Further Reflections on Disentangling Shape and Level Effects in Person-Centered Analyses: An Illustration Exploring the Dimensionality of Psychological Health.

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Abstract

Morin and Marsh (2015) proposed a methodological framework to disentangle *shape* and *level* effects in latent profile analyses. We discuss limitations of this framework (based on a logic similar to that of higher-order measurement models), and suggest that these limitations are easily solved by a more thorough examination of the variable-centered measurement models underlying profile indicators. This study presents complementary variable- and person-centered approaches aiming to assess the dimensionality of psychometric constructs. Psychometric measures often assess separate conceptually-related facets of global overarching constructs, based on the assumption that these overarching constructs exist as global entities including specificities mapped by the facets. The framework proposed here explicitly models this dimensionality in both variable- and person-centered analyses. To illustrate this revised psychometric framework, we use ratings of psychological health collected from 1232 teachers, and show how this revised framework provides a clearer picture of teachers' profiles of psychological health.

Key words: Variable-Centered, Person-Centered, ESEM, Bifactor, Latent Profiles, Dimensionality, Wellbeing.

This study is a methodological-substantive synergy (Marsh & Hau, 2007), aiming to offer further thoughts on a framework recently proposed by Morin and Marsh (2015) to disentangle *shape* (the tendency for a person to have a distinct pattern of profile indicators on which they are high, medium or low) from *level* (the tendency for a person to be high, medium or low across all profile indicators) effects in person-centered latent profile analyses (LPA). In essence, Morin and Marsh (2015 also see Marsh, Lüdtke, Trautwein, & Morin, 2009) argued that person-centered analyses resulting in profiles characterized mainly by differences in *level* were unlikely to be useful, but that typical latent profile analyses needed to be adapted to achieve a proper disaggregation of *shape* and *level* effects whenever both were expected to be present in the data. Methodologically, this study identifies limitations to the models proposed by Morin and Marsh (2015), proposes to go back to the variable-centered measurement models underlying profile indicators, and suggests that a bifactor representation of the data offers a solution to these limitations. Substantively, this investigation applied these propositions to the identification of profiles of teachers based on ratings of their psychological health.

Methodological Issues: Disentangling Shape and Level Effects in Latent Profile Analyses.

Disentangling Shape versus Level Effects in Latent Profile Analyses

In many research contexts, a global construct co-exists with specific dimensions assessed from the same set of indicators. In these situations, Morin and Marsh (2015) argued that it is critical to control for this global tendency shared across indicators (e.g., global level of effectiveness, global level of psychological health, global self-concept) before identifying patterns of relative strength and weaknesses on these indicators. Failure to control for this global tendency in LPA makes the identification of qualitatively distinct profiles significantly harder since strong *level* effects tend to create equally strong quantitative differences between profiles, thus concealing potentially interesting *shape* differences between profiles. Morin and Marsh (2015) contrasted the efficacy of four models to control for global levels of competencies shared across indicators. Model 1 was a LPA including no explicit control for possible *level* effects shared by profile indicators and was designed as a comparison benchmark for the other models. Model 2 was also a LPA, but this model also included a higher-order dimension reflecting *level* effects as an additional profile indicator. Model 3 was a factor mixture analysis (FMA) where a continuous latent factor representing *level* effects was estimated from the indicators, so that the latent profiles were estimated from the residual covariance among indicators not explained by this global factor. Model 4 was proposed to force the extraction of all *level* effects prior to the estimation of the profiles. In this model, all indicators were regressed on a higher-order dimension (as in Model 2) prior to the estimation of the LPA model. Morin and Marsh (2015) study showed that Model 3 provided the clearer results in terms of: (a) achieving a proper disaggregation of shape and level effects; (b) meeting theoretical expectations; (c) resulting in profiles with a high level of longitudinal stability, and (d) providing a better fit to the data. However, although promising, Morin and Marsh (2015) strategy presents some important limitations to which we now turn our attention.

The Importance of Preliminary Measurement Models

Morin and Marsh (2015) used factor scores saved from preliminary measurement models as profile indicators. Latent profile analyses are usually estimated using scale scores (i.e., taking the sum or average on the items and using this aggregated score as the indicator). Although latent variables controlled for measurement error (i.e., using items to estimate latent factors used as profile indicators) provide a stronger control for the biasing effects of measurement errors, applications of fully latent profile models are few (e.g., Morin, Scalas, & Marsh, 2015). Given the complexity of these models, it is often not feasible to implement a fully latent approach to their estimation. An alternative is to use factor scores from preliminary measurement models (Kam, Morin, Meyer, & Topolnytsky, 2015; Morin & Marsh, 2015). Although factors scores do not explicitly provide a complete control for measurement errors, by giving more weight to more reliable items (with higher factors loadings, and thus lower uniquenesses), they still provide a partial control for measurement errors.

In Morin and Marsh (2015), Models 1 and 3 relied on factors scores saved from a preliminary first-order measurement model, whereas Models 2 and 4 relied on factor scores saved from a higher-order factor model (both first-order and higher-order factor scores where saved). Alternative measurement models (e.g., first-order versus higher-order) are rarely equivalent, and the decision of which model to retain should be based on a thorough process guided by theory, substantive expectations, and a careful examination of parameter estimates. As such, the selection of the measurement model from which to extract factor scores should be based on a detailed examination of alternative possibilities designed to clearly identify the various sources of multidimensionality present in a measure. In particular, we argue that whenever global *level* effects are expected to be present in a measure, these should be explicitly modelled as part of the measurement model from which the factor scores are extracted, which may also provide a way to directly estimate the likely importance of these effects.

Recently, Morin, Arens and Marsh (2015) proposed an integrative framework for the investigation of the underlying structure of psychometric measures that has direct relevance to the issues considered here. Essentially, they argued that measurement models should take into account sources of *construct-relevant multidimensionality* present at the item level, "*which refers to the idea that the items forming an instrument may be associated with more than one source of true score variance (i.e., be associated with more than one content area)*" (p. 2). To do so, they proposed a combination of: (a) exploratory structural equation models (ESEM; Morin, Marsh & Nagengast, 2013), which take into account the fact that items are generally expected to present at least some degree of valid association with conceptually-related constructs other than the main constructs they are purported to measure, and (b) bifactor models (Reise, 2012), which take into account the possibility that items may sometimes simultaneously reflect both a global construct (e.g., global psychological health) as well as specific components (serenity, depression, etc.). We refer readers to Morin, Arens, et al. (2015) for additional discussions of these models and of their implications.

The key limitation of the framework proposed by Morin and Marsh (2015) to disentangle *shape* versus *levels* effects in the context of LPA is that it started from factor scores saved from measurement models which either did not include any explicit representation of global *level* effects (Models 1 and 3) or which relied on a higher-order (or hierarchical), rather than bifactor, representation of the overarching global construct (Models 2 and 4). In hierarchical models, items are used to define first-order factors, which are used to define a higher-order factor reflecting a shared tendency among first-order factors. Although intuitively appealing, hierarchical models present two critical limitations that make them particularly problematic when used to generate factor scores for subsequent analyses. Hierarchical models first rely on very strict implicit proportionality constraints in defining how the items relate to the higher-order factor and to the specific part of the first-order factors that is not explained by the higher-order factor (Reise, 2012). These implicit proportionality constraints imply that the ratio of global/specific variance will be exactly the same for all items associated with a specific first-order factor, and are unlikely to hold in many real life situations (Reise, 2012). Morin and Marsh's (2015) FMA Model 3 is also characterized by similar constraints as the continuous latent factor incorporated to control for global *level* effects is itself estimated from first-order factors scores.

