Multilevel Latent Profile Analyses: A Comprehensive Guide

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Abstract

The organizational sciences have recently seen an uptake in the use of both person-centered analyses, most typically implemented via latent profile analysis (LPA), and multilevel analyses. Yet their combination remains conceptually underdeveloped and forms the focus of the current article. On the one hand, LPA is perfectly suited to identification of subpopulations, or profiles, of participants characterized by distinct configurations on a set of variables. On the other hand, multilevel models are aptly suited to uncover, or control for, phenomena unfolding across individual, group, and organizational levels. In combination, multilevel-LPA provides the best of both worlds, enabling researchers to identify subpopulations of individuals and/or groups corresponding to distinct prototypical states, while modeling within-group and between-group variability. In the current article, we provide a comprehensive guide for multilevel-LPA implementation to monitor group contexts, climates, and cultures. We present six types of multilevel-LPA specifications—additive, dispersion, additive-dispersion, dispersion-heterogeneity, restrictive cross-level and full cross-level—that ought to be carefully selected based on the nature of the constructs being measured and the research questions being asked. In doing so, we aim provide researchers with the analytical and conceptual tools to select and apply the appropriate multilevel person-centered model to achieve their research objectives.

Organizations are inherently multilevel systems in which employees are nested within teams, departments, and broader units. Meaningful behavioral, psychological, and social phenomena rarely unfold uniformly across these levels, creating a complex system of interacting parts evolving both within (e.g., attributes, behaviors, cognitions) and between (e.g., social dynamics, psychological climates, culture) interacting individuals (Harvey et al., 2022). The ability to fully grasp this complexity requires similarly complex analytic frameworks. On the one hand, multilevel analyses have substantially advanced our understanding of how constructs relate to one another across levels, allowing us to disentangle relations unfolding at the employee, workgroup, or organizational level, as well as across levels (Morin et al., 2022, 2023[1]). Yet, these methods rely on an assumption of population homogeneity, thereby ignoring the possible presence of unobserved subpopulations of individuals, workgroups, or organizations that may differ meaningfully from the others in various ways. On the other hand, person-centered analyses (Morin et al., 2018[2]) are specifically designed to model this type of population heterogeneity, via the identification of distinct profiles of employees, workgroups, or organizations sharing distinctive configurations on a set of variables (e.g., latent profile analyses), relations among variables (e.g., mixture regression), trajectories (e.g., growth mixture analyses), or combinations thereof. Yet in organizational contexts, these profiles rarely exist in isolation: they are shaped by, and shape, the lower- and higher- level entities to which they are connected (Houle et al., 2025a).

Although the utility of both analytic frameworks is well established in the organizational sciences, their combination has yet to be fully introduced and demonstrated (for partial attempts, see Benitez et al., 2019; Collie et al., 2020, 2021; Finch & French, 2014; Gillet et al., 2024; Mäkikangas et al., 2018). Presumably, this may be related to the complexity of both analytic frameworks—person-centered and multilevel—which is increased in combination. For instance, constructs usually take on a different meaning across levels of analysis (e.g., age at the individual level becomes the age composition of a group at the work unit level). The same happens to profiles, which can also be *brought up* across levels in different ways. There thus seems to be a need for a user-friendly introduction of this joint analytic framework. In a spirit of substantive-methodological synergy (Hofmans et al., 2021; Marsh & Hau, 2007), we introduce these methods, with a focus on the meaning of different types of multilevel constructs from a person-centered perspective. Our goal is to provide researchers with the conceptual foundations and practical tools needed to implement multilevel person-centered analyses in their research. In doing so, we showcase how this analytic framework opens new possibilities for understanding individual/group dynamics, revealing patterns of convergence, divergence, and complexity that remain hidden in traditional approaches. Ultimately, our contribution is not only methodological, but also conceptual and practical, seeking to advance research by equipping researchers to ask more nuanced questions and generate richer insights to better inform interventions.

To this end, we introduce different types of multilevel latent profile analyses (ML-LPA), highlight when to prioritize each of them, and discuss their implementation in the *Mplus* statistical package (i.e., *Mplus* code is provided for all models). As such, this introduction is limited in three primary manners. First, we restrict our presentation to ML-LPA, although theoretical underpinnings and estimation procedures also apply to other types of multilevel person-centered analyses, at least those estimated using the generalized structural equation framework (GSEM: Muthén, 2002; Skrondal & Rabe-Hesketh, 2004). However, this means that we ignore many recent developments in the field of cluster analyses, which can be valuable for a variety of other applications (e.g., Brusco et al., 2012; Gao et al., 2023; Hofmans et al., 2018), such as multilevel density-based clustering or multilevel deep clustering (Woo et al., 2024). Second, although multilevel analyses can be extended to as many levels as one is willing to consider (e.g., occasion or episode, person, group, organization, industry, region, country), we limit our presentation to two levels of analysis, as person-centered extensions beyond two levels are not yet fully developed. For simplicity, we hereafter refer to the lower level of analysis as the person, or individual, level (L1), and the higher-level of analysis as the group, or collective, level (L2). Third, we discuss and illustrate how to estimate these models using Mplus (Muthén & Muthén, 2025). This decision is predicated both on the user-friendly nature of this statistical package, and on the fact as far as we know Mplus remains the only statistical package in which it is possible to implement the full range of models outlined in this manuscript[3].

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[1] User-friendly introductions to multilevel analyses are provided in Bliese et al. (2007), Costa et al. (2013), Gonzàlez-Romà, and Hernàndez (2017), Marsh et al. (2012), Morin et al. (2022, 2023), and Preacher et al. (2010, 2011, 2016).

[2] User-friendly introductions to various types of person-centered analyses are provided in Finch and Bronk (2011), Howard and Hoffman (2018), McLarnon and O'Neill (2018), McLarnon et al. (2021), Meyer and Morin (2016), Morin (2016), Morin et al. (2016b, 2016c, 2017, 2018), Morin and Litalien (2019), Schmiege et al. (2018), Spurk et al. (2020) and Woo et al. (2018, 2024).

[3] Partial implementations are, however, possible when using *R* (*R* Core Team, 2025), Latent GOLD (Vermunt & Magidson, 2025), or GLLAMM (Rabe-Hesketh et al., 2004).

This manuscript is organized in four sections. First, we introduce person-centered analyses generally, and latent profile analyses specifically. Second, we introduce key multilevel concepts relevant to the current presentation. Third, we outline the different types of ML-LPA models and provide a data illustration. Finally, we discuss the value of ML-LPA for organizational research and highlight promising avenues for future developments.

Section 1: Overview of Person-Centered Approaches

Variable-centered approaches rely on the often-unrealistic assumption of population homogeneity, assuming that the entire sample is drawn from the same population and that all results generalize to all participants. While interactions can be used to assess moderation, they are still assumed to apply equally to every member of the sample and are virtually impossible to properly interpret when more than three interacting variables are considered, especially when effects are nonlinear. In contrast, person-centered analyses identify subpopulations (commonly referred to as profiles) differing on a set of variables and/or on associations between variables (Morin et al., 2018). These profiles can be interpreted easily even when estimated from multiple indicators and can be used as moderators (McLarnon & O'Neil, 2018). Thus, person-centered approaches shift the focus from variables and their associations to persons (and/or groups in multilevel applications) and how they differ. Both approaches are different sides of the same coin, providing a complementary view of the same reality (e.g., Marsh et al., 2009b).

Morin et al. (2018) noted that person-centered approaches have three defining features. First, they are typological, in that profiles reflect qualitatively and quantitatively distinct subpopulations (Morin et al., 2018). Traditionally, for single-level person-centered analyses, this entails that the shape of the profiles, and not just the mean of the indicators, should differ meaningfully across profiles (Morin et al., 2016b, 2017). Multilevel person-centered analyses can differ in this regard from their single-level counterparts, as higher-level profiles (e.g., group level) can be defined, and differ from one another, in relation to the group-level variability of lower-level profiles (e.g., estimated at the person-level) rather than solely based on the higher-level configuration of profile indicators. We come back to this issue later.

Second, person-centered approaches, at least within GSEM, are prototypical, in that every participant has a probability of belonging to all profiles (Morin et al., 2018). Although participants can be assigned to the profile in which they have the highest likelihood of membership, this modal assignment is not recommended as these probabilities reflect the latent nature of these analyses. Just like a latent factor is corrected for inter-item unreliability (and thus more reliable than manifest scale scores), profiles are latent categorical (most typically nominal) variables corrected for classification error. In this sense, the modal assignment of participants to a single profile is like using scale scores when latent factors are available. Profiles can thus be seen as prototypes, of which participants are more or less representative.

Third, person-centered approaches are methodologically exploratory (Morin et al., 2018), in that any number of profiles can be extracted to represent the multivariate normal distribution of their indicators, and theory, logic, and common sense are needed to select the optimal solution. This does not mean that person-centered analyses cannot be used for confirmatory purposes. Just like exploratory factor analyses (Morin et al., 2020), person-centered research can be guided by hypotheses related to the number and nature of expected profiles. These hypotheses can help select the optimal solution and be more or less supported by results. Although some have proposed confirmatory implementations for studies relying on clear hypotheses (e.g., Finch & Bronk, 2011; Schmiege et al., 2018), these confirmatory solutions still need to be contrasted with a freely estimated exploratory solution to assess their value. Person-centered analyses are thus exploratory *methods* that can be used for exploratory or confirmatory *purposes*. This means that person-centered analyses do not require a deductive approach to yield statistically accurate results and can easily rely on theoretical hypotheses highlighting expectations (e.g., *we expect four profiles displaying some of the following configuration*) rather than on the rejection or acceptation of null (H0) statistical hypotheses (e.g., *we expect a statistically significant positive association between X and Y*). Because of this, person-centered evidence is cumulative: Multiple studies are needed to differentiate the core set of profiles that generalize across contexts from those that are context specific or likely to reflect sampling idiosyncrasies (e.g., Meyer & Morin, 2016). Fortunately, approaches have been proposed to assess the similarity of person-centered solutions across groups or over time (just like variable-centered tests of measurement invariance or predictive equivalence) to quantitatively test whether differences are meaningful or simply reflect random sampling variations (Morin et al., 2016c; Morin & Litalien, 2017)—see Collie et al. (2020, 2021) for extensions of such tests to ML-LPA.

Section 2: Conceptualizing Multilevel Constructs and Processes

Climate versus Context

Before turning our attention to ML-LPA, it is important to discuss the different types of multilevel constructs that can be studied, as each type of construct requires different analytic decisions (Morin et al., 2022, 2023). In typical multilevel analyses, two key types of constructs need to be differentiated when ratings obtained at the individual level are used to define the reality of groups or organizations (e.g., Chan, 1998; Chen, 2005; Cronin et al., 2011; Kozlowski, 2015; Kozlowski & Chao, 2012; Kozlowski & Klein, 2000). These constructs have been alternatively referred to as

(Morin et al., 2022, 2023): (i) context or climate variables based on conceptual considerations (Gagné et al., 2020; Marsh et al., 2012; Morin et al., 2014); (ii) compilation or consensus based on the aggregation process (Bliese et al., 2007; Klein & Kozlowski, 2000; Quigley et al. 2007), (iii) formative or reflective based on measurement analogies (Bliese et al., 2019; Lüdtke et al., 2008, 2011; Marsh et al., 2009a), or (iv) cumulative or emergent based on group dynamics (Cronin et al., 2011). Importantly, this technical, or statistical, distinction is irrelevant when individual ratings are only used to depict the L1 individual reality, or when measures are directly taken at the group or organization level (e.g., rates of turnover, absenteeism, productivity) to reflect the L2 collective reality.

The former construct (i.e., context, compilation, formative, cumulative) relies on ratings of meaningful individual characteristics (e.g., ethnicity) to assess the group reality, thereby taking up a new meaning at L2 (e.g., ethnic composition of the workgroup). In this case, the key question is to assess whether the *context* created by these ratings adds predictive power beyond the simple aggregation of individual effects. For instance, if extraverts are better at producing one outcome (e.g., sales) than introverts, then a workgroup including more extraverts will naturally produce more of this outcome than one including more introverts, as each extravert will produce slightly more than their introvert counterparts. The key *contextual* question here is whether specific workgroup compositions (e.g., 50%-50%, 70%-30%) will have an effect beyond the simple cumulation of individual effects. With contextual variables, both components of ratings (individual and collective) are relevant. One captures the effects of a key individual characteristic, whereas the other captures whether, once aggregated at the collective level, these individual characteristics create a context that is more than the sum of its parts.

The latter type of construct (climate, consensus, reflective, emergent) occurs when individuals are directly asked to assess their group reality (e.g., ratings of supervisory behaviors or the quality of group interactions). Here, aggregated ratings can provide a rigorous assessment of the L2 reality based on consensus among members[4]. In contrast, once the variance shared among group members (reflecting their shared perception of their collective reality) is extracted from individual ratings, the resulting L1 component reflects inter-individual differences in perceptions of the collective reality. This L1 component may reflect many different things (i.e., measurement error, inter-individual differences in perception, inter-individual differences in exposure to the collective reality, etc.) whose effects may, or may not, be relevant to consider in any given study. Moreover, when these individual effects are worth considering, it is only in terms of adding predictive value beyond that of aggregated collective ratings. For example, employees could be asked to describe the leadership behaviors of their supervisor, based on the assumption that their shared perception (the L2 aggregation) can provide a valid picture of the manager's supervisory style. Once the variance in individual ratings explained by these shared perceptions is removed, the resulting L1 component (the residual of shared perceptions) no longer reflects individual perceptions, but the extent to which these perceptions deviate from those shared by all group members. A key question could be whether these inter-individual differences in perceptions have predictive power beyond that of their aggregation at the group level and, if so, if they are predicted more by employees' personality, personal interactions, or work performance.

From an analytic perspective, the context *vs* climate distinction is critical, albeit only relevant when ratings provided at the lowest level (e.g., by the employees) are used to obtain a picture of their individual *and* collective reality. For both types of constructs, the L2 aggregation of individual ratings similarly reflects the collective reality. However, to properly separate the variance in ratings across levels, contextual constructs require individual ratings to be grand-mean centered to ensure that their L1 component retains the original meaning of the ratings as reflecting a meaningful individual characteristic (Marsh et al., 2012; Morin et al., 2014, 2022, 2023). As a result, the L1 component of these ratings still retains group-level and individual-level variability. In predictive multilevel analyses, this approach provides an estimate of L2 effects that directly reflects the added-value of the aggregation: whether the collective reality predicts more outcome variance than the simple sum of the individual effects.

In contrast, all variance in ratings shared among group members needs to be removed from the L1 component when working with climate constructs, as this L1 component needs to reflect inter-individual deviations in perceptions of the collective reality (Marsh et al., 2012; Morin et al., 2014, 2022, 2023). This can be achieved by using group-mean centering procedures, which result in an L1 component that no longer includes any group-level variation. In predictive multilevel analyses, this approach provides an estimate of L1 effects that directly reflects their added-value beyond that of the shared perception of the collective reality that is modelled at L2: Whether inter-individual differences in perceptions predicts some outcome variance beyond that explained by their collective component. Importantly, when relying on latent aggregation procedures—when the collective aggregation of individual ratings is

[4] Before multilevel structural equation modeling, which incorporates a latent aggregation process that directly focuses on inter-individual agreement (e.g., Asparouhov & Muthén, 2018) various measures were proposed to directly assess consensus, such as the r_{wg} index (James et al. 1984; Weller, 2007). These are still widely used today, although their continued application reflects historical convention more than methodological necessity.

automatically done using latent variable methods, thereby providing a control for inter-rater unreliability (Asparouhov & Muthén, 2018)—group-mean centering is automatically imposed. This forces researchers to subtract L1 effects from their L2 counterpart to properly estimate contextual effects (L2-L1=L2 contextual effect; Marsh et al., 2012; Morin et al., 2014, 2022, 2023), which can only be applied in the context of variable-centered analyses. Readers interested in a more formal discussion of centering are referred to Enders and Tofighi (2007).

We need to be careful, as we are using the labels *climate* and *context* as statistical terms with a clear definition, *climate* as a collective state estimated from the consensus among individual ratings of the collective, and *context* as a collective state formed by the compilation of meaningful individual characteristics. This is different from how these terms are used in applied research, with climate reflecting how people collectively feel at work (i.e., the atmosphere of a workplace; e.g., Schneider et al., 2017) and context referring external characteristics of one's environment (e.g., Johns, 2018). Many have since argued that if the goal is to measure the collective reality (rather than individual experiences), then ratings should explicitly refer to the collective reality (i.e., referent shift) (Marsh et al., 2012; Morin et al., 2014). Conversely, if ratings focus on individual experiences they should be treated as such and modeled as contextual variables. *Contextual* constructs thus refer to meaningful individual measures requiring grand mean centering to allow their L1 component to retain its original meaning while assessing the added value of the group context, whereas *climate* constructs refer to individual ratings of the group reality requiring group-mean centering to produce an L1 component reflecting inter-group (dis)agreement in perceptions of the collective reality[5].

Additive and Dispersion Models

Having conceptualized and operationalized contextual and climate constructs, we now consider two types of multilevel models commonly used to investigate these types of constructs, namely, *additive* and *dispersion* models. In *additive* models, lower-level (e.g., person) ratings are aggregated to obtain an estimate of the collective reality reflecting the combination of individual ratings (Chan, 1998). One important characteristic of additive models is that the collective aggregate typically ignores how much inter-individual variability is present among members of each group. This does not mean inter-individual differences are irrelevant, simply that they are only used to depict the L1 reality. In *dispersion* models, the variability of lower-level ratings informs the collective aggregate (i.e., inter-individual differences are used as an indicator of the L2 reality). As a result, each higher-level unit (e.g., groups, organizations) can be defined, solely (i.e., pure *dispersion* models) or partially (i.e., *additive-dispersion* models), by how much inter-individual variability is present among members of this collective entity.

