Multiple-Group Analysis of Similarity in Latent Profile Solutions

Alexandre J.S. Morin*, Institute for Positive Psychology & Education, Australian Catholic University

John P. Meyer*, University of Western Ontario

Jordane Creusier, University of Amiens, CRIISEA EA 4286, France

Franck Biétry, University of Caen, IAE, NIMEC EA 969, France

* The first two authors (J.P.M. & A.J.S.M.) contributed equally to this article and both should be considered first authors.

Acknowledgements

Preparation of this article was supported by a research grants from the Australian Research Council (LP140100100) awarded to the first and second authors.

Corresponding author:
Alexandre J.S. Morin
Institute for Positive Psychology and Education
Australian Catholic University
Strathfield Campus, Locked Bag 2002, Strathfield, NSW 2135, Australia
Phone: (+61) 02 9701 4661
Email : Alexandre.Morin@acu.edu.au
Web: http://www.acu.edu.au/ippe/

This is the final version of a manuscript that has been accepted for publication on 06 November 2015:

Morin, A.J.S., Meyer, J.P., Creusier, J., & Biétry, F. (Accepted). Multiple-group analysis of similarity in latent profile solutions. *Organizational Research Methods*

Short Bios

Alexandre J. S. Morin, PhD, is Professor at the Institute for Positive Psychology and Education at the Australian Catholic University (Strathfield, NSW, Australia; http://ippe.acu.edu.au/). He defines himself as a lifespan developmental psychologist with broad research interests anchored in the exploration of the social and organizational determinants of psychological wellbeing, self-concept, and commitments at various life stages. His research interests are centered on methodological-substantive synergies aimed at illustrating the usefulness of powerful new statistical methods (including exploratory structural equation models, mixture models, longitudinal models, latent curve models, and multilevel models). Alexandre has published over 100 publications, some of which appear in lading journals such as *Journal of Management*, *Organizational Research Methods*, *Structural Equation Modeling*, *Annual Review of Clinical Psychology*, *Child Development*, *Journal of Educational Psychology*, *Developmental Psychology*, and *Addiction*.

John Meyer, Ph.D., is professor and chair of the graduate program in industrial and organizational psychology at the University of Western Ontario, London, Ontario, Canada. His research interests include employee commitment, work motivation, leadership, and organizational change. His work has been published in leading journals in the field of I/O psychology (e.g., *Journal of Applied Psychology, Personnel Psychology*) and management (e.g., *Academy of Management Journal, Journal of Management*). He is also co-author of *Commitment in the Workplace: Theory, Research and Application* (Sage Publications, 1997) and *Best Practices: Employee Retention* (Carswell, 2000), and co-editor of *Commitment in Organizations: Accumulated Wisdom and New Directions* (Routledge, 2009).

Jordane Creusier, **Ph.D.,** is associate professor at the Amiens Institute of Technology, France. He is interested in organizational behavior and especially in well-being at work and commitment. He is also interested in methodological research. He has completed his PhD in 2013. Before, he was a quality manager for 5 years in agribusiness industry. His work has been published best French Journals such as *M@n@gement* and *Revue de Gestion des Ressources Humaines.*

Franck Biétry, **Ph.D.,** is associate professor of Human Resource Management at the University of Caen, France. His research activity is devoted to the study of organizational behaviors and industrial relations with particular emphasis on the analysis of unions, well-being and commitment.

Abstract

Despite the increased popularity of person-centered analyses, no comprehensive approach exists to guide the systematic investigation of the similarity (or generalizability) of latent profiles, their predictors, and their outcomes, across subgroups of participants or time points. We propose a 6-step process to assess *configural* (number of profiles), *structural* (within-profile means), *dispersion* (within-profile variability), *distributional* (size of the profiles), *predictive* (relations between predictors and profile membership), and *explanatory* (relations between profile membership and outcomes) similarity. We then apply this approach to data on organizational commitment mindsets collected in North America (n = 492) and France (n = 476). This approach provides a rigorous method to systematically and quantitatively assess the extent to which a latent profile solution generalizes across diverse samples, such as in the cross-national comparison in our illustrative example, or the extent to which interventions or naturalistic changes may impact the nature of a latent profile solution. This approach also helps to identify the nature of any differences that might be present, thus providing richer interpretations of observed differences and ideas for future research.

Key words. Profiles, similarity, cross-national comparison, organizational commitment.

Over the years, many scholars have noted the importance of testing the extent to which research results generalize across meaningful subgroups of participants defined on the basis of age, gender, profession, culture, or other forms of diversity (e.g., Ayman & Korabik, 2010; Lukaszewski & Stone, 2012). For example, despite repeated calls for cross-cultural research (e.g., Gelfand, Erez, & Aycan, 2007; Schaffer & Riordan, 2003; Spector, Liu, & Sanchez, 2015), the bulk of organizational research continues to be conducted predominantly with Western samples (see Tsui, Nifadkar, & Ou, 2007).

Key to the realization of systematic quantitative comparisons of the results obtained across meaningful subgroups of employees is the availability of a proper methodological and statistical approach to guide these comparisons (e.g., Riordan & Vandenberg, 1994; Spector et al., 2015). Such an approach has long been available for *variable-centered* studies (e.g., regressions, confirmatory factor analyses – CFA; structural equation models – SEM). Such studies operate under the assumption that all individuals from a sample are drawn from a single population for which a single set of "averaged" parameters can be estimated (e.g., Millsap, 2011; Vandenberg & Lance, 2000). In this case, comparison of results across groups typically starts with the investigation of the equivalence of the measurement model underlying the constructs (in terms of number of factors, type of model, and global patterns of associations between items and factors), namely configural invariance. From a model of configural invariance, additional levels of invariance can be tested, typically in sequence. Measurement invariance is critical to the ability to use psychometric measures in practice for assessment purposes among members of the various groups (e.g., cultures, gender, etc.) considered, as well as for any group-based comparison conducted in the context of research activities, as these test are specifically designed to ascertain the extent to which measurement properties generalize across these multiple groups (Millsap, 2011). A lack of measurement invariance suggests that measurement biases are present and may lead to erroneous conclusions when the measures are used for group-based comparisons purposes.

Depending on the specific aim of the research or the assessment, the level of invariance required (weak, strong, or strict) will differ. Tests of weak invariance determine whether the factor loadings are the same across groups (i.e., whether the latent constructs have the same meaning), and form an important prerequisite for any group-based comparisons involving relationships among constructs, or variability levels on specific constructs. Tests of strong invariance determine whether the factor loadings and item intercepts are the same across groups (whether participants' levels on the items are equivalent when their levels on the latent constructs are the same), and are a critical prerequisite to the unbiased comparison of latent means across groups. Finally, tests of strict invariance determine whether the factor loadings, items intercepts, and items uniquenesses (which incorporate the degree of random measurement error present in the items) are the same across groups, indicating similar degrees of precision in measurement. While not critical in the context of comparisons conducted within latent variable models corrected for measurement errors, tests of strict invariance are central to the utilization of any form of psychometric measure for assessment purposes, or to the use of scale scores (e.g., means, sum) in the context of group-based comparisons. Once the appropriate level of invariance has been established, it can be used as the starting model for subsequent tests of the equivalence of latent variances, covariances, regressions, or means across targeted groups of employees.

To date, a similar approach has yet to be developed for *person-centered* analyses, which relax the assumption that all individuals are from the same underlying population, and consider the possibility that the sample reflects multiple subpopulations characterized by different sets of parameters (e.g., Morin, Morizot, Boudrias, & Madore, 2011; Muthén, 2002). Among the various person-centered methodologies currently available, latent profile analysis (LPA) is arguably the most flexible and can be used to address a wide array of person-centered research questions (for a brief overview of more traditional approaches, see the online supplements). LPA aims to detect relatively homogeneous subpopulations of participants presenting qualitatively and quantitatively distinct configurations on a set of indicators (see Morin & Marsh, 2015). These subpopulations are referred to as *latent profiles*, and are represented as the categories of an underlying categorical latent variable. LPA is thus similar to a CFA, except that the latent variable is categorical (reflecting profiles that represent groupings of persons) rather than continuous (reflecting latent factors that represent groupings of variables) (Lubke & Muthén, 2005). These latent profiles are prototypical in nature, with each employee having a probability of membership in a profile group based on their degree of similarity with the profile's specific configuration.

Person-centered analyses are becoming increasingly popular in the organizational sciences (e.g., Dumenci, 2011; Lawrence & Zyphur, 2011; Meyer, Morin, & Vandenberghe, 2015; Wang & Hanges, 2011). However, they suffer from the same limitations as variable-centered analyses in terms of generalizability. In this case, the question is whether the profiles detected within a sample are meaningful, will replicate in other samples drawn from the same population, or will generalize across known subpopulations (e.g., gender, culture). These limitations pose a particular problem to person-centered analyses given that it is always hard to rule out the possibility that spurious profiles might emerge due to violations of the model's distributional assumptions when in fact none exist in the population (e.g., Bauer & Curran, 2003). Perhaps even more importantly, it is technically impossible to empirically distinguish a LPA model including k profiles from a common factor model including $k - 1$ factors (e.g., Steinley & McDonald, 2007) because both have identical covariance implications and can be considered "equivalent" models (e.g., Cudeck & Henly, 2003). Although prioritizing one model over the other remains a theoretical decision (Borsboom, Mellenbergh, & Van Heerden, 2003), the only way to really support a substantive interpretation of the profiles is to embark on a process of construct validation to demonstrate that the profiles either meaningfully relate to covariates, or can reliably be replicated across samples, time, and cultures (Kam, Morin, Meyer, & Topolnytsky, 2015; Marsh, Lüdtke, Trautwein, & Morin, 2009; Muthén, 2003). However, in order to systematically assess the extent to which a latent profile solution will replicate across these samples, time points, or cultures, a comprehensive approach to guide the investigation of profile similarity is required.

A Comprehensive Approach to Investigate the Similarity of Profile Solutions across Samples

So far, only a partial approach to guide the investigation of the similarity of profile solutions across subpopulations has been provided for latent class analyses where the profile indicators are categorical rather than continuous (e.g., Eid, Langeheine, & Diener, 2003; Kankaraš, Moors, & Vermunt, 2011; Kankaraš, Vermunt, & Moors, 2011). In this three-step approach, the first step tests whether the same numbers of latent classes or profiles are extracted in each group. The second step tests whether the response probabilities (the frequency of endorsement of each response category of the categorical profile indictors in a specific profile) are the same in each group. Finally, the last step tests whether the relative size of the latent profiles are the same across groups. The approach we propose here takes into account the fact that person-centered studies are often conducted with continuous indicators, so that the second step has been revised for LPA to allow independent tests of the similarity of the indicators' means and variances across groups. Furthermore, keeping in mind that demonstrating meaningful relations with covariates is a key aspect of establishing the construct validity of extracted profiles (Marsh et al., 2009; Muthén, 2003), we also expand the earlier approach to include tests of the similarity of the relations between profiles and hypothesized antecedents and outcomes.

Our objective in this article is to present organizational researchers with an easily accessible, non-technical introduction and illustration of the expanded approach than can easily be applied by any researcher already familiar with LPA including covariates. This expanded approach is summarized in Table 1. Although it focuses on the similarity of latent profile solutions across distinct groups of participants, the approach can easily be adapted to test the similarity of profiles over time (i.e., within latent transition analyses, e.g., Kam et al., 2015). In the online supplements, we provide annotated Mplus (Muthén & Muthén, 2013) scripts for all tests of similarity of latent profiles across groups, or time points.

Measurement Invariance and Profile Similarity. In presenting our approach, we intentionally use the term *similarity*, as opposed to *invariance*, to emphasize a key distinction between our objectives and those reflected in the variable-centered measurement invariance tradition. Indeed, tests of measurement invariance are intended to assess possible biases (i.e., problems) in measurement instruments when applied across distinct populations and time points. Evidence for measurement invariance is critical for meaningful comparisons across groups or times, including the comparisons involved in our approach. In contrast, the approach presented here involves a set of comparisons that allow for the detection of similarities and differences across groups or time. Although, as described below, evidence of similarity at some stages is required for progression to subsequent stages, differences do not represent an inherent limitation in the data, but rather indicate limits to the generalizability of profile solution that may deserve further exploration. In sum, evidence of both similarity and differences can provide important, albeit different, directions for subsequent investigation.

Generalized Structural Equation Modeling (GSEM). LPA has been around for quite some time (e.g., Lazarsfeld, & Henry, 1968), and is part of the greater family of mixture models (McLachlan & Peel, 2000) which provide a model-based approach to clustering based on the assumption that a sample includes a mixture of subpopulations. The flexibility of mixture models comes from their integration into the Generalized Structural Equation Modeling (GSEM) framework (Muthén, 2002), which allows for the estimation of relations between any type of continuous and categorical observed and latent variables. Although our focus is on LPA, the approach presented here is only made possible by the integration of LPA into the GSEM framework.

The multiple group approach typically used in variable-centered analyses theoretically allows for the estimation of completely distinct models (based on the same set of indicators) in the various groups considered. In contrast, the multiple-group approach to LPA involves the addition, made possible by the GSEM framework, of another latent categorical variable to the model for which group membership is non-probabilistic and defined a priori to represent the subgroups across which to test the similarity of profile solutions. This "known" latent categorical variable (cg) is allowed to predict the latent categorical variable representing the profiles (c), meaning that probability of membership into the various profiles (c) is allowed to differ as a function of group membership (cg). Because of this, the LPA model is required to be based on the same indicators, and to include the same number of profiles, across all known groups (reflected in cg) – making this approach slightly more restrictive than the multiple group approach to variable-centered analyses. However, the specific characteristics of these profiles (in terms of within-profile characteristics, relative size of the profiles, or relationships with covariates) are still allowed to differ across groups. In comparison, testing the longitudinal invariance of LPA solutions requires the utilization of latent transition analyses (also made possible by the GSEM framework), in which distinct latent categorical variables (c1 and c2) are estimated at each time point. In contrast to the multiple group approach, latent transitions analyses can be extended to tests of the longitudinal connections between any forms of mixture model, whether or not they are based on the same set of indicators or number of profiles (e.g., Nylund-Gibson, Grimm, Quirk, & Furlong, 2014). The approach proposed here has been developed to be applicable to tests of profile similarity conducted across groups of participants or time points, although the longitudinal approach provides more flexibility for tests of partial invariance. However, the basic approach has broad relevance to other forms of mixture models (e.g., factor mixture analyses, mixture regression analyses), often pending only a few minor adjustments aiming to test the similarity of the extra parameters estimated in these models across groups or time points.

Testing the Configural and Structural Similarity of the Profiles. The first step tests for the *configural* similarity of the profiles. This step determines whether the same number of latent profiles can be identified in all groups, using the same overarching model (i.e., based on the same indicators, with or without correlated uniquenesses, with or without the inclusion of method factors, etc.). To test for configural similarity, a series of latent profile solutions are estimated separately in each group, using the same set of profile indicators, to determine the optimal solution (in terms of number of profiles). Configural similarity is established when the optimal solution for both groups includes the same number of profiles (see later discussion on how to identify optimal solutions), and makes it possible to test whether the profiles themselves are similar across groups. In contrast, configural differences mean that the latent profile solution differs across groups, which are characterized by a different number of profiles. The second step tests for the *structural* similarity of the profiles. This step determines whether the profiles are characterized by similar levels on the profile indicators across groups. Evidence of structural similarity means that the nature of the profiles is similar across groups, and represents a logical prerequisite to investigation of other types of similarities or differences. In contrast, when the structure differs, then the profiles do not generalize and have a different meaning across groups.

Configural or structural differences might indicate problems with the operationalization of the constructs, perhaps suggesting the need to revisit preliminary variable-centered tests of measurement invariance to ensure that the profile indicators provide an unbiased reflection of the same construct across groups. Alternatively, configural or structural differences might also reflect true differences in the nature of the profiles themselves, i.e., in the ways the variables combine as a function of group characteristics (e.g., value differences in cross-cultural research; effects of an intervention in longitudinal research). If so, and assuming that random sampling variation can be ruled out as an explanation (ideally through replication), the researcher may need to use and/or develop theory to help explain these differences to serve as a guide for future research.

Arguably, profile similarity does not need to be an all or nothing phenomenon. For instance, in many contexts, it may prove particularly informative to pursue tests of partial similarity for a subset of profiles (i.e., keeping similarity constraints only for a subset of profiles and allowing the remaining profiles to differ). However, as reasonable as this approach might seem, the approach described here for multiple-group comparisons of latent profile solutions only makes it possible to test profile similarities when the same number of latent profiles are estimated in the various subgroups (see above discussion of the multiple group approach implemented in GSEM). Thus, pending further statistical advances in the implementation of the multiple groups approach to LPA, configural differences indicate that the only solution is to rely on separate LPA models, and to adopt a more qualitative emic comparison process in order to more systematically investigate group-specific differences. Nevertheless, when more than two groups are considered, it is still possible to observe configural similarities for a subset of these groups to which the next steps of the approach may be applied. Similarly, in the context of longitudinal comparisons, it remains possible to implement a model including a different number of latent profiles at each measurement point, and to systematically investigate whether a subset of the identified profiles may prove to be similar across time points.

When the results suggest the presence of structural differences in LPA solutions, tests of partial similarity may be conducted on a subset of profiles (i.e., such as constraining all profiles save one to be similar, then all profiles save two, etc.), indicators (i.e., such as in relaxing equality constraints on one profile indicator at a time), or groups (when more than two groups are considered). These models of partial structural similarity can then be retained for the next steps of the approach proposed here, which can then be applied to the structurally similar subset of profiles. For instance, if structural differences are limited to two profiles out of five, then the remaining tests of dispersion similarity can be limited to the remaining structurally-similar profiles. Alternatively, if structural differences are limited to a single indicator, then tests of dispersion similarity can be conducted on the remaining indicators. In these examples, however, nothing precludes tests of distribution similarity across all profiles, as even structurally different profiles may still be of the same size. Finally, when structural similarity holds for a subset of groups, then all subsequent tests may be conducted on this subset of groups.

Because tests for configural and structural similarity have to do with the nature of the profiles themselves, we position them as prerequisite to the following steps in the approach. Arguably, in most situations, observing that subgroups are characterized by distinct profiles is likely to render meaningless any further tests of whether these different profiles are equally homogenous, are of the same size, and similarly relate to meaningful covariates. However, we recognize that exceptions may exist, and that some situations may call for a different ordering of the tests proposed here. We see the ordering proposed here as a rough guideline rather than as a rigid 'golden rule' (Marsh, Hau, & Wen, 2004), and reinforce that theory and expectations should guide the decision whether to follow this sequence. The next steps may still apply to the subset of structurally similar profiles in models of partial similarity, to the subset of groups for which configural and structural similarity has been established, or to the subset of structurally similar profiles in a longitudinal model (irrespective of whether configural similarity is supported or not).

Testing the Dispersion and Distributional Similarity of the Profiles. The third step of the proposed approach tests the *dispersion similarity* of the structurally similar profiles. This step determines whether the within-profile variability of the indicators is similar across groups, and is not appropriate for latent class analyses (i.e., when profile indicators are categorical) as it requires the ability to estimate residual within-profile variability not explained by the latent categorical variable representing the profiles. Latent profiles are prototypical in nature and group individuals based on their similarity to the prototypical profile structure (as reflected by the mean of each indicator defining the profile). Thus, latent profile solutions do not assume that all individuals within a profile present the exact same score on each indicator, but allow for the estimation of within-profile variability. Testing for the dispersion similarity thus determines whether the identified profiles are more or less homogenous (e.g., internally consistent), and is not a pre-requisite for the other steps forming the proposed approach. For example, in a cross-cultural comparison study, dispersion differences might be due to differences in tightness (vs. looseness) in the regulation of cultural norms (Gelfand, Nishii, & Raver, 2006). That is, in *tighter* cultures, there is more pressure on individuals to comply with cultural norms, and this might reduce inter-individual variability around prototypical profiles. In longitudinal analyses, it might be that degree of dispersion reflects increasing or decreasing variability in work conditions that, although not sufficient to cause change in profiles, causes greater variability within profile group. Similarly, reduced levels of within-profile variability might reflect the influence of organizational socialization processes (Van Maanen, & Schein, 1979; Saks, Uggerslev, & Fassina, 2007).

The fourth step assesses the *distributional similarity* of the profiles. This step tests whether the relative size of the profiles is similar across groups. Distributional similarity shows that the relative frequency of the various profiles is similar across groups, while distributional differences suggests that some profiles are more or less prevalent in some groups than others. Distributional similarity is also not a pre-requisite to the other steps of the proposed approach. Distributional differences could again reflect the impact of cultural influence (or interventions in longitudinal research) that may limit the expression of specific profiles versus others, making them more or less frequent than in some cultural groups (or time points). Thus, evidence of distributional differences might be particularly interesting in that it could lead to investigation of potential determinants of the differences. Such an investigation would be further facilitated by the tests of similarity in steps five and six described below.

Taken together, neither of these two steps is necessary to the other tests of similarity forming the proposed approach. However, we recommend that they be conducted in this specific order, as each stage builds on the results from the previous one so that allowing profiles to present various degrees of within-class variability when this is not necessary is likely to impact the relative frequency of the profiles. As long as there are reasons to expect the profiles to generalize across subgroups, we believe that these two stages are likely to reveal the most frequent differences. For these two steps, it might be particularly informative to test for partial similarity to see whether dispersion similarity holds for specific profiles, indicators, or groups, as well as whether distribution similarity holds for a subset of profiles, or groups.

