiles, and represented in the model as a categorical latent variable (where the latent profiles represent the distinct categories).

Within GSEM, person-centered analyses present three key defining characteristics. First, they are *typological*: Their results provide a classification system helping to categorize individuals into qualitatively and quantitatively distinct profiles. Second, they are *prototypical*: All participants have a probability of membership in all profiles based on their degree of similarity with each prototypical latent profile. These profiles are called latent because they are represented by a latent categorical variable where each category represents an inferred, unobserved, prototypical, subpopulation. Finally, they are *exploratory*: Solutions including different numbers of profiles are typically contrasted in order to select the optimal solution in a mainly exploratory manner. Even though it is possible to devise confirmatory mixture models when theory is advanced enough to provide clear expectations regarding the exact nature of the profiles to be expected (Finch & Bronk, 2011), these models still need to be contrasted with unconstrained exploratory models to show that their fit to the data remains comparatively acceptable. In practice, the optimal number of profiles is determined based on inspection of: (a) the substantive meaning and theoretical conformity of the solution; (b) the statistical adequacy of the solution; (c) statistical indicators (additional details on model estimation and statistical indicators are provided in the online supplements).

Another key consideration is to demonstrate that the profiles are meaningful. It is important to keep in mind 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) and end up explaining equivalent variance. Similarly, it is hard to rule out the possibility that spurious profiles might emerge due to violations of the model's distributional assumptions even when none are present in the data (Bauer, 2007). Thus, in order to support a substantive interpretation, it remains necessary to embark on a process of construct validation to demonstrate that the profiles: (a) have heuristic value, (b) have theoretical conformity or value, (c) are meaningfully related to key covariates, and (d) generalize to new samples (Marsh et al., 2009; Morin, Morizot, et al., 2011).

The following sections include a user-friendly description of the main categories of mixture models available to person-centered commitment researchers: Latent profile analyses (LPAs), factor mixture analysis (FMAs), latent transition analyses (LTAs), mixture regression analyses (MRAs), and growth mixture analyses (GMAs). These models are graphically presented (and numbered) in Figure 2.

<Insert Figure 2 about here>

Latent profile analyses (Model 1)

LPAs are the most common form of mixture model used in commitment research (Meyer et al., 2013; Meyer & Morin, 2016), and aim to describe subgroups of participants differing from one another on their configuration on a series of commitment components. While CFAs estimate continuous latent variables (factors) representing groupings of indicators, LPAs estimate categorical latent variables (profiles) representing grouping of persons (Lubke & Muthén, 2005). LPAs can accommodate a variety of continuous, ordinal and categorical measurement scales (McLachlan & Peel, 2000), and take into account a multilevel structure (Henry & Muthén, 2010).

LPAs allow for the direct specification of alternative models whose adequacy can be compared with various relative fit indicators. For example, LPA models can be estimated while allowing profiles to be defined only on the basis of the indicators means, or also be defined while allowing the variance of the indicators to differ across profiles (Peugh & Fan, 2013). Contrary to cluster analyses, LPAs do not assume the variance of the indicators to be invariant (the same) across profiles. However, the invariance of the indicators' variances remains LPAs' default parameterization in some statistical packages, such as Mplus (Muthén, & Muthén, 2014). Relaxing this default helps to obtain less biased parameter estimates (Peugh & Fan, 2013), and provides a more flexible and realistic representation than relying on artificial constraints through which the level of inter-individual variability is forced to be equivalent from one profile to the other (Morin, Maïano, et al., 2011). Correlated uniquenesses can also be included. However, LPAs typically assume the conditional independence of the indicators, which are expected to be unrelated to one another conditional on the latent profiles. GSEM makes it possible to relax this assumption through the inclusion of correlations among the residual variances of the indicators, which may even be beneficial to the estimation process under some highly specific conditions (Peugh & Fan, 2013). Nevertheless, this assumption should only be relaxed with caution, and on the basis of strong a priori expectations of residual associations among the indicators (e.g., wording effects). Correlated uniquenesses drastically change the meaning of model, which aims to parsimoniously summarize the indicators' covariance by a finite number of latent profiles. Method factors, providing an explicit control for construct-irrelevant sources of covariance, should generally be preferred (Schweizer, 2012). GSEM also makes it possible to include method factors, so that the latent profiles can be estimated controlling for the effects of explicitly modelled residual associations (Lubke & Muthén, 2005; see later section on FMAs).