Another characteristic of hierarchical models that makes them particularly problematic when the objective is to save factor scores for subsequent analyses is that the higher-order factor score is psychometrically redundant with the first-order factors scores. In hierarchical models, the first-order factors include both the part of the variance in ratings that is explained by the higher-order factor (σ_h), as well as the part of the variance in ratings that is specific to the first-order factor ($\sigma_{f1\text{-}h}$). This specificity ($\sigma_{f1\text{-}h}$) is absorbed as part of the first-order factors' disturbances, and thus treated as a form of measurement error in hierarchical models, but remain included in estimates of first-order factor scores ($\sigma_{f1} = \sigma_h + \sigma_{f1\text{-}h}$). Thus, a model including both first-order and higher-order factors scores is likely to suffer from multicollinearity (because both first-order and higher-order factors include σ_h), which may explain the poor performance of Models 2 and 4 proposed by Morin and Marsh (2015).

In contrast, in a *f*-factor bifactor model, one Global (G) and *f*-1 Specific (S) orthogonal factors are used to explain the covariance among a set of *n* items. Bifactor models thus partitions the total covariance in ratings into a G component underlying all indicators, and *f*-1 S components reflecting the residual covariance not explained by the G-factor. For this reason, bifactor models directly test the presence of a global unitary construct underlying the answers to all items (G-factor) and whether this global construct co-exists with meaningful, and not redundant, specificities (S-factors) not explained by the G-factor, and are able to do so without imposing restrictive implicit proportionality constraints.

Alternative Approaches to Disentangle Shape from Level Effects in LPA

The foregoing discussion suggests that whenever global and specific constructs co-exist within a set of indicators, preliminary measurement models used to save factor scores for later person-centered investigation would do well to rely on bifactor (CFA or ESEM) models. Furthermore, even if the FMA approach (Model 3) recommended by Morin and Marsh (2015) presents logical similarities with a bifactor model (i.e., both incorporate a global factor to estimate specific factors or profiles controlled for this global tendency), it presents another limitation that is likely to be solved by the reliance on a preliminary bifactor model to generate factor scores for profile indicators. Indeed, in Model 3, the mean of the latent factor included to control for global *level* effects needs, for identifications purposes, to be constrained to equality across the latent profiles. A strong assumption of this FMA approach is thus that all of the extracted latent profiles present equal levels on the estimated global factor representing overarching *level* effects. In more practical terms, this means that the average level of the global construct (e.g., overall teaching competency or psychological health) is assumed to be the same in all profiles. Interestingly, the estimation of a revised version of Model 2 based on factor scores taken from a preliminary bifactor, rather than hierarchical, model would have provided a way to solve all of the limitations listed above by providing a direct estimate of non-redundant global and specific constructs relying on no form of implicit proportionality or equality constraints. We thus propose a revision of the Morin and Marsh's (2015) framework. This revised framework involves the estimation of three distinct models, labelled based on their correspondence with Morin and Marsh (2015; see Figure 1): (a) a LPA based on factors scores taken from a first-order model and providing a comparison benchmark for the other models (Model 1); (b) a LPA model based on factors scores taken from a bifactor model and thus incorporating properly disaggregated shape and level information (Model 2R); (c) A FMA including a generic continuous factor to account for level effects shared among indicators, where the indicators are also taken from a first-order factor model (Model 3), to provide a comparison benchmark with the model advocated by Morin and Marsh (2015).

Although our objective is primarily methodological, we illustrate this revised framework using teachers' ratings of their psychological health at work. However, it is important to note that a key criterion that needs to be met in order to support a substantive interpretation of the profiles as reflecting meaningful subpopulations has to do with their theoretical conformity (Marsh et al., 2009; Muthén, 2003). Theoretical meaningfulness is also a key criterion in the interpretation of the profiles, and in the comparison of the alternative models proposed here. For these reasons, and because we believe that no analysis should be conducted in disconnection from substantive theory and expectations, we now turn to a brief review of substantive issues relevant to the study of psychological health. Methodologically-oriented readers may feel free to skip the next sections.

Substantive Application: Exploring the Dimensionality of Psychological Health

The World Health Organization (2014) defines psychological health as a state characterized not only by the absence of signs of psychological distress, but also by the presence of more positive signs of psychological wellbeing, also referred to as thriving (Su, Tay, & Diener, 2014), or flourishing (Huppert & So, 2013). Although this definition seems to have reached the stage of consensus, many questions remain unanswered regarding the underlying structure of the psychological health construct. So far, research has generally supported the idea that psychological health is multidimensional, and that the underlying dimensions can be differentiated based on whether they reflect the more global facets of psychological wellbeing or distress (Gonzalez-Roma, Schaufeli, Bakker, & Lloret, 2006; Keyes, 2005; Massé, Poulin, Dassa, Lambert, Bélair, & Battaglini, 1998). An important assumption of these models is that psychological wellbeing and distress are distinct states rather than the endpoints of an underlying continuum, so that levels of psychological wellbeing and distress can vary independently from one another within the same person. To our knowledge, this assumption has never been formally assessed using methodologies allowing for a proper partitioning of the variance attributed to a global psychological health construct from the variance attributed to specific psychological well-being and distress dimensions.

Within a variable-centered perspective, bifactor models are naturally suited to the investigation of whether facets of psychological wellbeing and distress are underlying dimensions of an overarching global construct of psychological health, whether these dimensions really have added-value over and above the assessment of this overarching construct, or whether these dimensions reflect distinct correlated constructs. The fact that most available instruments assessing psychological health (e.g., Gonzalez-Roma et al., 2006; Massé et al., 1998) rely on multiple conceptually-related dimensions further suggests that there might be value in adopting an ESEM representation of the data.

Arguably, one of the most comprehensive inventory available to date to assess psychological health has been developed by Massé et al. (1998). Although Massé et al. results supported the idea that second-order factor representing psychological wellbeing and distress could be empirically differentiated, their results also showed that these two higher-order factors are correlated at $r = -.72$ and could be combined into an third-order factor representing psychological health. Their results also supported the idea that cross-loadings are present and need to be taken into account. Gilbert, Dagenais-Desmarais, and Savoie (2011) adapted Massé et al. (1998) questionnaire to focus on psychological health within the work context, on the basis of very slight modifications to the items. Their results failed to support the 10 dimensions initially proposed by Massé et al. (1998), rather revealing a more parsimonious 6-factor solution, three of which reflected psychological wellbeing (serenity, social harmony, and involvement) and three of which reflected psychological distress (anxiety-depression, irritability-aggression, and distance). These results, obtained through EFA, thus also suggest that it might be important to take cross-loadings into account. Unfortunately, the analyses reported by these authors were conducted separately for ratings of psychological wellbeing and distress, and the relations between both only assessed through correlations based on scale scores (r = -.407 to -.614), and were thus likely underestimated due to the lack of control for measurement errors. Taken together, these results support the need for further investigation of the underlying structure of measures of psychological health in order to obtain a more definitive test of whether the underlying dimensions really do reflect an overarching construct of psychological health, and whether meaningful specificity remains at the subscale level once this global construct is taken into account.