Testing the Predictive and Explanatory Similarity of the Profiles. The steps described in this section are ordered only for purposes of discussion, can be conducted as required in any order, and are only appropriate when the study aims to assess the relations between the latent profiles and covariates (predictors and/or outcomes). More precisely, whenever researchers are only interested in testing the similarity of a profile solution across groups or time points, then the previous four steps are sufficient. The last two steps are only useful when researchers also seek to test whether the relations between profiles and covariates are similar across groups or time points. In this context, once configural and structural similarity have been established, and, where appropriate, the degree of dispersion and distributional similarity of the profiles has been determined, covariates can be added to the most "similar" model from the foregoing steps. Although we acknowledge that statistical knowledge and recommendations in this area are evolving, our current recommendation is to include covariates to LPA models once the final unconditional solution has been selected (we discuss the reasons for this recommendation more extensively when address the implementation of these steps), hence the suggestion to complete all priori steps before including covariates to the model. The fifth step tests for the *predictive similarity* of the profiles. Evidence for predictive similarity suggests that the relations between predictors and profiles are the same across groups. In contrast, predictive differences suggest that the grouping variable moderates these relations. For example, different managerial practices might be necessary to foster optimal profiles for men and women, younger and older employees, or employees in different cultures. The sixth step assesses the *explanatory similarity* of the profiles. This step tests whether the relations between profiles and outcomes replicate across groups or, alternatively, if the grouping variable moderates the relations between profiles and outcomes. For example, desirable profiles in more individualistic cultures might lead to greater levels of organizational citizenships behaviors (Organ, 1988; Williams & Anderson, 1991) oriented toward other individuals (colleagues, supervisors) whereas they could lead to greater levels of organizational citizenship behaviors oriented toward the organization as a whole (i.e., the collectivity) in more collectivist cultures. Evidence of predictive or explanatory differences thus suggests that profile membership is differentially related to predictors or outcomes across groups. In this regard, differences may suggest that organizational cultures, norms, goals, values or even changes might impact the way predictors or outcomes relate to employees' profiles, even when these profiles remain essentially unchanged.

Evidence of predictive and explanatory similarity is particularly relevant for practical applications of knowledge based on the person-centered approach. Evidence that similar profiles exist in different groups is certainly useful to generate a common language and conceptual framework across groups, and documents the extent to which the identified profiles reflect something that is inherent to human nature. However, a major objective of developing this knowledge is to be able to convert it to practical applications, which requires documenting the likely consequences of these profiles, and demonstrating ways to influence their development. In this regard, it is critical to consider whether knowledge of likely determinants and consequences of profile membership, and resulting interventions, can be expected to generalize across groups. Evidence of predictive and explanatory similarity indicates that generalization is likely, whereas evidence of differences suggests that intervention strategies and/or expected outcomes will vary across groups and require independent investigation and tailored management practices. As for the previous steps, models of partial explanatory (i.e., on a subset of outcomes, profiles, or groups) or predictive (i.e., on a subset of predictors or groups) similarity may be pursued. The results from the non-similar part of these models can then be interpreted to reflect the fact that group membership moderates the relations between predictors, profiles, and outcomes.

Summary. In summary, this six-step procedure provides a comprehensive approach for researchers interested in assessing group similarities and differences in person-centered research. Being able to assess profile similarity can be important for many reasons. First, it provides a way to systematically assess the extent to which a latent profile solution will generalize across samples or time points, which has previously been identified as a key source of evidence in support of the construct validity and meaningfulness of a latent profile solution (e.g., Kam et al. 2015; Muthén, 2003). Similarly, it makes it possible to quantitatively compare latent profile solutions obtained in samples from different cultures, or before and after some key transition point (e.g., promotion) or intervention (e.g., organizational change), to rigorously assess the nature of these cultural or temporal influences on latent profile solutions. In these contexts, profile differences can place limits on the nature of comparisons that are possible, but can also offer directions for future research to investigate the sources or implications of the observed differences. In the next section, we illustrate the application and interpretation of this six-step procedure.

ILLUSTRATIVE EXAMPLE

We illustrate the application of the foregoing approach in a cross-cultural comparison of profiles of employees' commitment to their organizations using samples from France and North America. We also consider the relations between profile membership and employees' demographic characteristics and perceptions of human resources management (HRM) practices as predictors and turnover intentions and work exhaustion as outcomes. Within the organizational sciences, commitment is arguably the area where the person-centered approach has been the most developed, due to early theory developments that have generated a far-reaching interest (for a recent review, see Meyer, Stanley, & Vandenberg, 2013), making this area particularly well-suited to this illustration. For present purposes, we investigate how the three organizational commitment mindsets identified by Meyer and Allen (1991), affective (desire-based), normative (obligation-based) and continuance (cost-based), combine to form profiles. For interested readers, we provide a discussion of relevant theory and implications in the online supplements.

Participants and Procedures

The data were collected as part of a large online panel survey of North American and French employees recruited individually on the web. In North America, our survey was individually sent to a total of 973 employees of US organizations (covering most employment sectors), 492 (50.5 %) of whom returned completed questionnaires. In France, the French version of the same online survey was individually sent to a total of 991 employees, of whom 476 (48 %) returned completed questionnaires. For all instruments, we started from a validated English version of the measures and developed the French version using a formal translation back-translation method conducted by independent bilingual experts

(Brislin, 1986). All discrepancies between versions were adjusted by the experts in collaboration with the research team. Participants from both countries were asked to report their gender (North America: 58.1% female; France: 59.7% female), tenure (North America: 25.61% had two years or less; 30.69% had 2 to 5 years; 19.92% had 6 to 10 years; 23.78% had 10 years or more; France: 25.21% had two years or less; 24.16% had 2 to 5 years; 22.27% had 6 to 10 years; 28.36% had 10 years or more) and level of education (North America: 52.03% had a high school diploma or less, 35.37% had an undergraduate diploma, 12.60% had a graduate diploma; France: 9.45% had a high school diploma or less, 26.47% had an undergraduate diploma, 64.08% had a graduate diploma).

Measures

Commitment to the organization was assessed using a shortened 9-item version of Meyer, Allen and Smith's (1993) affective (AC; 3 items, e.g., "*I feel emotionally attached to this organization*"), normative (NC; 3 items, e.g., "*I would feel guilty if I left my organization now*"), and continuance (CC; 3 items, e.g., "*It would be very hard for me to leave my organization right now, even if I wanted to*") commitment scales. We used six items from Kehoe and Wright's (2013) scale to assess abilities-oriented (2 items, e.g., "*The company hires only the very best people for this job*"), opportunities-oriented (2 items, e.g., "*Associates in this job are allowed to make important work related decisions such as how the work is done or implement new ideas*") and motivation-oriented (2 items, e.g., "*Total pay for this job is the highest for the type of work in the area*") HRM practices. These items were selected from the larger Kehoe and Wright instrument in order to obtain a short abbreviated measure of the HRM practices best representing the model that guided previous meta-analyses (Combs, Liu, Hall, & Ketchen, 2006; Jiang, Lepak, Hu & Baer, 2012). To assess potentially relevant outcomes of the commitment mindset profiles, we included a 3-item measure of turnover intentions (Mobley, Griffeth, Hand, & Meglino, 1979; e.g. "*I am actively looking for another job*"), as well as a 5-item measure of work exhaustion (Schaufeli, Leiter, Maslash, & Jackson, 1996; e.g., "*I feel emotionally drained from my work*"). Responses to all instruments were made on a 7-point Likert-type scale ranging from *strongly disagree* (1) to *strongly agree* (7).

Confirmatory factor analyses (CFA) supported the adequacy of the a priori measurement models in both the North American and French sample: (a) Commitment (CFI and TLI ≥ .950; RMSEA ≤ .080); (b) HRM (CFI and TLI ≥ .900; RMSEA ≤ .080); (c) outcomes (CFI and TLI ≥ .900; RMSEA ≤ .080). These models all involved the estimation of correlated factors defined by their a priori items, without cross-loading or correlated uniquenesses. From these models, composite reliability was calculated with McDonald's (1970) omega (ω), which is similar to alpha but has the advantage of taking into account the strength of association between items and constructs as well as item-specific measurement errors (Sijtsma, 2009). Supporting the strength of the measurement model, these coefficients were all relatively high and satisfactory for the commitment (ω = 0.73 to 0.95) and outcome (ω = 0.91 to 0.95) measures, but were relatively low for the HRM measures (ω = 0.51 to 0.72).

Rather than using scale scores to estimate the commitment profiles, commitment factor scores were used as inputs for the main analyses. Mixture models (including LPAs) are usually estimated using scale scores (sum, or mean) on the profile indicators (here the commitment mindsets). Although it is well known that using latent variables controlled for measurement error (i.e., models where the items are used to estimate latent factors, which are then used as profile indicators) provides a stronger approach than the use of scale scores (e.g., Bollen, 1989), applications of fully-latent mixture models are few (e.g., Morin, Scalas, & Marsh, 2015). In fact, given the complexity of mixture models, it is often impossible in practice to implement a fully-latent approach to their estimation. An alternative, which is becoming more frequent in recent applications of mixture models, is to rely on factor scores saved from preliminary measurement models (e.g., Kam et al., 2015; Morin & Marsh, 2015). Factor scores do not explicitly control for measurement errors the way latent variables do. However, by giving more weight to items presenting lower levels of measurement errors, they still provide a partial implicit control for measurement errors, making them a stronger alternative than scale scores, particularly when using modern approaches to their estimation such as the regression approach implemented in Mplus (Skrondal & Laake, 2001). An added advantage of factors scores is that, when they are estimated from more complex measurement models (including method controls, cross loadings, bifactor models, etc., which is not the case in this demonstration), they tend to preserve the nature of the underlying measurement structure better than scale scores. More importantly, measurement models can be used to systematically assess the measurement invariance of the measures across time or groups (Millsap, 2011), and save factor scores from the most invariant measurement model can then be saved. This approach ensures comparability of the results over groups or time points for multiple-group, or longitudinal, applications of mixture models. In the present study, to ensure comparability in the commitment measures across countries, factors scores where saved from a model of strict measurement invariance (i.e., invariant loadings, intercepts, and uniquenesses) across countries (Millsap, 2011). Details on these tests, as well as correlations, means, variability, and composite reliability coefficients (with their 95% bias-corrected bootstrap confidence intervals, based on 10,000 bootstrap samples; e.g. Raykov, 2009) for all variables are reported in the online supplements.

Latent Profile Analyses

Latent Profile Analyses (LPA; Muthén, 2002) were conducted based on the factor scores reflecting levels of AC, NC, and CC, using the robust maximum likelihood (MLR) estimator available in Mplus 7.11 (Muthén & Muthén, 2013). The simpler country-specific models were estimated using 5000 random sets of start values with 100 iterations, and the 200 best solutions retained for final stage optimization (Hipp & Bauer, 2006). These values were respectively increased to 10,000, 500, and 500 in the more complex cross-national models. The means of the commitment variables were freely estimated in all profiles. Alternative models in which the variances of these variables were freely estimated in all profiles were also estimated (see e.g., Morin, Maïano et al., 2011). However, these models converged on improper solutions or did not converge, which suggests that they may have been overparameterized (Bauer & Curran, 2003; Chen, Bollen, Paxton, Curran, & Kirby, 2001) and that the more parsimonious fixed-variance models may be superior. Fixed-variance models were therefore used in subsequent analyses. Mplus code for all models is presented in the online supplements.

An important challenge in LPA is determining the number of profiles in the data. Statistical tests and indices are available to help this decision (McLachlan & Peel, 2000): the Akaike Information Criterion (AIC), the Bayesian information criterion (BIC), the Consistent AIC (CAIC), the sample-adjusted BIC (ABIC), the Lo, Mendell, and Rubin (2001) likelihood ratio test (LMR), and the Bootstrap Likelihood

Ratio Test (BLRT). Overall, a lower value on the AIC, CAIC, BIC and SABIC suggests a better-fitting model. Both the LMR and BLRT are tests that compare a k-profile model with a k-1-profile model. A significant p value indicates that the k-1-profile model should be rejected in favor of a k-profile model. Simulation studies indicate that the CAIC, the BIC, the ABIC, and the BLRT are particularly effective in choosing the model which best recovers the sample's true parameters, whereas the AIC is not and presents a marked tendency for overextraction (e.g., Henson, Reise, & Kim, 2007; McLachlan & Peel, 2000; Nylund, Asparouhov, & Muthén, 2007; Peugh & Fan, 2013; Tein, Coxe, & Cham, 2013; Tofighi & Enders, 2008; Tolvanen, 2007; Yang, 2006). For this reason, the AIC will only be reported to ensure a thorough disclosure of results but will not be used in the present study. These simulation studies also show that, when the recommended indicators fail to identify the optimal model, the BIC and CAIC tend to underestimate the true number of profiles, while the ABIC and BLRT tend to overestimate it.

Since these tests are all variations of tests of statistical significance, the class enumeration procedure can still be heavily influenced by sample size (Marsh et al., 2009). That is, with sufficiently large samples, these indicators may keep on suggesting the addition of latent profiles to the model without reaching a minimal point (CAIC, BIC, SABIC) or statistical non-significance (LMR, BLRT). In these cases, information criteria should be graphically presented through "elbow plots" illustrating the gains associated with additional profiles (Morin, Maïano et al., 2011; Morin & Marsh, 2015; Petras & Masyn, 2010). In these plots, the point after which the slope flattens indicates the optimal number of profiles in the data. Two important additional criteria used in this decision are (a) the substantive meaning and theoretical conformity of the profiles (Marsh et al., 2009; Muthén, 2003) and (b) the statistical adequacy of the solution (e.g., absence of negative variance estimates; Bauer & Curran, 2004). Finally, the entropy, which indicates the precision with which the cases are classified into the profiles, was also examined. Although the entropy should not be used to determine the optimal number of profiles (Lubke & Muthén, 2007), it provides a useful summary of classification accuracy. The entropy varies from 0 to 1, with higher values indicating fewer classification errors.

Additional studies also suggest that the CAIC, BIC, and SBIC can be used in the comparison of alternative models based on the same set of profile indicators and including the same number of latent profiles (e.g., Lubke & Neale, 2006, 2008; Petras & Masyn, 2010), such as in the comparisons of the nested multiple-group models forming the sequence of similarity tests considered here. However, it must be kept in mind that, so far, the relative efficacy of these indices for tests of profiles similarity has never been systematically investigated and is inferred. For this reason, we consider similarity to be supported as long as two of these indicators support the similarity of the profile solution, while acknowledging that best practices in this specific area is likely to evolve as statistical evidence accumulates.

At present, tests of *predictive* and *explanatory* similarity require the direct incorporation of covariates into the model, and have not yet been implemented using covariates specified as inactive (i.e., using auxiliary functions, e.g., Asparouhov & Muthén, 2014; Lanza, Tan & Bray, 2013; Vermunt, 2010). However, a strong assumption of latent profile models including covariates (predictors; outcomes) is that the nature of the profiles should remain unaffected by inclusion of the covariates into the model (Marsh et al., 2009; Morin, Maïano et al., 2011; Morin, Morizot, et al., 2011). Observing such a change indicates that the nature of profiles does depend on the choice of covariates, thus calling into question the assumption that the causal ordering is from the predictors to the profiles, and from the profiles to the outcomes (Marsh et al., 2009). To ensure that this did not happen, all models involving predictors and outcomes were estimated using the start values from the model retained from the first four steps. This is why our current recommendation is to include covariates once the class enumeration procedure and preliminary tests of similarity have been completed, although we recognize that statistical knowledge and recommendations in this area are evolving (e.g., Asparouhov & Muthén, 2014; Li & Hser, 2011; Muthén, 2004; Tofighi & Enders, 2007).

Configural Similarity of the Profiles

The first step in the approach examines whether the same number of profiles can be identified across samples (i.e. configural similarity). When confirmed, a multiple group LPA model can be estimated to implement the subsequent tests of similarity (e.g., using Mplus KNOWNCLASS function to identify the countries). Because previous research has generally yielded five to seven commitment mindset profiles (see Meyer et al., 2013), we examined solutions with up to eight profiles separately in both countries. The fit indices for these solutions are reported in Table 2. In the North American sample, most indices (BIC, CAIC, SABIC) continued to decrease with the addition of profiles, the BLRT was not helpful, and the LMR supported the 4-profile solution. A graphical depiction of these values, particularly the BIC and CAIC (see Figure S1a in the online supplements), shows a plateau at five profiles. Examination of the 5-profile solution, and bordering 4- and 6-profiles solutions, shows that all solutions were fully proper statistically. The 5-profile solution also appeared to present the greatest level of theoretical conformity.

In the French sample, the SABIC continued to decrease with the addition of profiles, the BIC reached a plateau at five profiles and thereafter showed only minimal decreases, the CAIC reached its lowest value at five profiles, the BLRT was not helpful, and the LMR supported five profiles. Once again, a graphical depiction of these values (see Figure S1b in the online supplements), shows a plateau at 5 profiles. Similarly, examination of the 5-profile solution, and bordering 4- and 6-profiles solutions, shows that all solutions were fully proper statistically, and that the 5-profiles solution had the greatest theoretical conformity. Based on these results, the 5-profile solution was retained for both samples, supporting the configural similarity of the model across France and North America.

Cross National Similarity (Structural, Dispersion, and Distributional) of the Profiles

A multiple-group 5-profile model was simultaneously estimated in both samples. From this model of configural similarity, we first estimated a model of structural similarity by constraining the within-profile means on the commitment mindsets to be equal across countries. Compared with the baseline configural similarity model, the structural similarity model resulted in a slightly higher value on the ABIC, but lower values on the BIC, and CAIC, thereby supporting the structural similarity of the 5-profile solution across countries. Second, we estimated a model of dispersion similarity by constraining the within-profile variability of the commitment mindsets to be equal across countries. Compared with the model of structural similarity, this model resulted in lower values on the BIC, CAIC, and ABIC, thereby supporting the dispersion similarity of the profiles across countries. Finally, we estimated a model of distributional similarity by constraining the sizes (class probabilities) of the latent profiles to be equal across countries.

Compared with the model of dispersion similarity, this model resulted in a substantial increase in the value of all information criteria, suggesting that the sizes of the profiles differ across countries. The model of dispersion similarity was thus retained for interpretation and for the next stages, allowing the relative size of the profiles to differ across countries.

The profiles from this final solution of dispersion similarity are illustrated in Figure 1. In Profile 1, AC and NC are well below average but combine with CC levels that are slightly higher but still below average. This pattern reflects a *CC-Dominant* profile. In Profile 2, all three mindsets are slightly below average, corresponding to a *Moderately Committed*. Profile 3 is characterized by AC, NC, and CC scores that are above average, with levels of AC and particularly NC that are higher than levels of CC. Because this profile appears to be dominated by AC and NC, we retained the label *AC/NC-Dominant* to describe this profile. For Profile 4, AC, NC and CC that are all slightly above average, with levels of NC that are higher than levels of AC and CC. Thus, we used the label *NC-Dominant* to describe this profile. Finally, Profile 5 is dominated by slightly above average levels of AC, combined with levels of NC and CC that are respectively well-below, and slightly below, average. Given the dominance of AC, we labeled this profile *AC-Dominant*. These results show clear qualitative differences between the estimated profiles, which are all similar to those found in previous research (see Meyer, Stanley, et al., 2013). The one exception is the *NC-Dominant* (Profile 4) which, although proposed by Meyer and Herscovitch (2001), has generally not been detected in previous person-centered analytic studies (Meyer, Stanley et al., 2013).

The retained model yields a reasonably high level of classification accuracy (i.e., reasonably distinct profiles), with an entropy value of .861 and average posterior probabilities of class membership (see Table S3 in the online supplements) in the dominant profile varying from .828 to .948 in North America (with relatively low cross-probabilities varying from 0 to 0.083) and from .800 to .913 in France (with relatively low cross-probabilities varying from 0 to 0.157). As noted previously, the results showed variations in the relative sizes of the profile groups across the North American and French samples. Interestingly, these results show the *CC-Dominant* (Profile 1) and *AC-Dominant* (Profile 5) profiles to be more prevalent in France (26.2% and 25.9% of the employees respectively) than in North America

(12.1% and 6.6% of the employees respectively). In contrast, the *AC/NC-Dominant* (Profile 3) and *NC-Dominant* (Profile 4) profiles, both dominated by NC, appear to be more prevalent in North America (31.4% and 26.5% of the employees, respectively) than in France (6.3% and 14.2% of the employees, respectively). Finally, the *Moderately Committed* (Profile 2) profile appeared equally prevalent in both countries (23.4% of the employees in North America and 27.5% of the employees in France).

Predictive Similarity of the Profiles

Starting from the model of dispersion similarity, predictors were then added to the model through a multinomial logistic regression, starting with the demographic characteristics (included in the model mainly to enrich the description of the profile) and then the perceived HRM practices. For both sets of predictors, we first estimated a model in which effects of the predictors were freely estimated across samples, and contrasted this model with one in which these paths for each predictor were constrained to equality across samples (i.e., predictive similarity). As shown in Table 2, the model of predictive similarity resulted in lower values for the BIC, CAIC, and ABIC when compared to the model where the predictions where freely estimated across countries. These results thus support the predictive similarity of the model. The results from the multinomial logistic regressions estimated in this model are reported in Table 3. In multinomial logistic regressions, each predictor has k-1 (with k being the number of profiles) complementary effects for each possible pairwise comparison of profiles. More specifically, the regression coefficients reflect the increases, for each one-unit increase in the predictor, that can be expected in the log odds of the outcome (i.e., the probability of membership in one profile versus another). To simplify interpretations, we also report odds ratios (OR), reflecting the change in likelihood of membership in a target profile versus a comparison profile associated for each unit of increase in the predictor. For example, an OR of 3 suggests that each unit of increase in the predictor is associated with participants being three-times more likely to be member of the target profile (versus the comparison profile). ORs under 1 correspond to negative coefficients and suggest that the likelihood of membership in the target profile is reduced (e.g., an OR of .5 shows that a one unit increase in the predictor reduces by 50% the likelihood of membership in the target, versus comparison, profile).

In terms of demographics, being female predicted an increased likelihood of membership into Profile 1 (*CC-Dominant*, 65.5% females) and 2 (*Moderately Committed*, 62.8% females) relative to Profile 4 (*NC-Dominant*, 51.6% females), but did not significantly differ across any of the other profiles (Profile 3, *AC/NC-Dominant*: 59.3% females; Profile 5, *AC-Dominant*: 54.6% females). As tenure increased, the likelihood of membership in Profile 5 (*AC-Dominant*) relative to the remaining profiles increased; there were no significant differences in membership likelihood across the other profiles. Education level had little implications for profile membership. The only exception was that the likelihood of membership in Profile 3 (AC/NC-Dominant) relative to Profile 2 (Moderately Committed) was significantly greater for those with higher levels of education.