Additive and dispersion models can be estimated for contextual and climate constructs. In the former, dispersion refers to the extent to which members from the same group differ from one another on key individual characteristics. In the latter, dispersion refers to the extent to which there is a consensus (or lack thereof) among group members' ratings of the group reality. An advantage of ML-LPA comes from its ability to combine additive and dispersion specifications. Indeed, it is possible for two group-level profiles to display similar mean-levels on their aggregated indicators, but to differ in terms of group members' consensus or variability in ratings of these indicators. Thus, the typological nature of collective (L2) profiles can be defined by three components: (i) collective means (defining the structure of the profile), (ii) collective variances (between-group variation among groups corresponding to the same profile), and (iii) inter-individual variances (i.e., the extent to which individuals associated with a specific L2 profile differ from other individual members of this profile). Moreover, it is also possible to define within-group dispersion from the prevalence of L1 profiles, providing a more nuanced understanding of how groups are composed of individuals with similar, or distinct, attitudes, behaviors, and perceptions, and how groups with distinct compositions differ in terms of group functioning despite similar group means on the constructs of interests.

Multilevel Measurement in ML-LPA: Key Considerations and Applied Guidelines

Thus far, we have assumed that profiles are estimated with manifest indicators (i.e. a sum score, or average score, reflecting individual characteristics (i.e., context) or perceptions of a collective (i.e., climate), and mentioned that LPA relies on a prototypical (or probabilistic) assignment of cases to profiles that yields results controlled for classification error. Although we briefly mentioned that latent aggregation procedures provide results controlled for inter-rater unreliability in the assessment of the collective reality (Asparouhov & Muthén, 2018), we did not fully develop this important control. Moreover, the former discussion completely neglected the fact that constructs are typically assessed using multiple indicators (i.e., items forming a specific questionnaire subscale), and thus also include typical forms of

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[5] Chan (1998) introduced a further distinction, involving *consensus* models. In these models, higher-level aggregates capture the extent to which individual members of a collective rate their personal experience (i.e., direct consensus; for instance by having members rate specific characteristics of their work role) or their environment (i.e., referent-shift consensus; for instance by having members rate the quality of group interactions) in a similar manner. The former type of consensus is connected to what we refer to as *contextual* variables, whereas the latter is connected to what we refer to as *climate* variables.

random measurement error (inter-item unreliability). When individual ratings are used to assess constructs at L1 and L2, this random measurement error is likely to play a role at both levels (Marsh et al., 2012; Morin et al., 2022, 2023), and can be controlled through latent variable methods (modeling latent factors from indicators rather than sum scores). Multilevel structural equation modeling (ML-SEM) is "doubly latent" given its ability to control for random measurement error (inter-item) at the individual and collective level, as well as inter-rater unreliability in the aggregation of individual ratings at the collective level (Lüdtke et al., 2008, 2011; Marsh et al., 2009a).

Unfortunately, experience shows that it is rarely possible to estimate fully latent LPA (where latent factors defined by their items are used to estimate latent profiles), multilevel or not. Models rarely converge, and when they do, typically converge on improper solutions after days, sometimes weeks, of estimation. This realization has led many to suggest that person-centered analyses should preferably be estimated using factor scores extracted from preliminary measurement models (e.g., Morin et al., 2016b, 2016c, 2017). Although factor scores are not as efficient as latent variables to control for inter-item unreliability, relative to scale scores they still provide a partial correction for inter-item unreliability while preserving the structure of the measurement model from which they are taken (e.g., loadings, methodological controls, measurement invariance, bifactor structure, missing data procedures; Devlieger, & Rosseel, 2017; Estabrook, & Neale, 2013; McNeish, 2023; McNeish & Wolf, 2020; Morin et al., 2016a, 2016b, 2017; Rhemtulla, & Savalei, 2025; Skrondal & Laake, 2001). These advantages are maintained when using factor scores extracted from multilevel measurement models, which afford a partial control for inter-rater unreliability and for inter-item unreliability across both levels of analysis, and preserve the natural group-mean centering that is required for climate constructs. We thus provide some recommendations for measurement in ML-LPA.

Context. There is no simple solution to estimate contextual effects in ML-LPA (such as the simple L2-L1 subtraction recommended for typical multilevel analyses): ratings must be grand-mean centered at both levels from the start, which means relying on manifest aggregation and foregoing latent aggregation procedures. As noted, latent aggregation procedures (Asparouhov & Muthén, 2018) are how multilevel analyses control for inter-rater unreliability (Morin et al., 2022, 2023). Although this control can also capture some sampling error (Marsh et al., 2009a, 2012), it is not required—or at least not as critically important—for contextual constructs. Contextual constructs are defined from the aggregation of meaningful individual characteristics that reflect the specific composition of the group at L2. Group members do not have to *agree*, or be similar, for the group aggregate to be reliable, meaningful, and trustworthy. This control is, however, critical for climate constructs, for which it is precarious to assign to a group a set of characteristics on which agreement is minimal, at least without controlling for this disagreement.

On this basis, with contextual constructs assessed through multi-item questionnaires, L1 scores should be estimated from a factor analytic model while controlling for the L2 nesting structure (Asparouhov, 2005). Factor scores can be saved from this model, thereby offering partial control for inter-item measurement error. Using these factor scores at L1, ML-LPA models can be specified using manifest aggregation procedures (Section 3) to properly estimate profiles at L1 and/or L2 while partially controlling for random measurement error at both levels.

Climate. When profiles are only estimated at L2 based on ratings obtained at L1, we can use L1 ratings (scale scores or ideally factor scores when using multi-item constructs) to estimate the ML-LPA model (Section 3) for climate constructs. Group-mean centering will be automatically implemented through latent aggregation procedures (Asparouhov & Muthén, 2018), providing control for inter-rater unreliability in the estimation of the L2 reality (Morin et al., 2022, 2023). However, when profiles are estimated at both levels from individual ratings, manifest aggregation is the only option (Section 3), thereby preventing the incorporation of a control for inter-rater unreliability. In this situation, multilevel measurement models make it possible to rely on latent aggregation procedures and to estimate latent variables at both levels, thereby controlling for inter-item and inter-rater unreliability. Factor scores saved from these models can then be used in the estimation of any type of ML-LPA model involving climate constructs.

Preliminary Verifications. When using any type of multilevel analysis, researchers first need to ensure that their constructs display enough variability at L2 to support multilevel analyses. This is commonly done by assessing a first type of intraclass correlation coefficient (ICC1). The ICC1 indicates the proportion of the total variance occurring at L2 (Morin et al., 2022), which should minimally exceed .05 (e.g., Gonzàlez-Romà & Hernàndez, 2017; Lüdtke et al., 2008, 2011; Morin et al., 2022, 2023) when one wants to estimate group profiles. A second intraclass correlation coefficient, the ICC2, provides a measure of the reliability of the group (L2) aggregate, and can be interpreted as any other indicator of reliability (such as α or ω; e.g., Klein & Kozlowski, 2000; Morin et al., 2014, 2022, 2023). A strong ICC2 is not a prerequisite to multilevel analyses but indicates that latent aggregation procedures may not be necessary, whereas a low one strongly advocates for these procedures. Third, inter-item reliability can be estimated at both levels using omega (ω) coefficient of composite reliability. Once again, a strong coefficient primarily indicates that latent variables may not be necessary, whereas low coefficients reinforce their importance. Multilevel measurement models are complex and may prove too much for a specific dataset. When this happens, models including partial corrections can be favored based on the weakest form of reliability, keeping in mind that the latter control is not necessary with contextual constructs. The calculation of these indicators, and the estimation of partial correction models, are presented in Morin et al. (2022, 2023).

Section 3: Multilevel Person-Centered Approaches for Latent Profile Analysis

To support researchers wishing to implement ML-LPA, we provide a guide to help them select the appropriate type of centering, model, and parameterization to address their research questions in Table 1. In addition, to facilitate understanding and application of the alternative approaches that can be implemented with multilevel latent profile analyses, we accompany our presentation with an empirical demonstration using a simulated dataset (available for practice).

For illustrative purposes, consider a large organization (e.g., 10,000+ employees) that conducts an organizational diagnostic of employees' psychological health using measures of burnout and engagement. Such a diagnostic could serve two purposes: first, to assess the overall psychological health of employees at Level 1 (L1), and second, to identify Level 2 units (L2) in which employees appear to be experiencing greater difficulties than in others. The organization decides to randomly sample 1,000 units, and 10 people per unit to conduct this diagnostic. To model this situation, a practice dataset was simulated using Microsoft Excel randarray() function in which we specified five *a priori* profiles at L1 empirically driven from the person-centered literature and graphically represented in Figure 1 (i.e., High Functioning, Overinvested, Average Functioning, Apathetic, and Low Functioning; e.g., Gillet et al., 2024; Houle et al., 2025a; Moeller et al., 2018) and 5 profiles at L2 differing in terms of L2 means and/or L1 variances (i.e., additive and/or dispersion), and in terms of relative prevalence of L1 profiles.

Model Estimation, Selection, and Comparison

The models for this illustration were estimated using the Mplus 9 statistical package (Muthén & Muthén, 2025), using the maximum likelihood estimator robust to non-normality (MLR). We would also be using Full Information Maximum Likelihood (FIML[6]) missing data procedures (Enders, 2022) if missing responses had been simulated. For each type of solution, models including 1 to 8 latent profiles were estimated using 10,000 random starts, 1,000 second stage optimizations, 100 final optimizations, and 1,000 iterations (Hipp & Bauer, 2006). Increasing these values beyond Mplus defaults is critical to ensure convergence on optimal solutions.

In practice, the optimal number of profiles to retain at each level is determined based on a consideration of the theoretical conformity, heuristic value, and statistical adequacy of each solution (Marsh et al., 2009b; Muthén, 2003). The selection of which subset of solutions to examine more closely is guided by the following statistical indicators: (i) Akaike Information Criterion (AIC), (ii) Consistent AIC (CAIC), (iii) Bayesian Information Criterion (BIC), (iv) Sample-size Adjusted BIC (ABIC; Sclove, 1987), (v) adjusted Lo-Mendel-Rubin (Lo et al., 2001) Likelihood Ratio Test (aLMR), and (iv) Bootstrap Likelihood Ratio Test (BLRT). Lower values for the AIC, BIC, CAIC, and ABIC indicate a better fitting model, while a statistically significant aLMR or BLRT supports the estimated model relative to one with fewer profiles. Whereas statistical simulation studies have supported the utility of the CAIC, BIC, and ABIC, they have failed to support that of the AIC and aLMR (e.g., Diallo et al., 2016, 2017; Peugh & Fan, 2013), which are reported to ensure transparency. As a result of their sample size dependency, it is frequent for these indicators to support different solutions, or to fail to support any specific solution, reinforcing the importance of using them only as rough guidelines (Marsh et al., 2009b). In the case where the fit indices continuously decrease (keep on suggesting adding profiles), the point at which indicators reach a plateau on a graphical representation (referred to as an elbow plot) can be used to guide model selection (Morin et al., 2011). We also report the entropy, a purely descriptive indicator of classification accuracy (ranging from 0 to 1, with higher values indicative of greater accuracy). Entropy should not, in and of itself, be used to guide the selection of the optimal number of profiles.

Within Profile Variability

Profiles can be defined by allowing only the means of their indicators to differ across profiles, or by allowing their mean and variance to differ across profiles (Morin & Litalien, 2019). In single level models, profiles are not typically interpreted by considering, and contrasting, within-profile levels of variability. However, statistical research has demonstrated that there is value (i.e., accuracy) to estimating a model in which indicators' variances can differ across profiles (Diallo et al., 2016; Morin et al., 2011; Peugh & Fan, 2013). This recommendation comes with the acknowledgement that this free estimation is not always possible (nonconvergence, improper estimates, etc.), in which case simpler models with equal variance may be favored (Diallo et al., 2016; Morin & Litalien, 2019). The recommendation to freely estimate variances whenever possible also applies to ML-LPA, at least when considering the variance of the indicators located at the same level as the profiles. In plain language, if we are estimating profiles of groups at L2, the within-profile L2 variance of the indicators would reveal the extent to which the groups

[6] FIML relies on missing at random (MAR) assumptions, which allows missingness to be conditioned on all variables included in the model (Enders, 2022).

corresponding to each profile differ from one another. However, as we will soon see, profiles estimated at L2 also account for the within-profile L1 variance. This provides a new type of information, depicting average within-group dispersion for each of the L2 profiles.

Level 2 Profiles: Additive, Dispersion, and Additive-Dispersion Models

ML-LPA can be used to estimate profiles at the group level (L2 only) or across levels (L1 profiles and L2 profiles). Across levels, profiles can be assessed from the same (or even different) set of indicators[7]. ML-LPA in which profiles are estimated solely at L2 using measures taken at the individual level can rely on five parameterizations: (1a) the L2 profiles means and variances can be freely estimated, and the L1 within-profile variances can be freely estimated in all L2 profiles (*additive-dispersion*); (1b) the L2 profiles means can be freely estimated, the L2 profile variances can be fixed to equality, and the L1 within-profile variances can be freely estimated in all L2 profiles (*additive-dispersion*); (2a) the L2 profiles means and variances can be freely estimated, and the L1 within-profile variances can be fixed to equality across L2 profiles (*additive only*); (2b) the L2 profiles means can be freely estimated, the L2 profile variances can be fixed to equality, and the L1 within-profile variances can be fixed to equality across L2 profiles (*additive only*); (3) the L2 profiles means and variances can be fixed to equality, and the L1 within-profile variances can be freely estimated in all L2 profiles (*dispersion only*). Researchers should not estimate all parametrizations, but start with the least restrictive model (e.g., Model 1a) and move to simpler models (e.g., Model 1b) when this initial estimation fails. Although our generic recommendation is to follow the aforementioned sequence (1a, 1b, 2a, 2b, 3), this selection should also be guided by theory, logic, and research objectives.

In ***additive-dispersion*** models, the L2 collective means (and possibly L2 variances), as well as the within-profile L1 variance (inter-individual differences among members of the groups matching each profile) are used to define the profiles. For instance, groups corresponding to profiles characterized by high average engagement and low average burnout (contextual) may display greater within-group homogeneity among members (i.e., lower L1 variance) than groups characterized by lower engagement and higher burnout. One possible explanation, in this example, is that burnout may be associated with more heterogeneous individual experiences: burned-out employees have fewer resources to cope with work-related tasks, are more cynical about work, take more sick leave, and perform less (e.g., Blais et al., 2023; Demerouti et al., 2010; Schaufeli et al., 2009). When some members experience more severe burnout, they may be less able to contribute to group functioning, leaving other group members on their own to cope with work demands with fewer shared resources. This uneven distribution of strain and contribution can amplify differences among members, thereby decreasing within-group similarity. In contrast, groups characterized by low burnout and high engagement may create a more mutually supportive context in which members have more resources to help one another, take less time off, and perform better. These dynamics can reinforce engagement and reduce the risk of burnout, thereby increasing within-group similarity.

Additive models are more restrictive, and constraint within-group variability to equality across the L2 profiles. This precludes testing hypotheses about connections between within-group variability and between-group mean levels, and centers the focus of the investigation squarely on means. Keeping with the previous example, we would still be able to investigate profiles differing in burnout and engagement at the group level but without having information about members' similarity, thus limiting our ability to control for, or investigate, psychological context.

Alternatively, in ***pure dispersion*** models, the L2 profiles are only defined using the within-group L1 variance, while constraining collective means (and possibly L2 variances) to equality across profiles. These profiles represent groups that are more or less homogenous in terms of composition (contextual) or perceptions (climate), whatever that composition or perception is. A key question is whether it makes sense to focus solely on homogeneity while ignoring the dominant composition or perception of the group. For instance, would the implications of homogeneous profiles differ if they include mainly white men versus mainly indigenous women? Conversely, groups composed of individuals differing drastically in burnout and engagement may struggle to develop strong social dynamics because of a volatile psychological context, whereas group members who are closer on these dimensions, whether at more favorable or less favorable levels, may find it easier to communicate, leading to stronger social dynamics. Here, ignoring means is justified as the question focuses on the context characterized by dispersion.

Context Versus Climate. Thus far, we have focused on contextual constructs (i.e., burnout and engagement) wherein L2 profiles represent the aggregate mean levels of each psychological state and the within-profile (L1) variances reflect the extent to which members of groups belonging to the same L2 profile share similar levels across constructs. The interpretation of within-profile variances differs for climate constructs where the L1 component

[7] Profiles estimated solely at L2 from measures taken at L2 or solely at L1 from measures taken at L1 can be interpreted as single-level profiles, with no additional caveat. Their multilevel component would be limited to predictors-outcomes and does not require distinct coverage.

reflects deviations from the group's consensual assessment of its collective reality. Consider individual ratings of team psychological safety, referring to beliefs that the team is safe for interpersonal risk taking—such that members feel able to ask questions, admit errors, and voice concerns without fear of embarrassment or punishment (Edmondson, 1999; Harvey et al., 2019a). When estimating psychological safety profiles at L2, the means capture the team's shared perceptions of psychological safety climate, whereas the within-profile (L1) variance reflects the extent to which individual ratings converge on—or deviate from—that shared climate. Conceptually, this within-team dispersion corresponds to climate strength (i.e., the extent of sharedness), and emergent-state perspectives emphasize that such sharedness can vary across teams (Carter et al., 2018). Thus, when estimating *additive-dispersion* models, researchers must first and foremost specify whether contextual or climate ratings are used and then apply the appropriate centering.