LPAs are a very flexible, and make it possible to directly assess the added value of alternative specifications (free estimation of indicators variance, correlated uniquenesses, and factor mixture models) in terms of improvements in the relative fit of the model. However, mixture models remain complex and computer-intensive, and have a tendency to converge on improper solutions, or fail to converge at all. When this occurs, it suggests that the model may have been overparameterized (e.g., too many profiles, too many parameters freely estimated across profiles) and that more parsimonious models may be superior. Our recommendation is to always start with theoretically "optimal" models, and then reduce model complexity when necessary.

LPAs with covariates (Model 2)

A key strength of LPAs is the possibility to directly include covariates (predictors, correlates or outcomes) to the model. Directly including covariates helps to limit Type 1 errors by combining analyses, and has been shown to reduce biases in the estimation of the relationships between covariates and the profiles (Bolck, Croon, & Hagenaars, 2004). With mixture models, it is particularly critical not to rely on two-steps strategies (i.e., exporting the most likely class membership of participants to an external data file, and relating this observed categorical variable to covariates using regressions or ANOVAs), which ignore the prototypical nature of the profiles (i.e., individuals' probability of membership in all profiles; Marsh et al., 2009). Covariates can be conceptualized as having an impact on profile membership (predictors), as being impacted by profile membership (outcomes), or as being related to profile membership with no assumption of directionality of the associations (correlates). Because these three types of covariates are included using different approaches, this distinction needs to be made a priori, on the basis of theoretical expectations and research background.

Predictors are included in the final model using a multinomial logistic regression representing the relationship between the predictor and the likelihood of membership into the various profiles. In multinomial logistic regressions, each predictor has *k*-1 (with *k* being the number of profiles) effects for each possible pairwise comparison of profiles. The regression coefficients reflect the expected increase, for each unit of increase in the predictor, in the log-odds of the outcome (the probability of membership in one profile versus another). Odds ratios (OR) are also typically reported, and reflect the change in the likelihood of membership in a target profile versus a comparison profile for each unit of increase in the predictor (e.g., OR = 2 means that each unit of increase in the predictor is associated with participants being twice more likely to be member of the target, versus comparison, profile).

Predictors are included to the model after the class enumeration procedure has been completed, and their inclusion or exclusion should not change the nature of the profiles (Marsh et al., 2009). Such a change would indicate a violation of the assumption that the direction of the relation goes from the predictors to the profiles, rather showing that predictors act as profile indicators (Marsh et al., 2009; Morin, Morizot et al., 2011). When this happens, alternative strategies involving estimating the model using starts values taken from the final unconditional model, or using ‘auxiliary’ approaches where the covariates are kept inactive, can provide valuable alternatives (Asparouhov & Muthén, 2014; Vermunt, 2010). These approaches are discussed and illustrated in the online supplements.

The typical way of including outcomes to the model involves including them as additional profile indicators. However, when multiple outcomes are considered, this method almost always results in a change in the nature of the profiles. Whenever this is the case, associations between inactive outcomes and the profiles can also be easily tested using a variety of auxiliary approaches (Asparouhov & Muthén, 2014; Lanza, Tan & Bray, 2013; Vermunt, 2010) illustrated in the online supplements.

Correlates are typically used for descriptive purposes and do not need to be directly included in the model. Thus, to properly assess the relationships between correlates and prototypical latent profiles (i.e., taking into account individual probabilities of memberships in all classes), auxiliary approaches should be preferred. The AUXILIARY *(e)* approach implemented in Mplus, which relies on Wald chi-square test of statistical significance based on pseudo-class draws and tests the equality of correlates means across profiles (Asparouhov & Muthén, 2007; Bolck et al., 2004), does not assume any directionality in the associations between profiles and correlates.