In terms of perceived HRM practices, the results showed that perceptions of abilities-oriented practices were associated with a slightly higher likelihood of membership into Profile 3 (*AC/NC-Dominant*) versus Profile 5 (*AC-Dominant*) and Profile 2 (*Moderately Committed*). For motivation-oriented practices, only contrasts involving Profile 1 (*CC-Dominant*) were significant: employees who perceived greater use of motivation-oriented HRM practices had a lower likelihood of membership in Profile 1 than Profiles 3 (*AC/NC-Dominant*), 4 (*NC-Dominant*) and 5 (*AC-Dominant*). In contrast, opportunities-oriented HRM practices present a far more extensive pattern of association with profile membership. Employees who perceived more opportunities-oriented practices had a greater likelihood of membership in Profile 3 (*AC/NC-Dominant*) than Profiles 1 (*CC-Dominant)*, 2 (*Moderately Committed*), and 5 (*AC-Dominant*). They had a greater likelihood of membership in Profiles 4 (*NC-Dominant*) than Profiles 1 (*CC-Dominant*) and 2 (*Moderately Committed*), a greater likelihood of membership in Profile 5 (*AC-Dominant*) than Profile 1 (*CC-Dominant*), and a greater likelihood of membership in Profile 1 (*CC-Dominant*) than Profile 2 (*Moderately Committed*). Overall, as shown in Figure 4, perceptions of HRM practices were most positive for *AC/NC-Dominant*, and least positive for *CC-Dominant*, employees.

Explanatory Similarity of the Profiles

To test for explanatory similarity, distal outcomes (turnover intentions and work exhaustion) were added directly to the dispersion similarity model described earlier. We first estimated a model in which the within-profile levels of both outcomes were freely estimated across samples, and contrasted this model with one in which these levels were constrained to be equal across samples (i.e., explanatory similarity). As shown in Table 2, compared with the model where the relations between profiles and outcomes were freely estimated across countries, the explanatory similarity model resulted in lower values for the BIC and CAIC, and in highly similar values for the AIC and ABIC. These results thus support the explanatory similarity of the model.

We used the MODEL CONSTRAINT command of Mplus to systematically test mean-level differences across pairs of profiles (using the multivariate delta method: e.g., Raykov & Marcoulides, 2004; for an application, see Kam et al., 2015). The mean levels of each outcome in the profiles are reported in Table 4. Levels of turnover intention were significantly greater in Profile 1 (*CC-Dominant*) than Profile 2 (*Moderately Committed*), and in Profile 2 than Profile 3 (*AC/NC-Dominant*). Indeed, turnover intentions were lowest in Profile3, although they did not differ significantly from Profiles 4 (*NC-Dominant*) and 5 (*AC-Dominant*). Turnover intentions in the latter two profiles were lower than for Profile 1 (*CC-Dominant*), but did not differ significantly from Profile 2 (*Moderately Committed*). Work exhaustion was significantly greater in Profile 1 (*CC-Dominant*) than all other profiles. The only other significant contrast was between Profiles 4 and 5: Profile 5 (*AC-Dominant*) employees reported the lowest level of work exhaustion, and significantly less than those with Profile 4 (*NC-Dominant*).

CONCLUSION

This illustrative example was intended to demonstrate one potential application of a comprehensive approach for the investigation of profile similarity across groups or time points. Obviously, each application will come with its own challenges. In particular, in our example, profile similarity was supported for most steps of the approach, and the observed differences in terms of profile dispersion revealed that the relative size of most profiles differed across countries. Realistically, we do not expect similar levels of profile similarity to necessarily be the norm, and expect that at least some forms of profile differences may be relatively common in practical applications. In such cases, the partial similarity approach described earlier when we presented the 6-step approach may prove particularly useful.

Furthermore, we do not argue that the present approach covers all possible differences in profiles solutions across groups of employees. For instance, steps can be added between the third and fourth steps to test for the similarity of: (a) the within-class correlations that may be added between indicators to relax the model's conditional independence assumption (Uebersax, 1999), (b) the continuous latent factors that are included in factor mixture models (Morin, Morizot et al, 2011; Morin & Marsh, 2015), or (c) the within-profile regression parameters that are also estimated as part of mixture regression models (e.g., Henson et al., 2007; Morin et al., 2015). Obviously, more complex forms of mixture models, such as growth mixture models (Qureshi, & Fang, 2011), may require more substantial modifications to the proposed sequence of tests. Nevertheless, the approach presented here is likely to address the more common sources of similarities and differences across groups in person-centered analyses.

It is also worth noting that hybrid variable- and person-centered approaches may be particularly helpful for psychometric investigations of measurement invariance. Indeed, combining the measurement invariance framework with person-centered analyses provides a way to directly assess the extent to which a measurement model generalizes (i.e. is invariant) across unobserved subgroups of participants (Carter, Dalal, Lake, Lin, & Zickar, 2011). These models can be further extended to incorporate observed covariates, in order to directly assess how participants' characteristics relate to their membership into latent profiles characterized by distinct response sets (Tay, Newman, & Vermunt, 2011), as well as a multilevel structure, in order to verify how membership into these various profiles differs as a function of hierarchical units (e.g., groups, organizations, countries) (Tay, Diener, Drasgow, & Vermunt, 2011).

Finally, it must be kept in mind that the statistical properties of the approach proposed here remains under-documented at best. For instance, although issues of statistical power are likely to influence the ability of each sequential test to detect meaningful profile differences, the extent to which statistical power will vary as a function of each sequential test to be performed (e.g., configural, structural), across statistical indicators (e.g., BIC, CAIC), or as a function of other sample characteristics (e.g., sample size, magnitude of group or time differences, degree of class separation, number of profile indicators, number of groups to be compared) remains unknown. Similarly, although the procedures used here to select the optimal number of the profiles present in the data, and to assess the extent of profile similarity across both samples, is based on current best practices in this area, it still includes some level of subjectivity due in part to the sample size dependency of the indicators and lack of statistical evidence regarding the relative performance of the various indicators to detect group differences in profile solutions. Clearly, simulation studies are needed to obtain a more precise overview of the performance and limitations of the proposed approach as a function of sample characteristics.

Overall, our objective was to introduce a sequential set of analytic procedures to guide future investigations of the similarity of latent profile solutions across subgroups of participants or time points. Although applied in this case to address cross-national differences in commitment mindset profiles, the sequence of similarity tests proposed here represents a flexible comprehensive approach that can be used to guide tests of the similarity of latent profiles solutions across any meaningful groups of participants (e.g., gender, type of employees, linguistic groups, etc.). Although similar analytical strategies were previously presented to guide tests of the similarity of latent class solutions based on categorical indicators across samples (e.g., Eid et al., 2003), the methodology presented here encompasses and extends these previous strategies to cover of a broader range of possible tests of similarity of latent profile solutions which can also be further extended to tests of the longitudinal similarity of profile solutions.

REFERENCES

Asparouhov, T., & Muthén, B.O. (2014). Auxiliary variables in mixture modeling: Three-step approaches using Mplus. *Structural Equation Modeling*, *21*, 1-13.

Ayman, R., & Korabik, K. (2010). Leadership: Why gender and culture matter. *American Psychologist*, *65,* 157-170.

Bauer, D.J. & Curran, P.J. (2003). Distributional assumptions of growth mixture models over-extraction of latent trajectory classes. *Psychological Methods*, *8*, 338-363.

Bauer, D. J. & Curran, P. J. (2004). The integration of continuous and discrete latent variable models: Potential problems and promising opportunities. *Psychological Methods*, *9*, 3-29.

Bollen, K.A. (1989). *Structural equations with latent variables*. New York, NY: Wiley.

Borsboom, D., Mellenbergh, G.J., & van Heerden, J. (2003). The theoretical status of latent variables. *Psychological Review*, *110*, 203–218.

Brislin, R.W. (1986). *The wording and translation of research instruments*. In W. L. Lonner & J. W. Berry (Eds.), Field Methods in Cross-Cultural Research: 137-164. Newbury Park: Sage.

Carter, N.T., Dalal, D.K., Lake, C.J., Lin, B.C., & Zickar, M.J. (2011). Using mixed-model item response theory to analyze organizational survey responses: An illustration using the Job Descriptive Index. *Organizational Research Methods*, *14*, 116-146.

Chen, F., Bollen, K.A., Paxton, P., Curran, P.J., & Kirby, J.B. (2001). Improper solutions in structural models: Causes, consequences, strategies. *Sociological Methods & Research*, *29*, 468-508.

Combs, J., Liu, Y., Hall, A. & Ketchen, D. 2006. How much do high-performance practices matter? A meta-analysis of effects on performance. *Personnel Psychology*, 59: 501-528.

Cudeck, R., & Henly, S.J. (2003). A realistic perspective on pattern representation in growth data: Comment on Bauer and Curran (2003). *Psychological Methods*, *8*, 378-383.

Dumenci, L. (2011). The psychometric latent agreement model (PLAM) for discrete latent variables measured by multiple items. *Organizational Research Methods, 14*, 91-115.

Eid, M., Langeheine, R., & Diener, E. 2003. Comparing typological structures across cultures by multigroup latent class analysis. *Journal of Cross-Cultural Psychology,* 34: 195–210.

Gelfand, M.J., Erez, M., & Aycan, Z. (2007). Cross-Cultural Organizational Behavior. *Annual Review of Psychology*, *54*, 479-514.

Gelfand, M.J., Nishii, L.H., & Raver, J.L. (2006). On the nature and importance of cultural tightness-looseness. *Journal of Applied Psychology*, *91*, 1225-1244.

Henson, J.M., Reise, S.P., & Kim, K.H. (2007). Detecting mixtures from structural model differences using latent variable mixture modeling: A comparison of relative model fit statistics. *Structural Equation Modeling*, *14*, 202-226.

Hipp, J.R., & Bauer, D.J. (2006). Local solutions in the estimation of growth mixture models. *Psychological Methods*, *11*, 36-53.

Jiang, K., Lepak, D.P., Hu, J., & Baer, J.C. (2012). How does human resource management influence organizational outcomes? A meta-analytic investigation of mediating mechanisms. *Academy of Management Journal*, *55*, 1264-1294.

Kam, C., Morin, A.J.S., Meyer, J.P., & Topolnytsky, L. (2015, in press). Are commitment profiles stable and predictable? A latent transition analysis. *Journal of Management*. Early View, doi: 10.1177/0149206313503010.

Kankaraš, M., Moors, G., & Vermunt, J.K. (2011). Testing for measurement invariance with latent class analysis. In E. Davidov, P. Schmidt, & J. Billiet (Eds.), *Cross-Cultural Analysis: Methods and Applications* (pp. 359-384). New York, NY: Routledge.

Kankaraš, M., Vermunt, J.K., & Moors, G. (2011). Measurement equivalence of ordinal items: A comparison of factor analytic, item response theory, and latent class approaches. *Sociological Methods & Research, 40*, 279-310.

Kehoe, R.R., & Wright, P.M. (2013). The impact of high-performance human resource practices on employees' attitudes and behaviors. *Journal of Management*, *39*, 366-391.

Lanza, S.T., Tan, X., & Bray, B.C. (2013). Latent class analysis with distal outcomes: A flexible model-based approach. *Structural Equation Modeling*, *20*, 1–26.

Lawrence, B.S., & Zyphur, M.J. (2011). Identifying organizational faultlines with latent class cluster analysis. *Organizational Research Methods*, *14*, 32-57.

Lazarsfeld, P. F., & Henry, N. W. (1968). *Latent structure analysis*. Boston: Houghton Mifflin.

Li, L., & Hser, Y.-I. (2011). On inclusion of covariates for class enumeration of growth mixture models. *Multivariate Behavioral Research*, *46*, 266–302.

Lo, Y., Mendell, N., & Rubin, D. (2001). Testing the number of components in a normal mixture. *Biometrika*, *88*, 767-778.

Lubke, G. & Muthén, B.O. (2007). Performance of factor mixture models as a function of model size, criterion measure effects, and class-specific parameters. *Structural Equation Modeling, 14*, 26–47.

Lubke, G. & Neale, M. (2006). Distinguishing between latent classes and continuous factors: Resolution by maximum likelihood? *Multivariate Behavioral Research*, *41*, 499-532

Lubke, G., & Neale, M. (2008). Distinguishing between latent classes and continuous factors with categorical outcomes: Class invariance of parameters of factor mixture models? *Multivariate Behavioral Research*, *43*, 592–620.

Lukaszewski, K.M., & Stone, D.L. (2012). Theory and research on social issues in organizations. *Journal of Managerial Psychology*, *27*, 324-329.

Marsh, H.W., & Hau, K.T. (2007). Latent variable models in educational psychology: Need for methodological-substantive synergies. *Contemporary Educational Psychology*, 32: 151-171.

Marsh, H.W., Hau, K.-T., & Wen, Z. (2004). In search of golden rules: Comment on hypothesis-testing approaches to cutoff values for fit indexes and dangers in overgeneralizing Hu & Bentler's (1999). *Structural Equation Modeling, 11*, 320-341.

Marsh, H.W., Lüdtke, O., Trautwein, U., & Morin, A.J.S. (2009). Classical latent profile analysis of academic self-concept dimensions: Synergy of person- and variable-centered approaches to theoretical models of self-concept. *Structural Equation Modeling*, *16*, 191-225.

McDonald, R.P. (1970). Theoretical foundations of principal factor analysis and alpha factor analysis. *British Journal of Mathematical and Statistical Psychology*, *23*, 1-21.

McLachlan, G., & Peel, D. (2000). *Finite Mixture Models.* New York: Wiley.

Meyer, J.P., Allen, N.J. & Smith, C. (1993). Commitment to organizations and occupations: Extension and test of a three-component model. *Journal of Applied Psychology*, 78, 538-551

Meyer, J.P., & Herscovitch, L. (2001). Commitment in the workplace: Toward the general model. *Human Resource Management Review, 11*, 299-326.

Meyer, J.P., Morin, A.J.S., & Vandenberghe, C. (2015). Dual Commitment to Organization and Supervisor: A Person-centered Approach. *Journal of Vocational Behavior*, *88*, 56-72

Meyer, J.P., Stanley, L.J., & Vandenberg, R.M. (2013). A person-centered approach to the study of commitment. *Human Resource Management Review*, *23*, 190-202.

Millsap, R.E. (2011). *Statistical approaches to measurement invariance*. NewYork: Taylor & Francis.

Mobley, W.H., Griffeth, R., Hand, H. & Meglino, B. (1979) A review and conceptual analysis of the employee turnover process. *Psychological Bulletin*, *86*, 493-522.

Morin, A.J.S., Maïano, C., Nagengast, B., Marsh, H.W., Morizot, J., & Janosz, M. (2011). General growth mixture analysis of adolescents' developmental trajectories of anxiety: The impact of untested invariance assumptions on interpretations. *Structural Equation Modeling*, *18*, 613-648.

Morin, A.J.S., & Marsh, H.W. (2015). Disentangling shape from level effects in person-centered analyses: An illustration based on university teacher multidimensional profiles of effectiveness. *Structural Equation Modeling*, *22*, 33-59.

Morin, A.J.S., Morizot, J., Boudrias, J.-S., & Madore, I. (2011). A multifoci person-centered perspective on workplace affective commitment: A latent profile/factor mixture Analysis. *Organizational Research Methods, 14*, 58-90.

Morin, A.J.S., Scalas, L.F., & Marsh, H.W. (2015). Tracking the elusive actual-ideal discrepancy model within latent subpopulations. *Journal of Individual Differences, 36*, 65-72.

Muthén, B.O. (2002). Beyond SEM: General latent modeling. *Behaviormetrika*, *29*, 81-117.

Muthén, B.O. (2003). Statistical and Substantive Checking in Growth Mixture Modeling: Comment on Bauer and Curran (2003). *Psychological Methods*, *8*, 369-377.

Muthén, B. (2004). Latent variable analysis: Growth mixture modeling. In D. Kaplan (Ed.), *Handbook of quantitative methodology for the social sciences* (pp. 345-368). Newbury Park, CA: Sage.

Muthén, L.K., & Muthén, B. (2013). *Mplus user's guide.* Los Angeles CA: Muthén & Muthén

Nylund, K.L., Asparouhov, T., & Muthén, B. (2007). Deciding on the number of classes in latent class analysis and growth mixture modeling. A Monte Carlo simulation study. *Structural Equation Modeling*, *14*, 535-569.

Organ, D.W. (1988). Organizational citizenship behavior. Lexington, MA: Lexington.

Petras, H., & Masyn, K. (2010). General growth mixture analysis with antecedents and consequences of change. In A.R. Piquero, & D. Weisburd (Eds.), *Handbook of Quantitative Criminology* (pp. 69-100). New York, NY: Springer.

Peugh, J. & Fan, X. (2013). Modeling unobserved heterogeneity using latent profile analysis: A Monte Carlo simulation. *Structural Equation Modeling*, *20*, 616-639.

Qureshi, I., & Fang, Y. (2011). Socialization in open source software projects: A growth mixture modeling approach. *Organizational Research Methods*, *14*, 208-238.

Raykov, T. (2009). Evaluation of scale reliability for unidimensional measures using latent variable modeling. *Measurement and Evaluation in Counseling and Development*, *42*, 223-232.

Raykov, T., & Marcoulides, G.A. (2004). Using the delta method for approximate interval estimation of parameter functions in SEM. *Structural Equation Modeling*, 11, 621-637.

Riordan, C.M., & Vandenberg, R.J. (1994). A central question in cross-cultural research: Do employees of different cultures interpret work-related measures in an equivalent manner. *Journal of Management*, *20*, 643-671.

Saks, A.M., Uggerslev, K.L., & Fassina, N.E. (2007). Socialization tactics and newcomer adjustment: A meta-analytic review and tests of a model. *Journal of Vocational Behavior, 70*, 413-446.

Schaufeli, W.B., Leiter, M.P., Maslach, C., & Jackson, S.E. (1996). MBI-General Survey. Dans C. Maslach., S. F.Jackson, & M. P. Leiter (Eds.), *Maslach Burnout Inventory manual* (3rd ed.). Palo Alto, CA: Consulting Psychologists.

Schaffer, B. S., & Riordan, C. M. 2003. A review of cross-cultural methodologies for organizational research: Best-practices. *Organizational Research Methods*, 6: 169-215.

Sijtsma, K. (2009) On the use, misuse, and the very limited usefulness of Cronbach's alpha [Introduction to the special issue]. *Psychometrika*, *74*,107-120

Skrondal, A., & Laake, P. (2001). Regression among factor scores. *Psychometrika*, *66*, 563-576.

Spector, P.E., Liu, C., & Sanchez, J.I. (2015, in press). Methodological and substantive issues in conducting multinational and cross cultural-research. *Annual Review of Organizational Psychology and Organizational Behavior*, *2*.

Steinley, D., & McDonald, R.P. (2007). Examining factor scores distributions to determine the nature of latent spaces. *Multivariate Behavioral Research*, *42*, 133-156.

Streiner, D.L. (2003). Starting at the beginning: An introduction to coefficient alpha and internal consistency. *Journal of Personality Assessment*, *80*, 99-103.

Tay, L., Diener, E., Drasgow, F., & Vermunt, J.K. (2011). Multilevel mixed-measurement IRT analysis: An explication and application to self-reported emotions across the world. *Organizational Research Methods*, *14*, 177-207.

Tay, L., Drasgow, D.A., & Vermunt, J.K. (2011). Using mixed-measurement item response theory with covariates (MM-IRT-C) to ascertain observed and unobserved measurement equivalence. *Organizational Research Methods*, *14*, 147-176.

Tein, J.-Y., Coxe, S., & Cham, H. (2013). Statistical power to detect the correct number of classes in latent profile analysis. *Structural Equation Modeling*, *20*, 640-657.

Tofighi, D., & Enders, C. K. (2007). Identifying the correct number of classes in growth mixture models. In G. R. Hancock & K. M. Samuelsen (Eds.), *Advances in latent variable mixture models* (pp. 317–341). Charlotte, NC: Information Age

Tofighi, D., & Enders, C. (2008). Identifying the correct number of classes in growth mixture models. In G. R. Hancock & K. M. Samuelsen (Eds.), Advances in latent variable mixture models (pp. 317-341). Charlotte, NC: Information Age Publishing.

Tolvanen, A. (2007). *Latent growth mixture modeling: A simulation study*. PhD dissertation, Department of Mathematics, University of Jyväskylä, Jyväskylä, Finland.

Tsui, A. S., Nifadkar, S. S., & Ou, A. Y. 2007. Cross-national, cross-cultural organizational behavior research: Advances, gaps, recommendations. *Journal of Management*, 33: 426-478.

Uebersax, J.S. (1999). Probit Latent Class Analysis with Dichotomous or Ordered Category Measures: Conditional Independence/Dependence Models. *Applied Psychological Measurement*, *23*, 283-297.

Vermunt, J.K. (2010). Latent class modeling with covariates: Two improved three-step approaches. *Political Analysis*, *18*, 450–469.

Vandenberg, R.J., & Lance, C.E. (2000). A review and synthesis of the measurement invariance literature: Suggestions, practices, and recommendations for organizational research. *Organizational*

Research Methods, *3*, 4–70.

Van Maanen, J., & Schein, E. H. (1979). Toward a theory of organizational socialization. In B. M. Staw (Ed.), Research in organizational behavior (Vol. 1). Greenwich, CT: JAI Press.

Wang, M., & Hanges, P.J. (2011). Latent class procedures: Applications to organizational research [Introduction to the Feature Topic]. *Organizational Research Methods*, *14*, 24-31.

Williams, L.J., & Anderson, S.E. (1991). Job satisfaction and organizational commitment as predictors of organizational citizenship and in-role behaviors. *Journal of Management*, *17*, 601–617.