Data Illustration. For this illustration we focus on Model 1a (additive-dispersion with free between- and within-profile variances) to demonstrate how to select the optimal solution using all relevant information. One to eight profiles were estimated and model fit for all models are reported in Table S1 of the online supplements. For additive-dispersion models, all information criteria decreased until eight profiles, but this decrease reached a plateau between four and five profiles. The BLRT also suggested adding profiles until the eight-profile solution. Based on the observed plateauing, we more thoroughly inspected the four- and five-profile solutions, as well as adjacent solutions including three and six profiles. These alternative solutions are graphically presented in Figure 2, while parameter estimates are reported in Table 2.

In the three-profile solution, the first profile displays a *High Functioning* configuration (i.e., high engagement and under average burnout) displaying higher levels of within-profile variability for burnout than for engagement. This shows that most group members belonging to this profile tend to be highly engaged, while they vary in terms of burnout levels. This first profile characterizes 19.96% of participants. The second profile characterizes 19.66% of participants displaying a similarly *Average Functioning* (average burnout and average engagement), as indicated by the low levels of within-profile variability. The third profile characterizes 60.37% of *Low Functioning* participants (average burnout and low engagement), although groups corresponding to this profile differ substantially from one another on both dimensions (high within-profile variability). When we add a fourth profile to the solution, the initial *Average Functioning* profile is separated in two distinct profiles, one displaying very high within-profile variability on both variables (33.02%; *Average Functioning–Diversified*) and another one with very low within-profile variability on both variables (19.66%; *Average Functioning–Unified*). Due to its high within-profile variability, the *Average Functioning–Diversified* absorbs some members of the *Low Functioning* profile, which is much smaller in size in the four-profile solution (28.28%) than in the three-profile solution (60.37%). From a substantive standpoint, the addition of the fourth profile thus adds heuristic value to the solution. Interestingly, this profile is distinct as a consequence of its within-group dispersion, which would be impossible to find with a purely *additive* model.

Adding a fifth profile also resulted in a meaningful addition, revealing a new type of *Low Functioning* profile with an apathetic configuration (low burnout and low engagement). This *Low Functioning–Apathetic* profile displays some levels of within profile variability and corresponds to a small (4%) but meaningful subset of the sample. However, adding a sixth profile resulted in the arbitrary division of the *High Functioning* profile into two similarly shaped profiles (one slightly more extreme than the other), thereby adding no heuristic value Based on this example, the 5-profile solution would be retained. Although this decision was made by co-authors unaware of the nature of the simulated dataset, it is interesting to note that five profiles were simulated. With *additive* models the selection of the optimal number of profiles would be based only on between profile means (and possibly variances), as the within-profile variances would be fixed to equality across L2 profiles. When estimating *pure dispersion* models, only the within- (and possibly between-) profile variances would be used to guide model selection.

Profiles Estimated at the Individual and Group Levels

Estimating profiles at two (or more) levels provides a valuable tool for understanding complex interplay between individual and collective dynamics. When profiles are estimated at both levels from different indicators, typical guidelines for the estimation of profiles solely at L1 or L2 apply. When profiles estimated across levels rely on the same set of indicators, three types of models can be used: *Dispersion-Heterogeneity*, *Restricted Cross-Level*, and *Full Cross-Level*.

A ***Dispersion-Heterogeneity*** specification focuses on defining the L1 reality (i.e., L1 profiles) prior to investigating the composition of the L2 units in terms of this L1 reality. In other words, group-level profiles are defined based on the relative prevalence of L1 profiles, without considering aggregated (L2) means or variances. This approach does not require aggregating individual ratings at the group level, allowing one to directly use the most relevant centering approach. This model is thus perhaps most useful for contextual constructs (e.g., identifying group profiles differing in the prevalence of members engagement and burnout profiles), unless the core focus of the study is on understanding perceptual differences in L2 ratings (i.e., revealing whether a team's psychological safety climate is broadly shared versus characterized by distinct perceptual profiles), at which point it can also be relevant for climate constructs.

A ***Restricted Cross-Level*** specification characterizes L2 profiles based on the aggregated group means of the L1 indicators while keeping the between profile variances free or equal within each level (i.e., at L1 and L2). In this model, profiles are estimated separately at L1 and L2, using the same set of indicators, but without considering the relative prevalence of the L1 profile in the definition of the L2 profiles. The interpretation of the L2 profiles thus align with that of the *Additive, Dispersion* or *Additive-Dispersion* profiles presented earlier. In this sense, this model prioritizes the extraction of L2 profiles defined based on L2 means and variances. However, once the estimation of the L2 profiles is complete, one can also obtain the relative prevalence of the L1 profile within each of the L2 profiles, for descriptive purposes.

A ***Full Cross-Level*** specification essentially combines the *Dispersion-Heterogeneity* model and the *Restricted Cross-Level* model, such that the L2 profiles are defined based on the aggregate group means (and possibly variance) of the L1 indicators alongside the relative distribution (or prevalence) of the L1 profiles. This adds complexity to the model estimation process, as the model now seeks to identify profiles that best characterizes L2 means, variances, and prevalence of L1 profiles simultaneously. Thus, should this model fail to converge one may opt for a *Restrictive Cross-Level* model if the focus is on finding optimal L2 profiles to characterize L2 means and variances, or the *Dispersion-Heterogeneity* model if the aim is to identify L2 profiles based on the distribution of the L1 profiles within L2 units.

This leads to a total of ***five alternative parameterizations***: (i) a *Dispersion-Heterogeneity* model can be used to estimate group profiles differing in the relative prevalence of the L1 profiles that characterize their members; (iia) the *Restricted Cross-Level* model can be used to estimate profiles at L2 based on the free estimation of aggregated means and variances at L2 and independent profiles at L1 based on the free estimation of the individual means and variances; (iib) the *Restricted Cross-Level* model can be used to estimate profiles at L2 based on the free estimation of aggregated means at L2 and independent profiles at L1 based on the free estimation of the individual means, while keeping the L2 variances equal across L2 profiles and the L1 variances equal across L1 profiles; (iiia) the *Full Cross-Level* model can be used to estimate profiles at L2 based on the free estimation of aggregated means and variances at L2 and of the relative prevalence of the L1 profiles, and profiles at L1 based on the free estimation of the individual means and variances; (iiib) the *Full Cross-Level* model can be used to estimate profiles at L2 based on the free estimation of aggregated means at L2 and of the relative prevalence of the L1 profiles, and profiles at L1 based on the free estimation of the individual means, while keeping the L2 variances equal across L2 profiles and the L1 variances equal across L1 profiles. Although it is theoretically possible to freely estimate the variances at one level only, unless all other approaches fail, we do not recommend this specification from the start to remain consistent across levels. Once again, our recommendation is to start with the most complete specification and reduce in complexity (from iiib, to iiia, then iib, iia, and i) when this initial estimation fail to produce acceptable solutions (i.e., nonconvergence, degenerate solutions, etc.), while urging researchers to use theory, logic, and objectives as additional guides.

Simultaneously estimating the profiles at both levels is not realistically feasible, as this would entail estimating all possible combinations (i.e., 64 for 1-8 profile at L1 and L2). Researchers should thus start by estimating profiles at one level while controlling for variability at the other level. Then, using the start values from the retained solution, profiles can be estimated at the other level. For ***contextual*** constructs (e.g., burnout, engagement) the interest lies first and foremost on the L1 profiles, which can then be used to inform the composition of the group. As such, for grand-mean centered constructs, we recommend first estimating the profiles at L1, then using the parameter estimates from the retained solution as fixed start values (using the Mplus @ command) to ensure that the L1 profiles remain stable when estimating the L2 profiles.

Conversely, when group-mean centering is used for ***climate*** constructs (e.g., psychological safety, leadership) the L2 profiles describe groups with a different configuration of group characteristics (as assessed by members), whereas the L1 profiles describe individuals whose perception of their group reality tends to be better, worse, or similar to that of their teammates. When estimated, these L1 profiles need to be interpreted as reflecting distinct ways in which individual perceptions differ from those of other members of the same L2 unit. For climate constructs, we thus recommend first estimating the L2 profiles, then using the parameter estimates from the retained solution as fixed start values (using the Mplus @ command) to ensure that the L2 profiles remain stable when estimating the L1 profiles.

Data Illustration. Using the same simulated dataset, we estimated 1-8 profiles using a *Full Cross-Level* parametrization with freely estimated variances at L1 and L2, treating the constructs as *contextual* and thus first estimated at L1. This model provides all relevant information from which decisions would be made when using a *Restrictive Cross-Level* model (i.e., L2 means and variances) or a *Dispersion-Heterogeneity* model (L2 prevalence of L1 profiles).

As shown in Table S1 of the online supplements, information criteria associated with the L1 solutions all kept on decreasing until eight profiles, but this decrease reached a clear inflexion point at five profiles. The BLRT also suggested adding profiles until the eight-profile solution. Based on the observed plateauing, we more thoroughly inspected the five-profile solution, as well as adjacent solutions including four and six profiles. These alternative solutions are graphically presented in Figure 3, while parameter estimates are reported in Table 3. The four-profile solution displayed well differentiated profiles encompassing 18% of *High Functioning* employees (i.e., high engagement and low burnout), 13.65% of *Overinvested* employees (i.e., high engagement and high burnout), 40.65% of *Average Functioning* employees (i.e., average engagement and burnout), and 27.79% of *Low Functioning* employees (i.e., low engagement and high burnout). The addition of a fifth profile resulted in a conceptually distinct *Apathetic* profile (11.55%), encompassing individuals previously belonging to the *Detrimental* and *Normative* profiles. Conversely, adding a sixth profile resulted in the arbitrary division of the *Apathetic* profile into two profiles, with one profile more extreme than the other. As this last distancing appeared irrelevant, the five-profile solution was retained for further analyses.

Starting from this solution, L2 profiles were estimated. As shown in the bottom of Table S1 in the online supplements, all information criteria all kept on decreasing until eight profiles, but this decrease reached a rough inflexion point around four to five profiles, although this inflexion point was not as clear as the former one. For this reason, we more thoroughly inspected solutions including four and five profiles, as well as adjacent solutions including three and six profiles. These solutions are presented in Figure 4 and parameter estimates reported in Table 4.

The three-profile solution revealed a first *Highly Invested Profile* corresponding to 52.04% of groups displaying on the average high engagement and average burnout, but encompassing a mixture of employees corresponding to the *High Functioning* (34.53%), *Overinvested* (26.70%) and *Average Functioning* (19.36%) L1 profiles, with a few also corresponding to the *Apathetic* (1.93%) and *Low Functioning* (17.48%) profiles. The second *Average Functioning* profile corresponded to 19.66% of groups displaying average engagement and average burnout and including a strong majority of employees corresponding to the *Average Functioning* (99.71%) L1 profile. The third *Low Functioning* profile corresponded to 28.30% of groups displaying average engagement and average burnout and including a mixture of employees corresponding to the corresponding to the *Average Functioning* (29.92%), *Apathetic* (38.64%) and *Low Functioning* (31.44%) L1 profiles.

Adding a fourth profile helped further differentiate some of the previously identified profiles. The *High Functioning* profile became smaller (20.11%) and is now primarily composed of employees corresponding to the *High Functioning* (44.06%) and *Overinvested* (44.04%) L1 profiles, while the nature and size of the *Low Functioning* profile remained essentially unchanged. Moreover, the *Average Functioning* profile was divided into two distinct profiles, both displaying close to average engagement and average burnout. However, one of these profiles displayed an *Average Functioning-Diversified* (31.93%) configuration, including employees corresponding to all L1 profiles, while the other one displayed an *Average Functioning-Unified* (19.66%) configuration, including employees corresponding primarily to the *Average Functioning* L1 profile (99.70%). Adding a fifth profile revealed a new, albeit smaller (4%) profile displaying an *Apathetic-Average* configuration characterized by low burnout and low engagement and including employees corresponding to the *Average Functioning* (49%) and *Apathetic* (51%) L1 profiles. Finally, adding a sixth profile resulted in the arbitrary division of the *Highly Invested* profile into two profiles displaying a very similar average configuration (*Highly Invested* versus *Moderately Invested*), with the main difference being one of composition, as the latter profile encompassed 30.17% of employees corresponding to the *Average Functioning* configuration, which was not represented in the former. On this basis, the was made to retain the five-profile solution, although we acknowledge that in some research areas, this last distinction might be worth considering. As for the additive-dispersion models, the decision of how many profiles to retain at both levels was made by co-authors unaware of the nature of the simulated dataset and still matched the nature of this dataset.

Although rarely used to guide model selection, the L2 variances provide some valuable information in the current illustration. For instance, it is interesting to note that for the five-profile solution, most groups fall close to their profile average (i.e., the L2 variance is low), with the highest level of variability observed for burnout in the *Highly Invested* profile. This reaffirms the use of the label *Highly Invested* as opposed to *High Functioning* as elevated burnout levels may still characterize some of these highly engaged groups. Moreover, relative to the four-profile solution, the L2 variance of burnout in the *Low Functioning* profile is also smaller in the 5-profile solution, indicating that adding an *Apathetic* profile helps better characterize workgroups that are more detrimental in terms of burnout and engagement levels.

Predictors and Outcomes in Multilevel LPA models

A key advantage of GSEM (Muthén, 2002) to estimate ML-LPA comes from the ability to directly integrate covariates (i.e., predictors and outcomes) into the retained model. The inclusion of covariates should not modify the nature of the retained model (e.g., Diallo et al., 2017; Nylund-Gibson, & Masyn, 2016). For this reason, covariates should be incorporated when the optimal solution has been identified and replicated using the parameter estimates from the retained solution as fixed (using the Mplus @ command) start values to ensure that the main model stays unchanged by covariate inclusion. However, parameters that are predicted (i.e., endogenous) in the subsequent models should never be fixed as these parameters do not have the same meaning conditionally than unconditionally (i.e., if predicting profile membership, the parameters reflecting the size of the profiles should be left free, although parameter estimates form the previous solutions can be used as suggestions, using the Mplus * command).

If predictors and outcomes are uniquely available at L2 (e.g., group productivity) then there is no within-group variability. As a result, the covariates can only be incorporated at L2 and should be grand-mean centered. When covariates are only integrated at L1, then they should be grand-mean centered if they refer to individual characteristic (that would be considered contextual constructs if aggregated to L2) or group-mean centered for ratings of the collective reality (that would be considered climate constructs if aggregated to L2). In the latter situation, it is important to keep in mind that group-mean centering would mean losing a valuable source of variation in covariate ratings, reflecting group-level variations. In most situations, we expect that covariates can be valuable to consider across both levels of analysis. In this situation, ratings of climate constructs should be group-mean centered and those of contextual constructs should be grand-mean centered. Importantly, when covariates are included at both levels of analysis using ratings obtained at the individual level, manifest aggregation procedures are required. As for profile indicators, covariates can be factor scores taken from preliminary measurement models.

Thus far, we have considered models in which profiles were: (i) only estimated at L2 based on L1 ratings of climate and contextual constructs (additive, dispersion, and additive-dispersion models), (ii) estimated at L2 based on the relative frequency of L1 profiles (dispersion-heterogeneity); (iii) estimated independently (restricted cross-level models) or not (full cross-level models) at both levels. In (i), predictors and outcomes can only be integrated at L2, making consideration of centering of L1 predictors and outcomes irrelevant as the L2 aggregate remains the same for both types of constructs. In (ii) and (iii), covariates should be integrated at both levels, and be centered according to their climate or contextual nature, keeping in mind that latent aggregation procedures should be used for contextual constructs in ML-LPA. In models including profiles at both levels, it is also possible to assess whether the L1 effects of predictors vary across L2 profiles, an approach that is also illustrated in the online supplements (Model 10).

Data Illustration. For present purposes, let us assume that the organization conducting the organizational health diagnostic wants to assess the role of socialization tactics as well as the impact of psychological health on absenteeism, both of which were assessed at the individual level. Socialization can be used to predict profile membership at L1 (do employees' socialization experiences influence their likelihood of belonging to different L1 profiles?) and at L2 (do aggregated socialization experiences influence the likelihood of group membership into different L2 profiles?). Absenteeism can be used as an outcome at both levels to identify the profiles displaying the highest levels at the individual (L1) or group level (L2). To illustrate this process, we rely on the cross-level model identified in the previous section.

Predictor (Socialization). Socialization was directly integrated into the final retained model including five L1 and five L2 profiles and parameter estimates are available in Table 5. At L1, employees reporting better socialization experiences were more likely to belong to either the *Highly Invested* and *Overinvested* profiles relative to all other profiles. Better socialization experiences also increased the likelihood of membership into the *Average Functioning* profile relative to the *Apathetic* and *Low Functioning* one, as well as into the *Apathetic* profile relative to the *Low Functioning* one. At L2, shared socialization experiences were systematically associated with a higher likelihood of belonging to more desirable (i.e., characterized by lower burnout and higher engagement) relative to less desirable profiles, with all pairwise profile comparisons being statistically significant. Thus, better socialization at the individual and group level is linked to better functioning, although it may also increase overinvestment tendencies at the individual level.