Factor mixture analyses (Model 3)

GSEM allows for the simultaneous inclusion of continuous (factors) and categorical (profiles) latent variables within the same model. FMAs include factors and profiles estimated from the same indicators. A complete review of FMAs is beyond the scope of this chapter. FMAs can be used to investigate the underlying continuous or categorical nature of psychological constructs (Clark et al., 2013; Masyn, Henderson, & Greenbaum, 2010), and to test the measurement invariance of psychometric measures across unobserved subpopulations (Tay, Newman, & Vermunt, 2011). Of direct relevance to commitment research, FMAs can integrate a continuous latent factor to control for a generic tendency shared among indicators. For example, Morin and Marsh (2015) used FMAs to estimate profiles of strengths and weaknesses in terms of teaching competencies (i.e., relations with students, marking), while controlling for global levels of effectiveness (i.e., for the fact that there are good and poor teachers). Their results clearly showed that FMAs resulted in more clearly differentiated profiles than LPAs. Based on theory that posits that commitment will be expressed through distinct complementary mindsets (AC, NC, CC), there are no apparent reasons to expect the need to apply a similar control for global commitment levels in the estimation of mindset profiles. In contrast, it could be argued that global tendencies to commit in an affective, or normative, manner need to be controlled in multi-target research. Arguably, continuance commitment is not likely to reflect such a global tendency. For instance, Morin, Morizot et al. (2011) used a similar FMA approach to identify profiles of AC directed to seven targets, while controlling for individual differences in the propensity to commit affectively.

Testing the similarity of profile solutions across meaningful subgroups of participants.

As noted previously, a key test of the meaningfulness of a profile solution involves verifying the extent to which this solution generalizes to different subgroups of participants, samples, and cultures. Arguably, evidence for generalizability in person-centered research is built on an accumulation of studies, from which it becomes possible to identify a core set of profiles emerging with regularity, together with a set of more peripheral profiles emerging more irregularly under specific conditions (for an extended discussion, see Solinger, Van Olffen, Roe & Hofmans, 2013). So far, person-centered commitment research has been mainly limited to single sample studies conducted in Western countries (but see Morin, Meyer, et al., 2015). Although a few studies (Meyer, Kam et al., 2013; Meyer, Morin, & Vandenberghe, 2015) have tested the extent to which profiles replicate across samples, they have done so based on qualitative visual comparisons of profile solutions (for review see Meyer & Morin, 2016). Thus far, there has yet to be a true quantitative comparison of commitment profile solutions across meaningful subgroups of participants (defined based on age, gender, profession, culture, etc.). Clearly, the systematic assessment of the generalizability of profile solutions, their development, and their consequences across subpopulations represents a key direction for future commitment research. Fortunately, Morin, Meyer, Creusier, and Biétry (2016) recently proposed a comprehensive approach to investigate the similarity of profiles solutions across samples, which can also easily be extended to tests of longitudinal similarity (i.e., LTAs) and MRAs. This approach is presented in Table 1 (for details of implementation, see the online supplements).

<Insert Table 1 about here>

Latent transition analyses (Model 4)

LTAs estimate LPA solutions at multiple time points, and the connections (i.e., transitions) between the profiles across these time points (Collins & Lanza, 2010). In their simplest expression, LTAs estimate LPA solutions based on the same set of indicators and including the same number of profiles at both time points. However, LTAs can also be used to model the connections between any type of mixture models (Nylund-Gibson, Grimm, Quirk, & Furlong, 2014). The bulk of research on commitment profiles has been cross-sectional (Meyer et al., 2013). This lack of evidence regarding the longitudinal stability of commitment profiles represents an important limitation. Indeed, the demonstration that commitment profiles are stable is critical to support the idea that person-centered results can be used to guide managerial strategies to select, promote, or differentially manage employees with specific profiles. LTAs allow for the investigation of two types of stability in latent profile solutions over time (Kam et al., 2015). A first involves the stability of the profile structure within a sample, over time (*within-sample stability*): Whether the same number of profiles presenting a similar configuration can be identified over time. This form of stability directly relates to the taxonomy of similarity tests presented in Table 1 (also see the online supplements). A second form of stability pertains to the consistency of individual employees' profiles over time (*within-person stability*): Whether individual employees correspond to the same profiles over time. Applying LTAs to mindset profiles of organizational commitment over an eight-month period, Kam et al. (2015) showed that the profiles presented a very high level of within-sample and within-person stability. Based on these promising results, further investigations of the temporal stability of commitment profiles should be seen as a future priority for person-centered commitment research.