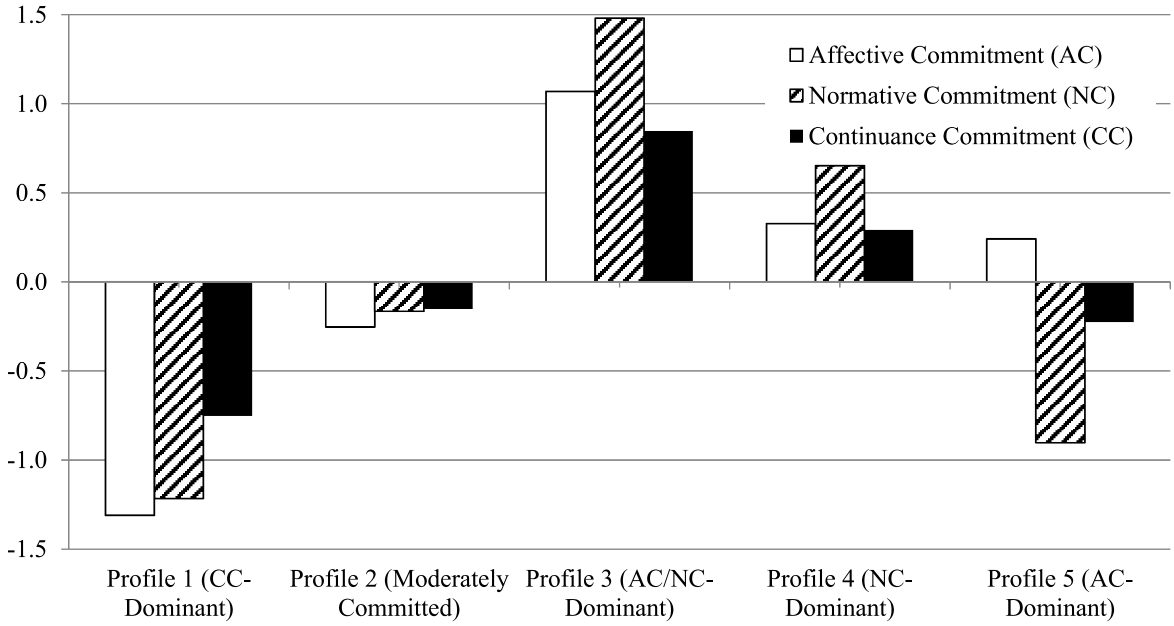

Figure 1. Characteristics of the Latent Profiles Based on the Cross-Cultural Model.
Note. The results were standardized to a mean of 0 and a standard deviation of 1 to help in the interpretation of this histogram.

Table 1

Sequence of Tests of similarity for Multiple-Groups Latent Profile Analyses

Profile Similarity	Description	Method	Prerequisite
1 – Configural	• Tests if the same number of latent profiles can be identified in all groups, using the same overarching model. • Configural differences mean that the profiles differ across groups and need to be contrasted using a qualitative process (the method described here is technically impossible to implement at the moment with different number of profiles in the various groups).	The class enumeration procedure is conducted separately across groups to see if the optimal number of profiles is equal in each group. A multiple-group model of configural similarity can then be estimated as a baseline comparison model for the subsequent steps.	None
2 – Structural	• Tests whether the indicators' levels are the same across groups. • If the structure of the profiles differs across groups, subsequent analyses should be conducted separately across groups, but tests of partial structural similarity can be pursued.	Equality constraints are imposed on the within-profile means across groups, and the fit of this model is contrasted with that of the previous model to assess if the constraints are supported.	1
3 – Dispersion	• Tests whether the indicators' variability (i.e., within-profile inter-individual differences) is the same across groups. • Not applicable with categorical indicators (latent class analyses). • If the dispersion of the profile differs across groups, then tests of partial dispersion similarity can be pursued. • Tests of dispersion similarity should be limited to the subset of structurally similar profiles, indicators, or groups.	Equality constraints are imposed on the within-profile variances across groups, and the fit of this model is contrasted with that of the previous model to assess if the constraints are supported.	1-2
4 – Distributional	• Tests whether the relative size of the profiles is similar across groups. • If the distribution of the profile differs across groups, then tests of partial distribution similarity can be pursued. • Tests distribution similarity can, whenever it makes sense to do so, be conducted irrespective of whether the profiles are structurally similar.	Equality constraints are imposed on the relative sizes of all profiles (i.e., class probabilities) across groups and the fit of this model is contrasted with that of the previously retained model to assess whether these constraints are supported by the data.	1
5 – Predictive	• Predictors are included to the most "similar" model from the aforementioned sequence (steps 2 to 4). • Tests if the predictors-profiles relations are the same across groups. • Only appropriate when predictors are included in the study. • When predictions differ across groups, then tests of partial predictive similarity can be pursued.	Predictors are included, ensuring that they do not change the nature of the profiles (e.g., using starts values from the most "similar" model). The effects of these predictors are then constrained to equality across groups, and the fit of both models is contrasted to assess whether these constraints are supported by the data.	1-2
6 – Explanatory	• Outcomes are included to the most "similar" model (steps 2 to 4). • Tests if the profiles-outcomes relations are the same across groups or time points. • Only appropriate when outcomes are included in the study. • When relations with outcomes differ across groups, then tests of partial explanatory similarity can be pursued.	Outcomes are included, ensuring that they do not change the nature of the profiles (e.g., using starts values from the most "similar" model). The levels of these outcomes in each profile are then constrained to equality across groups, and the fit of both models is contrasted to assess whether these constraints are supported by the data.	1-2

Table 2

Fit Results from the Latent Profiles Analyses conducted in this Study.

	k	LL	#fp	SC	AIC	BIC	CAIC	SABIC	Entropy	LMR	BLRT
Class Enumeration: France											
1 Profile	1	-2553.499	6	0.803	5118.998	5142.991	5148.991	5124.948	---	---	---
2 Profiles	2	-2437.786	10	0.997	4895.573	4937.227	4947.227	4905.488	0.774	≤ .001	≤ .001
3 Profiles	3	-2388.028	14	1.123	4804.057	4862.372	4876.372	4817.938	0.815	0.021	≤ .001
4 Profiles	4	-2345.720	18	1.131	4727.439	4802.417	4820.417	4745.287	0.791	0.002	≤ .001
5 Profiles	5	-2320.166	22	1.093	4684.332	4775.971	4797.971	4706.146	0.825	0.015	≤ .001
6 Profiles	6	-2307.613	26	1.059	4669.225	4775.526	4801.526	4693.006	0.805	0.067	≤ .001
7 Profiles	7	-2293.626	30	1.055	4647.252	4772.215	4802.215	4676.999	0.858	0.078	≤ .001
8 Profiles	8	-2281.904	34	1.076	4631.808	4773.432	4807.432	4665.521	0.873	0.152	≤ .001
Class Enumeration: North America											
1 Profile	1	-2807.290	6	0.798	5626.581	5651.771	5657.771	5632.727	---	---	---
2 Profiles	2	-2608.637	10	1.121	5237.273	5279.258	5289.258	5247.518	0.789	≤ .001	≤ .001
3 Profiles	3	-2539.340	14	1.454	5106.680	5165.459	5179.459	5121.023	0.809	0.080	≤ .001
4 Profiles	4	-2514.314	18	1.239	5064.628	5140.201	5158.201	5083.069	0.819	0.049	≤ .001
5 Profiles	5	-2478.780	22	1.385	5001.561	5093.927	5115.927	5024.099	0.853	0.223	≤ .001
6 Profiles	6	-2450.532	26	1.216	4953.064	5062.225	5088.225	4979.701	0.841	0.021	≤ .001
7 Profiles	7	-2429.954	30	1.180	4919.908	5045.862	5075.862	4950.643	0.853	0.047	≤ .001
8 Profiles	8	-2410.394	34	1.238	4888.789	5031.537	5065.537	4923.621	0.862	0.302	≤ .001
Cross-Cultural Similarity											
Configural	5	-5469.780	45	1.233	11029.561	11248.946	11293.946	11106.027	0.888	---	---
Structural (Means)	5	-5521.245	30	1.119	11102.490	11248.747	11278.747	11153.467	0.858	---	---
Dispersion (Means & Variances)	5	-5524.841	27	1.148	11103.682	11235.313	11262.313	11149.562	0.861	---	---
Distributional (Means, Variances, Probabilities)	5	-5612.265	23	1.153	11270.531	11382.661	11405.661	11309.614	0.859	---	---
Deterministic Similarity: Demographics											
Freely Estimated Across Countries	5	-5474.727	51	1.116	11051.453	11300.090	11351.09	11138.114	0.867	---	---
Equality Across Countries	5	-5491.136	39	1.133	11060.271	11250.405	11289.405	11126.542	0.864	---	---
Predictive Similarity: HRM Practices											
Freely Estimated Across Countries	5	-5417.545	51	1.135	10937.091	11185.727	11236.727	11023.752	0.865	---	---
Equality Across Countries	5	-5426.872	39	1.156	10931.745	11121.879	11160.879	10998.015	0.864	---	---
Explanatory Similarity: Outcomes											
Freely Estimated Across Countries	5	-9341.152	22	0.993	18726.305	18833.560	18855.560	18763.688	0.867	---	---
Equality Across Countries	5	-9369.311	12	1.032	18762.621	18821.124	18843.124	18783.012	0.865	---	---

Note. LL = Model loglikelihood; #fp = Number of free parameters; AIC = Akaïke information criterion; CAIC = Consistent AIC; BIC = Bayesian information criterion; SABIC = Sample-size adjusted BIC; LMR: Lo, Mendell, & Rubin likelihood ratio test; BLRT = Bootstrap likelihood ratio test; HRM= Human Resources Management.

Table 3

Results from the Multinomial Logistic Regression Evaluating the Effects of Predictors on Latent Profile Membership

	Latent profile 1 Vs 5		Latent profile 2 Vs 5		Latent profile 3 Vs 5		Latent profile 4 Vs 5		Latent profile 1 Vs 4	
	Coef. (SE)	OR	Coef. (SE)	OR	Coef. (SE)	OR	Coef. (SE)	OR	Coef. (SE)	OR
Demographics										
Gender (fem.)	0.517 (0.300)	1.677	0.515 (0.319)	1.673	0.342 (0.301)	1.407	-0.060 (0.289)	0.942	**0.577 (0.242)***	**1.781**
Tenure	**-0.784 (0.156)****	**0.457**	**-0.877 (0.181)****	**0.416**	**-0.762 (0.166)****	**0.467**	**-0.774 (0.163)****	**0.461**	-0.010 (0.112)	0.990
Education	-0.143 (0.148)	0.867	-0.213 (0.157)	0.808	0.149 (0.169)	1.161	-0.039 (0.156)	0.962	-0.104 (0.145)	0.901
HRM practices										
Abilities	0.057 (0.110)	1.058	0.077 (0.110)	1.080	**0.277 (0.124)***	**1.319**	0.042 (0.109)	1.043	0.014 (0.103)	1.014
Opportunities	**-0.479 (0.118)****	**0.619**	-0.122 (0.099)	0.885	**0.263 (0.130)***	**1.301**	0.097 (0.112)	1.102	**-0.576 (0.109)****	**0.562**
Motivation	**-0.294 (0.120)***	**0.746**	-0.010 (0.111)	0.990	0.168 (0.120)	1.183	0.063 (0.105)	1.065	**-0.356 (0.102)****	**0.700**
	Latent profile 2 Vs 4		Latent profile 3 Vs 4		Latent profile 1 Vs 3		Latent profile 2 Vs 3		Latent profile 1 Vs 2	
Predictor	Coef. (SE)	OR	Coef. (SE)	OR	Coef. (SE)	OR	Coef. (SE)	OR	Coef. (SE)	OR
Demographics										
Gender (fem.)	**0.575 (0.257)***	**1.777**	0.402 (0.257)	1.494	0.175 (0.252)	1.191	0.173 (0.251)	1.189	0.002 (0.242)	1.002
Tenure	-0.103 (0.153)	0.902	0.012 (0.119)	1.012	-0.022 (0.110)	0.978	-0.115 (0.128)	0.891	0.093 (0.131)	1.097
Education	-0.175 (0.161)	0.840	0.187 (0.169)	1.206	-0.292 (0.153)	0.747	**-0.362 (0.152)***	**0.696**	0.070 (0.127)	1.073
HRM practices										
Abilities	0.035 (0.111)	1.035	0.235 (0.126)	1.264	-0.220 (0.114)	0.802	**-0.200 (0.101)***	**0.819**	-0.167 (0.119)	0.846
Opportunities	**-0.219 (0.084)****	**0.803**	0.166 (0.114)	1.180	**-0.742 (0.128)****	**0.476**	**-0.385 (0.102)****	**0.680**	**0.490 (0.132)****	**1.633**
Motivation	-0.073 (0.091)	0.930	0.105 (0.105)	1.111	**-0.461 (0.116)****	**0.630**	-0.178 (0.094)	0.837	0.086 (0.125)	1.090

Note. SE: standard error of the coefficient; OR: Odds Ratio; HRM: Human Resources Management; The coefficients and OR reflects the effects of the predictors on the likelihood of membership into the first listed profile relative to the second listed profile.

Table 4

Characteristics of the Profiles of Dual Commitment on the Outcomes.

	Profile 1	Profile 2	Profile 3	Profile 4	Profile 5	Tests of significance
Turnover Intention	5.257	3.088	2.370	2.826	2.656	1 > 2 > 3; 1 > 2 = 4 = 5; 3 = 4 = 5.
Work Exhaustion	4.315	3.706	3.308	3.662	3.133	1 > 2 = 3 = 4; 1 > 2 = 4> 5; 3 = 5.

Online Supplemental Materials for:

Multiple-Group Analysis of Similarity in Latent Profile Solutions

Authors' note:

These online technical appendices are to be posted on the journal website and hot-linked to the manuscript. If the journal does not offer this possibility, these materials can alternatively be posted on one of our personal websites (we will adjust the in-text reference upon acceptance).

We would also be happy to have some of these materials brought back into the main manuscript, or included as published appendices if you deem it useful. We developed these materials to provide additional technical information and to keep the main manuscript from becoming needlessly long.

Sections

Traditional Approaches to Person-Centered Research

Midpoint Split. At the most basic level, studies interested in the identification of distinct profiles of employees presenting may rely on a midpoint split approach. More precisely, this approach divides employees into subgroups according to whether they presented a high or low level on a set of indicators, defining high and low levels according to some indicator of the sample-specific midpoint on the various measures used to assess the profile indicators. Although interesting for initial exploratory purposes, this approach is importantly limited by its reliance on artificially-created subgroups that may not exist in nature and may conceal potentially important subgroups (such as employees with average levels on the indicators) (Meyer et al., 2013; Morin, Morizot et al., 2011). Importantly, when the objective is to test the extent to which profiles generalize to multiple samples or time points, this approach would be limited to tests of whether the relative frequency of each of the artificially created profile is stable across groups or time points, but does not allow for more precise tests of whether the nature of the profiles is stable.

Interaction Effects. Within the variable-centered approach, it is also possible to investigate whether the effects of a specific indicator on a set of outcomes changes as a function of employees levels on another indicator using tests of interactions (Marsh, Hau, Wen, Nagengast, & Morin, 2013). Although these studies may indeed provide an efficient test of whether the effects of some indicator is the same for all employees based on their levels on one or more other indicators, they still present multiple limitations in contrast to the latent profile analysis approach that is the focus of this article. First, interaction effects involving more than three indicators are likely to be impossible to properly interpret. In contrast, profiles can easily be identified, and interpreted, even if based on multiple indicators. Second, interactions effects still assume the linearity of the effects across levels of the interacting variables. It is possible to incorporate non-linear terms in addition to the interactions themselves and even interactions among non-linear terms (Edwards, 2007). However, interpretative limits are then likely to be reached with as few as two interacting terms. Interestingly, tests of the extent to which interactive effects generalize to multiple subgroups of participants or time points are possible within the variable-centered framework (e.g., Vandenberg & Lance, 2000), although more limited in scope to those proposed in the current study when the focus of the study is person-, rather than variable-centered.

Cluster Analyses. Cluster analyses are naturally suited to the identification of profiles. However, cluster analyses present multiple technical limitations (e.g., Meyer et al., 2013; Morin, Morizot et al., 2011; Vermunt & Magidson, 2002) that can be avoided by the reliance on more flexible mixture models such as latent profile analyses. For instance, cluster analyses do not provide clear guidelines to help in the identification of the correct number of profiles present in the data. Similarly, cluster analyses results are highly sensitive to the distributions of the variables used in the clustering process, and to the retained classification algorithm. More importantly, cluster analyses rely on rigid assumptions that often fail to hold with real-life data and can easily be relaxed in the context of mixture models (e.g., Muthén, 2002; Vermunt & Magidson, 2002) such as conditional independence (i.e., the indicators are uncorrelated conditional on the classification; e.g., Uebersax, 1999), class-invariant variances (the variances of the indicators are the same across profiles; e.g., Morin, Maïano, et al., 2011; Peugh & Fan, 2013), and exact assignment whereby each individual is assumed to correspond entirely to a single profile (although recent clustering methods provide ways to circumvent at least some of these limitations, such as fuzzy clustering which allows participants to assume partial membership into multiple profiles, see Brusco, Steinley, Cradit, & Singh, 2012). Although it is true that simulation studies have shown cluster analyses to be quite efficient at recovering true classification patterns present at the population level (e.g., Steinley & Brusco, 2011), this efficiency is limited to situations where the only objective of the research is to achieve a classification of participants into distinct subgroups based on indicators presenting no form of residual relations with one another. In contrast, whenever these assumptions need to be relaxed to properly model the data, or when there is a need to incorporate predictors or outcomes to the model, then mixture models are preferable to cluster analyses. Indeed, being solely a classification process, cluster analyses do not provide the possibility to directly incorporate predictors or outcomes into the model without relying on suboptimal two-steps strategies (e.g., Bolck, Croon, & Hagenaars, 2004). Finally, and most importantly, the multiple group and longitudinal approaches to latent profiles analyses used in the current study to assess the similarity of profile solutions across groups or time points is not yet available for cluster analyses, making it impossible to use cluster analyses for more than qualitative visual comparisons of profile solutions observed across subgroups of participants.

References

Bolck, A., Croon, M., & Hagenaars, J. (2004). Estimating latent structure models with categorical variables: One-step versus three-step estimators. *Political Analysis*, *12*, 3-27.

Brusco, M.J., Steinley, D., Cradit, J.D., & Singh, R. (2011). Emergent clustering methods for empirical OM research. *Journal of Operations Management*, *30*, 454-466.

Edwards, J.R. (2007). Polynomial regression and response surface methodology. In C. Ostroff & T.A. Judge (Eds.), *Perspectives on organizational fit* (pp. 361-372). San Francisco: Jossey-Bass.

Marsh, H.W., Hau, K.T., Wen, Z., Nagengast, B., & Morin, A.J.S. (2013). Moderation. In T.D. Little (Ed.), *Oxford Handbook of Quantitative Methods, V2* (pp. 361-386), New York: Oxford University.

Meyer, J.P., Stanley, L.J., & Vandenberg, R.M. (2013). A person-centered approach to the study of commitment. *Human Resource Management Review*, *23*, 190-202.

Morin, A. J. S., Maïano, C., Nagengast, B., Marsh, H. W., Morizot, J., & Janosz, M. (2011). Growth mixture modeling of adolescents trajectories of anxiety: The impact of untested invariance assumptions on substantive interpretations. *Structural Equation Modeling*, 18, 613–648.

Morin, A.J.S., Morizot, J., Boudrias, J.-S., & Madore, I., (2011). A multifoci person-centered perspective on workplace affective commitment: A latent profile/factor mixture Analysis. *Organizational Research Methods, 14*, 58-90.

Muthén, B.O. (2002). Beyond SEM: General latent variable modeling. *Behaviormetrika*, *29*, 81-117.

Peugh, J., & Fan, X. (2013). Modeling unobserved heterogeneity using latent profile analysis: A Monte Carlo simulation. *Structural Equation Modeling*, 20, 616–639.

Steinley, D., & & Brusco, M.J. (2011). Evaluating mixture modeling for clustering: Recommendations and cautions. *Psychological Methods*, *16*, 63-79.

Uebersax, J.S. (1999). Probit Latent Class Analysis with Dichotomous or Ordered Category Measures: Conditional Independence/Dependence Models. *Applied Psychological Measurement*, *23*, 283-297.

Vandenberg, R.J., & Lance, C.E. (2000). A review and synthesis of the measurement invariance literature: Suggestions, practices, and recommendations for organizational research. *Organizational Research Methods*, *3*, 4–70.

Vermunt, J.K., & Magidson, J. (2002). Latent class cluster analysis. In J. Hagenaars & A. McCutcheon (Eds.), *Applied latent class models* (pp. 89-106). New York: Cambridge.

Theoretical Introduction to Substantive Issues About Commitment

A Person-centered Approach to the Study of Commitment

It is well documented that employees who are committed to their organization are more likely to remain working for this organization. However, research suggests that the implications for job performance and discretionary effort depend on the specific mindsets underlying commitment (e.g., Meyer, Stanley, Herscovitch, & Topolnytsky, 2002). As predicted by Meyer and Allen's (1991, 1997) three-component model (TCM) of commitment, employees who have a strong desire (affective commitment: AC) or sense of obligation (normative commitment: NC) to remain in their organizations are more likely to strive to meet organizational objectives than those who do not, and to go beyond the call of duty in doing so. However, employees who remain because of the costs associated with leaving or a lack of perceived alternatives (continuance commitment: CC) may do only what is required to keep their jobs without getting involved beyond these minimal requirements. Recent research suggests that strong AC and NC may also have beneficial effects for employee well-being, whereas CC can have negative effects (Meyer & Maltin, 2010). Given its implications for organizations and employees, it is not surprising that research has also been conducted to understand how commitment develops and what Human Resources Management (HRM) practices are most effective in fostering the desired commitment mindsets, particularly AC (see Klein, Becker, & Meyer, 2009; Meyer et al., 2002).