Outcome (Absenteeism). Absenteeism was directly integrated to the final model, and contrasted across profiles using the multivariate delta method (Raykov & Marcoulides, 2004). Parameter estimates are in Table 6. At L1, absenteeism was lowest in the *Highly Invested* profile, followed by the *Overinvested* profiles, then by the *Average Functioning* profile, the *Apathetic* profile, and highest in the *Low Functioning* profile. At L2, aggregated absenteeism was lowest in the *Highly Invested* profile, followed by the *Average Functioning-Diversified* profile, then by the *Average Functioning-Unified* profile, and equally lowest in the *Apathetic-Average* and *Low Functioning* profiles. These fictitious results suggest that nurturing engagement while preventing burnout may help reduce absenteeism, both at the individual and at the collective level, although the benefits of reducing burnout are moot without nurturing engagement at the group level.

Discussion

As organizations increasingly embed data-driven processes into routine operations, the breadth and sophistication of available multilevel data expand in ways that directly enhance the feasibility of ML-LPA. ML-LPA create new opportunities for researchers to analyse richer and more ecologically valid datasets, thereby advancing organizational theory and practice. The goal of this article was to equip readers with a clear understanding of the various ML-LPA model types and to illustrate how these approaches enable researchers and practitioners to address complex questions concerning the interactive functioning of individuals and groups.

Rethinking the Study of Groups in Organizations

ML-LPA offers a fundamental reorientation in how we can conceptualize, design, and analyze research on groups in organizations. Moving beyond assumptions of population homogeneity and linearity, this framework treats groups not as simple collections of individuals with average scores on key variables, but as dynamic collectives characterized by specific compositions of individuals with differing perceptions, attitudes, and behaviors. This analytic capacity encourages a more intentional design of studies to better capture individual and collective experiences, with careful centering and aggregation decisions guided by construct type (climate vs. context) rather than habit or convenience, and with robust, theory-informed indicators developed at both levels through measurement models and factor scores. In doing so, ML-LPA enables researchers to identify meaningful heterogeneity in how groups function, evolve, and perform, and to more accurately reflect the true multilevel complexity of the workplace.

For example, from a theoretical standpoint, ML-LPA provides a unique opportunity for team scholars to treat emergent states (e.g., psychological safety, trust, cohesion) as configurational phenomena, rather than averaged variables (e.g., Carter et al., 2018; Harvey et al., 2019b). Although team research often models emergent states as an average team measure, research shows that it is not always uniformly shared within teams, and that outcomes differ depending on within-team agreement (i.e., climate strength) (Koopmann et al., 2016). ML-LPA can capture this heterogeneity by distinguishing level (additive) from sharedness/fragmentation (dispersion), allowing researchers to identify distinct team contexts. These profiles move beyond the question of whether teams are "high" or "low" on specific phenomena towards discovering optimal team configurations, where variability can be a hindrance or a strength.

From an applied standpoint, the illustration provided earlier was inspired by an organizational diagnostic of employees' psychological health and associated behavioral costs to help inform interventions and organizational change (e.g., Blais et al., 2023; Houle et al., 2025b). Integrating ML-LPA to psychological health diagnostics within social entities could prove highly beneficial to our understanding how group member's poor psychological health radiates outwards, leading to indirect economic consequences linked to team functioning. For example, a group composed mainly of *Apathetic* and *Overinvested* employees may perform worse than a group composed mainly of *Average Functioning* employees, despite group means being similar. Moreover, the overall size of the L2 profiles inform on how many groups have optimal versus detrimental compositions, serving as a foundation for targeted group interventions.

Future Directions

It is also important to highlight that our focus was solely on LPA. Multilevel person-centered approaches encompass a broader family of models—including mixture regression, factor mixture analyses (combining variable and person-centered approaches), latent transition analyses and growth mixture modeling—with each raising distinct conceptual considerations when extended to multilevel analyses. Arguably, the statistical mechanics are already in place to support these analyses. However, as we suggested in the introduction, finding how to properly use and interpret these types of models is a completely different question. In mixture regression, the goal is to identify subpopulations characterized by qualitatively different relations among variables (e.g., distinct slopes linking job demands to strain), rather than by distinct configurations of variables. Extending this approach to multilevel data requires careful thought about what within- and between-level latent profiles represent, which relations should be allowed to differ across levels, and which relations should be used to define the profiles at each level. For instance, one may want to assess whether teams are characterized by the prevalence of individuals showing different demand–strain relations, whether teams themselves differ in the aggregate strength or form of these relations, or both. The additive and dispersion logic can in principle be adapted to mixture regression, but doing so requires conceptual work to define what "level" and "sharedness" mean when the focal quantity is a regression rather than a configuration.

Longitudinal ML-LPA, or ML-Latent Transition Analysis (ML-LTA) is also a possibility. Although implementing ML-LTA for *Additive*, *Dispersion* and *Additive-Dispersion* models should be straightforward based on the current introduction for someone familiar with longitudinal tests of profile similarity and LTA (e.g., Morin & Litalien, 2019), conceptual work remains to be done to grasp how to properly integrate and interpret transitions at both levels in *Dispersion-Heterogeneity* and *Cross-Level (Full* and *Restricted)* models for different types of constructs. ML-LTA undoubtedly offers researchers a very neat empirical pathway to theorize and test how group and individual dynamics emerge, stabilize, and change (Cronin et al., 2011).

Growth mixture modeling raises a different set of challenges. When trajectories are nested within higher-order units (e.g., employees within teams, students within schools), researchers must decide whether latent trajectory profiles are best modeled at the individual level (with team-level variation in prevalence), at the team level (with teams differing in their mean trajectory), or jointly. Each specification implies different assumptions about how change unfolds and aggregates, and each carry different interpretive and computational demands. Moreover, time itself might unfold differently across levels. For instance, whereas daily variations may be relevant to consider at the individual level, the month or week might be more relevant to consider at the team level, whereas years or trimester may be more critical at the organizational level. Estimation challenges are also likely, as convergence problems familiar in single-level growth mixture models are likely to become more severe in multilevel extensions.

Conclusion

Many areas of research throughout the social, educational, and organizational sciences are naturally multilevel. Employees are nested within workgroups, workgroups within organizations. Students are nested within classrooms, classrooms and teachers are nested within schools. Soldiers are nested within platoons, platoon within commands, etc. Many of those research areas have also learned the benefits of person-centered analyses as a useful and heuristic way to circumvent the restrictive assumption of population homogeneity. The ML-LPA outlined in this article are likely to be immensely useful as these sciences keep on evolving, especially now that largescale datasets potentially suitable to such analyses are becoming more prevalent. As the approaches outlined in the article have yet to be systematically applied in research, it is hard to fully grasp, at this specific point in time, their various limitations, as well as the challenges that will emerge from their interpretation. By introducing these methods, our goal was to stimulate applied research into implementing ML-LPA to achieve a more holistic picture of how collective entities and their members jointly function, with the hope that increasing applications will lead to further developments and a better understanding of limitations and directions for future development. In any case, we felt that what was primarily needed at this stage was a rigorous conceptual and interpretational coverage of the possibilities offered by ML-LPA, hoping that we succeed in conveying their value, and the realism of their implementation.

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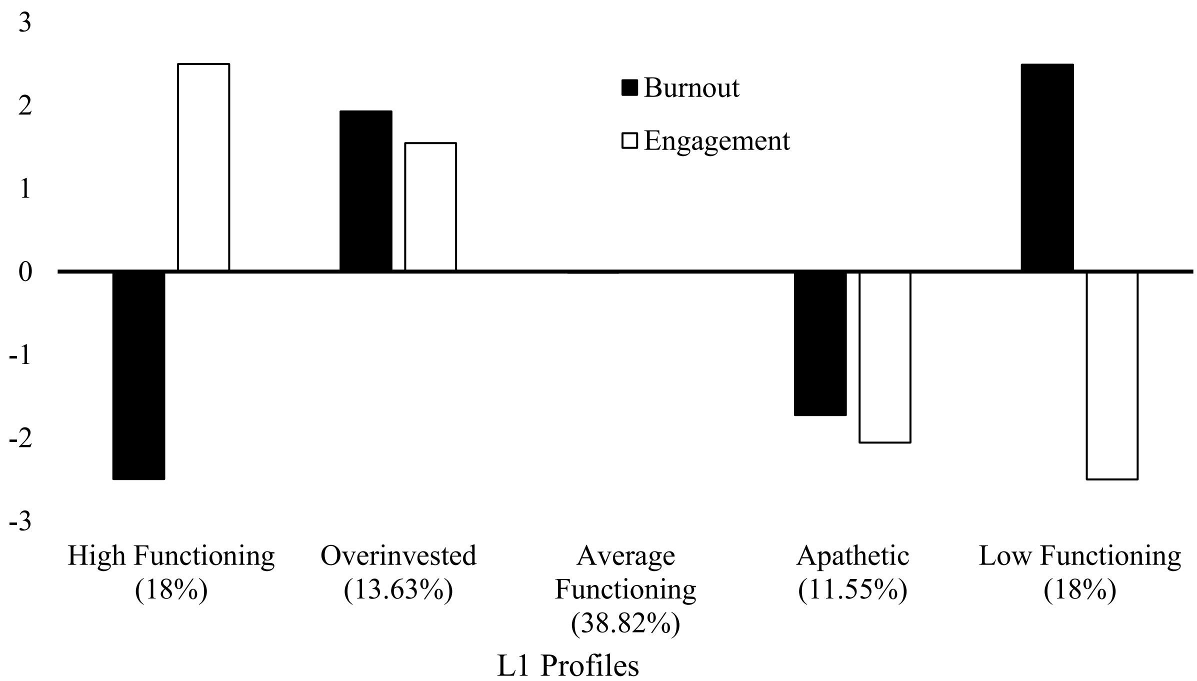


Figure 1. Level 1 latent profiles depicting distinct psychological states

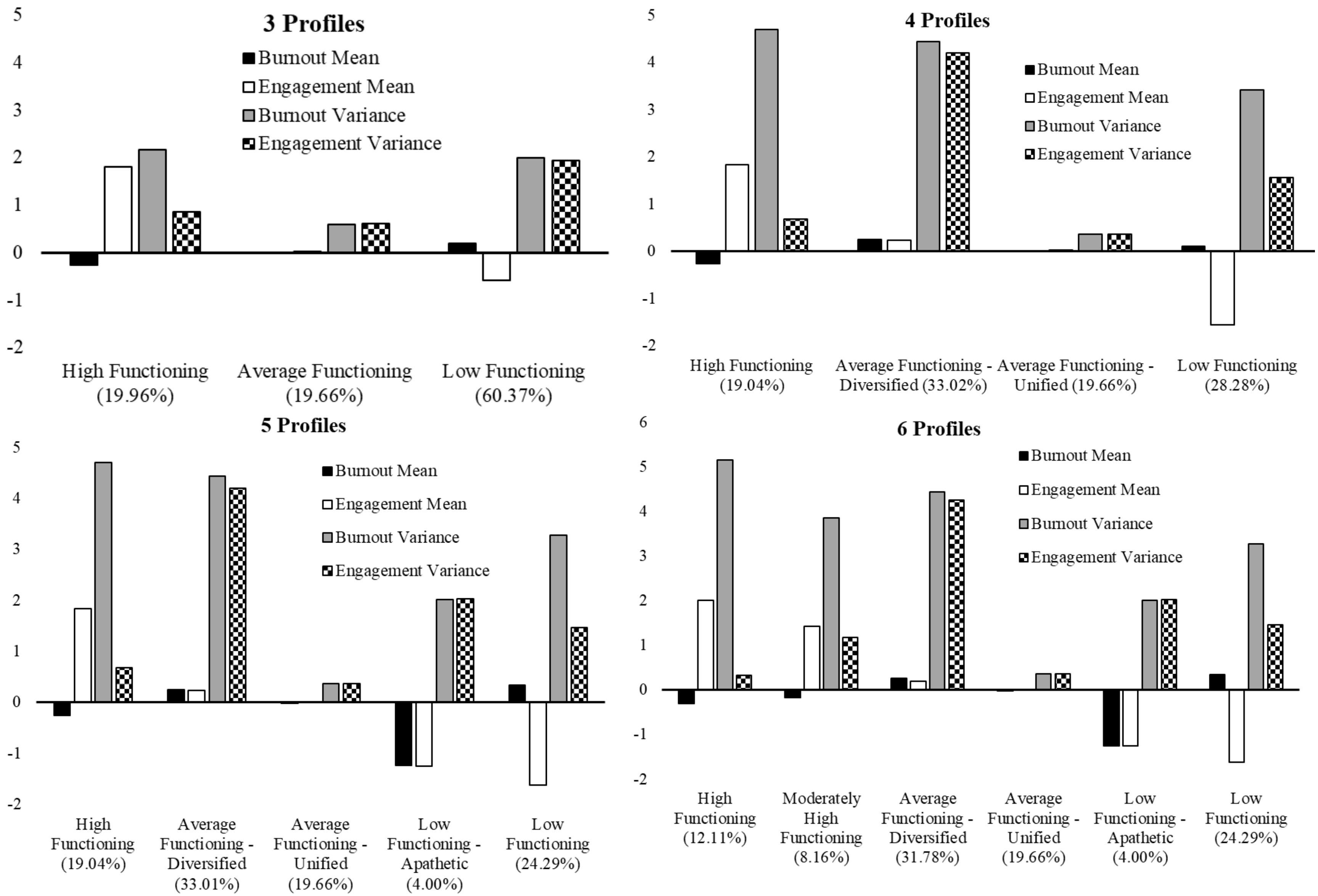


Figure 2. *Illustration of the Alternative Additive-Dispersion Models (Level 2 Profiles)*