A person-centered perspective also provides a way to address the same question by more directly testing the assumption that levels of psychological wellbeing and distress can vary independently from one another among individuals. Thus, the observation of *shape*-differentiated profiles will support the added value of considering distinct dimensions of psychological health, whereas the observation of profiles presenting only *level*-differences would support the idea that there is little added-value to considering separate dimensions once individuals' global levels of psychological health are taken into account. However, as noted above, whenever there are reasons to expect that both *level* (due to the existence of a global psychological health construct) and *shape* (due to the added-value of specific dimensions) effects will be present (which can be tested using variable-centered approaches) then the models described in Figure 1 can be contrasted to obtain a clearer picture.

So far, we are aware of a single application of a person-centered approach to the study of psychological health defined by both well-being and distress dimensions. Using Gilbert et al.'s (2010) measure, Savoie, Brunet, Boudrias and Gilbert (2010) used a median split approach to characterize individuals presenting high, versus low, levels of psychological wellbeing and distress at work. Arguably, this median split approach present severe limitations as a person-centered approach as it forces the extraction of profiles which may not exist in reality (e.g., Morin, Morizot, Boudrias, & Madore, 2011). However, the obtained results remain informative when one considers the relative size of the extracted profiles, showing that over 96% of the respondents presented fully balanced profiles characterized by high levels of wellbeing and low levels of distress (94%) or high levels of distress and low levels of wellbeing (2%). When considering specific dimensions, however, they found that a significant number of teachers (12%) presented a low level of involvement while not presenting high scores of distance, a profile they referred to as alienated or disconnected. Although these results beg for replication, they clearly suggest that strong *level* effects are likely to be present, supporting the need to rely on models providing a way to properly disaggregate *shape*, and *level* effects.

Method

Participants

A total of 1232 teachers were recruited to participate in a comparative France-Canada study on teachers' psychological health at work (Boudrias et al., 2014). The procedure and period of data collection were slightly different in France and Canada. However, participants in both countries completed the same French questionnaires and provided informed consent to participate in the study.

In France, 391 teachers from 57 schools located in Northern France were recruited individually at their workplace in 2008-2009. Participants were instructed to complete the questionnaires on their personal time within two weeks and return them to the research assistants. Participants worked in primary schools (33%), Collèges (33%), Lycées (29%), or at multiple levels (5%). In Canada, 841 teachers were recruited in 27 schools located in the province of Quebec in 2009-2010. Teachers who volunteered to participate completed the questionnaire during a paid pedagogical day. Participants taught in primary (41%), secondary (55%) and vocational training (4%) schools. The total sample includes 67% of women and the following age distribution: less than 30 (19%), 31-40 (32%), 41-50 (30%), 51 and above (19%). The mean teaching experience is 14.4 years (SD = 9.8). The two subsamples are comparable on age, gender, and teaching level (primary vs. secondary and above), but differ in term of teaching experience (France = 16.8 years, SD = 11.3; Canada = 13.3 years, SD = 8.8).

Measures

Psychological health at work was measured with the 45 items from Gilbert et al.'s (2011) instrument. Twenty-two items assess three wellbeing dimensions: serenity (10 items, α=.86), harmony (7 items, α=.82) and involvement (5 items, α=.84). Twenty-three items assess three dimensions of psychological distress: anxiety/depression (9 items, α=.91), irritability (7 items, α=.85) and distance (7 items, α=.88). The full set of items used in this instrument is reported in Tables S1 and S2 of the online supplements. Participants were asked to indicate the extent (1 = *almost never* to 5 = *almost always*) to which they had experienced symptoms recently at work. The scale score reliability coefficients obtained in this study (reported above) are in line with those reported by Gilbert et al. (2011: α = .82 to .91). Previous research on this questionnaire revealed one-year longitudinal stability coefficients ranging from.44 to .56 for the psychological distress dimensions and from .65 to .70 for the well-being dimensions (Leclerc, Boudrias & Savoie, 2014), as well as satisfactory evidence of criterion-related validity involving relations with job demands and resources, personal resources, intrinsic needs satisfaction, and job performance (Boudrias et al., 2014; Leclerc et al., 2014).

Analyses

Preliminary Variable-Centered Measurement Models

Preliminary measurement models were estimated using the Mplus 7.2 (Muthén & Muthén, 2014) robust weighted least square estimator using diagonal weight matrices (WLSMV). WLSMV estimation is more naturally suited to the ordered-categorical nature of the Likert scales used in the present study than traditional maximum likelihood (ML) estimation or robust alternatives (MLR) (Finney, & DiStefano, 2013). Indeed, ML/MLR estimation assumes that the underlying response scale is continuous, and that responses are normally distributed. Although ML/MLR are to some extent robust to non-normality, assumptions of underlying continuity are harder to approximate when few response categories are used (i.e., five or less as in this study), or when responses categories follow asymmetric thresholds (as is the case in this study). In these conditions, WLSMV estimation has been found to outperform ML/MLR estimation (e.g., Finney & DiStephano, 2013). A key limitation of WLSMV, when compared to ML/MLR, is the reliance on a slightly less efficient way of handling missing data (Asparouhov & Muthén, 2010), which is not an issue here given the very low level of missing data (0.1% to 1.2% per item; M = 0.6%).

Participants responses to the instrument were modelled based on the four models proposed by

Morin, Arens et al. (2015: CFA, bifactor-CFA, ESEM, and bifactor-ESEM). In the CFA model, each item was only allowed to load on the factor it was assumed to measure and cross-loadings on other factors were not allowed. This model included six correlated factors representing the previously described subscales (Harmony, Serenity, Involvement, Irritability, Anxiety/Depression, and Distance). In the ESEM model the same set of six a priori factors were represented using a confirmatory oblique target rotation (Browne, 2001), were all cross-loadings were "targeted" to be as close to zero as possible, while the main loadings were freely estimated. In the bifactor-CFA model, all items were allowed to simultaneously load on one G-Factor and on one of six S-Factors corresponding to the a priori psychological health factors, with no cross-loadings allowed between S-Factors. The G-Factor and all S-Factors were specified as orthogonal in order to ensure the interpretability of the solution in line with bifactor assumptions (Morin, Arens et al., 2015). Finally, in the B-ESEM model, the same set of six S-Factor and one G-Factor were estimated using orthogonal bi-factor target rotation (Reise, 2012). In this model, all items were allowed to define a G-Factor, while the six S-Factors were defined from the same pattern of target and non-target factor loadings as in ESEM[1].

Because participants were recruited from two countries, we also systematically tested the measurement invariance of the retained first-order (ESEM or CFA) and bifactor (ESEM or CFA) measurement model across countries[2]. These tests followed the typical sequential strategy adapted for ordered-categorical indicators (Guay, Morin, Litalien, Valois, & Vallerand, 2015; Morin, Moullec et al., 2011): (i) configural invariance, (ii) metric/weak invariance (invariance of the factor loadings); (iii) scalar/strong invariance (loadings and thresholds); (iv) strict invariance (loadings, thresholds and uniquenesses), (v) invariance of the latent variances-covariances (loadings, thresholds, uniquenesses and variances-covariances), and (vi) latent means invariance (loadings, thresholds, uniquenesses, variances-covariances and latent means).