Until recently, most of the research addressing both the development and consequences of commitment has been *variable-centered*. That is, measures of the different commitment mindsets (AC, NC, CC) are included along with measures of theoretical antecedents or outcomes in analyses (e.g., multiple regression; structural equation modeling) designed to test the hypothesized relations between the constructs of interest. For the most part, studies examining relations between the commitment mindsets and outcome variables (e.g., turnover intentions; well-being) have focused on independent or additive effects (in the regression sense) of the commitment mindsets, though a few studies also examined interactive effects (e.g., Jaros, 1997; Johnson, Groff, & Taing, 2009). Although findings have been consistent with predictions from the TCM, a variable-centered approach is not well-suited to testing some of the more complex aspects of the model (Meyer, Stanley, et al., 2013). For example, Meyer and Allen (1991) proposed that employees can experience all three mindsets to varying degrees, and that the way in which commitment is experienced and expressed behaviorally will depend on how the mindsets combine. Meyer and Herscovitch (2001) offered propositions regarding how the mindsets combine to create *commitment profiles* and the implications of these profiles for behavioral outcomes. Implied within these propositions are complex interactions best tested using a *person-centered* approach (Marsh et al., 2009).

A number of person-centered studies of commitment mindsets have been published (e.g., Kam et al., 2015; Markovits, Davis, & van Dick, 2007; Meyer, Kam, Goldenberg, & Bremner, 2013; Meyer, L. Stanley, & Parfyonova, 2012; Meyer et al., 2015; Morin, Meyer, McInerney, Marsh, & Ganotice, 2015; Somers, 2009; Stanley, Vandenberghe, Vandenberg, & Bentein, 2013; Wasti, 2005). From these studies, five profiles have emerged with considerable regularity: (a) Fully Committed (High AC, High NC, High CC); (2) AC/NC-Dominant (High AC, High NC, Low CC); (3) AC-Dominant (High AC, Low NC, Low CC); (4) CC-Dominant (Low AC, Low NC, High CC); and (5) Weakly Committed (Low AC, Low NC, Low CC). A few other profiles have been found occasionally, albeit not has consistently, including AC/CC-Dominant (High AC, Low NC, High CC), NC/CC-Dominant (Low AC, High NC, High CC), and Moderately Committed (average levels of AC, NC, and CC). Consistent with previous variable-centered research (see Meyer et al., 2002), these studies have generally found more positive outcomes associated with profiles characterized by strong as opposed to weak AC. However, interestingly, both organization- (e.g., intention to remain) and employee-relevant (e.g., well-being) outcomes have been shown to be greater among employees with AC/NC-Dominant or Fully Committed profiles, suggesting important synergistic effects (e.g., Meyer, Kam et al., 2013; Meyer, L. Stanley et al., 2012; Somers, 2009). The highest levels of turnover intentions and burnout and lowest levels of performance and well-being have been found among Weakly Committed and CC-Dominant profiles. However, in contrast to the message drawn from variable-centered research, CC does not always signal a problem (Meyer, L. Stanley et al., 2012). Indeed, strong CC is one of the elements of a Fully Committed profile and may reflect the perception that a major cost of leaving would be the loss of those factors contributing to the strong AC and/or NC. Rather, CC appears to be a problem only when it reflects the sole basis for remaining, thwarting satisfaction of the need for autonomy (Meyer, Becker, & Vandenberghe, 2004).

Only a few studies to date have addressed potential antecedents that might be involved in the formation of commitment mindset profiles (e.g., Gellatly, Hunter, Currie, & Irving, 2009; Kam et al., 2015; Meyer, Kam et al., 2013; Meyer, L. Stanley et al., 2012; Meyer et al., 2015). The findings suggest that employees with profiles similar to those associated with the more desirable outcome also report the most positive work experiences (e.g., need satisfaction; fair treatment; trust in management; better perceptions of the organization's Human Resource Management [HRM] practices). In this study, we focused HRM practices as potential predictors of commitment mindset profiles for the illustration of tests of the predictive similarity of the profiles. This decision is based largely on previous variable-centered research demonstrating the importance of HRM practices for firm performance, both in North America (Guest, 2002) and Europe (Appelbaum, Bailey, Berg, & Kalleberg, 2000), as well as the mediating role played by employee commitment to the organization (Combs, Liu, Hall, & Ketchen, 2006). Among the mechanisms used to explain the impact of high quality HRM practices on commitment and performance are reciprocity (Blau, 1964) and empowerment (Butts, Vandenberg, Dejoy, Schaffer, & Wilson, 2009). Though there is no consensus on the operationalization of HRM practices (Boxall &Purcell, 2003; Posthuma, Campion, Masimova, & Campion, 2013), many scholars have recommended an AOM (ability, opportunity, and motivation) organizing framework. Indeed, Jiang, Lepak, Hu and Baer (2013) used this framework in their meta-analysis of the effects of HRM practices on a variety of outcomes, including employee commitment (also see Combs et al., 2006). We adopted a similar framework in this study.

A Cross-Cultural Perspective on Commitment Profiles

Most studies reviewed so far have been conducted in North America. In the few studies conducted outside of North America, (e.g., Markovits et al., 2007; Morin et al., 2015; Wasti, 2005), the profiles identified appear similar to those reported in North America, but this comparison remains purely subjective. There has yet to be a true quantitative cross-national comparison commitment profiles, their development, or their consequences. Therefore, the primary objective of the present study was to directly compare the profile structure for samples of employees from France and North America.

French and North American samples have been included in several multi-national studies of cultural values (e.g., Hofstede, 1980; 2001; House, Hanges, Javidan, Dorfman, & Gupta, 2004; Schwartz, 2006) and all have detected differences. For example, Schwartz (2006) reported that France scores lower than the US on measures of embeddedness (degree to which individuals are viewed as embedded within a collective), hierarchy (degree of reliance on a hierarchical system of shared roles), and mastery (encouragement to master, direct, and change the natural and social environment), and higher than the US on affective autonomy (pursuit of affectively positive experiences), intellectual autonomy (pursuit of own ideas and intellectual direction), and egalitarianism (recognition of other people as moral equals). Interestingly, these same cultural values were found in a recent meta-analysis to relate to the strength of the commitment mindsets, particularly NC, across countries (Meyer, D. Stanley et al., 2012). The values found to correlate positively with NC tended to be those for which France scored lower than the US, and the values found to correlate negatively with NC tended to be those for which France scored higher. Although there were too few French studies included in the meta-analysis to provide direct comparisons, these findings provide indirect evidence to suggest that, in general, NC might be weaker among French compared to North American employees. Consistent with this interpretation, studies looking at the relations between commitment mindsets and relevant work outcomes in Europe (Eisenga, Teelken, & Doorewaard, 2010; Vandenberghe Stinglhamber, Bentein, & Delhaise, 2001) found that the predictive power of NC was lower in these countries compared to what is typically observed in North America (e.g., Meyer et al., 2002).

Existing evidence for the relative stability of profile structure across studies (Meyer, Stanley et al., 2013), samples (Meyer, Kam et al., 2013; Meyer et al., 2015) and time (Kam et al., 2015), combined with preliminary evidence for a similar structure outside North America (Markovits et al., 2007; Morin et al., 2015; Wasti, 2005), lead us to hypothesize that the number (configural similarity) and nature (structural similarity) of commitment profiles would be same for our French and North American samples. Although there is evidence for differences in cultural values (Schwartz, 2006) across the two samples, which may have implications for the strength of NC (Meyer, D. Stanley et al., 2012), we did not consider these differences sufficient to cause configural or structural differences. However, because NC strength differs across the profiles observed most frequently in person-centered research (e.g., Fully Committed, AC/NC-dominant, versus Weakly Committed and CC-Dominant), national differences in NC strength could lead to sample differences in within-profile variability (dispersion differences) and/or profile frequency (distributional differences).

The proposed approach also allows for tests of predictive and explanatory similarity of profile solution. To illustrate these tests, we also assess cross-national similarity with regard to antecedents (perceptions of HRM practices) and outcomes (turnover intentions; work exhaustion) of commitment profiles. In the absence of previous person-centered research, several variable-centered meta-analytic (e.g., Fischer & Mansell, 2009; Jaramillo, Mulki, & Marshall, 2005; Meyer et al., 2002) and cross-national (e.g., Eisenga et al., 2010; Felfe, Yan, & Six, 2008; Glazer, Daniel, & Short, 2004; Kwantes, 2003; Ménard, Brunet, Savoie, van Daele, & Flament, 2011) studies have been conducted to test for differences in the ways commitment mindsets relate to antecedents and outcomes. Evidence for differences in the strength of relations, or for the moderating effects of cultural values, have been weak and inconsistent. As noted previously, there has also been little consistency in the theoretical predictions and/or explanations regarding culture differences in the development or consequences of the commitment mindsets. Therefore, all things considered, we had little basis to expect differences in the way commitment profiles relate to HRM or to turnover intentions and work exhaustion, rather more parsimoniously predict predictive and explanatory similarity across samples.

References Used in this Supplemental Section but not in the Main Manuscript.

Appelbaum, E., Bailey, T., Berg, P., & Kalleberg, A.L. (2000). *Manufacturing advantage: Why high performance work systems pay off*. Ithaca: Cornell University.

Blau, P. M. (1964). *Exchange and power in social life*. New York: Wiley.

Boxall, P.F., & Purcell, J. (2003). *Strategy and human resource management*. New York, NY: Palgrave Macmillan.

Butts M.M., Vandenberg R.J., Dejoy D.M., Schaffer B.S., & Wilson M.G. (2009). Individual reactions to high involvement work processes: investigating the role of empowerment and perceived organizational support. *Journal of Occupational Health Psychology*, *14*, 122-136.

Eisinga, R., Teelken, C., & Doorewaard, H. (2010). Assessing cross-national invariance of the three-component model of organizational commitment: A six-country study of European university faculty. *Cross-cultural Research*, *44*, 341-373.

Felfe, J., Yan, W., & Six, B. (2008). The impact of individual collectivism on commitment and its influence on organizational citizenship behaviour and turnover in three countries. *International Journal of Cross Cultural Management*, *8*, 211-237.

Fischer, R., & Mansell, A. (2009). Commitment across cultures: A meta-analytical approach. *Journal of International Business Studies*, *40*, 1339-1358.

Gellatly, I.R., Hunter, K.H., Currie, L.G., & Irving, P.G. (2009). HRM practices and organizational commitment profiles. *The International Journal of Human Resource Management, 20*, 869-884.

Glazer, S., Daniel, S.C., & Short, K.M. (2004). A study of the relationship between organizational commitment and values in four countries. *Human Relations*, *57*, 323-345.

Guest, D. (2002). Human resource management, corporate performance and employee wellbeing: Building the worker into HRM. *The Journal of Industrial Relations*, *44*, 335-358.

Hofstede, G. (1980). *Cultures Consequences: International differences in work values.* London: Sage.

Hofstede, G. (2001). *Cultures Consequences: Comparing values, behaviors, institutions, and organizations Across Nations* (2nd Ed.). London: Sage.

House, R.J., Hanges, P.J., Javidan, M., Dorfman, P.W., & Gupta P. (2004), *Culture, leadership, and* *organizations: The GLOBE Study of 62 Societies*. Thousand Oaks, CA: Sage.

Jaramillo, F., Mulki, J.P., & Marshall, G.W. (2005). A meta-analysis of the relationship between organizational commitment and salesperson job performance: 25 years of research. *Journal of Business Research*, *58*, 705-714.

Jaros, S. J. 1997. An assessment of Meyer and Allen's (1991) three-component model of commitment and turnover intentions. *Journal of Vocational Behavior*, 51: 319–337.

Johnson, R.E., Groff, K., & Taing, M. (2009). Interactions among organizational commitments: Complementary, competitive, synergistic? *British Journal of Management*, *20*, 431-447.

Klein, H.J., Becker, T.E., & Meyer, J.P. (2009). *Commitment in Organizations: Accumulated Wisdom and New Directions*. Florence, KY: Routledge/Taylor and Francis Group.

Kwantes, C.T. (2003). Organizational citizenship and withdrawal behaviors in USA and India: Does commitment make a difference? *International Journal of Cross-cultural Management*, *3*, 5-26.

Markovits, Y., Davis, A.J., & van Dick, R. (2007). Organizational commitment profiles and job satisfaction among Greek private and public sector employees. *International Journal of Cross-cultural Management*, *7*, 77-99.

Ménard, J., Brunet, L., Savoie, A., van Daele, A., & Flament, A. (2011). Cross-national deviance in the workplace: Diverging impact of organizational commitment in Canada and Belgium. *European Journal of Work and Organizational Psychology*, *20*, 266-284.

Meyer, J.P., & Allen, N.J. (1991). A three-component conceptualization of organizational commitment. *Human Resource Management Review, 1,* 64-89.

Meyer, J.P., & Allen, N.J. (1997). *Commitment in the workplace: Theory, research, and application.* Thousand Oaks, CA: Sage.

Meyer, J.P., Becker, T.E., & Vandenberghe, C. (2004). Employee commitment and motivation: A conceptual analysis and integrative model. *Journal of Applied Psychology, 89,* 991-1007.

Meyer, J.P., Kam, C., Goldenberg, I., & Bremner, N.L. (2013). Organizational commitment in the military: Application of a profile approach. *Military Psychology*, *25*, 381-401.

Meyer, J.P., & Maltin, E.R. (2010). Employee commitment and well-being: A critical review, theoretical framework and research agenda. *Journal of Vocational Behavior, 77*, 323-337.

Meyer, J.P., Stanley, D.J., Herscovitch, L., & Topolnytsky, L. (2002). Affective, continuance and normative commitment to the organization: A meta-analysis of antecedents, correlates and consequences. *Journal of Vocational Behavior, 61*, 20-52.

Meyer, J.P., Stanley, D.J., Jackson, T.A., McInnis, K.J., Maltin, E.R., & Sheppard, L. (2012). Affective, continuance, and normative commitment levels across cultures: A meta-analysis. *Journal of Vocational Behavior*, *80*, 225-245.

Meyer, J.P., Stanley, L.J., & Parfyonova, N.M. (2012). Employee commitment in context: The nature and implication of commitment profiles. *Journal of Vocational Behavior, 80*, 1-6.

Morin, A.J.S., Meyer, J.P., McInerney, D. M., Marsh, H.W., & Ganotice, F. (2015, in press). Profiles of Dual Commitment to the Occupation and Organization: Relations to Wellbeing and Turnover Intentions. *Asia Pacific Journal of Management*.

Posthuma, R.A., Campion, M.C., Masimova, M., & Campion, M.A. (2013). A high performance work practices taxonomy: Integrating literature and directing future research. *Journal of Management*, *39*, 1184-1220.

Schwartz, S. H. (2006). A theory of cultural value orientations: Explication and applications. *Comparative Sociology*, *5*, 137-182.

Somers, M.J. (2009). The combined influence of affective, continuance, and normative commitment on employee withdrawal. *Journal of Vocational Behavior*, *74*, 75-81.

Stanley, L., Vandenberghe, C., Vandenberg, R., & Bentein, K. (2013). Commitment profiles and employee turnover. *Journal of Vocational Behavior*, *82*, 176-187.

Vandenberghe, C., Stinglhamber, S., Bentein, K., & Delhaise, T. (2001). An examination of the cross-cultural validity of a multidimensional model of commitment in Europe. *Journal of Cross-Cultural Psychology, 32,* 322-347.

Wasti, S. A. (2005). Commitment profiles: Combinations of organizational commitment forms and job outcomes. *Journal of Vocational Behavior, 67,* 290-308.

Confirmatory Factor Analyses

Confirmatory factor analytic models based on the Meyer et al. (1993) organizational commitment scale (the exact items labels are reported on the next page) were estimated using Mplus 7.11 (Muhtén & Muthén, 2013) and the robust maximum Likelihood (MLR) estimator. This estimator provides standard errors and tests of fit that are robust in relation to non-normality and the use of ordered-categorical variables involving at least five response categories (for a review, see Finney & DiStephano, 2006, 2013). First, the a priori 3-factor (reflecting AC, NC, and CC) measurement model was estimated separately in each sample. Then, before saving the factor scores in order to use them as indicators of the latent profiles in the main analyses, we first wanted to ensure that the measurement model operated in the same manner in both countries. In other words, we wanted to systematically assess whether the meaning (and underlying measurement model) of the constructs remained the same in both countries. We thus conducted tests of measurement invariance of this a priori measurement model in the following sequence (Meredith, 1993; Millsap, 2011): (i) configural invariance, (ii) Weak invariance (loadings), (iii) strong invariance (loadings and intercepts), (iv) strict invariance (loadings, intercepts and uniquenesses). In each sequence of invariance the preceding model served as reference.

Assessment of model fit was based on multiple indicators (Hu & Bentler, 1999; Marsh, Hau, & Grayson, 2005): the chi-square (χ^2), the comparative fit index (CFI), the Tucker-Lewis index (TLI), the root mean square error of approximation (RMSEA), the 90% confidence interval of the RMSEA, and the standardized root mean square residual (SRMR). Values greater than .90 for the CFI and TLI indicate adequate model fit, although values greater than .95 are preferable. Values smaller than .08 or .06 for the RMSEA and than .10 and .08 for the SRMR support respectively acceptable and excellent model fit. Like the chi square, chi square difference tests present a known sensitivity to sample size and minor model misspecifications so that recent studies suggest complementing this information with changes in CFIs and RMSEAs (Chen, 2007; Cheung & Rensvold, 2002; Vandenberg & Lance, 2000). A ΔCFI of .01 or less and a ΔRMSEA of .015 or less between a more restricted model and the preceding one indicate that the invariance hypothesis should not be rejected. It should also be noted that for indices incorporating a penalty for lack of parsimony such as the TLI and RMSEA, it is possible for a more restrictive model to result in better fit than a less restricted model; thus changes in TLI should also be inspected (Marsh et al., 2005). In addition, for consistency the latent profile models reported in the main manuscript, we also report AIC, CAIC, BIC, and ABIC with lower values suggesting a better-fitting model.

The results from these various models are reported in supplementary Table S1. These results clearly support show that the a priori 3-factor model provides an adequate level of fit to the data, in addition to supporting its strict measurement invariance across samples. The parameter estimates from this model were used to compute the scale score reliability coefficients associated with each of the a priori factors in both countries using McDonald (1970) omega (ω) coefficient:

$$\omega = \frac{(\sum|\lambda_i|)^2}{[(\sum|\lambda_i|)^2 + \sum\delta_i]}$$

where $|\lambda_i|$ are the factor loadings associated with a factor in absolute values, and δi, the item uniquenesses. The numerator, were the factor loadings are summed, and then squared, reflects the proportion of the variance in in indicators that reflect true score variance, whereas the denominator reflects total amount of variance in the items including both true score variance and random measurement errors (the sum of the items uniquenesses associated with a factor). We also report 95% bias-corrected bootstrap (using 10,000 bootstrap samples) confidence intervals for these coefficients (Raykov, 2009).

To ensure that the latent profiles estimated in each countries were based on fully comparable measures of commitment, the factor scores used in main analyses were saved from the model of strict measurement invariance. Furthermore, in order to keep the result in meaningful measurement units based on a synthesis of all items forming each factor (rather than on a referent indicator or standardized units) in a manner directly comparable to aggregate scale scores often used in this area of research, this model was identified using Little, Sledgers and Card (2006) effects coding method which amounts to constraining the non-standardized factor loadings to average 1 within each factors, and to constrain the item intercepts to sum to zero within each factor.

Affective Commitment Items
I feel emotionally attached to this organization
This organization has a great deal of personal meaning for me;
I feel a strong sense of "belonging" to this organization;

Continuance Commitment Items
It would be very hard for me to leave this organization right now, even if I wanted to;
Too much of my life would be disrupted if I decided I wanted to leave my organization now;
I feel that I have too few options to consider leaving this organization;

Normative Commitment Items
Even if it were to my advantage, I do not feel it would be right to leave my organization now
I would be guilty if I left my organization now
I would not leave this organization right now because I feel an obligation to the people in it;

References Used in this Supplemental Section but not in the Main Manuscript.

Chen, F.F. (2007). Sensitivity of goodness of fit indexes to lack of measurement. *Structural Equation Modeling*, *14*, 464–504.
Cheung, G.W. (2008). Testing equivalence in the structure, means, and variances of higher-order constructs with structural equation modeling. *Organizational Research Methods*, *11*, 593-613.
Finney S. J., & DiStefano, C. (2006). Non-normal and categorical data in structural equation modeling. In G. R. Hancock, & R. O. Mueller (Eds.), *Structural Equation Modeling: A Second Course* (pp. 269-314). Greenwich, CO: IAP.
Finney S. J., & DiStefano, C. (2013). Non-normal and categorical data in structural equation modeling. In G. R. Hancock, & R. O. Mueller (Eds.), *Structural Equation Modeling: A Second Course*, *second edition* (pp. 439-492). Greenwich, CO: IAP.
Hu, L.-T., & Bentler, P.M. (1999). Cutoff criteria for fit indexes in covariance structure analysis: Conventional criteria versus new alternatives. *Structural Equation Modeling, 6,* 1–55.
Little, T.D., Sledgers, D.W., & Card, N.A. (2006). A non-arbitrary method of identifying and scaling latent variables in SEM and MACS models. *Structural Equation Modeling*, *13*, 59-72.
Marsh, H. W., Hau, K., & Grayson, D. (2005). Goodness of Fit in Structural Equation Models. In Maydeu-Olivares, Albert (Ed); McArdle, John J. (Ed), *Contemporary psychometrics: A festschrift for Roderick P. McDonald.* (pp. 275-340). Mahwah, NJ, US: Lawrence Erlbaum Associates Publishers.
Vandenberg, R.J., & Lance, C.E. (2000). A review and synthesis of the measurement invariance literature: Suggestions, practices, and recommendations for organizational research. *Organizational Research Methods*, *3*, 4-70.