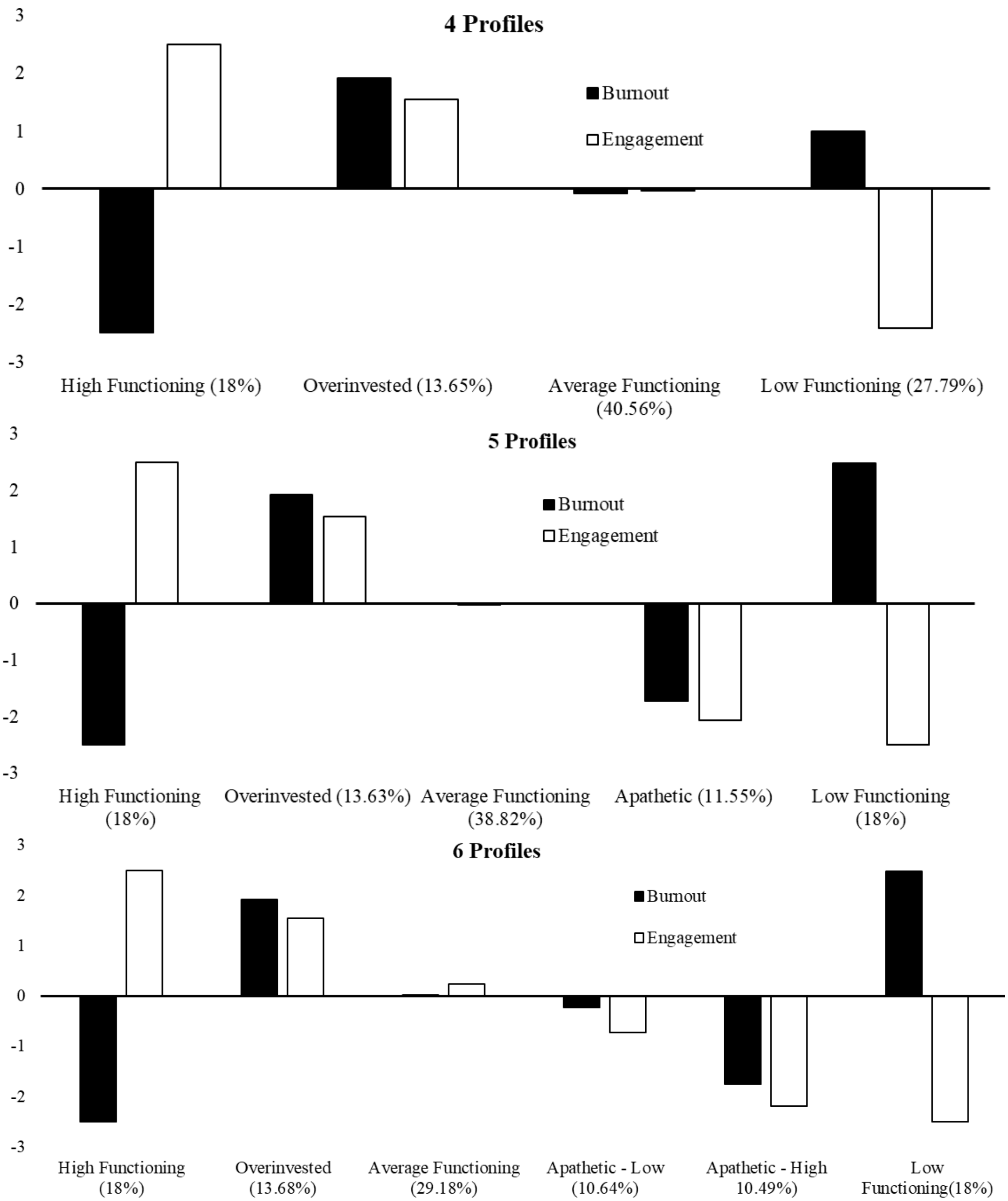
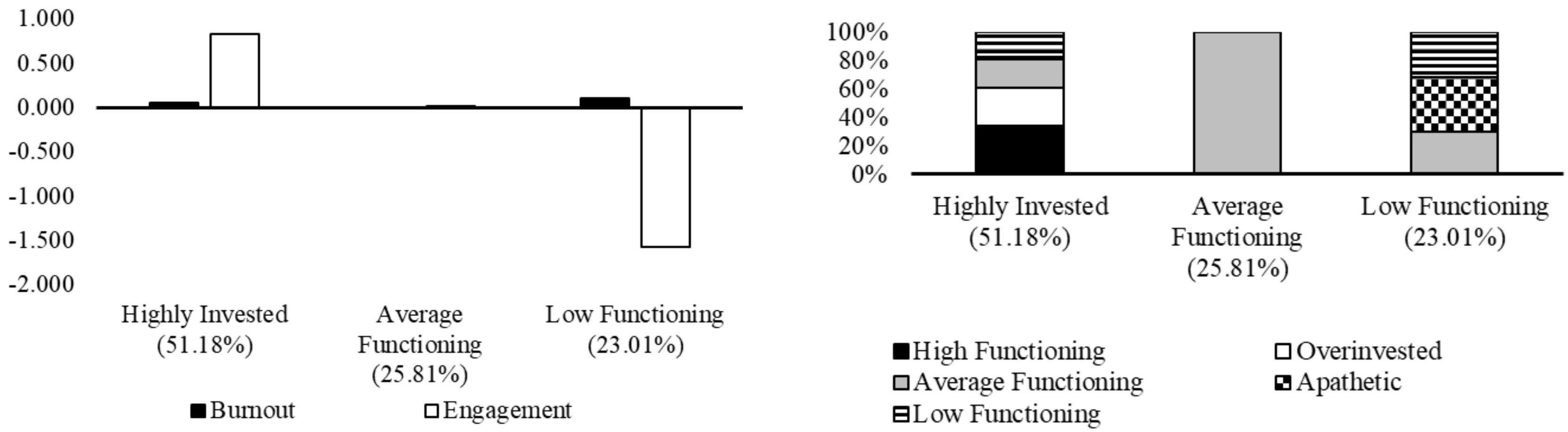
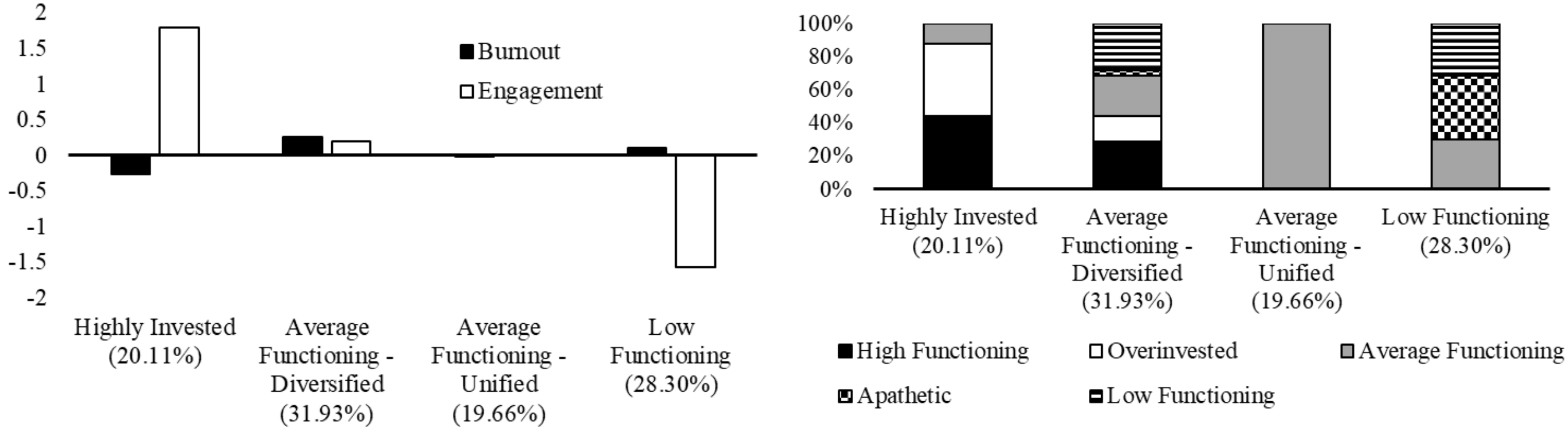


Figure 3. *Illustration of the Alternative Level 1 Profiles (Step 1 in the Estimation of Contextual Full Cross-Level Profiles)*

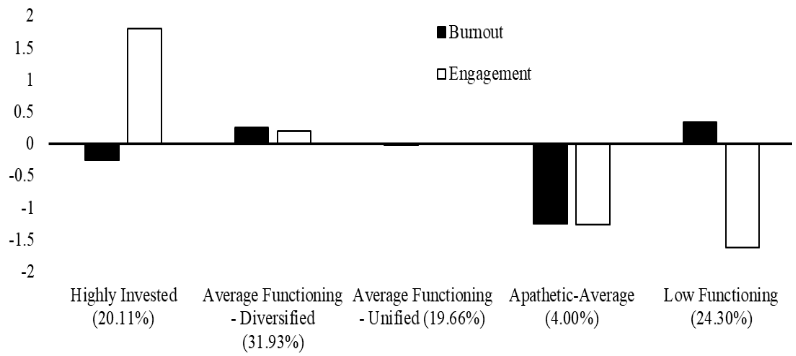


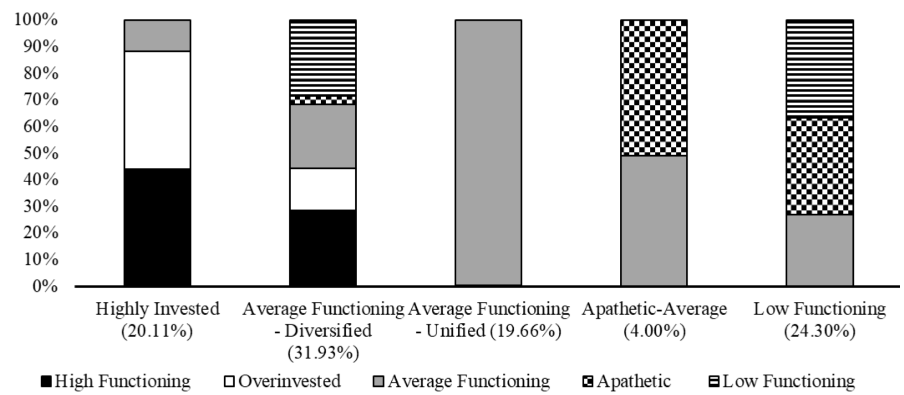
3 Profiles



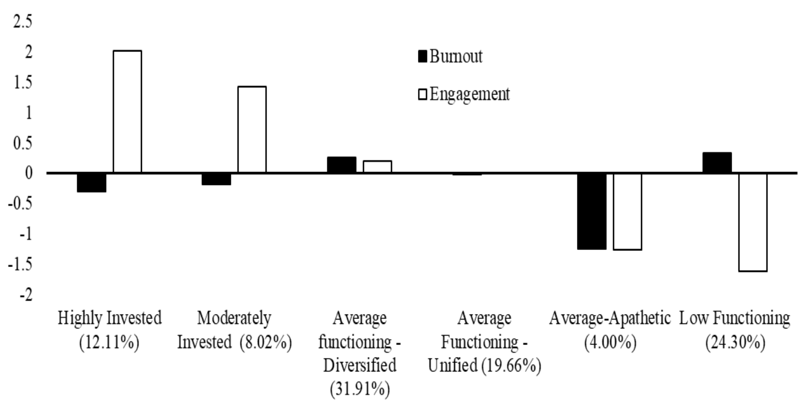
4 Profiles

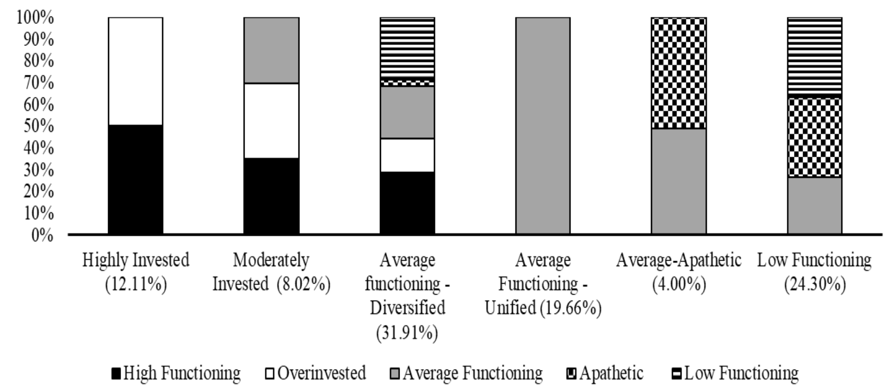
Figure 4. *Illustration of the Alternative Level 2 Profiles (Contextual Full Cross-Level Profiles)*





5 Profiles





6 Profiles

Figure 4 (Continued)

Table 1

Decision Sequence for Multilevel Latent Profile Analyses

Step 1			
A. Type of construct?	B. Measurement	C. Successful	D. Use
Contextual	Estimate Factor scores at Level 1 (L1)	Yes	Rely on L1 factor scores and manifest aggregation
		No	Stop or use on scale scores
Climate	Estimate Factor scores at L1 and Level 2 (L2: multilevel measurement)	Yes	Rely on L1 and L2 factor scores with latent aggregation
		No	Estimate factor scores at L1 and rely on manifest aggregation for cross-level models, and latent aggregation for additive-dispersion models

Step 2		
A. Profiles at both levels?	B. Model	C. Parameterization
Yes	Cross-level models or dispersion-heterogeneity model	Try in order (unless there is a strong theoretical rationale to favor or reject a specific type of model): if specification 1 fails, move to 2, then to 3, etc. **1.** L2 freely estimated between-profile means, between-profile variances and within-group composition based on L1 profiles (full cross-level) **2.** L2 freely estimated between-profile means and between-profile variances (restricted cross-level) **3.** Try a dispersion-heterogeneity model If none of these models converge, revert to additive-dispersion models
No	Additive-dispersion models	Try in order (unless there is a strong theoretical rationale to favor or reject a type of model): if specification 1 fails, move to 2, then to 3, etc. **1.** Free between-profile means, between-profile variances and within-group variances (additive-dispersion) **2.** Free between-profile means and within-group variances (additive-dispersion). If models 1 and 2 fail to converge, select either an additive-only (3 or 4) or dispersion-only (5) model **3.** Free between-profile means and between-profile variances (additive) **4.** Free between-profile means (additive) **5.** Free within-profile variances (dispersion only) If none of these models converge, consider moving to single-level LPA.

Table 2

Parameter Estimates (and 95% Confidence Intervals in Parenthesis) from the Alternative Additive-Dispersion Models (Level 2 Profiles)

3 Profiles	High Functioning	Average Functioning	Low Functioning			
	(19.98%)	(19.66%)	(60.37%)			
Level 2 (L2) Burnout Mean	-.257 (-.342;-.172)	-.014 (-.042;.014)	.188 (.145;.231)			
L2 Engagement Mean	1.804 (1.754;1.854)	.009 (-.016;.034)	-.582 (-.661;-.503)			
L1 Burnout Variance	4.656 (4.510;4.801)	.358 (.331;.385)	3.965 (3.888;.4.041)			
L1 Engagement Variance	.730 (.648;.812)	.363 (.332;.394)	3.753 (3.636;3.869)			
L2 Burnout Variance	.403 (.346;.460)	.038 (.030;.045)	.287 (.244;.330)			
L2 Engagement Variance	.109 (.093;.124)	.030 (.023;.037)	.928 (.866;.989)			
4 Profiles	High Functioning	Average Functioning-Diversified	Average Functioning–Unified	Low Functioning		
	(19.04%)	(33.02%)	(19.66%)	(28.28%)		
L2 Burnout Mean	-.263 (-.355;-.171)	.246 (.193;.298)	-.014 (-.042;.014)	.102 (.029;.175)		
L2 Engagement Mean	1.830 (1.752;1.909)	.229 (.159;.298)	.009 (-.016;.034)	-1.570 (-1.613;-1.527)		
L1 Burnout Variance	4.699 (4.513;4.886)	4.433 (4.343;4.524)	.358 (.331;.385)	3.406 (3.314;3.499)		
L1 Engagement Variance	.677 (.540;.814)	4.204 (4.080;4.329)	.363 (.332;.394)	1.553 (1.496;1.611)		
L2 Burnout Variance	.418 (.347;.489)	.214 (.189;.238)	.038 (.030;.045)	.366 (.285;.447)		
L2 Engagement Variance	.098 (.073;.122)	.197 (.152;.242)	.030 (.023;.037)	.129 (.103;.155)		
5 Profiles	High Functioning	Average Functioning-Diversified	Average Functioning-Unified	Low Functioning- Apathetic	Low Functioning	
	(19.04%)	(33.01%)	(19.66%)	(4.00%)	(24.29%)	
L2 Burnout Mean	-.263 (-.355;-.171)	.246 (.194;.298)	-.014 (-.042;.014)	-1.247 (-1.311;-1.184)	.340 (.312;.368)	
L2 Engagement Mean	1.830 (1.752;1.909)	.229 (.159;.298)	.009 (-.016;.034)	-1.260 (-1.322;-1.199)	-1.625 (-1.671;-1.579)	
L1 Burnout Variance	4.699 (4.513;4.886)	4.433 (4.343;4.524)	.358 (.331;.385)	2.016 (1.908;2.124)	3.280 (3.187;3.372)	
L1 Engagement Variance	.677 (.540;.814)	4.205 (4.080;4.329)	.363 (.332;.394)	2.026 (1.899;2.154)	1.458 (1.401;1.514)	
L2 Burnout Variance	.418 (.346;.489)	.213 (.189;.237)	.038 (.030;.045)	.042 (.024;.059)	.046 (.038;.054)	
L2 Engagement Variance	.098 (.073;.122)	.197 (.152;.241)	.030 (.023;.037)	.039 (.023;.056)	.125 (.099;.152)	
6 Profiles	High Functioning	Moderately High Functioning	Average Functioning-Diversified	Average Functioning-Unified	Low Functioning–Apathetic	Low Functioning
	(12.11%)	(8.16%)	(31.78%)	(19.66%)	(4.00%)	(24.29%)
L2 Burnout Mean	-.303 (-.434;-.173)	-.179 (-.250;-.108)	.261 (.211;.310)	-.014 (-.042;.014)	-1.247 (-1.311;-1.184)	.340 (.312;.367)
L2 Engagement Mean	2.016 (1.983;2.050)	1.425 (1.387;1.463)	.193 (.148;.237)	.009 (-.016;.034)	-1.260 (-1.322;-1.199)	-1.625 (-1.671;-1.578)
L1 Burnout Variance	5.163 (5.005;5.321)	3.869 (3.7374.002)	4.451 (4.362;4.541)	.358 (.331;.385)	2.016 (1.908;2.124)	3.280 (3.187;3.372)
L1 Engagement Variance	.327 (.310;.344)	1.182 (1.088;1.277)	4.265 (4.176;4.354)	.363 (.332;.394)	2.026 (1.899;2.154)	1.458 (1.401;1.515)
L2 Burnout Variance	.572 (.501;.642)	.099 (.076;.122)	.213 (.188;.237)	.038 (.030;.045)	.042 (.024;.059)	.046 (.038;.054)
L2 Engagement Variance	.035 (.029;.041)	.024 (.017;.031)	.167 (.147;.187)	.030 (.023;.037)	.039 (.023;.056)	.125 (.099;.152)

Table 3

Parameter Estimates from the Alternative Level 1 Profiles (Step 1 in the Estimation of Contextual Full Cross-Level Profiles)

4 Profiles	High Functioning (18%)	Overinvested (13.65%)	Average Functioning (40.56%)	Low Functioning (27.79%)		
Burnout Mean	-2.497 (-2.510;-2.483)	1.925 (1.878;1.971)	-.086 (-.110;-.061)	.999 (.914;1.084)		
Engagement Mean	2.497 (2.484;2.511)	1.546 (1.527;1.565)	-.036 (-.059;-.013)	-2.415 (-2.444;-2.386)		
Burnout Variance	.084 (.081;.088)	.645 (.614;.676)	.458 (.437;.480)	4.425 (4.289;4.560)		
Engagement Variance	.086 (.082;.089)	.106 (.100;.112)	.389 (.376;.402)	.390 (.369;.410)		
5 Profiles	High Functioning (18%)	Overinvested (13.63%)	Average Functioning (38.82%)	Apathetic (11.55%)	Low Functioning (18%)	
Burnout Mean	-2.497 (-2.510;-2.483)	1.928 (1.882;1.974)	-.014 (-.035;.008)	-1.726 (-1.758;-1.694)	2.487 (2.461;2.514)	
Engagement Mean	2.497 (2.484;2.511)	1.547 (1.529;1.566)	.006 (-.015;.027)	-2.057 (-2.110;-2.004)	-2.501 (-2.528;-2.474)	
Burnout Variance	.084 (.081;.088)	.641 (.610;.672)	.372 (.360;.383)	.287 (.257;.318)	.336 (.322;.350)	
Engagement Variance	.086 (.082;.089)	.105 (.100;.111)	.362 (.351;.374)	.624 (.586;.662)	.333 (.319;.347)	
6 Profiles	High Functioning (18%)	Overinvested (13.68%)	Average Functioning (29.18%)	Apathetic-Low (1.64%)	Apathetic-High (1.49%)	Low Functioning (18%)
Burnout Mean	-2.497 (-2.510;-2.483)	1.924 (1.879;1.969)	.009 (-.014;.032)	-.225 (-.295;-.154)	-1.752 (-1.786;-1.719)	2.487 (2.460;2.514)
Engagement Mean	2.497 (2.484;2.511)	1.549 (1.530;1.567)	.245 (.200;.289)	-.732 (-.771;-.693)	-2.189 (-2.243;-2.135)	-2.501 (-2.527;-2.474)
Burnout Variance	.084 (.081;.088)	.643 (.612;.674)	.343 (.332;.354)	.588 (.532;.643)	.293 (.261;.325)	.336 (.322;.350)
Engagement Variance	.086 (.082;.089)	.104 (.099;.110)	.229 (.209;.249)	.033 (.024;.042)	.495 (.460;.531)	.333 (.319;.347)