We relied on the following goodness-of-fit indices to describe the fit of the alternative models

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[1] Alternative bifactor-CFA and bifactor-ESEM models including two G-factors representing psychological wellbeing and psychological distress were also estimated, but these alternative models failed to result in a meaningful improvement in the fit of the model, and resulted in highly correlated G-factors (r values close to .80) so that these models were not retained.
[2] The reason why both a first-order, and a bifactor, measurement models were retained at this stage is that both are needed for the estimation of the person-centered models described in Figure 1 (Models 1 and 3 are based on factor scores saved from first-order models, while Model 2R relies on factor scores from a bifactor model).

(Marsh, Hau, & Grayson, 2005): The WLSMV chi square (χ^2), the comparative fit index (CFI), the Tucker-Lewis index (TLI), the root mean square error of approximation (RMSEA) with its 90% confidence interval. According to typical interpretation guidelines (e.g., Marsh et al., 2005; Yu, 2002), values greater than .90 and .95 for the CFI and TLI are considered to be respectively indicative of adequate and excellent fit to the data, while values smaller than .08 or .06 for the RMSEA support respectively acceptable and excellent model fit. In tests of measurement invariance, the following guidelines were used (Chen, 2007): a CFI diminution of .01 or less and a RMSEA augmentation of .015 or less between a model and the preceding model indicate that the measurement invariance hypothesis should not be rejected. With WLSMV, χ^2 values are not exact, but adjusted to obtain a correct p value. This is why WLSMV χ^2 and CFI can be nonmonotonic with model complexity.

Person-Centered Analyses

LPA and FMA were used to extract profiles of teachers based on their levels of psychological health at work as a function of the three parameterizations illustrated in Figure 1 (Model 1, 2R, and 3). Invariant factor scores saved from the best fitting first-order (CFA or ESEM) and bifactor (CFA or ESEM) models (in which factors were estimated in standardized units M = 0, SD = 1) were used as profile indicators. Analyses were conducted using Mplus 7.2 (Muthén & Muthén, 2014) MLR estimator, using 5,000 random starts, 200 iterations for these random starts and the 300 bests retained for final stage optimization. All of the reported models converged on a replicated solution and can confidently be assumed to reflect a "real" maximum likelihood. For each parameterization, models with 1 to 8 latent profiles were estimated with the indicators' (psychological health scores) intercepts and residuals freely estimated in all profiles (Morin, Maïano, et al., 2011; Peugh & Fan, 2013).

Model 1 parameterization corresponds to classical LPA, using factor scores from the best fitting first-order (CFA or ESEM) model as profile indicators. Model 2R parameterization also corresponds to classical LPA, but this time using factor scores from the best fitting bifactor (CFA or ESEM) model as profile indicators. Finally, Model 3 parameterization corresponded the FMA model advocated by Morin and Marsh (2015), using factor scores saved from the best fitting first-order (CFA or ESEM) model as profile indicators. In Model3, a global latent factor, specified as invariant across profiles, was included to reflect global *level* effects shared among indicators.

The decision of how many profiles to retain is typically guided by an examination of the substantive meaning and theoretical conformity of the extracted profiles (Marsh et al., 2009; Muthén, 2003) as well as the statistical adequacy of the solution (e.g., absence of negative variance estimates). A number of statistical indices are also available to guide this decision (McLachlan & Peel, 2000): (i) The Akaïke Information Criterion (AIC), (ii) the Consistent AIC (CAIC), (iii) the Bayesian Information Criterion (BIC), (iv) the sample-size Adjusted BIC (ABIC), (v) the standard and adjusted Lo, Mendell and Rubin LRTs (LMR/aLMR, as these tests typically yield the same conclusions, we only report the aLMR); and (iv) the Bootstrap Likelihood Ratio Test (BLRT). A lower value on the AIC, CAIC, BIC and ABIC suggests a better-fitting model, while a significant p-value on the aLMR and BLRT supports a model with one less profile. Annotated Mplus input codes for all variable- and person-centered models used in this study are provided in the online supplements.

Results

Variable-Centered Measurement Models

Table 1 presents the goodness-of-fit indices associated with the alternative measurement models. While the CFA solution provided an acceptable fit to the data according to the CFI (.927), TLI (.922), and RMSEA (.065), the bifactor-CFA clearly proved suboptimal according to CFI and TLI value ≤ .900. In contrast, both the ESEM and bifactor-ESEM models resulted in a substantial improvement in fit, providing an excellent fit to the data according to the CFI (.962 and .972), TLI (.949 and .960), and RMSEA (.053and .046). Interestingly, the fit of the bifactor-ESEM also proved to be higher than the fit of the ESEM solution according the ΔCFI (+.010), ΔTLI (+.011), and ΔRMSEA (-.007, with non-overlapping confidence intervals). Although the ESEM solution itself provided a fully satisfactory level of fit to the data, Morin, Arens et al. (2015) simulated data results show than even a well-fitting ESEM model may hide an underlying bifactor structure so that the parameter estimates from both models still need to be systematically compared. Thus, based strictly on this statistical information, it appears that the bifactor-ESEM solution should be retained, unless the G-Factor estimated as part of this solution proves to be weakly defined through low factor loading. In this situation, the ESEM model would represent a viable alternative. However, model selection should always be conditional on a detailed examination of the parameter estimates and theoretical conformity. Following Morin, Arens et al.'s (2015) recommendations, we first compare the CFA and ESEM solutions to investigate the presence of construct-relevant psychometric multidimensionality due to the conceptually-related constructs. We then contrast the ESEM and bifactor-ESEM solutions to investigate the presence of construct-relevant psychometric multidimensionality due to hierarchically-ordered constructs.

ESEM versus CFA. Parameter estimates for the CFA and ESEM solutions are presented in Table S3 of the online supplements. Interestingly, the CFA solution reveals factors that are very well-defined through high factor loadings (λ = .492 to .918; M = .756). In the ESEM solution, apart from a few items presenting relatively weak factor loadings on their target factors (W12: .293 on Harmony ; W20: .480 on Involvement; D17 and D18: .161 and .354 on Distance), and higher cross-loadings on non-target factors (W12: .361 on Involvement; W20: -.626 on Distance; D17 and D18: .497 and .402 on Anxiety/Depression)[3], the remaining items reveal well-defined Harmony (λ = .370 to .732; M = .494), Serenity (λ = .529 to .804; M = .626), Involvement (λ = .600 to .802; M = .676), Anxiety/Depression (λ = .375 to .707; M = .549), and Distance (λ = .477 to .599; M = .530) factors. In contrast, the Irritability factor seems to be mainly defined by four out of seven indicators (D1, D5, D12, D5: λ = .578 to .867; M = .708), with the remaining indicators (D2, D8, and D22) presenting lower factor loadings (λ = .271, .500, and .379) and multiple cross-loadings, suggesting that they may be more potent indicators of global psychological heath than of their specific factors. The observation that many high cross-loadings are present in the ESEM solution ($|\lambda|$ = .000 to .626; M = .142) also suggests the presence of an unmodeled global construct. For instance, out of 225 possible cross-loadings: only 48 (21%) are non-significant, 36 are between |.200| and |.300|, 11 are between |.300| and |.400|, and 6 are over |.400|.