Mixture Regression Analyses (Model 5)

MRAs have been very rarely used in research so far (e.g., Morin, Scalas et al., 2014), and never in commitment research. MRAs aim to identify latent profiles of participants differing from one another at the level of estimated relations (regressions) between constructs. Thus, whereas LPAs regroup participants based on their configuration on a set of commitment components, MRAs identify subpopulations in which the relationships among constructs differ. For example, variable-centered research shows that AC predicts higher levels of well-being and retention (e.g., Morin et al., 2013). MRAs make it possible to investigate whether these relationships differ in specific subpopulations. For example, MRAs could reveal a profile in which AC relates as expected to well-being and retention, a second profile in which AC relates only to retention, and a final profile in which AC presents a negative relation with wellbeing suggesting that there might be risks to extreme levels of AC (e.g., Morin et al., 2013). In the estimation of MRAs, the outcomes' means and variance (representing the intercepts and residuals of the regression) need to be freely estimated across profiles to obtain profile-specific regression equations. More complex applications are possible, such as combining LPAs and MRAs to profile employees based on both their configuration of indicators, and relationships between indicators. For example, one could combine the previous example (where AC predicts retention and wellbeing) with LPAs (including AC, NC and CC). MRAs may reveal that the first profile (both predictions in the expected direction) includes morally-committed (AC/NC-dominant) employees, that the second profile (AC only predicts retention) includes trapped (CC-dominant) employees, whereas a third profile includes emotionally committed (AC-dominant) employees. The estimation of this type of MRAs requires the free estimation of the predictors' means and variances in the extracted profiles. Such models also reveal potential interactions among predictors, resulting in profiles in which the relations among constructs may differ as a function of predictors' levels (e.g., Bauer, 2005). Given the complexity of these models, our recommendation is the same as for LPAs: Start with the estimation of theoretically optimal models. When these fail to converge on proper solutions, fall back to simpler models where, in order, the variances of the predictors, the means of the predictors, and the variances of the outcomes, are constrained to equality across profiles.

Growth mixture analyses (Model 6)

GMAs identify subgroups presenting distinct longitudinal trajectories on one – or many – commitment component(s) over time. GMAs are complex and could easily deserve a complete chapter. For this reason, a complete coverage of GMAs remains beyond the scope of this chapter, and readers are referred to Morin, Maïano et al. (2011) and Ram and Grim (2009). However, GMAs are built from latent curve models (LCMs, see Bentein, this volume), and more extensively described in the online supplements. In LCMs, commitment components are assessed over multiple time points and trajectories at the sample level are estimated through intercept and slope(s) factors that differ between individuals. In its simplest expression, GMAs extracts latent profiles differing on these growth factors (i.e., presenting different intercept and slope factors). More complex GMAs may extract subgroups differing on all LCMs parameters, and may even allow for the extraction of subgroups with trajectories following distinct functional forms (linear, quadratic, etc.). For example, in a study of recently promoted employees' trajectories of AC to the organization, one might observed a profile showing a steady decline in AC over time (suggesting that the promotion had negative consequences), a second showing a linear increase (suggesting satisfaction with the new role), and a third group showing an initial decrease followed by an increase (suggesting initial difficulties of adaptation, followed by a successful mastery of the new role). So far, a single study has applied a restricted form of GMAs to the study of newcomers' organizational AC (Solinger et al., 2013). This study revealed five distinct longitudinal profiles of employees, characterized by a "high match", "moderate match", or "low match" with the organization (i.e., persistently high, moderate, or low AC, respectively), by a "learning to love" profile (increasing AC level), or by a "Honeymoon hangover" profile (increasing AC level, followed by a decrease). Clearly, these results beg replication and investigation of possible interventions to favor the emergence of the most desirable profiles. From our standpoint, examining profiles of longitudinal trajectories of commitment components represents another key area for future commitment research. This approach is particularly well-suited to investigations of the effects of interventions, changes, or life transitions (allowing for the identification of subgroups showing differential reactivity to the intervention).

One critical issue that often tends to be misunderstood in applied research is that LCM/GMA estimate longitudinal trajectories as a function of time. Thus, a strong assumption of these models is that the time can be assessed as a function of a meaningful referent (Metha & West, 2000). Unfortunately, typical organizational studies where a sample of employees presenting a variety of age and tenure levels is recruited and followed over time do not meet this assumption. Suitable applications require trajectories to be explicitly modelled as a function of age or tenure levels, or as a function of key transition points that similarly concern all participants (intervention or experiment, organizational change, retirement, change of employment, etc.). Otherwise, time effects will be confounded with other, unmodelled, effects of age, tenure, etc. that vary across employees.