Table 4

Parameter Estimates from the Alternative Level 2 Profiles (Step 2 in the Estimation of Contextual Full Cross-Level Profiles)

	Level 2: 3 Profiles			
	Highly Invested (51.18%)	Average Functioning (25.81%)	Low Functioning (23.01%)	
Burnout Mean	.056 (.007;.105)	-.014 (-.042;.014)	.102 (.029;.174)	
Engagement Mean	.827 (.754;.899)	.009 (-.016;.034)	-1.570 (-1.613;-1.527)	
Burnout Variance	.350 (.311;.389)	.038 (.030;.045)	.366 (.286;.447)	
Engagement Variance	.759 (.706;.812)	.030 (.023;.037)	.129 (.103;.155)	
Prevalence of Level 1 Profiles				
Highly Invested	34.53%	.15%	0%	
Overinvested	26.70%	.14%	0%	
Average Functioning	19.36%	99.71%	29.92%	
Apathetic	1.93%	0%	38.64%	
Low Functioning	17.48%	0%	31.44%	
	Level 2: 4 Profiles			
	Highly Invested (20.11%)	Average Functioning-Diversified (31.93%)	Average Functioning-Unified (19.66%)	Low Functioning (28.30%)
Burnout Mean	-.256 (-.341;-.172)	.258 (.208;.307)	-.014 (-.042;.014)	.102 (.029;.174)
Engagement Mean	1.800 (1.755;1.845)	.197 (.153;.242)	.009 (-.016;.034)	-1.570 (-1.613;1.527)
Burnout Variance	.401 (.346;.446)	.213 (.189;.238)	.038 (.030;.045)	.366 (.286;.447)
Engagement Variance	.110 (.096;.125)	.170 (.150;.191)	.030 (.023;.037)	.129 (.103;.155)
Prevalence of Level 1 Profiles				
Highly Invested	44.06%	28.53%	.15%	0%
Overinvested	44.04%	15.73%	.14%	0%
Average Functioning	11.90%	24.06%	99.70%	29.92%
Apathetic	0%	3.19%	0%	38.64%
Low Functioning	0%	28.49%	0%	31.44%

Table 4 (Continued)

	Level 2: 5 Profiles				
	Highly Invested (20.11%)	Average Functioning-Diversified (31.93%)	Average Functioning-Unified (19.66%)	Apathetic-Average (4.00%)	Low Functioning (24.30%)
Burnout Mean	-.256 (-.341;-.172)	.258 (.208;.307)	-.014 (-.042;.014)	-1.247 (-1.311;-1.184)	.339 (.312;.367)
Engagement Mean	1.800 (1.755;1.845)	.197 (.153;.242)	.009 (-.016;.034)	-1.260 (-1.322;-1.199)	-1.624 (-1.670;-1.578)
Burnout Variance	.401 (.346;.456)	.213 (.189;.238)	.038 (.030;.045)	.042 (.024;.059)	.046 (.038;.054)
Engagement Variance	.110 (.096;.125)	.170 (.150;.191)	.030 (.023;.037)	.039 (.023;.056)	.125 (.099;.152)
Prevalence of Level 1 Profiles					
Highly Invested	44.06%	28.53%	.15%	0%	0%
Overinvested	44.04%	15.73%	.14%	0%	0%
Average Functioning	11.90%	24.06%	99.70%	49.00%	26.73%
Apathetic	0%	3.19%	0%	51.00%	36.65%
Low Functioning	0%	28.49%	0%	0%	36.62%

	Level 2: 6 Profiles					
	Highly Invested (12.11%)	Moderately Invested (8.02%)	Average Functioning-Diversified (31.91%)	Average Functioning-Unified (19.66%)	Apathetic-Average (4.00%)	Low Functioning (24.30%)
Burnout Mean	-.300 (-.427;-.172)	-.182 (-.251;-.113)	.258 (.209;.308)	-.014 (-.042;.014)	-1.247 (-1.311;-1.184)	.339 (.312;.367)
Engagement Mean	2.016 (1.984;2.048)	1.430 (1.397;1.464)	.197 (.152;.241)	.009 (-.016;.034)	-1.260 (-1.322;-1.199)	-1.624 (-1.670;-1.578)
Burnout Variance	.573 (.503;.644)	.098 (.075;.120)	.213 (.189;.238)	.038 (.030;.045)	.042 (.024;.059)	.046 (.038;.054)
Engagement Variance	.035 (.029;.042)	.023 (.017;.029)	.169 (.149;.190)	.030 (.023;.037)	.039 (.023;.056)	.125 (.099;.152)
Prevalence of Level 1 Profiles						
Highly Invested	50.04%	34.99%	28.53%	0.15%	0%	0%
Overinvested	49.96%	34.84%	15.71%	0.14%	0%	0%
Average Functioning	0%	30.17%	24.05%	99.70%	49.00%	26.73%
Apathetic	0%	0%	3.19%	0%	51.00%	36.65%
Low Functioning	0%	0%	28.52%	0%	0%	36.62%

Table 5

Predictive Results (Multinomial Logistic Regressions) from the Full Cross-Level Profiles: Level 1 (Top) and Level 2 (Bottom)

Level 1								
	Highly Invested *vs* Low Functioning Coefficient (Standard Error)	OR	Overinvested *vs* Low Functioning Coefficient (Standard Error)	OR	Average Functioning *vs* Low Functioning Coefficient (Standard Error)	OR	Apathetic *vs* Low Functioning Coefficient (Standard Error)	OR
Socialization	5.942 (.147)**	≥100	5.959 (.148)**	≥100	2.564 (.068)**	12.988	1.313 (.052)**	3.717
	Highly Invested *vs* Apathetic Coefficient (Standard Error)	OR	Overinvested *vs* Apathetic Coefficient (Standard Error)	OR	Average Functioning *vs* Apathetic Coefficient (Standard Error)	OR	Highly Invested *vs* Average Functioning Coefficient (Standard Error)	OR
Socialization	4.628 (.136)**	≥100	4.646 (.137)**	≥100	1.250 (.050)**	3.490	3.378 (.124)**	29.312
	Overinvested *vs* Average Functioning Coefficient (Standard Error)	OR	Highly Invested *vs* Overinvested Coefficient (Standard Error)	OR				
Socialization	3.395 (.126)**	29.815	-.017 (.050)	.983				
Level 2								
	Highly Invested *vs* Low Functioning Coefficient (Standard Error)	OR	Average Functioning-Diversified *vs* Low Functioning Coefficient (Standard Error)	OR	Average Functioning-Unified *vs* Low Functioning Coefficient (Standard Error)	OR	Apathetic-Average *vs* Low Functioning Coefficient (Standard Error)	OR
Socialization	21.629 (1.561)**	≥100	12.557 (1.043)**	≥100	9.771 (.988)**	≥100	1.506 (.542)**	4.509
	Highly Invested *vs* Apathetic-Average Coefficient (Standard Error)	OR	Average Functioning-Diversified *vs* Apathetic-Average Coefficient (Standard Error)	OR	Average Functioning-Unified *vs* Apathetic - Average Coefficient (Standard Error)	OR	Highly Invested *vs* Average Functioning - Unified Coefficient (Standard Error)	OR
Socialization	20.123 (1.571)**	≥100	11.051 (1.049)**	≥100	8.265 (1.004)**	≥100	11.858 (1.201)**	≥100
	Average Functioning-Diversified *vs* Average Functioning-Unified Coefficient (Standard Error)	OR	Highly Invested vs Average Functioning-Diversified Coefficient (Standard Error)	OR				
Socialization	2.786 (.270)**	16.216	9.072 (1.166)**	≥100				

Note. ** $p < .01$; * $p < .05$; OR: odds ratio.

Table 6

Associations with Outcomes from the Full Cross-Level Profiles: Level 1 (Top) and Level 2 (Bottom)

Level 1						
	Highly Invested Mean (95% CI)	Overinvested Mean (95% CI)	Average Functioning Mean (95% CI)	Apathetic Mean (95% CI)	Low Functioning Mean (95% CI)	Summary of Statistically Significant Differences
Absenteeism	-1.987 (-2.020;-1.954)	-1.902 (-1.940;-1.863)	.728 (.681;.775)	2.116 (1.955;2.278)	2.325 (2.228;2.363)	1<2<3<4<5
Level 2						
	Highly Invested Mean (95% CI)	Average Functioning-Diversified Mean (95% CI)	Average Functioning-Unified Mean (95% CI)	Apathetic-Average Mean (95% CI)	Low Functioning Mean (95% CI)	Summary of Statistically Significant Differences
Absenteeism	-1.738 (-1.795;-1.681)	-.258 (-.323;-.193)	.294 (.252;.335)	1.255 (1.171;1.339)	1.180 (1.139;1.220)	1<2<3<4=5

Note. CI: Confidence Interval

Online Supplemental Material for:

Multilevel Person-Centered Analyses: A Comprehensive Guide

Table S1

Model Fit Results: Alternative Specifications Tested in the Data Illustration

Model	*LL*	*#fp*	S.C.	AIC	CAIC	BIC	ABIC	Ent.	aLMR	BLRT
Additive-Dispersion Models: Level 2 (L2) Profiles with Free Group-Level Means and Variances and Free Within-Profile L1 Variances										
1 L2 Profile	-43034.029	8	1.701	86084.058	86149.741	86141.741	86116.318	NA	NA	NA
2 L2 Profiles	-40294.326	17	1.161	80622.653	80762.228	80745.228	80691.205	1.000	<.001	<.001
3 L2 Profiles	-38170.155	26	1.096	76392.310	76605.779	76579.779	76497.155	.996	<.001	<.001
4 L2 Profiles	-36939.476	35	1.061	73948.952	74236.314	74201.314	74090.089	.991	<.001	<.001
5 L2 Profile	-36571.077	44	.930	73230.155	73591.410	73547.410	73407.584	.992	<.001	<.001
6 L2 Profiles	-36218.556	53	.748	72543.111	72978.259	72925.259	72756.833	.996	<.001	<.001
7 L2 Profiles	-36011.247	62	.702	72146.493	72655.534	72593.534	72396.507	.997	.912	<.001
8 L2 Profiles	-35841.662	71	.691	71825.324	72408.258	72337.258	72111.631	.995	<.001	<.001
Free Means and Variances—Level 1 (L1) Profiles										
1 L1 Profile	-40599.071	4	.729	81206.142	81238.984	81234.984	81222.272	NA	NA	NA
2 L1 Profiles	-35799.565	9	.754	71617.131	71691.024	71682.024	71653.423	.985	<.001	<.001
3 L1 Profiles	-34069.787	14	.802	68167.573	68282.518	68268.518	68224.028	.941	<.001	<.001
4 L1 Profiles	-31867.548	19	.781	63773.096	63929.092	63910.092	63849.713	.962	<.001	<.001
5 L1 Profile	-29860.708	24	.805	59769.416	59966.464	59942.464	59866.195	.973	<.001	<.001
6 L1 Profiles	-29529.160	29	.852	59116.320	59354.420	59325.420	59233.262	.944	<.001	<.001
7 L1 Profiles	-29238.048	34	.877	58544.097	58823.248	58789.248	58681.201	.920	<.001	<.001
8 L1 Profiles	-29065.224	39	.844	58208.448	58528.651	58489.651	58365.715	.905	<.001	<.001
Full Cross-Level Profiles—L2 Profiles with Free Group-Level Means, Variances and Prevalence of the L1 Profiles										
5 L1 Profiles and 1 L2 Profiles	-32379.196	8	2.460	64774.392	64840.075	64832.075	64806.652	.972; 1.000	NA	NA
5 L1 Profiles and 2 L2 Profiles	-32203.439	13	1.864	64432.878	64539.612	64526.612	64485.300	.972; .996	NA	NA
5 L1 Profiles and 3 L2 Profiles	-32015.633	18	1.649	64067.266	64215.053	64197.053	64139.851	.972; .805	NA	NA
5 L1 Profiles and 4 L2 Profiles	-31862.400	23	1.476	63770.800	63959.638	63936.638	63863.547	.972; .980	NA	NA
5 L1 Profiles and 5 L2 Profiles	-31754.682	28	1.365	63565.364	63795.253	63767.253	63678.273	.972; .981	NA	NA
5 L1 Profiles and 6 L2 Profiles	-31677.766	33	1.288	63421.532	63692.473	63659.473	63554.604	.972; .884	NA	NA
5 L1 Profiles and 7 L2 Profiles	-31622.507	38	1.273	63321.014	63633.007	63595.007	63474.249	.972; .937	NA	NA
5 L1 Profiles and 8 L2 Profiles	-31583.052	43	1.253	63252.103	63605.148	63562.148	63425.500	.972; .919	NA	NA

Note. *LL*: loglikelihood; #fp: free parameters; S.C.: scaling correction; AIC: Akaïke information criterion; CAIC: consistent AIC; BIC: Bayesian information criterion; ABIC: sample-size adjusted BIC; Ent.: Entropy; aLMR = Lo-Mendel and Rubin's likelihood ratio test; BLRT = bootstrap likelihood ratio test; NA = not applicable.

Additive-Dispersion Model (Contextual). *L2 Profiles Estimated from L1 Contextual Ratings: Free Collective Means and Variances and Free Within-Profile Variances*

```
Data:
File is Data.dat;
Variable:
Names are X1 X2 ID Group;
MISSING are all (-999);
IDVAR = ID;
USEV = X1 X2;
CLASSES = BC(2);
Cluster = Group;
Between = BC MX1 MX2;
Within = X1 X2;
Define:
!Creating the L2 means using manifest aggregation procedures
MX1 = Cluster_Mean (X1);
MX2 = Cluster_Mean (X2);
!Using grand mean-centering for all variables.
Center X1 X2 MX1 MX2 (Grandmean);
ANALYSIS:
TYPE = MIXTURE Twolevel;
ESTIMATOR = MLR;
Process = 4;
Starts = 10000 1000 100;
STITERATIONS = 1000;
MODEL:
! This section allows the within-profile variance to differ across L2 profiles
%WITHIN%
%Overall%
%BC#1%
X1 X2;
%BC#2%
X1 X2;
!This section specifies 2 profiles at level 2
%BETWEEN%
%Overall%
! Collective profile means and variances are freely estimated
! To constrain collective variance to equality, remove the line "MX1 MX2;" from both profiles
%BC#1%
[MX1 MX2];
MX1 MX2;
%BC#2%
[MX1 MX2];
MX1 MX2;
OUTPUT:
STDYX SAMPSTAT CINTERVAL RESIDUAL svalues TECH1 TECH7 TECH11 TECH14;
```

Additive-Dispersion Model (Climate). *L2 Profiles Estimated from L1 Climate Ratings: Free Collective Means and Variances and Free Within-Profile Variances*

```
Data:
File is Data.dat;
Variable:
Names are X1 X2 ID Group;
MISSING are all (-999);
IDVAR = ID;
USEV = X1 X2;
CLASSES = BC(2);
Cluster = Group;
Between = BC;
ANALYSIS:
TYPE = MIXTURE Twolevel;
ESTIMATOR = MLR;
Process = 4;
Starts = 10000 1000 100;
STITERATIONS = 1000;
MODEL:
%WITHIN%
%Overall%
! This section allows the within-profile variance to differ across L2 profiles
%BC#1%
X1 X2;
%BC#2%
X1 X2;
!This section specifies 2 profiles at level 2
%BETWEEN%
%Overall%
! Collective profile means and variances are freely estimated
! To constrain collective variance to equality, remove the line "X1 X2;" from both profiles
%BC#1%
[X1 X2];
X1 X2;
%BC#2%
[X1 X2];
X1 X2;
OUTPUT:
STDYX SAMPSTAT CINTERVAL RESIDUAL svalues TECH1 TECH7 TECH11 TECH14;
```