Table S1.

Preliminary Confirmatory Factor Analyses Conducted on the Organizational Commitment Scales.

Model	MLRχ²(df)	CFI	TLI	RMSEA	RMSEA 90% CI	SRMR	AIC	CAIC	BIC	ABIC
North America										
A priori 3-factor model	81.002(24)*	0.968	0.952	0.069	0.053-0.086	0.048	15556.242	15712.196	15682.196	15586.977
France										
A priori 3-factor model	67.220(24)*	0.975	0.962	0.062	0.044-0.079	0.052	15073.500	15228.463	15198.463	15103.247
Multiple-Group										
Configural invariance	149.643(48)*	0.971	0.957	0.066	0.054-0.078	0.050	30629.742	30982.256	30922.256	30731.697
Weak invariance (λ)	173.856(54)*	0.966	0.955	0.068	0.057-0.079	0.058	30643.813	30961.075	30907.075	30735.572
Strong invariance (λ, π)	197.501(60)*	0.961	0.953	0.069	0.058-0.080	0.058	30657.353	30939.364	30891.364	30738.917
Strict invariance (λ, π, δ)	206.087(69)*	0.961	0.959	0.064	0.054-0.074	0.059	30686.983	30916.117	30877.117	30753.254

Note. *MLR* χ^2 = chi square test of model fit associated with the robust Maximum Likelihood estimator; *df*= degrees of freedom; *CFI* = Comparative fit index; TLI = Tucker-Lewis index; *RMSEA* = Root mean square error of approximation; *90% CI* = 90% Confidence Interval for the RMSEA; SRMR = Standardized Root Mean Square Residual; AIC = Akaïke information criterion; CAIC = Consistent AIC; BIC = Bayesian information criterion; SABIC = Sample-size adjusted BIC; * $p < 0.01$.

Table S2.

Correlations, Descriptive Statistics, and Scale Score Reliability Coefficients for all Variables.

	AC	NC	CC	Gender	Tenure	Education	HRM_A	HRM_O	HRM_M	Exhaustion	Turnover
AC		0.700**	0.368**	0.055	0.080	0.096*	0.447**	0.420**	0.447**	-0.341**	-0.455**
NC	0.507**		0.489**	0.061	0.011	0.114**	0.403**	0.415**	0.392**	-0.181**	-0.381**
CC	0.343**	0.443**		-0.018	0.110*	0.000	0.149**	0.169**	0.197**	0.083*	-0.106*
Gender	-0.152**	-0.146**	-0.072		0.105*	0.026	-0.022	-0.040	-0.016	-0.034	-0.009
Tenure	0.167**	-0.217**	0.139**	-0.006		0.032	0.051	-0.047	0.009	0.009	-0.085
Education	-0.006	0.022	-0.177**	-0.018	-0.251**		0.157**	0.107*	0.105*	-0.008	-0.023
HRM_A	0.021	0.043	0.111*	-0.035	0.034	-0.059		0.649**	0.661**	-0.102*	-0.220**
HRM_O	0.372**	0.275**	0.021	-0.103*	−0.076	0.122**	0.078		0.630**	-0.131**	-0.183**
HRM_M	0.210**	0.201**	0.082	-0.130**	-0.029	0.016	0.199**	0.294**		-0.155**	-0.194**
Exhaustion	-0.117**	-0.018	0.082	-0.007	0.030	-0.089*	0.528**	-0.140**	-0.037		0.604**
Turnover	-0.409**	-0.389**	-0.273**	0.067	0.003	-0.026	0.110*	-0.238**	-0.139**	0.404**	
North America											
Mean	4.708	4.263	4.810	58.1% fem.	2.419	2.622	4.538	4.485	4.202	3.691	3.269
Standard Deviation	1.794	1.737	1.367	--	1.110	0.806	1.675	1.683	1.784	1.911	2.044
Reliability (ω)	0.951	0.898	0.834	--	--	--	0.627	0.631	0.722	0.948	0.924
95% CI for ω	0.936/0.963	0.874/0.918	0.795/0.865				0.535/0.697	0.548/0.700	0.656/0.773	0.937/0.957	0.905/0.940
France											
Mean	3.982	2.835	4.179	59.7% fem.	2.538	4.620	3.632	3.791	3.584	3.592	3.202
Standard Deviation	1.605	1.452	1.298	--	1.149	0.931	1.293	1.570	1.395	1.560	1.984
Reliability (ω)	0.945	0.877	0.734	--	--	--	0.514	0.598	0.543	0.906	0.907
95% CI for ω	0.931/0.957	0.849/0.899	0.676/0.776				0.449/0.570	0.531/0.654	0.490/0.591	0.889/0.919	0.887/0.924

Note. AC: Affective Commitment; NC = Normative Commitment; CC: Continuance Commitment; HRM_A: Human Resources Management Abilities-oriented practices; HRM-O: Human Resources Management Opportunities-oriented practices; HRM_M: Human Resources Management Motivation-oriented practices; CI = bias-corrected bootstrap confidence interval; * $p < .05$. ** $p < .01$.

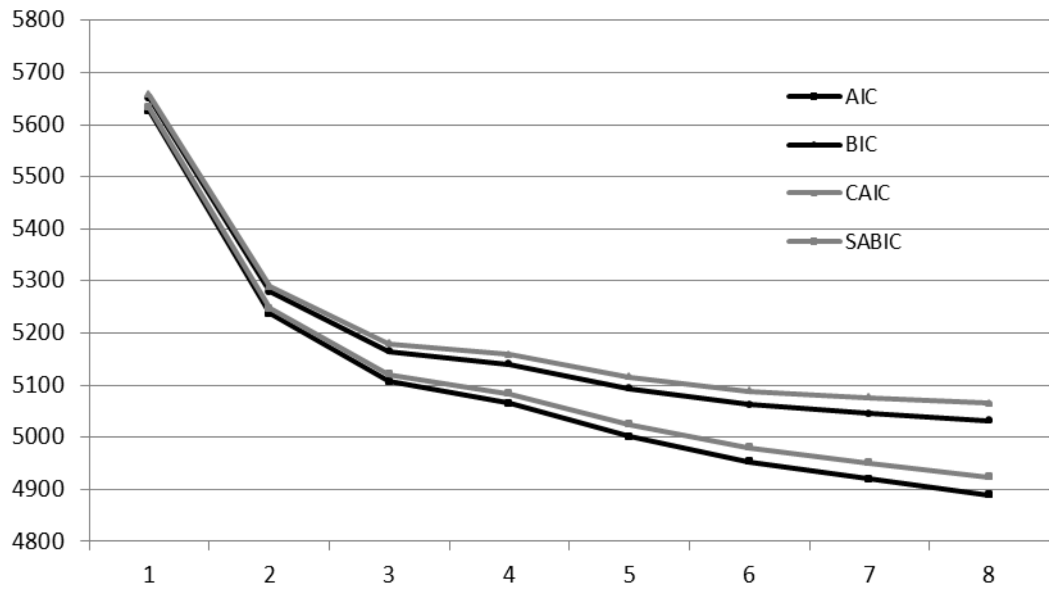

Figure S1a. Elbow Plot of the Fit Indices of the Latent Profile Analyses (North America).

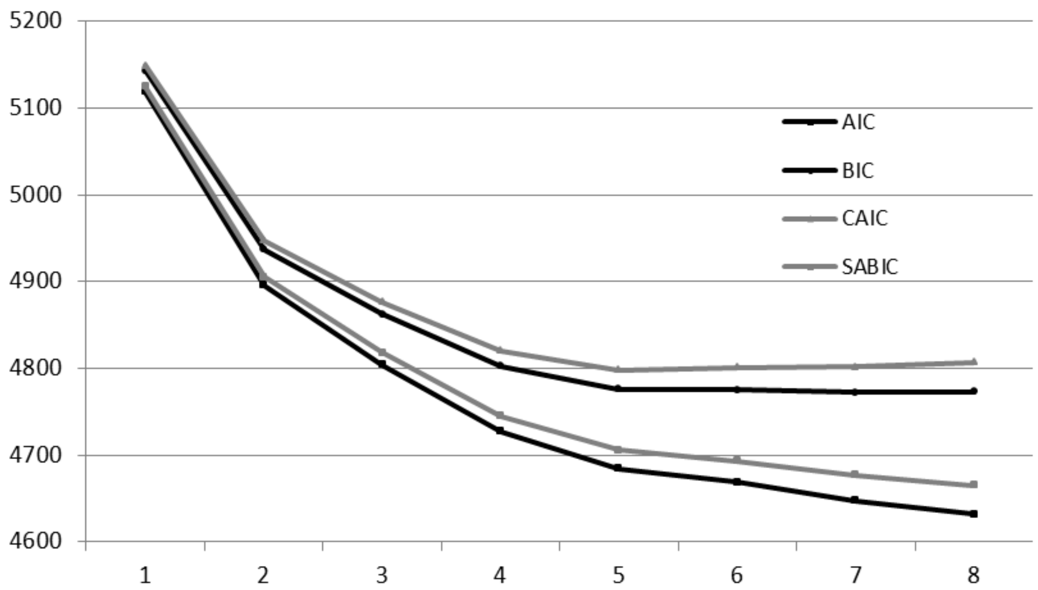

Figure S1b. Elbow Plot of the Fit Indices of the Latent Profile Analyses (France).

Table S3.

Classification Probabilities for Most Likely Latent Profile Membership (Row) by Latent Profile (Column) for the Final Cross-Cultural Model.

Profiles	Profile 1	Profile 2	Profile 3	Profile 4	Profile 5
North America					
1	0.920	0.024	0.000	0.000	0.056
2	0.017	0.850	0.000	0.078	0.056
3	0.000	0.000	0.948	0.052	0.000
4	0.000	0.072	0.066	0.862	0.000
5	0.083	0.089	0.000	0.000	0.828
France					
1	0.913	0.012	0.000	0.000	0.075
2	0.010	0.836	0.000	0.064	0.089
3	0.000	0.000	0.843	0.157	0.000
4	0.000	0.111	0.057	0.832	0.000
5	0.113	0.087	0.000	0.000	0.800

Discussion of the Substantive Implications of our Results for Commitment Research

Substantive Contribution: Cross-Cultural Generalizability of Commitment Profiles

Over and above this methodological contribution, this study also contributed substantively to a growing body of research examining the nature, development and consequences of commitment mindset profiles. Importantly, it is the first study to address the issue of cross-national stability. Previously, it has been shown that profile structure remains relatively constant across studies (see Meyer, Stanley et al., 2013), across samples (Meyer, Kam et al., 2013), and over time (Kam et al., 2015). However, most of this research was conducted in North America, so it is important to determine whether similar stability can be observed elsewhere.

Profile Structure. In this study, we found that a common five-profile structure characterized both the North American and French samples. The profiles detected in these samples – *CC-Dominant*, *Moderately Committed*, *AC/NC-Dominant*, *NC-Dominant*, *AC-Dominant* – were generally similar to those obtained in previous research. The only profile obtained in our study that has not been commonly identified in previous research was the *NC-Dominant* profile. This profile differs only slightly from the profiles showing close to, or slightly above, average levels of commitment found in previous studies as these also generally tend to reveal slight elevations of one component relative to the others (NC in this study) (e.g., Kam et al., 2015; Meyer, Kam et al., 2013; Meyer, Stanley et al., 2013; Wasti, 2005). Therefore, this is not a radical departure. Overall, this evidence for stability across studies, and in this case across countries, provides important support for the potential utility of the person-centered approach to commitment research. It is now increasingly apparent that there is heterogeneity in commitment mindset profiles among employees, and that research generally is able to identify a common set of recurring profiles. It is also becoming apparent that employees with these profiles differ in meaningful and predictable ways with regard to work-relevant behaviors and well-being, with the optimal profiles being *AC-Dominant*, *AC/NC-Dominant*, and *Fully Committed*.

Although our results revealed the presence of the same number of profiles, presenting the same structure and levels of within-group variability, across our North American and French samples, these profiles were not equally frequent in both countries. Interestingly, the differences were consistent and somewhat predictable from previous cross-cultural studies of values (e.g., Schwartz, 2006) and commitment strength (Meyer, D. Stanley et al., 2012). Specifically, we noted earlier that France differed from North America on several of the values found to be associated with national levels of NC (e.g., embeddedness, hierarchy). This led us to expect that employees in France might be less likely than those in North America to have commitment profiles with elevated levels of NC. Our findings indicate that this was indeed the case. More precisely, the profiles found to be more frequent in North America than in France (*AC/NC-Dominant*: 31.4% vs. 6.3%; *NC-Dominant*: 26.5% vs. 14.2%) were characterized by higher levels of NC than AC and CC. In contrast, the profiles found to be more frequent in France than in North America (*CC-Dominant*: 26.2% vs. 12.1%; *AC-Dominant*: 25.0% vs.6.6%), were characterized by relatively low levels of NC. Although potentially meaningful given the outcomes associated with these profiles, the differences are subtle and only involved the frequency of similar profiles in both samples, rather than drastically different profiles. We might expect greater differences in future research involving more diverse cultures. However, if the profiles do indeed reflect basic human tendencies rather than culturally-specific characteristics, major cross-cultural differences on profiles configuration or structure would be unlikely.

Outcomes of Commitment Profiles. A few notable findings have emerged in studies to date with regard to the outcomes associated with commitment profiles (Meyer, L. Stanley et al., 2012; Meyer, Kam et al., 2013; Somers, 2009; Wasti, 2005). First, it has become apparent that a combination of strong AC and NC (as reflected in *AC/NC-Dominant* and *Fully Committed* profiles) is often associated with equally, and often more, positive outcomes than strong AC alone. This finding is contrary to Meyer and Herscovitch's (2001) original proposal that the most positive outcomes would be expected for those with "pure AC". More recently, Meyer and Parfyonova (2010) proposed that employees with strong NC in combination with strong AC might be more likely to engage in activities that require some personal sacrifice, because it is the right thing to do, whereas those with strong AC alone may be more inclined to restrict their behaviors to what they enjoy. In the present study, the lowest levels of turnover intention and work exhaustion were associated with the *AC/NC-Dominant* and *AC-Dominant* profiles. Although the differences between these two profiles were not significant, turnover intentions were slightly lower among *AC/NC-Dominant* employees, and work exhaustion was slightly lower among *AC-Dominant* employees. If Meyer and Parfyonova are correct, we might have detected larger differences favoring the *AC/NC-Dominant* group had we included outcomes (e.g., OCB) requiring greater levels of discretionary efforts (e.g., Wasti, 2005).

Second, it is now becoming clear that the implications of CC for behavior and well-being depend on the strength of both the AC and NC mindsets within commitment profiles. Strong CC tends to be associated with positive outcomes when combined with strong AC and NC (i.e., *Fully Committed*), and with negative outcomes when combined with weak AC and NC (*CC-Dominant*). In the present study, the highest rates of turnover intention and work exhaustion were obtained in the *CC-Dominant* profile where CC was weak in absolute terms, but was the strongest of the three mindsets in a relative sense. In contrast, turnover intention and work exhaustion levels were among the lowest in the *AC/NC-Dominant* profile where CC was strongest in absolute terms, but combined with even stronger AC and NC. This suggests that CC might be experienced differently when accompanied by strong versus weak AC and NC. When AC and NC are weak, employees might feel highly constrained by their circumstances and feel that their work behaviors are mainly determined by the avoidance of the potential costs of job loss. Conversely, when AC and NC are strong, the potential costs inherent in CC are likely to reflect the loss of those things (captured in AC and NC) that make them want to stay. This could help explain the inconsistent relations obtained between CC and work behavior in variable-centered research (Meyer et al., 2002). Moreover, it argues against the general view emanating from variable-centered research that CC represents a form of commitment that might best be avoided (Meyer & Allen, 1997; Meyer et al., 2004). Our results rather suggest that there might be benefits to CC, as long as it is combined with AC and/or NC.

In addition to verifying previous finding regarding outcomes associated with the different commitment profiles, our study provides the first evidence of explanatory similarity across cultures. That is, we found that the links between profile membership and both turnover intention and work exhaustion were the same for our French and North American samples. Evidence of explanatory similarity across cultures, although not essential, contributes to our confidence in the generalizability of the TCM and its utility for managing commitment. Of course, more research is required to address explanatory similarity across more diverse cultures.

Antecedents of Commitment Profiles. Despite evidence that they are differentially associated with multiple meaningful outcomes (see Meyer, Stanley et al., 2013), relatively little attention has been paid to date to the investigation of the predictors of profile membership and development (for exceptions, see Gellatly et al., 2009; Kam et al., 2015; Meyer, L. Stanley et al., 2012). In the present study, we included abbreviated perceptual measures of three critical types of HRM practices (e.g., Combs et al., 2006; Jiang et al., 2013; Gellatly et al., 2009; Posthuma et al., 2013): ability-oriented, motivation-oriented, and opportunity-oriented.

Two important findings emerge from our analyses of the relations between employees' perceptions of the HRM practices used in their workplaces and their commitment profiles. First, we noted that the profiles associated with the most desirable outcomes – *AC/NC-Dominant* and *AC-Dominant* – had the most positive perceptions of HRM practices. Conversely, those employees with profiles associated with the most negative outcomes – *CC-Dominant* and *Moderately Committed* – had the least positive perceptions of HRM practices. Although we cannot draw conclusions with regard to causality, this evidence is consistent with the notion that high involvement HRM practices exert their positive effects on organizational outcomes in part through their effects on employee commitment (Combs et al., 2006; Jiang et al., 2012).

The second important finding is the evidence for predictive similarity across the North American and French samples. Again, evidence that the same profiles emerge, but also that they have similar sets of antecedents, contributes to the demonstration of the potential utility of results based on this person-centered approach to the study of commitment mindsets. With due consideration to the fact that the two samples were drawn from Western cultures, our findings suggest that this is the case, at least within similar cultures. More precisely, this evidence for both structural and predictive similarity suggests that intervention strategies guided by these findings should also generalize. However, it is critically important to keep in mind that, in part due to the limited number of items included in these subscales, composite reliability estimates for the HRM practices obtained in the current study remained particularly low, suggesting that current estimates of the relationships between HRM practices and profiles might have been downwardly biased by unreliability. Clearly, future studies would do well to explore these relations more thoroughly while relying on stronger, and more reliable, measures of HRM practices.

Limitations and Future Directions

Our study constitutes a first attempt to test for profile similarity across countries, and presents an comprehensive approach for doing so. As such, it makes both substantive and methodological contributions to the literature. However, as we noted elsewhere, our two samples were from Western countries and, although they have been shown to differ somewhat in cultural values (e.g., Schwartz, 2006), there is a need to replicate our findings in even more diverse cultures, as well as across subpopulations. It is particularly important to determine whether we can demonstrate configural and structural similarity in these more diverse cultures. If so, it suggests that the TCM remains a viable framework for understanding commitment in these cultures. Such findings would also help to verify that commitment profiles reflect basic human processes governing the way people relate to collectives such as work organizations, rather than more ephemeral reactions to situational influences that vary from culture to culture. The other forms of similarity investigated in this study are less crucial to the value of the TCM per se; rather, among other things, evidence of non-similarity might suggest cultural differences in the ways employees are managed, in how employees respond to particular policies and practices, and how commitment manifests itself in behavior. If one or more forms of non-similarity are detected, research might be conducted to determine whether they can be explained in terms of cultural values, economic conditions, geopolitical factors or other situational determinants that organizations should take into account in the management of their workforce.

The samples used in the present investigation were convenience panel samples of employees recruited online, which precluded direct tests of variability of the results across subgroups including different occupations or profession, hierarchical levels, unionized vs. non-unionized employees and so on. Similarly, although we can expect some of the constructs considered here to exhibit significant variations at the organizational level (e.g., commitment, HRM practices) that might need to be controlled for the analyses, the recruitment process used in this study was conducted at the individual level, precluding any consideration of effects located at the organizational level. Fortunately, lack of control for organizational nesting has been shown not to impact the class enumeration process in the context of latent profiles analyses (Chen, Kwok, Luo, & Willson, 2010), which means that we can be confident that commitment mindsets are best reflected in a set of five profiles in both countries.

Given our primary interest in developing and applying a sequential strategy for testing for similarity pertaining to commitment profiles, we included only a few of the many variables that we would expect to predict, and result from, profile membership. We included turnover intention because it is the most widely studied outcome of commitment, and included work exhaustion, one of the more common indicators of burnout, as a more employee-relevant outcome. Future research should include a wider range of outcomes, including actual turnover, job performance, OCB, and well-being. On the antecedent side, we used abbreviated measures of HRM practices used in previous research as predictors of commitment (e.g., Gellatly et al., 2009). Although we found evidence that perceptions of the ability-, motivation-, and opportunity- oriented practices were conceptually distinct and had distinctive patterns of association with the commitment profiles, their reliabilities were marginal and therefore we focused more on the general pattern of findings than on distinctive influences. Given our finding that perceptions of HRM practices did predict profile membership, and that the relations were equivalent across samples, future research using longer and more rigorous measures seems warranted.

Finally, all measures used in our study were self-reported at a single point in time. From a purely methodological standpoint, the implications of using all self-report measures are mitigated when hypotheses involve complex interactions among variables, such as those that are naturally reflected in analyses of profiles (Siemsen, Roth, & Oliveira, 2010). That said, there would be definite benefits in future research to include objective measures of both work conditions (e.g., HRM practices) that might be instrumental in shaping commitment profiles, and objective measures of potential outcomes (e.g., actual turnover and job performance). More limiting is the use of a cross-sectional design. However, at this stage, we were most interested in the cross-national similarity in the nature, development, and outcomes of commitment profiles than we were in demonstrating true causal effects. As we become more confident in the nature of profiles and their similarity across cultures, it will be important to turn our attention to causal effects involved in both the formation and consequences of these profiles.

References Used in this Supplemental Section but not in the Main Manuscript.

Chen, Q., Kwok, O.-M., Luo, W., & Willson, V.L. (2010). The impact of ignoring a level of nesting structure in multilevel growth mixture models: A Monte Carlo study. *Structural Equation Modeling*, *17*, 570-589.