It is also noteworthy that the estimated factor correlations are much lower in the ESEM ($|r|$ = .189 to .570; M = .327; SD = .099) than the CFA ($|r|$ = .457 to .896; M = .670; SD = .126) solution, suggesting that ESEM results in a clearer differentiation between the factors. Simulation studies

[3] It is interesting to note that the unexpected pattern of loadings and cross-loadings observed for these items makes sense substantively. For instance, item W12 assess whether participants "are curious and interested in all sorts of things" which can as easily reflect a sense of harmony as a sense of Involvement. Item W20 cross-loads negatively on the Distance factor (Distress), which is the logical opposite of the Involvement factor (Wellbeing). Finally, items D17 (I generally lack initiative and drive) and D18 (I feel useless), although they are designed to assess Distance, clearly also tap into known manifestations of depression.

clearly show that ESEM tends to provide a better representation of the true correlations between factors when cross-loadings are present in the population model, yet unbiased estimates of the same correlations when no cross-loadings are present in the population models (e.g., Asparouhov, Muthén, & Morin, 2015). In this context, the observation of reduced factor correlations argues in favor of an ESEM solution. Furthermore, the fact that the correlations remain significant suggests that a global overarching construct may also be present, and thus that a bifactor representation may be desirable.

ESEM versus Bifactor-ESEM. The bifactor-ESEM solution provides the highest level of fit to the data of all models considered here. The parameter estimates from this model are reported in Table 2. These results first reveal a well-defined G-Factor associated with strong and positive target loadings from most items ($|\lambda|$ =.293 to .890, M = .620, with positive loadings from all Wellbeing items and negative loadings from all Distress items), an impressive feat for a G-factor defined by 45 items designed to assess six distinct dimensions. The weaker items from the ESEM solution (W12, W20, D17, and D18, as well as D2, D8, and D22) still present a weak pattern of association with their main factors and elevated cross-loadings on non-target factors. However, with the exception of W12 (which should be targeted for re-assessment in future investigation of this questionnaire), these items now present a high level of association with the G-factor ($|\lambda|$ =.506 to .745, M = .653), supporting our assertion that these items may be clearer indicators of global psychological health levels than of their specific factors. It is also interesting to note that the Wellbeing S-Factors retain a meaningful level of specificity once the G-Factor is taken into account in the model: Harmony (λ =.313 to .665; M = .430), Serenity (λ =.369 to .670; M = .487), and Involvement (λ =.495 to .690; M = .574). However, the Distress S-Factors do not retain as much specificity once the variance in the items attributable to Global psychological health levels is taken into account: Irritability (λ =.141 to .585; M = .386), Serenity (λ =.058 to .382; M = .220), and Involvement (λ =.045 to .383; M = .252). More precisely, the items defining these S-Factors now present a much weaker level of association with their S-Factor than with the G-Factor. However, although not defined as strongly as the Wellbeing S-Factors, 20 out of 23 target loadings on these Distress S-Factors remain significant, supporting the need to control for their content specificity in the model. It is also important to keep in mind that in latent models controlled for measurement errors, even weakly defined factors remain perfectly reliable. Finally, the superiority of the bifactor-ESEM solution is also apparent from the observation of substantially reduced cross-loadings ($|\lambda|$ = .001 to .317; *M* = .081) when compared to ESEM, in particular, in this solution, 68 (30%) cross loadings are now non-significant, while 22 remained between |.200| and |.300|, 6 between |.300| and |.400|, and 3 over |.400|.

Measurement Invariance. For purposes of the present demonstration, factors scores were generated for both the ESEM and bifactor-ESEM solutions. However, because our sample includes participants from two countries, it was important to verify the measurement invariance of these models across countries. The results from these tests are reported in the lower section of Table 1. The model of configural invariance provides an excellent fit to the data for both the ESEM (CFI = .969; TLI = .959; RMSEA = .048) and bifactor-ESEM models (CFI = .976; TLI = .966; RMSEA = .044). Invariance constraints across groups were then progressively added to the factor loadings (weak invariance), thresholds (strong invariance), uniquenesses (strict invariance), latent variances and covariances, and latent means of these models. None of these steps resulted in a decrease in model fit exceeding the recommended cut-off scores for the fit indices (ΔCFI and ΔTLI ≥ .01; ΔRMSEA ≥ .015). Adding invariance constraints on the factor loadings even resulted in an increase in fit for the fit indices including a correction for parsimony. Although the changes in fit indices associated with the invariance of the variance and covariances for ESEM were borderline (ΔCFI and ΔTLI = .010), these constraints were retained in the models used to generate the factor scores in order to facilitate the interpretation of the profiles as being based on indicators that are fully equivalent across countries. Indeed, saving factor scores based on a model in which both the variances and the latent means are invariant (i.e., respectively constrained to take a value of 1 and 0 in both groups) provides scores on profile indicators that can be readily interpreted as deviations from the grand mean expressed in standard deviation units. For both models, factors scores were saved from the most invariant models.

Person-Centered Analyses

Table 3 presents the goodness-of-fit indices for the three alternative models. Model 1 and 3 were both estimated using factor scores saved from the fully invariant ESEM solution, whereas Model 2R was estimated using factor scores from the fully invariant bifactor-ESEM solution. Examination of these results reveals that the AIC continues to improve when latent profiles are added for each of the alternative parameterizations. In contrast, the CAIC reaches its lowest point for solutions including 5 (Model 1 and 2R) or 3 (Model 3) profiles, the BIC reaches its lowest point for solutions including 4 (Model 3), 5 (Model 2R), or 6 (Model 1) profiles, and the ABIC reaches its lowest point for solutions including 6 profiles (Model 1 and 3). In addition, the aLMR apparently supports solutions including 3 (Model 2R), 4 (Model 3) or 7 (Model 1) profiles, while the BLRT supports the 6-profile solution (Models 2R and 3). In accordance with previous recommendations (e.g., Morin, Maïano et al., 2011) we also examined elbow plots to help in the selection of the final solution. These elbow plots are reported in figures S1 to S3 of the online supplements. For Models 1 and 2R, these plots showed a relatively clear plateau at 5 profiles (generally supporting the conclusions from the CAIC and BIC), after which improvement in fit becomes minimal. Examination of these 5-profile solutions shows them to be fully proper and interpretable. However, the 5-profile solution obtained for Model 1 did not bring any meaningful information when compared to the 4-profile solution (resulting in the extraction of one additional *level*-differentiated profile representing less than 1% of the sample). In contrast, the 5-profile solution obtained for Model 2R proved to be substantively superior to the 4-profile solution (revealing an additional profile presenting a well-differentiated *shape*). The 4-profile solution was thus retained for Model 2R, while the 4-profile solution was retained for Model 1. In contrast, for Model 3, the elbow plot seems to support a 3-profile solution, which is in roughly line with the conclusions from the CAIC and BIC. Once again, examination of this solution reveals that it is proper, and superior to adjacent solutions.