Additive Only Model (Contextual). *L2 Profiles Estimated from L1 Contextual Ratings: Free Collective Means and Variances and Equal Within-Profile Variances*

```
Data:
File is Data.dat;
Variable:
Names are X1 X2 ID Group;
MISSING are all (-999);
IDVAR = ID;
USEV = X1 X2 MX1 MX2;
CLASSES = BC(2);
Cluster = Group;
Between = BC MX1 MX2;
Within = X1 X2;
Define:
!Creating the L2 means using manifest aggregation procedures
MX1 = Cluster_Mean (X1);
MX2 = Cluster_Mean (X2);
!Using grand mean-centering for all variables.
Center X1 X2 MX1 MX2 (Grandmean);
ANALYSIS:
TYPE = MIXTURE Twolevel;
ESTIMATOR = MLR;
Process = 4;
Starts = 10000 1000 100;
STITERATIONS = 1000;
MODEL:
!Within-profile (L1) variances are fixed to equality (simply not asked to vary across profiles)
%WITHIN%
%Overall%
X1 X2;
!This section specifies 2 profiles at level 2
%BETWEEN%
%Overall%
! Collective profile means and variances are freely estimated
! To constrain collective variance to equality, remove the line "MX1 MX2;" from both profiles
%BC#1%
[MX1 MX2];
MX1 MX2;
%BC#2%
[MX1 MX2];
MX1 MX2;
OUTPUT:
STDYX SAMPSTAT CINTERVAL RESIDUAL svalues TECH1 TECH7 TECH11 TECH14;
```

Additive Only Model (Climate). *L2 Profiles Estimated from L1 Climate Ratings: Free Collective Means and Variances and Equal Within-Profile Variances*

```
Data:
File is Data.dat;
Variable:
Names are X1 X2 ID Group;
MISSING are all (-999);
IDVAR = ID;
USEV = X1 X2;
CLASSES = BC(2);
Cluster = Group;
Between = BC;
ANALYSIS:
TYPE = MIXTURE Twolevel;
ESTIMATOR = MLR;
Process = 4;
Starts = 10000 1000 100;
STITERATIONS = 1000;
MODEL:
%WITHIN%
!Within-profile (L1) variances are fixed to equality (simply not asked to vary across profiles)
%Overall%
X1 X2;
!This section specifies 2 profiles at level 2
%BETWEEN%
%Overall%
! Collective profile means and variances are freely estimated
! To constrain collective variance to equality, remove the line "X1 X2;" from both profiles
%BC#1%
[X1 X2];
X1 X2;
%BC#2%
[X1 X2];
X1 X2;
OUTPUT:
STDYX SAMPSTAT CINTERVAL RESIDUAL svalues TECH1 TECH7 TECH11 TECH14;
```

Dispersion Only Model (Contextual). *L2 Profiles Estimated from L1 Contextual Ratings: Equal Collective Means and Variances and Free Within-Profile Variances*

```
Data:
File is Data.dat;
Variable:
Names are X1 X2 ID Group;
MISSING are all (-999);
IDVAR = ID;
USEV = X1 X2;
CLASSES = BC(2);
Cluster = Group;
Between = BC MX1 MX2;
Within = X1 X2;
Define:
!Creating the L2 means using manifest aggregation procedures
MX1 = Cluster_Mean (X1);
MX2 = Cluster_Mean (X2);
!Using grand mean-centering for all variables.
Center X1 X2 MX1 MX2 (Grandmean);
ANALYSIS:
TYPE = MIXTURE Twolevel;
ESTIMATOR = MLR;
Process = 4;
Starts = 10000 1000 100;
STITERATIONS = 1000;
MODEL:
! This section allows the within-profile variance to differ across L2 profiles
%WITHIN%
%Overall%
%BC#1%
X1 X2;
%BC#2%
X1 X2;
%BETWEEN%
%Overall%
! Collective profile means and variances are constrained to equality across profiles
! using the labels M1-M2 (means) and V1-V2 (variances)
%BC#1%
[MX1 MX2] (M1-M2);
MX1 MX2 (V1-V2);
%BC#2%
[MX1 MX2] (M1-M2);
MX1 MX2 (V1-V2);
OUTPUT:
STDYX SAMPSTAT CINTERVAL RESIDUAL svalues TECH1 TECH7 TECH11 TECH14;
```

Dispersion Only Model (Climate). *L2 Profiles Estimated from L1 Climate Ratings: Equal Collective Means and Variances and Free Within-Profile Variances*

```
Data:
File is Data.dat;
Variable:
Names are X1 X2 ID Group;
MISSING are all (-999);
IDVAR = ID;
USEV = X1 X2;
CLASSES = BC(2);
Cluster = Group;
Between = BC;
ANALYSIS:
TYPE = MIXTURE Twolevel;
ESTIMATOR = MLR;
Process = 4;
Starts = 10000 1000 100;
STITERATIONS = 1000;
MODEL:
%WITHIN%
%Overall%
! This section allows the within-profile variance to differ across L2 profiles
%BC#1%
X1 X2;
%BC#2%
X1 X2;
%BETWEEN%
%Overall%
! Collective profile means and variances are constrained to equality across profiles
! using the labels M1-M2 (means) and V1-V2 (variances)
%BC#1%
[X1 X2] (M1-M2);
X1 X2 (V1-V2);
%BC#2%
[X1 X2] (M1-M2);
X1 X2 (V1-V2);
OUTPUT:
STDYX SAMPSTAT CINTERVAL RESIDUAL svalues TECH1 TECH7 TECH11 TECH14;
```

Dispersion Heterogeneity Model (Contextual or Climate). *Multilevel Latent Profile Analysis using the Frequency of L1 Profile Membership to Define Level 2 Profiles.*

To estimate this type of model, we first need to identify the nature of the Level 1 profiles in a single-level analysis controlling for the nesting structure. The optimal solution is then selected using typical procedures (see Morin & Litalien, 2019) to compare solutions including different number of profiles. For illustration purposes, we provide the code for a five-profile solution.

```
Data:
File is Data.dat;
Variable:
names are X1 X2 ID Group;
MISSING are all (-999);
IDVAR = ID;
USEV = X1 X2;
CLASSES = C(5);
Cluster is Group;
Define
Center X1 X2 (Grandmean);
! alternatively, replace “Grandmean” for “Groupmean” if group mean centering is required (climate).
ANALYSIS:
TYPE = MIXTURE COMPLEX;
ESTIMATOR = MLR;
Process = 4;
Starts = 10000 1000 100;
STITERATIONS = 1000;
MODEL:
%OVERALL%
! To constrain variances to equality, remove the line “X1 X2;” from all profiles
% C#1%
[X1 X2];
X1 X2;
%C#2%
[X1 X2];
X1 X2;
%C#3%
[X1 X2];
X1 X2;
%C#4%
[X1 X2];
X1 X2;
%C#5%
[X1 X2];
X1 X2;
OUTPUT:
STDYX SAMPSTAT CINTERVAL RESIDUAL svalues TECH1 TECH7 TECH11 TECH14;
```

These profiles are assumed to represent what happens at the individual level and should not be allowed to change when the higher-level structure is added to the model (i.e., we want to estimate L2 profiles representing the frequency of occurrence of those L1 profiles without changing them). We also want to maximally limit the influence of the L1 structure on model fit assessment to make sure that model fit information primarily helps compare the L2 profiles. For this reason, we now use the start values from the optimal L1 solution (i.e., the parameter estimates) to fix them (using the @ function) in the estimation of the multilevel solution, while keeping the random start function for the estimation of L2 profiles. These start values can be obtained either by copying the parameter estimates from the final solution, or in the SVALUES section of the output (which directly provides them). The resulting code is presented on the next page. Importantly, although the SVALUES function works for many types of model, it does not provide proper values for cross-level models. Thus, users should first ensure that the values included in the SVALUES section correspond to their parameter estimates before using them. Otherwise, they need to copy their parameter estimates manually to reproduce their solution.

```
Data:
File is Data.dat;
Variable:
names are X1 X2 ID Group;
MISSING are all (-999);
IDVAR = ID;
USEV = X1 X2;
Between = BC;
Within = X1 X2;
CLASSES = BC(2) C(4);
Cluster is Group;
Center X1 X2 (Grandmean);
! alternatively, replace “Grandmean” for “Groupmean” if group mean centering is required (climate).
ANALYSIS:
TYPE = MIXTURE Twolevel;
ESTIMATOR = MLR;
Process = 4;
Starts = 10000 1000 100;
STITERATIONS = 1000;
MODEL:
%WITHIN%
%OVERALL%
! Values taken from the previous solution, and equal for each L2 profiles (e.g., BC#1 = BC#2).
 %BC#1.C#1%
 [burn@-2.49658];
 [eng@2.49721];
 burn@0.08409;
 eng@0.08564;
 %BC#1.C#2%
 [burn@1.92801];
 [eng@1.54718];
 burn@0.64117;
 eng@0.10539;
 %BC#1.C#3%
 [burn@-0.01351];
 [eng@0.00624];
 burn@0.37173;
 eng@0.36234;
 %BC#1.C#4%
 [burn@-1.72604];
 [eng@-2.05703];
 burn@0.28702;
 eng@0.62374;
 %BC#1.C#5%
 [burn@2.48742];
 [eng@-2.50084];
 burn@0.33606;
 eng@0.33277;
 %BC#2.C#1%
 [burn@-2.49658];
 [eng@2.49721];
 burn@0.08409;
```

```
  eng@0.08564;
  %BC#2.C#2%
  [burn@1.92801];
  [eng@1.54718];
  burn@0.64117;
  eng@0.10539;
  %BC#2.C#3%
  [burn@-0.01351];
  [eng@0.00624];
  burn@0.37173;
  eng@0.36234;
  %BC#2.C#4%
  [burn@-1.72604];
  [eng@-2.05703];
  burn@0.28702;
  eng@0.62374;
  %BC#2.C#5%
  [burn@2.48742];
  [eng@-2.50084];
  burn@0.33606;
  eng@0.33277;!
!!The L2 profiles are simply defined by the following code
%BETWEEN%
%Overall%
C on BC;
OUTPUT:
STDYX SAMPSTAT CINTERVAL RESIDUAL svalues TECH1 TECH7 TECH11 TECH14;
```

Cross-Level Profiles (Contextual or Climate) *using Fixed L1 Profiles and Freely Estimated Between Group Means and Variances.*

```
Data:
File is Data.dat;
Variable:
Names are X1 X2 ID Group;
MISSING are all (-999);
IDVAR = ID;
USEV = X1 X2 MX1 MX2;
CLASSES = BC(2) WC(2);
Cluster = Group;
Between =BC MX1 MX2;
Within= WC X1 X2;
Define:
MX1 = Cluster_mean (X1);
MX2 = Cluster_mean (X2);
Center X1 X2 MX1 MX2 (Grandmean); !Adjust centering to Groupmean for climate constructs.
ANALYSIS:
TYPE = MIXTURE Twolevel;
ESTIMATOR = MLR;
Process = 4;
Starts = 10000 1000 100;
STITERATIONS = 1000;
MODEL:
  %WITHIN%
  %Overall%
  BURN ENG;
  %BETWEEN%
  %Overall%
  MBURN MENG;
!Once the final solution is selected add the following line of code to obtain the composition of L1 profiles across L2 units:
!WC on BC;
  MODEL WC:
  %WITHIN%
  %WC#1%
  [burn@-2.49658];
  [eng@2.49721];
  burn@0.08409;
  eng@0.08564;
  %WC#2%
  [burn@1.92801];
  [eng@1.54718];
  burn@0.64117;
  eng@0.10539;
  %WC#3%
  [burn@-0.01351];
  [eng@0.00624];
  burn@0.37173;
  eng@0.36234;
  %WC#4%
  [burn@-1.72604];
  [eng@-2.05703];
  burn@0.28702;
  eng@0.62374;
  %WC#5%
```

```
  [burn@2.48742];
  [eng@-2.50084];
  burn@0.33606;
  eng@0.33277;
  Model BC:
  %Between%
  %bc#1%
  [MBURN MENG];
  MBURN MENG;
  %bc#2%
  [MBURN MENG];
  MBURN MENG;
OUTPUT:
STDYX SAMPSTAT CINTERVAL RESIDUAL svalues TECH1 TECH7 TECH11 TECH14;
```

Cross-Level Profiles (Climate) *Estimated using Doubly Latent Factor Scores and Freely Estimated Between Profile Means and Variances*

```
Data: File is Fscores.dat;
Variable:
Names are X1_W X2_W X1_B X2_B ID Group;
MISSING are all (-999);  IDVAR = ID;
! Variables are L1 (_W) and L2 (_B) factor scores from a preliminary measurement model.
! Factor scores will preserve the centering from the preliminary measurement model
USEV = X1_W X2_W X1_B X2_B;
CLASSES = BC(2) WC(2);
Cluster is Group;
Between = BC X1_B X2_B; Within = WC X1 X2;
ANALYSIS:
TYPE = MIXTURE Twolevel;
ESTIMATOR = MLR;
Process = 4;
Starts = 10000 1000 100;
STITERATIONS = 1000;
MODEL:
%WITHIN%
%Overall%
X1_W X2_W;
%BETWEEN%
%Overall%
X1_B X2_B;
!Once the final solution is selected add the following line of code to the model estimated from start values !to obtain the composition of L1 profiles across L2 units:
!WC on BC;
! The following section defines the L1 profiles.
! To constrain variances to equality, remove the line “X1_W X2_W;” from all profiles
MODEL WC:
%WITHIN%
%WC#1%
X1_W X2_W;
[X1_W X2_W];
%WC#2%
X1_W X2_W;
[X1_W X2_W];
! The following section defines the L2 profiles.
! To constrain variances to equality, remove the line “X1_B X2_B;” from all profiles
MODEL BC:
%BETWEEN%
%bc#1%
[X1_B@1.00];  [X2_B @-.800];
X1_B@.401;  X2_B@.110;
%bc#2%
[X1_B@-.50];  [X2_B @.700];
X1_B@.150;  X2_B@.230;
OUTPUT: STDYX SAMPSTAT CINTERVAL RESIDUAL svalues TECH1 TECH7 TECH11 TECH14;
```

Cross-Level Profiles (Contextual) *using Fixed L1 Profiles and Freely Estimated Between Group Means, Variances and Within Group Composition based on L1 Profiles.*

```
Data:
File is Data.dat;
Variable:
Names are X1 X2 ID Group;
MISSING are all (-999);
IDVAR = ID;
USEV = X1 X2 MX1 MX2;
CLASSES = BC(2) WC(2);
Cluster = Group;
Between =BC MX1 MX2;
Within= WC X1 X2;
Define:
MX1 = Cluster_mean (X1);
MX2 = Cluster_mean (X2);
Center X1 X2 MX1 MX2 (Grandmean);
ANALYSIS:
TYPE = MIXTURE Twolevel;
ESTIMATOR = MLR;
Process = 4;
Starts = 10000 1000 100;
STITERATIONS = 1000;
MODEL:
 %WITHIN%
 %Overall%
 BURN ENG;
 %BETWEEN%
 %Overall%
 MBURN MENG;
WC on BC;
 MODEL WC:
 %WITHIN%
 %WC#1%
 [burn@-2.49658];
 [eng@2.49721];
 burn@0.08409;
 eng@0.08564;
 %WC#2%
 [burn@1.92801];
 [eng@1.54718];
 burn@0.64117;
 eng@0.10539;
 %WC#3%
 [burn@-0.01351];
 [eng@0.00624];
 burn@0.37173;
 eng@0.36234;
 %WC#4%
 [burn@-1.72604];
 [eng@-2.05703];
 burn@0.28702;
 eng@0.62374;
 %WC#5%
 [burn@2.48742];
```

```
  [eng@-2.50084];
  burn@0.33606;
  eng@0.33277;
  Model BC:
  %Between%
  %bc#1%
  [MBURN MENG];
  MBURN MENG;
  %bc#2%
  [MBURN MENG];
  MBURN MENG;
OUTPUT:
STDYX SAMPSTAT CINTERVAL RESIDUAL svalues TECH1 TECH7 TECH11 TECH14;
```

***Cross-Level Profiles (Climate) Estimated using Doubly-Latent Factor Scores**, Fixed L2 Profiles, and Freely Estimated Between Profile Means, Variances, and Within-Group Composition based on L1 Profiles*

```
Data:
File is Fscores.dat;
Variable:
Names are X1_W X2_W X1_B X2_B ID Group;
MISSING are all (-999);
IDVAR = ID;
! Variables are L1 (_W) and L2 (_B) factor scores from a preliminary measurement model.
! Factor scores will preserve the centering from the preliminary measurement model
USEV = X1_W X2_W X1_B X2_B;
CLASSES = BC(2) WC(2);
Cluster is Group;
Between = BC X1_B X2_B;
Within = WC X1 X2;
ANALYSIS:
TYPE = MIXTURE Twolevel;
ESTIMATOR = MLR; Process = 4;
Starts = 10000 1000 100;
STITERATIONS = 1000;
MODEL:
%WITHIN%
%Overall%
X1_W X2_W;
%BETWEEN%
WC on BC;
%Overall%
X1_B X2_B;
! The following section defines the L1 profiles.
! To constrain variances to equality, remove the line “X1_W X2_W;” from all profiles
MODEL WC:
%WITHIN%
%WC#1%
X1_W X2_W;
[X1_W X2_W];
%WC#2%
X1_W X2_W;
[X1_W X2_W];
! The following section defines the L2 profiles.
! To constrain variances to equality, remove the line “X1_B X2_B;” from all profiles
MODEL BC:
%BETWEEN%
%bc#1%
[X1_B@1.00];  [X2_B @-.800];
X1_B@.401;  X2_B@.110;
%bc#2%
[X1_B@-.50];  [X2_B @.700];
X1_B@.150;  X2_B@.230;
OUTPUT: STDYX SAMPSTAT CINTERVAL RESIDUAL svalues TECH1 TECH7 TECH11 TECH14;
```