Gellatly, I.R., Hunter, K.H., Currie, L.G., & Irving, P.G. (2009). HRM practices and organizational commitment profiles. *The International Journal of Human Resource Management, 20*, 869-884.

Meyer, J.P., & Allen, N.J. (1997). *Commitment in the workplace: Theory, research, and application.* Thousand Oaks, CA: Sage.

Meyer, J.P., Becker, T.E., & Vandenberghe, C. (2004). Employee commitment and motivation: A conceptual analysis and integrative model. *Journal of Applied Psychology, 89,* 991-1007.

Meyer, J.P., Kam, C., Goldenberg, I., & Bremner, N.L. (2013). Organizational commitment in the military: Application of a profile approach. *Military Psychology*, *25*, 381-401.

Meyer, J.P., & Parfyonova, N.M. (2010). Normative commitment in the workplace: A theoretical analysis and re-conceptualization. *Human Resource Management Review, 20*, 283−294.

Meyer, J.P., Stanley, D.J., Herscovitch, L., & Topolnytsky, L. (2002). Affective, continuance and normative commitment to the organization: A meta-analysis of antecedents, correlates and consequences. *Journal of Vocational Behavior, 61*, 20-52.

Meyer, J.P., Stanley, D.J., Jackson, T.A., McInnis, K.J., Maltin, E.R., & Sheppard, L. (2012). Affective, continuance, and normative commitment levels across cultures: A meta-analysis. *Journal of Vocational Behavior*, *80*, 225-245.

Meyer, J.P., Stanley, L.J., & Parfyonova, N.M. (2012). Employee commitment in context: The nature and implication of commitment profiles. *Journal of Vocational Behavior, 80*, 1-6.

Posthuma, R.A., Campion, M.C., Masimova, M., & Campion, M.A. (2013). A high performance work practices taxonomy: Integrating literature and directing future research. *Journal of Management*, *39*, 1184-1220.

Schwartz, S. H. (2006). A theory of cultural value orientations: Explication and applications. *Comparative Sociology*, *5*, 137-182.

Siemsen, E., Roth, A., & Oliveira, P. (2010). Common method bias in regression models with linear, quadratic, and interaction effects. *Organizational Research Methods*, *13*, 456-476.

Somers, M.J. (2009). The combined influence of affective, continuance, and normative commitment on employee withdrawal. *Journal of Vocational Behavior*, *74*, 75-81.

Wasti, S. A. (2005). Commitment profiles: Combinations of organizational commitment forms and job outcomes. *Journal of Vocational Behavior, 67,* 290-308.

TITLE: Mplus Input Code to Estimate a 5-Class Latent Profile Solution Without Covariates and Outcomes in a Single Country.

```
! In all input files, statements preceded by ! are annotations.
! Use the following statement to identify the data set. Here, the data set is labelled FSCORES.dat.
DATA: FILE IS FSCORES.dat;
! The variables names function identifies all variables in the data set, in order of appearance,
! whereas the usevar command identifies the variables used in the analysis.
VARIABLE:
NAMES = ID GENDER TENURE EDUCATIO WE QU HR_AB HR_OP HR_MO
FAC FCC FNC G;
USEVARIABLES = FAC FCC FNC;
! The variable G is the grouping variables identifying both samples. Here, we select the Group with a
value of 2 (i.e., France).
USEOBS G EQ 2;
! To estimate the model in the North American sample, replace this statement by:
! USEOBS G EQ 1;
! The following identifies the number of latent profiles requested in the analysis.
CLASSES = c (5);
! The next section defines the analysis. By default, the Maximum Likelihood (ML) estimator is used.
ANALYSIS:
! The following set up is to estimate the model using 3 processors, 5000 starts values, 200 final stage
optimizations, and 100 iterations.
Processor = 3;
TYPE = MIXTURE; STARTS = 5000 200; STITERATIONS = 100;
! The following are to increase the defaults starts and iteration for the BLRT.
LRTBOOTSTRAP = 100; LRTSTARTS = 10 5 80 20;
! The next statement defines the model. Here, a simple latent profile model is specified with variances
        equal across profiles.
MODEL:
! In this input, the overall model statement would define sections of the models that are common
across profiles.
! Here, there is no need to include anything in this section.
! The %c#1% to %c#5% sections are class-specific statement with which to specify which part of the
model is freely estimated in each profile.
! For a simple latent profile model, simply include the means of the indicators (using []) in all profiles.
! To also freely estimate all variances, add the following in each class-specific statement:
! FAC FCC FNC;
%OVERALL%
%c#1%
[FAC FCC FNC];
! Add the following statement to request class-varying variances for the profile indicators.
! FAC FCC FNC;
%c#2%
[FAC FCC FNC]; ! FAC FCC FNC;
%c#3%
[FAC FCC FNC]; ! FAC FCC FNC;
%c#4%
[FAC FCC FNC]; ! FAC FCC FNC;
%c#5%
[FAC FCC FNC]; ! FAC FCC FNC;
! Specific sections of output are requested. TECH11 estimates LMR, and TECH14 estimates BLRT.
OUTPUT:
STDYX SAMPSTAT CINTERVAL SVALUES RESIDUAL TECH1 TECH7 TECH11 TECH14;
```

TITLE: Mplus Input Code to Estimate a Configural Similarity Model for a Latent Profile Solution Without Covariates and Outcomes.

```
! Annotations only focus on functions not previously defined.
DATA: FILE IS FSCORES.dat;
VARIABLE:
NAMES = ID GENDER TENURE EDUCATIO WE QU HR_AB HR_OP HR_MO
FAC FCC FNC G;
USEVARIABLES = FAC FCC FNC;
! The variable G is the grouping variables identifying both samples.
! To estimate a multiple group latent profile model, we identify these two sample using the
! knownclass function. We create a latent categorical variable defining this known classification.
! Here, we label this variable CG and then define the 2 values of CG (based on the value of the
! observed variable G where 1 = North America and 2 = France).
! Then the CLASSES function is used to label all latent categorical variables: CG (previously defined,
! with 2 levels, based on the observed grouping variable), and C (estimated as part of the latent profile
! analyses, defining the profiles themselves, here requesting that 5 profiles be estimated in both
! samples defined by CG).
knownclass = cg (g = 1 g = 2);
CLASSES = cg (2) c (5);
ANALYSIS:
Processor = 3;
TYPE = MIXTURE;
STARTS = 10000 500;
STITERATIONS = 500;
MODEL:
%OVERALL%
! The following statements in the %OVERALL% section indicate that the class sizes (class
! probabilities) are freely estimated in all samples.
! Only k-1 statements are required (i.e. 4 for a 5 class model)
c#1 on cg#1;
c#2 on cg#1;
c#3 on cg#1;
c#4 on cg#1;
! Class specific statements now need to be defined using a combination of both the known classes CG
! and the estimated classes C.
! Labels in parentheses identify parameters that are estimated to be equal.
! Lists of constraints (e.g., m1-m3) apply to the parameters in order of appearance (e.g., m1 applies to
! ACC, m2 to FCC, and m3 to FNC).
! Here, the means are freely estimated in all combinations of profiles and countries and the variances
! are constrained to be equal across profiles (as in the default models estimated in each countries) and
! freely estimated in both countries.
%cg#1.c#1%
[FAC FCC FNC] (m1-m3);
FAC FCC FNC (v1-v3);
%cg#1.c#2%
[FAC FCC FNC] (m4-m6);
FAC FCC FNC (v1-v3);
%cg#1.c#3%
[FAC FCC FNC] (m7-m9);
FAC FCC FNC (v1-v3);
%cg#1.c#4%
[FAC FCC FNC] (m10-m12);
FAC FCC FNC (v1-v3);
%cg#1.c#5%
```

```
[FAC FCC FNC] (m13-m15);
FAC FCC FNC (v1-v3);
%cg#2.c#1%
[FAC FCC FNC] (dm1-dm3);
FAC FCC FNC (dv1-dv3);
%cg#2.c#2%
[FAC FCC FNC] (dm4-dm6);
FAC FCC FNC (dv1-dv3);
%cg#2.c#3%
[FAC FCC FNC] (dm7-dm9);
FAC FCC FNC (dv1-dv3);
%cg#2.c#4%
[FAC FCC FNC] (dm10-dm12);
FAC FCC FNC (dv1-dv3);
%cg#2.c#5%
[FAC FCC FNC] (dm13-dm15);
FAC FCC FNC (dv1-dv3);
OUTPUT:
STDYX SAMPSTAT CINTERVAL SVALUES RESIDUAL TECH1 TECH7;
```

TITLE: Mplus Input Code to Estimate a Structural Similarity Model for a Latent Profile Solution Without Covariates and Outcomes.

```
! Annotations only focus on functions not previously defined.
DATA: FILE IS FSCORES.dat;
VARIABLE:
NAMES = ID GENDER TENURE EDUCATIO WE QU HR_AB HR_OP HR_MO
FAC FCC FNC G;
USEVARIABLES = FAC FCC FNC;
knownclass = cg (g = 1 g = 2); CLASSES = cg (2) c (5);
ANALYSIS:
Processor = 3; TYPE = MIXTURE;
STARTS = 10000 500; STITERATIONS = 500;
MODEL:
%OVERALL%
! The following statements in the %OVERALL% section indicate that the class sizes (class
! probabilities) are freely estimated in all samples.
c#1 on cg#1;
c#2 on cg#1;
c#3 on cg#1;
c#4 on cg#1;
! Here, the means are freely estimated in all profiles but constrained to be equal across countries.
! The variances are constrained to be equal across profiles and freely estimated in both countries.
%cg#1.c#1%
 [FAC FCC FNC] (m1-m3);
 FAC FCC FNC (v1-v3);
 %cg#1.c#2%
 [FAC FCC FNC] (m4-m6);
 FAC FCC FNC (v1-v3);
 %cg#1.c#3%
 [FAC FCC FNC] (m7-m9);
 FAC FCC FNC (v1-v3);
 %cg#1.c#4%
 [FAC FCC FNC] (m10-m12);
 FAC FCC FNC (v1-v3);
 %cg#1.c#5%
 [FAC FCC FNC] (m13-m15);
 FAC FCC FNC (v1-v3);
 %cg#2.c#1%
 [FAC FCC FNC] (m1-m3);
 FAC FCC FNC (dv1-dv3);
 %cg#2.c#2%
 [FAC FCC FNC] (m4-m6);
 FAC FCC FNC (dv1-dv3);
 %cg#2.c#3%
 [FAC FCC FNC] (m7-m9);
 FAC FCC FNC (dv1-dv3);
 %cg#2.c#4%
 [FAC FCC FNC] (m10-m12);
 FAC FCC FNC (dv1-dv3);
 %cg#2.c#5%
 [FAC FCC FNC] (m13-m15);
 FAC FCC FNC (dv1-dv3);
OUTPUT: STDYX SAMPSTAT CINTERVAL SVALUES RESIDUAL TECH1 TECH7;
```

TITLE: Mplus Input Code to Estimate a Dispersion Similarity Model for a Latent Profile Solution Without Covariates and Outcomes.

```
! Annotations only focus on functions not previously defined.
DATA: FILE IS FSCORES.dat;
VARIABLE:
NAMES = ID GENDER TENURE EDUCATIO WE QU HR_AB HR_OP HR_MO
FAC FCC FNC G;
USEVARIABLES = FAC FCC FNC;
knownclass = cg (g = 1 g = 2); CLASSES = cg (2) c (5);
ANALYSIS:
Processor = 3; TYPE = MIXTURE;
STARTS = 10000 500; STITERATIONS = 500;
MODEL:
%OVERALL%
! The following statements in the %OVERALL% section indicate that the class sizes (class
! probabilities) are freely estimated in all samples.
c#1 on cg#1;
c#2 on cg#1;
c#3 on cg#1;
c#4 on cg#1;
! Here, the means are freely estimated in all profiles but constrained to be equal across countries.
! The variances are constrained to be equal across combinations of profiles and countries.
%cg#1.c#1%
[FAC FCC FNC] (m1-m3);
FAC FCC FNC (v1-v3);
%cg#1.c#2%
[FAC FCC FNC] (m4-m6);
FAC FCC FNC (v1-v3);
%cg#1.c#3%
[FAC FCC FNC] (m7-m9);
FAC FCC FNC (v1-v3);
%cg#1.c#4%
[FAC FCC FNC] (m10-m12);
FAC FCC FNC (v1-v3);
%cg#1.c#5%
[FAC FCC FNC] (m13-m15);
FAC FCC FNC (v1-v3);
%cg#2.c#1%
[FAC FCC FNC] (m1-m3);
FAC FCC FNC (v1-v3);
%cg#2.c#2%
[FAC FCC FNC] (m4-m6);
FAC FCC FNC (v1-v3);
%cg#2.c#3%
[FAC FCC FNC] (m7-m9);
FAC FCC FNC (v1-v3);
%cg#2.c#4%
[FAC FCC FNC] (m10-m12);
FAC FCC FNC (v1-v3);
%cg#2.c#5%
[FAC FCC FNC] (m13-m15);
FAC FCC FNC (v1-v3);
OUTPUT: STDYX SAMPSTAT CINTERVAL SVALUES RESIDUAL TECH1 TECH7;
```

TITLE: Mplus Input Code to Estimate a Distributional Similarity Model for a Latent Profile Solution Without Covariates and Outcomes.

```
! Annotations only focus on functions not previously defined.
DATA: FILE IS FSCORES.dat;
VARIABLE:
NAMES = ID GENDER TENURE EDUCATIO WE QU HR_AB HR_OP HR_MO
FAC FCC FNC G;
USEVARIABLES = FAC FCC FNC;
knownclass = cg (g = 1 g = 2); CLASSES = cg (2) c (5);
ANALYSIS:
Processor = 3; TYPE = MIXTURE;
STARTS = 10000 500; STITERATIONS = 500;
MODEL:
%OVERALL%
! Taking out the following statements in the %OVERALL% section constrains the class sizes (class
! probabilities) to be equal across samples.
c#1 on cg#1;
c#2 on cg#1;
c#3 on cg#1;
c#4 on cg#1;
! Here, the means are freely estimated in all profiles but constrained to be equal across countries.
! The variances are constrained to be equal across combinations of profiles and countries.
%cg#1.c#1%
[FAC FCC FNC] (m1-m3);
FAC FCC FNC (v1-v3);
%cg#1.c#2%
[FAC FCC FNC] (m4-m6);
FAC FCC FNC (v1-v3);
%cg#1.c#3%
[FAC FCC FNC] (m7-m9);
FAC FCC FNC (v1-v3);
%cg#1.c#4%
[FAC FCC FNC] (m10-m12);
FAC FCC FNC (v1-v3);
%cg#1.c#5%
[FAC FCC FNC] (m13-m15);
FAC FCC FNC (v1-v3);
%cg#2.c#1%
[FAC FCC FNC] (m1-m3);
FAC FCC FNC (v1-v3);
%cg#2.c#2%
[FAC FCC FNC] (m4-m6);
FAC FCC FNC (v1-v3);
%cg#2.c#3%
[FAC FCC FNC] (m7-m9);
FAC FCC FNC (v1-v3);
%cg#2.c#4%
[FAC FCC FNC] (m10-m12);
FAC FCC FNC (v1-v3);
%cg#2.c#5%
[FAC FCC FNC] (m13-m15);
FAC FCC FNC (v1-v3);
OUTPUT: STDYX SAMPSTAT CINTERVAL SVALUES RESIDUAL TECH1 TECH7;
```

TITLE: Mplus Input Code to Estimate a Latent Profile Solution With Predictors Effects Freely Estimated Across Samples.

```
! Annotations only focus on functions not previously defined.
DATA: FILE IS FSCORES.dat;
VARIABLE:
NAMES = ID GENDER TENURE EDUCATIO WE QU HR_AB HR_OP HR_MO
FAC FCC FNC G;
! Here we include demographic predictors to the variable list.
USEVARIABLES = GENDER TENURE EDUCATIO  FAC FCC FNC;
knownclass = cg (g = 1 g = 2); CLASSES = cg (2) c (5);
ANALYSIS:
Processor = 3; TYPE = MIXTURE;
! Using the starts values obtained in the most "similar" model (here the dispersion similarity model) !
to ensure that the profile solution remains unchanged. Thus random starts can be set to 0.
STARTS = 0;
MODEL:
%OVERALL%
! The following are the starts values provided as part of the output for the dispersion similarity
! model. These describe the class probabilities, and the fact that they differ across samples.
c#1 ON cg#1*0.59543; c#2 ON cg#1*1.20799;
c#3 ON cg#1*2.98158; c#4 ON cg#1*1.99188;
[ cg#1*0.03306 ]; [ c#1*0.01098 ]; [ c#2*0.06172 ]; [ c#3*-1.41848 ]; [ c#4*-0.60085 ];
! For identification purposes, the effects of the predictors on class membership needs to be constrained
! to zero in the overall statement, in order to be freely estimated in all known samples (i.e. countries).
c#1-c#4 ON GENDER@0 TENURE@0 EDUCATIO@0 ;
! Here, two distinct sections are needed to define the parameters that are allowed to differ or
! constrained to be equal across latent profiles (section MODEL C: of the input) and one to specify the
! parameters that are allowed to differ across observed samples (countries, section MODEL CG: of
! the input). We use the starts values provided as part of the output for the dispersion similarity
MODEL C:
%C#1%
 [ fac*2.07339 ] (m1);  [ fcc*3.46368 ] (m2);  [ fnc*1.43624 ] (m3);
fac*1.23943 (v1); fcc*1.35965 (v2); fnc*0.25620 (v3);
%C#2%
 [ fac*3.91824 ] (m4);  [ fcc*4.28314 ] (m5);  [ fnc*3.27793 ] (m6);
fac*1.23943 (v1); fcc*1.35965 (v2); fnc*0.25620 (v3);
%C#3%
 [ fac*6.21865 ] (m7);  [ fcc*5.65603 ] (m8);  [ fnc*6.15181 ] (m9);
fac*1.23943 (v1); fcc*1.35965 (v2); fnc*0.25620 (v3);
%C#4%
 [ fac*4.92928 ] (m10);  [ fcc*4.89787 ] (m11); [ fnc*4.70847 ] (m12);
fac*1.23943 (v1); fcc*1.35965 (v2); fnc*0.25620 (v3);
%C#5%
 [ fac*4.77663 ] (m13);  [ fcc*4.18769 ] (m14); [ fnc*1.98809 ] (m15);
fac*1.23943 (v1); fcc*1.35965 (v2); fnc*0.25620 (v3);
! In this section, we specify that the effects of the predictors on class membership are freely estimated
! in each sample (i.e. countries).
MODEL cg:
  %cg#1%
  c#1-c#4 ON GENDER TENURE EDUCATIO ;
  %cg#2%
  c#1-c#4 ON GENDER TENURE EDUCATIO ;
OUTPUT: STDYX SAMPSTAT CINTERVAL SVALUES RESIDUAL TECH1 TECH7;
```

TITLE: Mplus Input Code to Estimate a Predictive Similarity Latent Profile Solution.

```
! Annotations only focus on functions not previously defined.
DATA: FILE IS FSCORES.dat;
VARIABLE:
NAMES = ID GENDER TENURE EDUCATIO WE QU HR_AB HR_OP HR_MO
FAC FCC FNC G;
USEVARIABLES = GENDER TENURE EDUCATIO  FAC FCC FNC;
knownclass = cg (g = 1 g = 2); CLASSES = cg (2) c (5);
ANALYSIS:
STARTS = 0;
MODEL:
%OVERALL%
c#1 ON cg#1*0.59543; c#2 ON cg#1*1.20799;
c#3 ON cg#1*2.98158; c#4 ON cg#1*1.99188;
[ cg#1*0.03306 ]; [ c#1*0.01098 ]; [ c#2*0.06172 ]; [ c#3*-1.41848 ]; [ c#4*-0.60085 ];
! Here, the effects of the predictors on class membership is freely estimated in the overall statement.
! By default, this is estimated as equal across samples (i.e. countries).
c#1-c#4 ON GENDER TENURE EDUCATIO;
MODEL C:
%C#1%
 [ fac*2.07339 ] (m1);  [ fcc*3.46368 ] (m2);  [ fnc*1.43624 ] (m3);
fac*1.23943 (v1); fcc*1.35965 (v2); fnc*0.25620 (v3);
%C#2%
 [ fac*3.91824 ] (m4);  [ fcc*4.28314 ] (m5);  [ fnc*3.27793 ] (m6);
fac*1.23943 (v1); fcc*1.35965 (v2); fnc*0.25620 (v3);
%C#3%
 [ fac*6.21865 ] (m7);  [ fcc*5.65603 ] (m8);  [ fnc*6.15181 ] (m9);
fac*1.23943 (v1); fcc*1.35965 (v2); fnc*0.25620 (v3);
%C#4%
 [ fac*4.92928 ] (m10);  [ fcc*4.89787 ] (m11); [ fnc*4.70847 ] (m12);
fac*1.23943 (v1); fcc*1.35965 (v2); fnc*0.25620 (v3);
%C#5%
 [ fac*4.77663 ] (m13);  [ fcc*4.18769 ] (m14); [ fnc*1.98809 ] (m15);
fac*1.23943 (v1); fcc*1.35965 (v2); fnc*0.25620 (v3);
!There is no need for inputs sections related to CG.
OUTPUT: STDYX SAMPSTAT CINTERVAL SVALUES RESIDUAL TECH1 TECH7;
```