Results from the solutions retained for Models 1 and 3 (see Figures S4 and S5 in the online supplements) revealed profiles presenting clear *level*-related differences, and almost no *shape*-related differences, thus arguing against the meaningfulness of these models. Indeed, these two solutions suggest that psychological health may best be represented as a single underlying dimension, which contradicts the results from previous variable-centered analyses. Importantly, these results suggest that the apparent superiority of the FMA approach reported by Morin and Marsh (2015) may not hold in all situations, and may pose problems when the constructs used to assess the profiles are known to follow a bifactor structure so that extracting *level* effects as part of the profile-estimation process may leave too little residual specificity to form meaningful profiles. We now turn our attention to Model 2R.

Results from Model 2R. Results from the 5-profile solution retained for Model 2R are presented in Figure 2. In this solution, profiles present much clearer *shape*-related differences, with the G-Factor indicator providing a clear pointer of the global level of psychological health observed in each profile. This solution thus supports, and enriches, the conclusions from the variable-centered analyses, showing that a global underlying psychological wellbeing dimension does coexist with meaningful specificity at the subscale level. In this solution, Profile 1 presents a moderately high level of global psychological health, and relatively low levels on the specific indicators of psychological distress. However, over and above this global level of psychological health, this profile is characterized by relatively low scores on the specific indicators of psychological wellbeing (Harmony, Serenity, Involvement). Thus, this profile seems characterized by satisfactory levels of psychological health, without appearing to thrive. This “Adapted” profile characterizes 11.12% of the sample. In contrast, Profile 2 presents moderately low levels of global psychological health, as well as high levels of Irritability and Anxiety/Depression. While the specific levels of Harmony, Serenity and Distance observed in this profile remain average, this profile is also characterized by relatively high levels of involvement over and above global levels of wellbeing, which may explain their apparent Irritability and Anxiety/Depression. This “Stressfully Involved” profile characterizes 14.29% of the sample. Profile 3 rather seems to represent a more “Normative” profile, representing 60.96% of the sample characterized by average levels of global psychological health, fully on par with average levels on all other specific indicators. This profile is consistent with the results from our variable centered analyses which suggested the existence of a very well-defined G-factor, co-existing with weaker S-factors. When examined through the perspective of person-centered analyses, this translates into one dominant “Normative” profile corresponding to participants for which no meaningful information is added by ratings on the S-factors. In contrast, and supporting the idea that there remains meaningful specificity in the dimensions of psychological health, these S-factors clearly bring valuable information to the definition of the remaining four profiles, describing a total of close to 40% of the sample.

In this regard, Profile 4 is particularly interesting. Indeed, whereas this profile is characterized by relatively low levels of global psychological health, it also present moderately high levels of Harmony and Serenity, moderately low levels of Irritability and Anxiety/Depression, moderately low levels of

Involvement, and moderately high levels of Distance. This suggests that these relatively unwell teachers still manage to attain some level of equilibrium and serenity through a process of distancing themselves from their schools and limiting their involvement. This "Harmoniously Distanced" profile characterizes 12.26% of the sample. Finally, teachers from Profile 5 clearly thrive in their schools, presenting very high levels of psychological health, coupled with high levels of Harmony, Serenity, and Involvement, coupled with average levels on all Distress indicators. This "Flourishing" profile represents only 1.38% of the sample. It should be kept in mind that, albeit small, the importance of this profile is supported by the observation that it emerged quickly in the class enumeration process, being already present in the 4-profile solution, and remaining present in the 6-, 7-, and 8- profile solutions.

Discussion

Shape and Level Effects: The importance of Preliminary Measurement Models

Morin and Marsh (2015) noted that a key implicit assumption of person-centered analyses is that extracted profiles should be qualitatively (*shape*) different from one another and that a latent profile solution where the profiles are simply ordered based on quantitative (*level*) differences would have very little heuristic value and would better represented by variable-centered methodologies. However, psychological and educational research often focuses on multidimensional constructs aiming to assess specific complementary dimensions of global underlying constructs, for which equally strong level and shape effects can be expected. Although theoretical frameworks often explicitly or implicitly posit such global overarching constructs, practical applications often simply ignore this global overarching construct to focus on the dimensions, typically represented as correlated factors. Doing so creates the risk of converging on biased estimates of the key relations between these constructs, which are then estimated while ignoring the fact that part of the shared variance among these dimensions could be meaningful in its own right as a reflection of the global overarching construct. In person-centered analyses, the most likely outcome of this phenomenon is the extraction of profiles for which *shape*-related differences are obscured by the lack of control of equally strong *level*-related effects.

Observing *level*-differentiated profiles suggests the presence of an overarching construct underlying the various dimensions used in the latent profile model. However, observing *level*-differentiated profiles in models in which *shape* and *level* effects are not properly disaggregated from one another does not answer the question of whether enough specificity remains within the dimensions to create meaningful shape differences in latent profiles once global levels effects are properly controlled. Morin and Marsh (2015) proposed alternative models all aimed at providing various levels of controls for level-effects in order to estimated clearer shape-differentiated profiles. However, two of the models proposed by these authors were plagued by the reliance on indicators formed on the basis of suboptimal higher-order measurement models, which rely on highly restrictive proportionality constraints (e.g., Reise, 2012; Morin, Arens et al., 2015) and introduce a conceptual redundancy in the latent profile model given that the first-order factors are not properly disaggregated for the covariance explained by the higher-order factor. Although the remaining FMA model proposed by these authors also relied on similar proportionality constraint, it resulted in a proper disaggregation of *shape* versus *level* effects in Morin and Marsh (2015) study. However, our results suggested that the superiority of this FMA approach may not hold in all situations. This may be explained by a second equally restrictive implicit assumption of this model, which assumes that all of the extracted latent profiles present equal levels on the estimated global factor representing overarching *level* effects.

To solve this apparent dilemma, we illustrated the importance of adopting a proper variable-centered measurement model as a starting point to person-centered analyses. We proposed that the observation of level-differentiated profiles may suggest the need to revisit the preliminary measurement models underling the profile indicators or better, that person-centered analyses should start with a careful examination of the measurement models underlying the profile indicators. As advocated by Morin, Arens et al. (2015) we proposed to conduct this investigation within the newly developed bifactor-ESEM framework, which provides a way to systematically assess the presence of construct-relevant psychometric multidimensionality related to the hierarchical and conceptually-related nature of the constructs. The first source of construct-relevant multidimensionality is directly related to the level effects explained by the presence of an overarching global construct and can be identified by the comparison of classical correlated factor models with bifactor models. In contrast, the second source can be identified by a comparison of ESEM and CFA models. Previous research shows that ignoring any one of these two sources of construct-relevant multidimensionality, when they are present in the data, may lead to inflated estimates of the other source or to inflated estimates of factor correlations when both sources are ignored (Asparouhov et al., 2015; Morin, Arens et al., 2015).

A critical advantage of relying on a bifactor-ESEM representation of the data becomes obvious whenever this initial psychometric measurement model is used in subsequent analyses. In particular, the adoption of a bifactor model makes it possible to explicitly represent the global overarching construct, while simultaneously taking into account the specific information brought to the model by the specific dimensions. Perhaps even more importantly, adopting a person-centered model based on factor scores saved from preliminary bifactor models (Model 2R) makes it possible to estimate profiles differing from one another on the basis of both *shape*-related differences (defined from the specific dimensions) and global *levels* on the overarching construct (defined by the G-factor). In the current study, this alternative person-centered model proved superior to the alternative models in providing the more easily interpretable solution, which was fully in line with the conclusion from the variable-centered analyses regarding the co-existence of global and specific constructs.