Conclusion

Person-centered methodologies are well-suited to testing multiple aspects of commitment theory not easily addressed using the more traditional variable-centered techniques. However, it is particularly important to keep in mind that person- and variable-centered approaches should be viewed as complementary, and that their combination is likely to provide an incredibly rich view of the reality under study. This chapter aimed to provide a simple introduction to the multiple possibilities provided by GSEM, with the hope of stimulating researchers to think creatively about the wide range of questions that can be addressed with these evolving methodologies. Clearly, it was neither possible, nor feasible, to present all possibilities provided by GSEM within a single non-technical chapter. Throughout this chapter, many additional possibilities were also highlighted, hoping to stimulate curiosity about this rich analytical framework. However, mixture models remain complex, and present multiple challenges to inexperienced researchers. It is thus strongly recommended that researchers start with simpler models (LPAs, LPAs with covariates, FMAs), before moving on to more complex models (multiple-group LPAs, or LTAs), and to even more complex models (MRAs and GMAs). From our standpoint, mixture models require a strong understanding of CFA/SEM, multiple group analyses and tests of measurement invariance (Vandenberg & Morelli, this volume), and GMAs should be anchored in a solid understanding of LCMs (Bentein, this volume).

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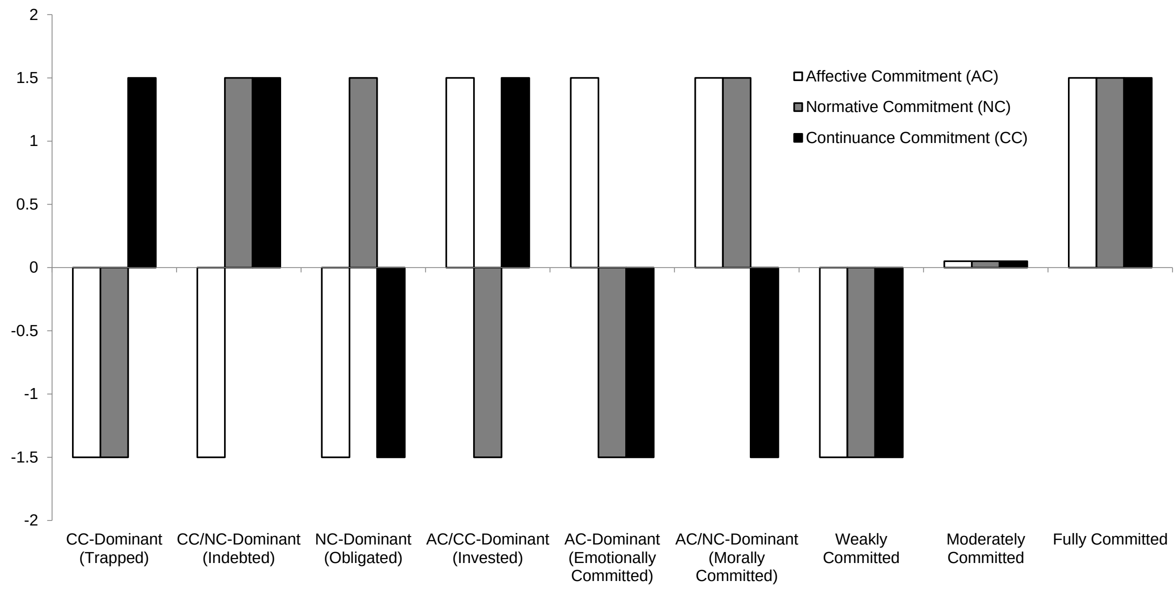