TITLE: Mplus Input Code to Estimate a Latent Profile Solution With Outcomes Levels Freely Estimated Across Samples.

```
! Annotations only focus on functions not previously defined.
DATA: FILE IS FSCORES.dat;
VARIABLE:
NAMES = ID GENDER TENURE EDUCATIO WE QU HR_AB HR_OP HR_MO
FAC FCC FNC G;
! Here we include outcomes to the variable list.
USEVARIABLES =  WE QU FAC FCC FNC;
knownclass = cg (g = 1 g = 2); CLASSES = cg (2) c (5);
ANALYSIS:
Processor = 3; TYPE = MIXTURE;
! Using the starts values obtained in the most "similar" model (here the dispersion similarity model) !
to ensure that the profile solution remains unchanged. Thus random starts can be set to 0.
STARTS = 0;
MODEL:
%OVERALL%
! The following are the starts values provided as part of the output for the dispersion similarity
! model. These describe the class probabilities, and the fact that they differ across samples.
c#1 ON cg#1*0.59543; c#2 ON cg#1*1.20799;
c#3 ON cg#1*2.98158; c#4 ON cg#1*1.99188;
[ cg#1*0.03306 ]; [ c#1*0.01098 ]; [ c#2*0.06172 ]; [ c#3*-1.41848 ]; [ c#4*-0.60085 ];
%CG#1.C#1%
 [ fac@2.07339 ] (m1); [ fcc@3.46368 ] (m2); [ fnc@1.43624 ] (m3);
fac@1.23943 (v1); fcc@1.35965 (v2); fnc@0.25620 (v3);
! Statements related to the outcomes are added in each specific profile/sample combination and labels
! are used to specify that mean levels on these outcomes are freely estimated in all profiles by samples
! (i.e. countries) combinations.
[WE] (oa1);
[QU] (ob1);
%CG#1.C#2%
[ fac@3.91824 ] (m4); [ fcc@4.28314 ] (m5); [ fnc@3.27793 ] (m6);
fac@1.23943 (v1); fcc@1.35965 (v2); fnc@0.25620 (v3);
[WE] (oa2);
[QU] (ob2);
%CG#1.C#3%
[ fac@6.21865 ] (m7); [ fcc@5.65603 ] (m8); [ fnc@6.15181 ] (m9);
fac@1.23943 (v1); fcc@1.35965 (v2); fnc@0.25620 (v3);
[WE] (oa3);
[QU] (ob3);
%CG#1.C#4%
[ fac@4.92928 ] (m10); [ fcc@4.89787 ] (m11); [ fnc@4.70847 ] (m12);
fac@1.23943 (v1); fcc@1.35965 (v2); fnc@0.25620 (v3);
[WE] (oa4);
[QU] (ob4);
%CG#1.C#5%
[ fac@4.77663 ] (m13); [ fcc@4.18769 ] (m14); [ fnc@1.98809 ] (m15);
fac@1.23943 (v1); fcc@1.35965 (v2); fnc@0.25620 (v3);
[WE] (oa5);
[QU] (ob5);
%CG#2.C#1%
[ fac@2.07339 ] (m1); [ fcc@3.46368 ] (m2); [ fnc@1.43624 ] (m3);
fac@1.23943 (v1); fcc@1.35965 (v2); fnc@0.25620 (v3);
[WE] (oa11);
```

```
[QU] (ob11);
%CG#2.C#2%
[ fac@3.91824 ] (m4); [ fcc@4.28314 ] (m5); [ fnc@3.27793 ] (m6);
fac@1.23943 (v1); fcc@1.35965 (v2); fnc@0.25620 (v3);
[WE] (oa21);
[QU] (ob21);
%CG#2.C#3%
[ fac@6.21865 ] (m7); [ fcc@5.65603 ] (m8); [ fnc@6.15181 ] (m9);
fac@1.23943 (v1); fcc@1.35965 (v2); fnc@0.25620 (v3);
[WE] (oa31);
[QU] (ob31);
%CG#2.C#4%
[ fac@4.92928 ] (m10); [ fcc@4.89787 ] (m11); [ fnc@4.70847 ] (m12);
fac@1.23943 (v1); fcc@1.35965 (v2); fnc@0.25620 (v3);
[WE] (oa41);
[QU] (ob41);
%CG#2.C#5%
[ fac@4.77663 ] (m13); [ fcc@4.18769 ] (m14); [ fnc@1.98809 ] (m15);
fac@1.23943 (v1); fcc@1.35965 (v2); fnc@0.25620 (v3);
[WE] (oa51);
[QU] (ob51);
OUTPUT: STDYX SAMPSTAT CINTERVAL SVALUES RESIDUAL TECH1 TECH7;
```

TITLE: Mplus Input Code to Estimate an Explanatory Similarity Latent Profile Solution.

```
! Annotations only focus on functions not previously defined.
DATA: FILE IS FSCORES.dat;
VARIABLE:
NAMES = ID GENDER TENURE EDUCATIO WE QU HR_AB HR_OP HR_MO
FAC FCC FNC G;
! Here we include outcomes to the variable list.
USEVARIABLES =  WE QU FAC FCC FNC;
knownclass = cg (g = 1 g = 2); CLASSES = cg (2) c (5);
ANALYSIS:
Processor = 3; TYPE = MIXTURE;
STARTS = 0;
MODEL:
%OVERALL%
! The following are the starts values provided as part of the output for the dispersion similarity
! model. These describe the class probabilities, and the fact that they differ across samples.
c#1 ON cg#1*0.59543; c#2 ON cg#1*1.20799;
c#3 ON cg#1*2.98158; c#4 ON cg#1*1.99188;
[ cg#1*0.03306 ]; [ c#1*0.01098 ]; [ c#2*0.06172 ]; [ c#3*-1.41848 ]; [ c#4*-0.60085 ];
%CG#1.C#1%
 [ fac@2.07339 ] (m1); [ fcc@3.46368 ] (m2); [ fnc@1.43624 ] (m3);
fac@1.23943 (v1); fcc@1.35965 (v2); fnc@0.25620 (v3);
! Statements related to the outcomes are added in each specific profile/sample combination and labels
! are used to specify that mean levels on these outcomes arte freely estimated in all profiles, but
! constrained to equality across samples (i.e. countries).
[WE] (oa1);
[QU] (ob1);
%CG#1.C#2%
[ fac@3.91824 ] (m4); [ fcc@4.28314 ] (m5); [ fnc@3.27793 ] (m6);
fac@1.23943 (v1); fcc@1.35965 (v2); fnc@0.25620 (v3);
[WE] (oa2);
[QU] (ob2);
%CG#1.C#3%
[ fac@6.21865 ] (m7); [ fcc@5.65603 ] (m8); [ fnc@6.15181 ] (m9);
fac@1.23943 (v1); fcc@1.35965 (v2); fnc@0.25620 (v3);
[WE] (oa3);
[QU] (ob3);
%CG#1.C#4%
[ fac@4.92928 ] (m10); [ fcc@4.89787 ] (m11); [ fnc@4.70847 ] (m12);
fac@1.23943 (v1); fcc@1.35965 (v2); fnc@0.25620 (v3);
[WE] (oa4);
[QU] (ob4);
%CG#1.C#5%
[ fac@4.77663 ] (m13); [ fcc@4.18769 ] (m14); [ fnc@1.98809 ] (m15);
fac@1.23943 (v1); fcc@1.35965 (v2); fnc@0.25620 (v3);
[WE] (oa5);
[QU] (ob5);
%CG#2.C#1%
[ fac@2.07339 ] (m1); [ fcc@3.46368 ] (m2); [ fnc@1.43624 ] (m3);
fac@1.23943 (v1); fcc@1.35965 (v2); fnc@0.25620 (v3);
[WE] (oa1);
[QU] (ob1);
%CG#2.C#2%
[ fac@3.91824 ] (m4); [ fcc@4.28314 ] (m5); [ fnc@3.27793 ] (m6);
```

```
fac@1.23943 (v1); fcc@1.35965 (v2); fnc@0.25620 (v3);
[WE] (oa2);
[QU] (ob2);
%CG#2.C#3%
[ fac@6.21865 ] (m7); [ fcc@5.65603 ] (m8); [ fnc@6.15181 ] (m9);
fac@1.23943 (v1); fcc@1.35965 (v2); fnc@0.25620 (v3);
[WE] (oa3);
[QU] (ob3);
%CG#2.C#4%
[ fac@4.92928 ] (m10); [ fcc@4.89787 ] (m11); [ fnc@4.70847 ] (m12);
fac@1.23943 (v1); fcc@1.35965 (v2); fnc@0.25620 (v3);
[WE] (oa4);
[QU] (ob4);
%CG#2.C#5%
[ fac@4.77663 ] (m13); [ fcc@4.18769 ] (m14); [ fnc@1.98809 ] (m15);
fac@1.23943 (v1); fcc@1.35965 (v2); fnc@0.25620 (v3);
[WE] (oa5);
[QU] (ob5);

MODEL CONSTRAINT:
  ! New parameters are created using this function and reflect pairwise mean differences between
  ! profiles. So the first of those (y12) reflect the differences between the means of profiles 1 and 2.
  ! This will be included in the outputs as new parameters reflecting the significance of
  ! the differences between the means, without those parameters having an impact on the model.
NEW (y12); y12 = oa1-oa2;
NEW (y13); y13 = oa1-oa3;
NEW (y14); y14 = oa1-oa4;
NEW (y15); y15 = oa1-oa5;
NEW (y23); y23 = oa2-oa3;
NEW (y24); y24 = oa2-oa4;
NEW (y25); y25 = oa2-oa5;
NEW (y34); y34 = oa3-oa4;
NEW (y35); y35 = oa3-oa5;
NEW (y45); y45 = oa4-oa5;
NEW (z12); z12 = ob1-ob2;
NEW (z13); z13 = ob1-ob3;
NEW (z14); z14 = ob1-ob4;
NEW (z15); z15 = ob1-ob5;
NEW (z23); z23 = ob2-ob3;
NEW (z24); z24 = ob2-ob4;
NEW (z25); z25 = ob2-ob5;
NEW (z34); z34 = ob3-ob4;
NEW (z35); z35 = ob3-ob5;
NEW (z45); z45 = ob4-ob5;
OUTPUT: STDYX SAMPSTAT CINTERVAL SVALUES RESIDUAL TECH1 TECH7;
```

Input Codes for Tests of Longitudinal Similarity using Latent Transition Analyses.

For the following illustrations, let's imagine a data set including the following variables:
FAC1 FCC1 FNC1: Commitment factors at Time 1.
FAC2 FCC2 FNC2: Commitment factors at Time 2.
PRED1 PRED2: Predictors at Times 1 and 2.
OUT1 OUT2: Outcomes at Times 1 and 2,
Let's also imagine that the optimal solution includes 3 profiles at each time points, identified by c1 (Time 1) and c2 (Time 2).

Leading to the following DATA section (that will not be repeated):

```
DATA: FILE IS FSCORES.dat;
VARIABLE:
NAMES = ID FAC1 FCC1 FNC1 FAC2 FCC2 FNC2 PRED1 PRED2 OUT1 OUT2G;
USEVARIABLES = FAC1 FCC1 FNC1 FAC2 FCC2 FNC2; ! For models without covariates
USEVARIABLES = FAC1 FCC1 FNC1 FAC2 FCC2 FNC2 PRED1 PRED2; ! For models with predictors
USEVARIABLES = FAC1 FCC1 FNC1 FAC2 FCC2 FNC2 OUT1 OUT2; ! For models with outcomes
CLASSES = c1 (3) c2 (3);
```

The ANALYSIS section remains as above.

TITLE: Mplus Input Code to Estimate a Configural Similarity Latent Transition Solution.

```
MODEL
%OVERALL%
c2 on c1;
MODEL C1:
%c1#1%
 [FAC1 FNC1 FCC1] (m1-m3);
FC1 FNC1 FCC1 (v1-v3);
%c1#2%
 [FAC1 FNC1 FCC1] (m4-m6);
FC1 FNC1 FCC1 (v1-v3);
! FAC1 FNC1 FCC1 (v4-v6); ! to obtain free estimates of variances in all profiles.
%c1#3%
 [FAC1 FNC1 FCC1] (m7-m9);
FC1 FNC1 FCC1 (v1-v3);
! FAC1 FNC1 FCC1 (v7-v9); ! to obtain free estimates of variances in all profiles.
MODEL C2:
%c2#1%
[FAC2 FNC2 FCC2] (mm1-mm3);
FAC2 FNC2 FCC2 (vv1-vv3);
%c2#2%
 [FAC2 FNC2 FCC2] (mm4-mm6);
FAC2 FNC2 FCC2 (vv1-vv3);
! FAC2 FNC2 FCC2 (vv4-vv6); ! to obtain free estimates of variances in all profiles.
%c2#3%
 [FAC2 FNC2 FCC2] (mm7-mm9);
FAC2 FNC2 FCC2 (vv1-vv3);
! FAC2 FNC2 FCC2 (vv7-vv9); ! to obtain free estimates of variances in all profiles.
```

TITLE: Mplus Input Code to Estimate a Structural Similarity Latent Transition Solution.

```
MODEL
%OVERALL%
c2 on c1;
MODEL C1:
%c1#1%
 [FAC1 FNC1 FCC1] (m1-m3);
FC1 FNC1 FCC1 (v1-v3);
%c1#2%
 [FAC1 FNC1 FCC1] (m4-m6);
FC1 FNC1 FCC1 (v1-v3);
! FAC1 FNC1 FCC1 (v4-v6); ! to obtain free estimates of variances in all profiles.
%c1#3%
 [FAC1 FNC1 FCC1] (m7-m9);
FC1 FNC1 FCC1 (v1-v3);
! FAC1 FNC1 FCC1 (v7-v9); ! to obtain free estimates of variances in all profiles.
MODEL C2:
%c2#1%
[FAC2 FNC2 FCC2] (m1-m3);
FAC2 FNC2 FCC2 (vv1-vv3);
%c2#2%
 [FAC2 FNC2 FCC2] (m4-m6);
FAC2 FNC2 FCC2 (vv1-vv3);
! FAC2 FNC2 FCC2 (vv4-vv6); ! to obtain free estimates of variances in all profiles.
%c2#3%
 [FAC2 FNC2 FCC2] (m7-m9);
FAC2 FNC2 FCC2 (vv1-vv3);
! FAC2 FNC2 FCC2 (vv7-vv9); ! to obtain free estimates of variances in all profiles.
```

TITLE: Mplus Input Code to Estimate a Dispersion Similarity Latent Transition Solution.

```
MODEL
%OVERALL%
c2 on c1;
MODEL C1:
%c1#1%
 [FAC1 FNC1 FCC1] (m1-m3);  FC1 FNC1 FCC1 (v1-v3);
%c1#2%
 [FAC1 FNC1 FCC1] (m4-m6);  FC1 FNC1 FCC1 (v1-v3);
! FAC1 FNC1 FCC1 (v4-v6); ! to obtain free estimates of variances in all profiles.
%c1#3%
 [FAC1 FNC1 FCC1] (m7-m9);  FC1 FNC1 FCC1 (v1-v3);
! FAC1 FNC1 FCC1 (v7-v9); ! to obtain free estimates of variances in all profiles.
MODEL C2:
%c2#1%
[FAC2 FNC2 FCC2] (m1-m3);  FAC2 FNC2 FCC2 (v1-v3);
%c2#2%
[FAC2 FNC2 FCC2] (m4-m6);  FAC2 FNC2 FCC2 (v1-v3);
! FAC2 FNC2 FCC2 (v4-v6); ! to obtain free estimates of variances in all profiles.
%c2#3%
[FAC2 FNC2 FCC2] (m7-m9); FAC2 FNC2 FCC2 (v1-v3);
! FAC2 FNC2 FCC2 (v7-v9); ! to obtain free estimates of variances in all profiles.
```

TITLE: Mplus Input Code to Estimate a Distributional Similarity Latent Transition Solution.

```
MODEL
%OVERALL%
c2 on c1;
[ c1#1] (p1); [ c1#2] (p2);
[ c2#1] (p1); [ c2#2] (p2);
MODEL C1:
%c1#1%
 [FAC1 FNC1 FCC1] (m1-m3);  FC1 FNC1 FCC1 (v1-v3);
%c1#2%
 [FAC1 FNC1 FCC1] (m4-m6);  FC1 FNC1 FCC1 (v1-v3);
%c1#3%
 [FAC1 FNC1 FCC1] (m7-m9);  FC1 FNC1 FCC1 (v1-v3);
MODEL C2:
%c2#1%
[FAC2 FNC2 FCC2] (m1-m3); FAC2 FNC2 FCC2 (v1-v3);
%c2#2%
[FAC2 FNC2 FCC2] (m4-m6); FAC2 FNC2 FCC2 (v1-v3);
%c2#3%
[FAC2 FNC2 FCC2] (m7-m9); FAC2 FNC2 FCC2 (v1-v3);
```

TITLE: Mplus Input Code to Estimate a Latent Transition Solution with Predictors (Relations Freely Estimated at Both Time Points).

```
! To ensure stability, starts values from the previously most "similar" solution should be used.
MODEL
%OVERALL%
c2 on c1;
[ c1#1] (p1); [ c1#2] (p2);
[ c2#1] (p1); [ c2#2] (p2);
c1 ON Pred1;
c2 ON Pred2;
MODEL C1:
%c1#1%
 [FAC1 FNC1 FCC1] (m1-m3); FC1 FNC1 FCC1 (v1-v3);
%c1#2%
 [FAC1 FNC1 FCC1] (m4-m6); FC1 FNC1 FCC1 (v1-v3);
%c1#3%
 [FAC1 FNC1 FCC1] (m7-m9); FC1 FNC1 FCC1 (v1-v3);
MODEL C2:
%c2#1%
[FAC2 FNC2 FCC2] (m1-m3); FAC2 FNC2 FCC2 (v1-v3);
%c2#2%
[FAC2 FNC2 FCC2] (m4-m6); FAC2 FNC2 FCC2 (v1-v3);
%c2#3%
[FAC2 FNC2 FCC2] (m7-m9); FAC2 FNC2 FCC2 (v1-v3);
```

TITLE: Mplus Input Code to Estimate a Latent Transition Solution with Predictors (Predictive Similarity).

```
! To ensure stability, starts values from the previously most "similar" solution should be used.
MODEL
%OVERALL%
c2 on c1;
[ c1#1] (p1); [ c1#2] (p2);
[ c2#1] (p1); [ c2#2] (p2);
c1 ON Pred (pr1-pr2); ! one less label than the number of latent profiles
c2 ON Pred2 (pr1-pr2);
MODEL C1:
%c1#1%
 [FAC1 FNC1 FCC1] (m1-m3); FC1 FNC1 FCC1 (v1-v3);
%c1#2%
 [FAC1 FNC1 FCC1] (m4-m6); FC1 FNC1 FCC1 (v1-v3);
%c1#3%
 [FAC1 FNC1 FCC1] (m7-m9); FC1 FNC1 FCC1 (v1-v3);
MODEL C2:
%c2#1%
[FAC2 FNC2 FCC2] (m1-m3); FAC2 FNC2 FCC2 (v1-v3);
%c2#2%
[FAC2 FNC2 FCC2] (m4-m6); FAC2 FNC2 FCC2 (v1-v3);
%c2#3%
[FAC2 FNC2 FCC2] (m7-m9); FAC2 FNC2 FCC2 (v1-v3);
```

TITLE: Mplus Input Code to Estimate a Latent Transition Solution with Outcomes (Relations Freely Estimated at Both Time Points).

```
! To ensure stability, starts values from the previously most "similar"  solution should be used.
MODEL
%OVERALL%
c2 on c1;
[ c1#1] (p1); [ c1#2] (p2);
[ c2#1] (p1); [ c2#2] (p2);
MODEL C1:
%c1#1%
 [FAC1 FNC1 FCC1] (m1-m3); FC1 FNC1 FCC1 (v1-v3);
[Out1] (oa1);
%c1#2%
 [FAC1 FNC1 FCC1] (m4-m6); FC1 FNC1 FCC1 (v1-v3);
[Out1] (oa2);
%c1#3%
 [FAC1 FNC1 FCC1] (m7-m9); FC1 FNC1 FCC1 (v1-v3);
[Out1] (oa3);
MODEL C2:
%c2#1%
[FAC2 FNC2 FCC2] (m1-m3); FAC2 FNC2 FCC2 (v1-v3);
[Out2] (ob1);
%c2#2%
[FAC2 FNC2 FCC2] (m4-m6); FAC2 FNC2 FCC2 (v1-v3);
[Out2] (ob2);
%c2#3%
[FAC2 FNC2 FCC2] (m7-m9); FAC2 FNC2 FCC2 (v1-v3);
[Out2] (ob3);
MODEL CONSTRAINT:
NEW (y12); y12 = oa1-oa2;
NEW (y13); y13 = oa1-oa3;
NEW (y23); y23 = oa2-oa3;
NEW (z12); z12 = ob1-ob2
NEW (z13); z13 = ob1-ob3;
NEW (z23); z23 = ob2-ob3;
```

TITLE: Mplus Input Code to Estimate a Latent Transition Solution with Predictors (Explanatory Similarity).

```
! To ensure stability, starts values from the previously most “similar”  solution should be used.
MODEL
%OVERALL%
c2 on c1;
[ c1#1] (p1); [ c1#2] (p2);
[ c2#1] (p1); [ c2#2] (p2);
MODEL C1:
%c1#1%
 [FAC1 FNC1 FCC1] (m1-m3); FC1 FNC1 FCC1 (v1-v3);
[Out1] (oa1);
%c1#2%
 [FAC1 FNC1 FCC1] (m4-m6); FC1 FNC1 FCC1 (v1-v3);
[Out1] (oa2);
%c1#3%
 [FAC1 FNC1 FCC1] (m7-m9); FC1 FNC1 FCC1 (v1-v3);
[Out1] (oa3);
MODEL C2:
%c2#1%
[FAC2 FNC2 FCC2] (m1-m3); FAC2 FNC2 FCC2 (v1-v3);
[Out2] (oa1);
%c2#2%
[FAC2 FNC2 FCC2] (m4-m6); FAC2 FNC2 FCC2 (v1-v3);
[Out2] (oa2);
%c2#3%
[FAC2 FNC2 FCC2] (m7-m9); FAC2 FNC2 FCC2 (v1-v3);
[Out2] (oa3);
MODEL CONSTRAINT:
NEW (y12); y12 = oa1-oa2;
NEW (y13); y13 = oa1-oa3;
NEW (y23); y23 = oa2-oa3;
```