It is interesting to recall that Morin and Marsh (2015) also proposed a repeated measure ANOVA-based approach to conduct a preliminary investigation of the likely amount of variability in profile indicators attributable to *shape* versus *level* effects. Unfortunately, their approach was limited to the availability of longitudinal data. In contrast, the bifactor approach advocated here provides a similar way to estimate the amount of variability in ratings (at the item level) that could be attributable to *level* (as represented by the percentage of variance in ratings explained by the G-factor) versus *shape* (as represented by the percentage of variance in ratings explained by the S-factors) effects should the factors from the target measurement model be used as latent profile indicators. In the current study, the results from our final bifactor-ESEM model clearly support the need to account for strong level-related effects in ratings (explaining an average of 40.97% of the variability in ratings) in order to be able to define profiles reflecting the still significant shape-related effects (explaining an average of 25.53% of the variability in ratings). These percentages of variance in ratings attributable to various factors can easily be calculated as the sum of squared loadings of the items on relevant factors.

Thus, we systematically compared alternative person-centered models (see Figure 1) for purposes of this illustration; we do not argue that future person-centered applications should systematically embark on a comparison of these alternative approaches. Rather, we argue that any application of person-centered analyses based on indicators formed on the basis of scale scores taken from multidimensional psychometric measures should be solidly anchored in a thorough preliminary investigation of the measurement model underlying answers to the instrument(s) from which the indicators are taken. As advocated by Morin, Arens et al. (2015) whenever there are theoretical reasons to expect that answers to the instrument may reflect a global underlying construct (which calls for a bifactor model), yet also form multiple conceptually-related dimensions (which calls for an ESEM model), then the bifactor-ESEM framework appears appropriate. Interestingly, these preliminary measurement models will provide a direct estimate of the specific amount of the variance in ratings likely to be attributed to level (G-factor) versus shape (S-factors) in later person-centered applications. From these estimates, it then becomes relatively simple to select the most appropriate latent profile model: (1) Model 1 whenever the G-factors turns out to be negligible; (2) Model 2R whenever the G-factor turns out to be substantively meaningful.

Substantive Implications for the Study of Psychological Health

The results obtained in this study also have implications for the study of psychological health. Preliminary variable-centered analyses supported the presence of global underlying dimension of psychological health (Massé et al., 1998), while also demonstrating that a complete representation of this concept also requires the consideration of multiple dimensions reflecting both the presence of psychological wellbeing and the absence of psychological distress (Massé et al., 1998; Keyes, 2005; World Health Organization, 2014). Our results also showed that psychological distress items tend to more strongly contribute to the assessment of the global psychological health construct, and to retain a lower level of specificity once this global construct is taken into account, a result consistent with previous research (Linley et al., 2009; Massé et al., 1998). This result suggests that the psychological health global construct seem to be influenced by the experience of psychological distress to a greater extent than by positive experiences of wellbeing, which also retain a greater level of subscale-related specificity. Thus, while global levels of psychological health reflect both the absence of distress and the presence of wellbeing, as proposed by the World Health Organization (2014), psychological wellbeing retains a greater level of specificity that goes beyond the psychological health construct.

Results from the retained person-centered model (Model 2R) revealed the presence of 5 theoretically meaningful profiles. It is interesting to note that these profiles differ from those reported by Savoie et al. (2010) based on median split approach, which showed that the great majority of teachers (94%) presented a well-adjusted profile characterized by high levels of wellbeing and low levels of distress. In contrast, the current study reveal that the dominant Normative profile (Profile 3) represents 60% of the sample characterized by average levels of global psychological health that are fully aligned with equally average levels on the various wellbeing and distress dimensions. Among the other profiles, two (Profiles 1 and 5) are characterized by well-adapted psychological health profiles and represent a total of 13% of the sample, whereas two others (Profiles 2 and 4) are characterized by more problematic psychological health profiles and represent a total of 27% of the sample.

The observation of a large "Normative" profile characterized by average levels of psychological health across all indicators suggests that for 60% of the population, psychological health can be represented by a single global indicator around which there is inter-individuals variability. This result is consistent with prior variable-centered research showing a high correlation between psychological wellbeing and distress (Boudrias et al., 2014; Massé et al., 1998). In contrast, the remaining four profiles clearly show that important information would be lost if one was to summarize ratings of psychological health through a single overarching score. The "Adapted" profile shows a relatively high level of global psychological health, with comparatively low levels on all of the specific wellbeing and distress dimensions. In the interpretation of this profile, we need to keep in mind that the global psychological health construct was defined more strongly by the distress indicators than by the wellbeing indicators. As such, the observed high level of psychological health observed in this profile appears consistent with the low levels of psychological distress also observed in this profile. In comparison with this profile, teachers corresponding to the "Flourishing" profile appear to thrive, presenting, in addition to high levels of global psychological health and low levels of distress, very high levels of wellbeing. This "Flourishing" profile tends to supports the idea that the highest levels of psychological health can only attained when individuals also experience the positive affects associated with wellbeing (Keyes, 2005; Huppert & So, 2013; Su, Tay, & Diener, 2014). The fact that this profile remains very small in this study (1.36%) in comparison to studies on more general population (Huppert & So, 2013; Keyes, 2005) might be explained by our focus on a sample of teachers, a professional group displaying higher than average rates of stress and burnout (Johnson et al., 2005).

The two remaining profiles seem to reflect well differentiated strategies of coping with less than desirable professional situations (e.g., Taris, Horn, Schaufeli, & Schreurs, 2004). The "Stressfully Involved" profile characterizes teachers perceiving their professional situation as highly stressful, and yet remaining highly involved at work, perhaps as a way to cope with professional stress through attempts at regaining some form of control (e.g., Sonnentag, & Fritz, 2007). In contrast, teachers corresponding to the "Harmoniously Distanced" profile appear to have distanced themselves from a work situation that does not seem to generate so much stress for them, possibly as a result of this process of detachment (or alienation, e.g., Savoie et al., 2010; Sonnentag, & Fritz, 2007). Although this process detachment appears to allow these teachers to attain some levels of harmony and serenity in the face of a potentially difficult situation, this is not without consequences, as shown by their relatively low levels of global psychological health. Keyes (2005) describes this type of situation as languishing, a more passive form of adaptation to difficult situations. In contrast, the "Stressfully Involved" profile is more likely to end up experiencing symptoms of burnout, to end up on medical leave, and to potentially leave their schools or the teaching profession (e.g., Weber, Weltle & Lederer, 2007). As a result, both profiles are likely to be associated with substantial costs for educational systems, and thus deserve to be more thoroughly examined in future studies.

Conclusion

In conclusion, this study suggests that, whenever there are reasons to expect psychometric measures to assess specific complementary dimensions of global underlying constructs, we encourage researchers to use a methodological framework similar to the one proposed here. Doing so will allow them to achieve a greater level of clarity in their understanding of the underlying structure of these psychological or educational constructs, both within variable-centered approaches (global, versus specific constructs) and within person-centered approaches (level, versus shape effects). Naturally, future research should devote attention to the conditions under which the methodologies proposed here generalize, those under which the alternative framework proposed by Morin and Marsh (2015, particularly their Model 3) continues to perform adequately, and to essentially test how well do the present substantive and methodological conclusions replicate across conditions, samples, and cultures.