Figure 1a. Prototypical Profiles

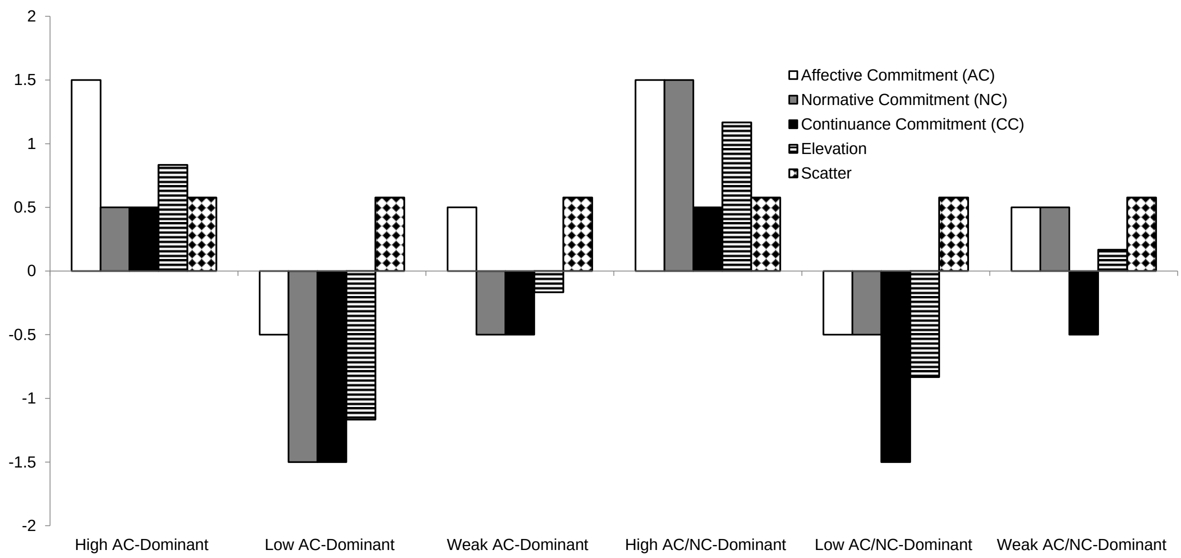
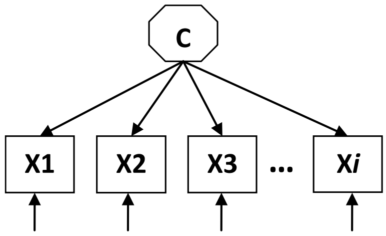
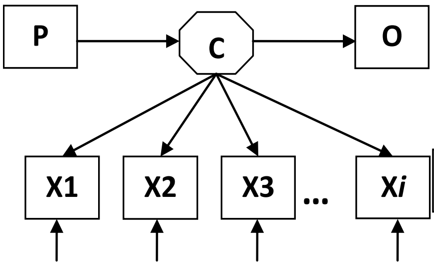


Figure 1b. Profiles Differing in Terms of Elevation and Scatter



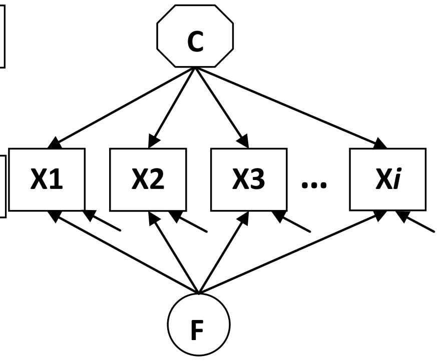
Model 1
Latent Profile Analyses

This model estimates *C* latent profiles differing from one another based on their configuration on *i* indicators (X1 to X*i*).



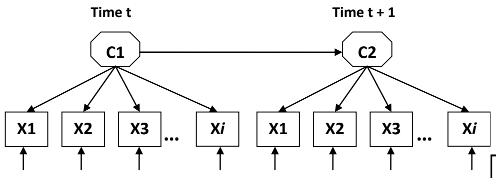
Model 2
Latent Profile Analyses with Covariates

This model integrates predictors (P) and outcomes (O) to Model 1. In this model, P influences the likelihood of memberships into the latent profiles, and the likelihood of membership into the latent profiles influences O.



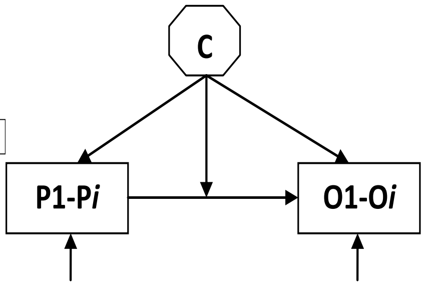
Model 3
Factor Mixture Analyses

This model simultaneously estimate *C* latent profiles and F common factors from the same *i* indicators (X1 to X*i*). In this chapter, we discuss the use of F to control for global tendencies shared across indicators.