Cross-Level Profiles (Climate) Estimated using Manifest Scores*, Fixed L2 Profiles, and Freely Estimated Between Profile Means, Variances, and Within-Group Composition based on L1 Profiles*

```
Data:
File is Data.dat;
Variable:
Names are X1 X2 ID Group;
MISSING are all (-999);  IDVAR = ID;
USEV = X1 X2 MX1 MX2;
CLASSES = BC(2) WC(2);
Cluster = Group;
Between =BC MX1 MX2;
Within= WC X1 X2;
Define:
MX1 = Cluster_mean (X1);
MX2 = Cluster_mean (X2);
Center X1 X2 (Groupmean);
Center MX1 MX2 (Grandmean);
ANALYSIS:
TYPE = MIXTURE Twolevel;
ESTIMATOR = MLR; Process = 4;
Starts = 10000 1000 100;  STITERATIONS = 1000;
MODEL:
%WITHIN%
%Overall%
X1 X2;
%BETWEEN%
%Overall%
MX1 MX2; WC on BC;
! The following section defines the L1 profiles.
! To constrain variances to equality, remove the line "X1 X2;" from all profiles
MODEL WC:
%WITHIN%
%WC#1%
X1 X2;
[X1 X2];
%WC#2%
X1 X2;
[X1 X2];
! The following section defines the L2 profiles.
! To constrain variances to equality, remove the line "MX1 MX2;" from all profiles
MODEL BC:
%BETWEEN%
%BC#1%
[MX1@1]; [MX2@-.6];
MX1@.7; MX2;@.3
%BC#2%
[MX1@-1.2]; [MX2@.95];
MX1@.5 MX2@.6;
OUTPUT: STDYX SAMPSTAT CINTERVAL RESIDUAL svalues TECH1 TECH7 TECH11 TECH14;
```

Additive and Dispersion Model (Contextual or Climate) with Predictors (P) and Outcomes (O) Assessed through Individual Ratings. *L2 Profiles Estimated from L1 Ratings, with Parameter Estimates Taken from the Previously Described Additive-Dispersion Models*

```
Data: File is Data.dat;
Variable:
Names are X1 X2 P1 O1 ID Group;
MISSING are all (-999);
IDVAR = ID;
USEV = X1 X2 MX1 MX2 MP1 MO1;
CLASSES = BC(2);
Cluster = Group;
Between = BC MX1 MX2 MP1 MO1;
DEFINE:
MX1 = Cluster_Mean (X1); MX2 = Cluster_Mean (X2);
MP1 = Cluster_mean (P1); MO1 = Cluster_Mean (O1);
!Using grand mean-centering for all variables.
Center P1 O1 X1 X2 (Grandmean); ! Change to Groupmean for climate constructs
Center MX1 MX2 MP1 MO1 (Grandmean); ! Change to Groupmean for climate constructs
ANALYSIS:
TYPE = MIXTURE Twolevel;
ESTIMATOR = MLR;
Process = 4;
Starts = 10000 1000 100;
STITERATIONS = 1000;
MODEL:
%WITHIN%
%Overall%
%BC#1%
X1@.5; X2.@.2;
%BC#2%
X1@.2; X2@.8;
%BETWEEN%
%Overall%
MP1 MO1;
!The following line uses MP1 to predict profile membership
BC ON MP1;
%BC#1%
[X1@1]; [X2@-.8];
X1@.10; X2@.4;
[MO1] (op1);
%BC#2%
[X1@-1.5]; [X2@1.4];
X1@.7; X2@.2;
[MO1] (op2);
!The following section will test if the mean outcome level differs across profiles.
MODEL CONSTRAINT:
NEW (diffo1);
Diffo1 = op1-op2;
OUTPUT: STDYX SAMPSTAT CINTERVAL RESIDUAL svalues TECH1 TECH7 TECH11 TECH14;
```

Dispersion-Heterogeneity Model with Predictors (P) and Outcomes (O) Assessed through Individual Ratings

(Example Built from Previous Models)

```
Data:
File is Data.dat;
Variable:
names are X1 X2 P1 O1 ID Group;
MISSING are all (-999);
IDVAR = ID;
USEV = X1 X2 P1 O1 MP1 MO1;
Between = BC MP1 MO1;
Within = X1 X2 P1 O1;
CLASSES = BC(2) WC(4);
Cluster is Group;
DEFINE:
Center X1 X2 (Grandmean);
! alternatively, replace "Grandmean" for "Groupmean" if group mean centering is required (climate).
MP1 = Cluster_Mean (P1);
MO1 = Cluster_Mean (O1);
!Group-mean center the L1 component of climate variables or Grand Mean for contextual variables
Center P1 O1 (Groupmean);
! Grand mean center the L2 component of all covariates.
Center MP1 MO1 (Grandmean);
ANALYSIS:
TYPE = MIXTURE Twolevel;
ESTIMATOR = MLR;
Process = 4;
Starts = 0;
STITERATIONS = 1000;
MODEL:
%WITHIN%
%OVERALL%
WC ON P1;
P1 O1;
%BC#1.WC#1%
[burn@-2.49658];
[eng@2.49721];
burn@0.08409;
eng@0.08564;
[O1] (wo1p1);
%BC#1.WC#2%
[burn@1.92801];
[eng@1.54718];
burn@0.64117;
eng@0.10539;
[O1] (wo1p2);
%BC#1.WC#3%
[burn@-0.01351];
[eng@0.00624];
burn@0.37173;
eng@0.36234;
[O1] (wo1p3);
%BC#1.C#4%
[burn@-1.72604];
[eng@-2.05703];
burn@0.28702;
```

```
eng@0.62374;
[O1] (wo1p4);
%BC#1.C#5%
[burn@2.48742];
[eng@-2.50084];
burn@0.33606;
eng@0.33277;
[O1] (wo1p5);
%BC#2.WC#1%
[burn@-2.49658];
[eng@2.49721];
burn@0.08409;
eng@0.08564;
[O1] (wo1p1);
%BC#2.WC#2%
[burn@1.92801];
[eng@1.54718];
burn@0.64117;
eng@0.10539;
[O1] (wo1p2);
%BC#2.WC#3%
[burn@-0.01351];
[eng@0.00624];
burn@0.37173;
eng@0.36234;
[O1] (wo1p3);
%BC#2.C#4%
[burn@-1.72604];
[eng@-2.05703];
burn@0.28702;
eng@0.62374;
[O1] (wo1p4);
%BC#2.C#5%
[burn@2.48742];
[eng@-2.50084];
burn@0.33606;
eng@0.33277;
[O1] (wo1p5);
%BETWEEN%
%Overall%
WC on BC;
BC ON MP1;
MP1 MO1
%BC#1%
[MO1] (bo1p1);
%BC#2%
[MO1] (bo1p2);
MODEL CONSTRAINT:
! calculate outcome differences for outcome 1 at L1
NEW (wdo1p1p2 wdo1p1p3 wdo1p1p4 wdo1p2p3 wdo1p2p4 wdo1p3p4);
wdo1p1p2 = wo1p1 - wo1p2;
wdo1p1p3 = wo1p1 - wo1p3;
wdo1p1p4 = wo1p1 - wo1p4;
wdo1p1p5 = wo1p1 - wo1p5;
wdo1p2p3 = wo1p2 - wo1p3;
wdo1p2p4 = wo1p2 - wo1p4;
```

```
wdo1p2p5 = wo1p2 - wo1p5;
wdo1p3p4 = wo1p3 - wo1p4;
wdo1p3p5 = wo1p3 - wo1p5;
wdo1p4p5 = wo1p4 - wo1p5;
! calculate outcome differences for outcome 1 at L2
NEW (bdo1p1p2);
bdo1p1p2 = bo1p1 - bo1p2;
OUTPUT:
STDYX SAMPSTAT CINTERVAL RESIDUAL svalues TECH1 TECH7 TECH11 TECH14;
```

Cross-Level Profiles (Contextual or Climate from L1 ratings) with Predictors (P) and Outcomes (O) Assessed through Individual Ratings *(Example Built from Previous Models)*

```
Data: File is LPA.csv;
Variable:
names are
ID TEAMID BURN ENG SOC ABS;
MISSING are all (-999);
IDVAR = ID;
USEV =
BURN ENG SOC ABS MBURN MENG MSOC MABS;
CLASSES = bc(5) WC(5);
Cluster is TEAMID;
Between are BC MBURN MENG MSOC MABS;
Within = WC BURN ENG SOC ABS;
Define:
MBURN = Cluster_mean (BURN);
MENG = Cluster_mean (ENG);
MSOC = Cluster_mean (SOC);
MABS = Cluster_mean (ABS);
Center BURN ENG SOC ABS(Grandmean); Change to Groupmean for climate constructs
Center MENG MBURN MSOC mabs (Grandmean);
ANALYSIS:
TYPE = MIXTURE Twolevel;
ESTIMATOR = MLR;
Process = 4;
!Starts = 0;
STITERATIONS = 1000;
!Convergence = .0005;
!H1Convergence = .0005;
!MConvergence = .0005;
ALGORITHM=INTEGRATION;
Integration = montecarlo;
MODEL:
%WITHIN%
%Overall%
BURN ENG;
WC on SOC;
SOC ABS;
%BETWEEN%
%Overall%
mburn@0.21342 (3);
meng@0.17016 (4);
WC on BC;
BC on MSOC;
MSOC MABS;
MODEL WC:
%WITHIN%
%WC#1%
[burn@-2.49658];
[eng@2.49721];
burn@0.08409;
eng@0.08564;
[ABS] (wo1p1);
%WC#2%
[burn@1.92801];
```

```
[eng@1.54718];
burn@0.64117;
eng@0.10539;
[ABS] (wo1p2);
%WC#3%
[burn@-0.01351];
[eng@0.00624];
burn@0.37173;
eng@0.36234;
[ABS] (wo1p3);
%WC#4%
[burn@-1.72604];
[eng@-2.05703];
burn@0.28702;
eng@0.62374;
[ABS] (wo1p4);
%WC#5%
[burn@2.48742];
[eng@-2.50084];
burn@0.33606;
eng@0.33277;
[ABS] (wo1p5);
Model BC:
%Between%
%bc#1%
[MBURN@-.256];
[MENG@1.800];
MBURN@.401;
MENG@.110;
[MABS] (bo1p1);
%bc#2%
[MBURN@.258];
[MENG@.197];
MBURN@.213;
MENG@.170;
[MABS] (bo1p2);
%bc#3%
[MBURN@-.014];
[MENG@.009];
MBURN@.038;
MENG@.030;
[MABS] (bo1p3);
%bc#4%
[MBURN@-1.247];
[MENG@-1.260];
MBURN@.042;
MENG@.039;
[MABS] (bo1p4);
%bc#5%
[MBURN@.339];
[MENG@-1.624];
MBURN@.046;
MENG@.125;
[MABS] (bo1p5);
MODEL CONSTRAINT:
! calculate outcome differences for outcome 1 at L1
```

```
NEW (wdo1p1p2);
wdo1p1p2 = wo1p1 - wo1p2;
NEW (wdo1p1p3);
wdo1p1p3 = wo1p1 - wo1p3;
NEW (wdo1p1p4);
wdo1p1p4 = wo1p1 - wo1p4;
NEW (wdo1p1p5);
wdo1p1p5 = wo1p1 - wo1p5;
NEW (wdo1p2p3);
wdo1p2p3 = wo1p2 - wo1p3;
NEW (wdo1p2p4);
wdo1p2p4 = wo1p2 - wo1p4;
NEW (wdo1p2p5);
wdo1p2p5 = wo1p2 - wo1p5;
NEW (wdo1p3p4);
wdo1p3p4 = wo1p3 - wo1p4;
NEW (wdo1p3p5);
wdo1p3p5 = wo1p3 - wo1p5;
NEW (wdo1p4p5);
wdo1p4p5 = wo1p4 - wo1p5;
! calculate outcome differences for outcome 1 at L2
NEW (bdo1p1p2);
bdo1p1p2 = bo1p1 - bo1p2;
NEW (bdo1p1p3);
bdo1p1p3 = bo1p1 - bo1p3;
NEW (bdo1p1p4);
bdo1p1p4 = bo1p1 - bo1p4;
NEW (bdo1p1p5);
bdo1p1p5 = bo1p1 - bo1p5;
NEW (bdo1p2p3);
bdo1p2p3 = bo1p2 - bo1p3;
NEW (bdo1p2p4);
bdo1p2p4 = bo1p2 - bo1p4;
NEW (bdo1p2p5);
bdo1p2p5 = bo1p2 - bo1p5;
NEW (bdo1p3p4);
bdo1p3p4 = bo1p3 - bo1p4;
NEW (bdo1p3p5);
bdo1p3p5 = bo1p3 - bo1p5;
NEW (bdo1p4p5);
bdo1p4p5 = bo1p4 - bo1p5;
```

Cross-Level Profiles (Climate) with Predictors (P) and Outcomes (O) from Doubly Latent Factor Scores
(Example Built from Previous Models)

```
Data:
File is Fscores.dat;
Variable:
Names are X1_W X2_W X1_B X2_B P1_W O1_W P1_B O1_B ID Group;
MISSING are all (-999);
IDVAR = ID;
! Variables are L1 (_W) and L2 (_B) factor scores from a preliminary measurement model.
! Factor scores will preserve the centering from the preliminary measurement model
USEV = X1_W X2_W X1_B X2_B P1  O1 P1_B O1_B ;
CLASSES = BC(2) WC(2);
Cluster is Group;
Between = BC X1_B X2_B P1_B O1_B;
Within = WC X1 X2 P1 O1;
ANALYSIS:
TYPE = MIXTURE Twolevel;
ESTIMATOR = MLR;
Process = 4;
Starts = 10000 1000 100;
STITERATIONS = 1000;
MODEL:
%WITHIN%
%Overall%
X1_W X2_W;
WC ON P1;
P1 O1;
%BETWEEN%
%Overall%
WC on BC;
X1_B X2_B;
BC ON P1_B;
P1_B O1_B;
! The following section defines the L1 profiles.
! To constrain variances to equality, remove the line “X1_W X2_W;” from all profiles
MODEL WC:
%WITHIN%
%WC#1%
X1_W@1 X2_W@-1;
[X1_W@.9 X2_W@.5];
[O1] (wo1p1);
%WC#2%
X1_W@-1 X2_W@1;
[X1_W@.5 X2_W@.2];
[O1] (wo1p2);
! The following section defines the L2 profiles.
! To constrain variances to equality, remove the line “X1_B X2_B;” from all profiles
MODEL BC:
%BETWEEN%
%BC#1%
[X1_B@.5 X2_B@-.3];
X1_B@.3 X2_B@.2;
[O1_B] (bo1p1);
%BC#2%
[X1_B@-.7 X2_B@.2];
X1_B@.4 X2_B@.8;
```

```
[O1_B] (bo1p2);
MODEL CONSTRAINT:
! calculate outcome differences for outcome 1 at L1
NEW (wdo1p1p2);
wdo1p1p2 = wo1p1 - wo1p2;
! calculate outcome differences for outcome 1 at L2
NEW (bdo1p1p2);
bdo1p1p2 = bo1p1 - bo1p2;
OUTPUT:
STDYX SAMPSTAT CINTERVAL RESIDUAL svalues TECH1 TECH7 TECH11 TECH14;
```

Cross-Level Profiles (Climate or Contextual) Constructs Estimated using L1 Ratings with Predictors (P) Assessed through Individual Ratings whose effects are allowed to differ across (be moderated by) L2 profiles *(Example Built from Previous Model)*

```
Data:
File is Fscores.dat;
Variable:
Names are X1 X2 P1 P2 ID Group;
MISSING are all (-999);
IDVAR = ID;
USEV = X1 X2 MX1 MX2 P1 P2 MP1 MP2;
CLASSES = BC(2) WC(2);
Cluster is Group;
Between = MX1 MX2 MP1 MP2;
Within = WC X1 X2 P1 P2;
DEFINE:
MX1 = Cluster_Mean (X1);
MX2 = Cluster_Mean (X2);
MP1 = Cluster_Mean (P1);
MP2 = Cluster_Mean (P2);
!Group-mean center the L1 component of climate variables
Center P1 (Groupmean);
!Grand-mean center the L1 component of contextual variables
Center P2 X1 X2 (Grandmean);
! Grand mean center the L2 component of all covariates.
Center MP1 MP2 (Grandmean);
ANALYSIS:
TYPE = MIXTURE Twolevel;
ESTIMATOR = MLR;
Process = 4;
Starts = 10000 1000 100;
STITERATIONS = 1000;
MODEL:
%WITHIN%
%Overall%
X1_W X2_W;
! Predictors effects fixed at 0 in general to allow them to vary across profiles below.
WC ON P1@0 P2@0;
P1 P2;
%BETWEEN%
%Overall%
MX1@.5 MX2@.5;
BC ON MP1 MP2;
MP1 MP2;
! The following section defines the L1 profiles.
! To constrain variances to equality, remove the line "X1 X2;" from all profiles
MODEL WC:
%WITHIN%
%WC#1%
X1@.2 X2@.5;
[X1@1 X2@-1];
%WC#2%
X1@.6 X2@.5;
[X1@-1 X2@.8];
! The following section defines the L2 profiles.
```

```
! To constrain variances to equality, remove the line "MX1 MX2;" from all profiles
MODEL BC:
%BETWEEN%
%BC#1%
[MX1@.6 MX2@-.4];
MX1@.7 MX2@.2;
WC ON P1 P2;
%BC#2%
[MX1@-.7 MX2@.8];
MX1@.2 MX2@.6;
WC ON P1 P2;
OUTPUT:
STDYX SAMPSTAT CINTERVAL RESIDUAL svalues TECH1 TECH7 TECH11 TECH14;
```