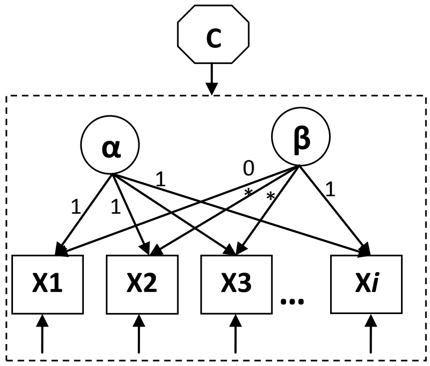
Model 4
Latent Transition Analyses

This model estimates *C* latent profiles at two separate time points (C1 and C2), and the probabilities for individuals to transition from C1 to C2 over time. Latent transition analyses can be used to assess the invariance of a latent profile solution over time. However, latent transition analyses do not require the mixture model estimated at C1 to be equivalent to the mixture model estimated at C2.



Model 5
Mixture Regression Analyses

This model estimates *C* latent profiles differing at the level of relationships (regressions) among a set of predictors (P1 to P_i) and outcomes (O1 to O_i). Mixture regression analyses identify subpopulations among which these relationships differ. Mixture regression analyses can be combined with latent profile analyses to identify profiles differing on the basis of both these relationships, but also the configuration of indicators.



Model 6
Growth Mixture Analyses

This model estimates *C* latent profiles presenting different longitudinal trajectories on one or more variables over *i* time points. Individual trajectories are estimated through a latent growth model (Bentein, this volume), any part of which is allowed to differ across profiles.

Figure 2. A Graphical Presentation and Brief Description of Key Models Described in this Chapter.

Table 1.
Taxonomy of Similarity Tests for Profile Solutions

	Description	LPA	LTA	MRA
(1) Configural Similarity	• Tests if the same number of latent profiles can be identified across groups or time points. • Configural similarity is required to pursue the sequence of similarity tests. • Failure to support configural similarity means that the latent profiles differ across groups or time points and need to be contrasted using a qualitative process.	X	X	X
(2) Structural Similarity	• Prerequisite: Configural similarity. • Tests whether the indicators' within-profile levels are the same across groups or time points. • Configural and structural similarity are required to pursue the sequence of similarity tests. • If the number and/or structure of the profiles differ across groups or time points, all subsequent analyses must be conducted separately across groups or time points.	X	X	X
(3) Dispersion Similarity	• Prerequisite: Configural and structural similarity. • Tests whether the indicators' within-profile variability is the same across groups or time points. • Latent profiles do not assume that all members of a profile share the exact same configuration of indicators. This step tests whether within-profile inter-individual differences are stable across groups or time points. • Not applicable when profile indicators are categorical.	X	X	X
(4) Structural Similarity	• Prerequisite: Configural and structural similarity. • Tests whether the relative size of the profiles is similar across groups or time points.	X	X	X
(5) Predictive Similarity	• Prerequisite: Configural and structural similarity. • This step includes predictors of profile membership to the most similar (2-4) model. • Tests if the predictors-profiles relationships are the same across groups or time points. • This test requires the direct incorporation of predictors to the model. • This step is only appropriate when predictors are included in the study.	X	X	X
(6) Explanatory Similarity	• Prerequisite: Configural and structural similarity. • This step includes outcomes of profile membership to the most similar (2-4) model. • Tests if the profiles-outcomes relationships are the same across groups or time points. • This test requires the direct incorporation of outcomes to the model. • This step is only appropriate when outcomes are included in the study.	X	X	X
(7) Regression Similarity	• Prerequisite: Configural similarity. • Tests whether the regressions that define the mixture regression profiles are the same across groups or time points. • This step is only relevant to mixture regression analyses. • This step is the second step of the taxonomy for mixture regression analyses. • For mixture regression analyses this step is the second step of the similarity taxonomy.			X
Recommended order	Steps that are a prerequisite to subsequent steps are bolded.	**1-2**-3-4-5-6	**1-2**-3-4-5-6	**1-7-2**-3-4-5-6

Note: LPA: Latent Profile Analyses; LTA: Latent Transition Analyses; MRM: Mixture Regression Analyse