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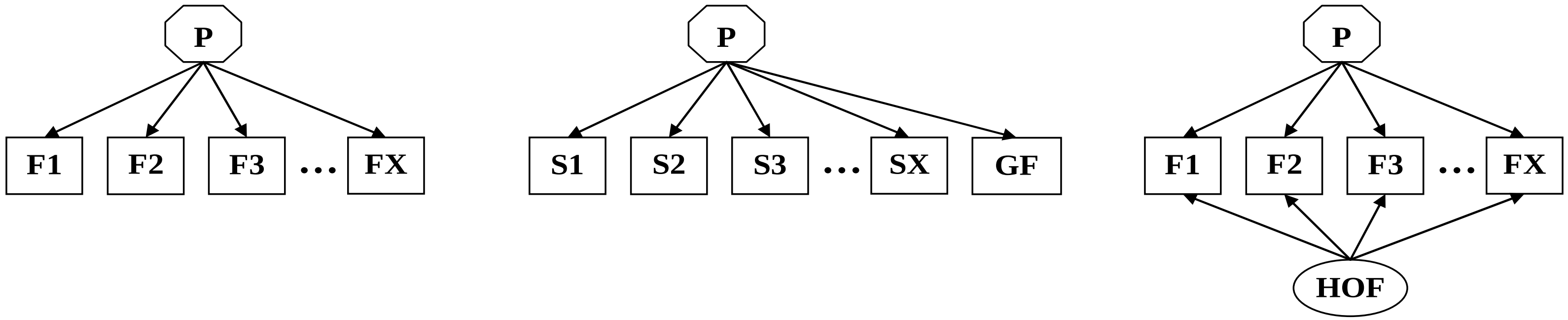

Model 1: Latent Profile Analysis (LPA) (*Morin & Marsh, 2015*).

Model 2R: LPA Incorporating Global- and Specific- Indicators (New)

Model 3: Factor Mixture Analysis (*Morin & Marsh, 2015*).

Figure 1. *Alternative Models Estimated in this Study.*
Note. Squares: observed variables; ovals: continuous latent variables; octagons: categorical latent variables (the profiles: P); F1-FX: first-order factor scores; HOF: higher-order latent factor estimated from the profile indicators; S1-SX: represent specific factor scores (bifactor); GF: global factor score (bifactor).

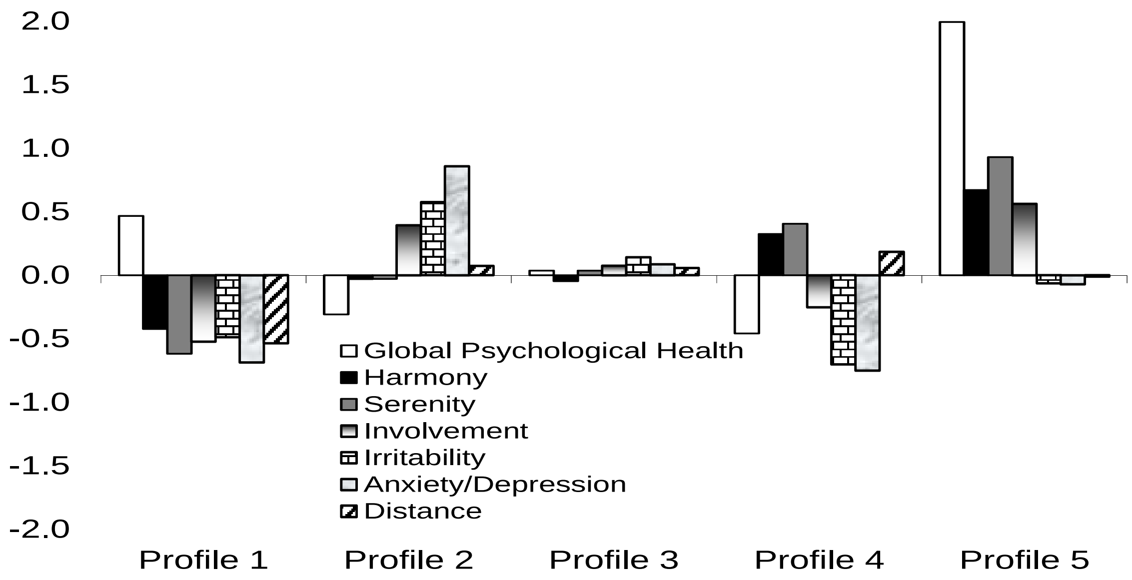

Figure 2. *Results from the Latent Profile Model Based on Bifactor Factor Scores (Model 2R)*

Table 1.

Fit Results from the Alternative Measurement Models for the Well-Being scale (WLSMV)

	χ^2	df	CFI	TLI	RMSEA	RMSEA 90% CI	*MD*$\Delta\chi^2$	Δdf	ΔCFI	ΔTLI	ΔRMSEA
ICM-CFA	5772.746*	930	.927	.922	.065	.063-.067					
Bifactor-CFA	7802.243*	900	.895	.885	.079	.077-.081					
ESEM	3235.114*	735	.962	.949	.053	.051-.054					
Bifactor-ESEM	2536.199*	696	.972	.960	.046	.044-.048					
Measurement Invariance: ESEM											
Configural Invariance	3567.634*	1470	.969	.959	.048	.046-.050	---	---	---	---	---
Weak Invariance	3216.755*	1704	.978	.974	.038	.036-.040	390.310*	234	+.009	+.015	-.010
Strong Invariance	3302.005*	1827	.979	.977	.036	.034-.038	243.817*	123	+.001	+.003	-.002
Strict Invariance	3159.452*	1872	.981	.980	.033	.031-.035	79.813*	45	+.002	+.003	-.003
Variance-Covariance Invariance	2509.120*	1893	.991	.990	.023	.021-.025	41.891*	21	+.010	+.010	-.010
Latent Means Invariance	2588.385*	1899	.990	.990	.024	.022-.027	34.707*	6	-.001	.000	+.001
Measurement Invariance: Bifactor-ESEM											
Configural Invariance	3028.239*	1392	.976	.966	.044	.042-.046	---	---	---	---	---
Weak Invariance	2808.425*	1658	.983	.980	.034	.031-.036	401.768*	266	+.007	+.014	-.010
Strong Invariance	2913.268*	1780	.983	.982	.032	.030-.034	226.931*	122	+.000	+.002	-.002
Strict Invariance	2845.369*	1825	.985	.984	.030	.028-.032	80.479*	45	+.002	+.002	-.002
Variance-Covariance Invariance	2355.654*	1853	.993	.992	.021	.018-.024	53.808*	28	+.008	+.008	-.009
Latent Means Invariance	2438.451*	1860	.992	.991	.022	.020-.025	38.356*	7	-.001	-.001	+.001

Notes. CFA = Confirmatory factor analysis; ESEM = Exploratory structural equation modelling; χ^2 = WLSMV chi square; df = Degrees of freedom; CFI = comparative fit index; TLI = Tucker-Lewis index; RMSEA = root mean square error of approximation; CI = confidence interval; Δ = Change from the previous model in the sequence; MD$\Delta\chi^2$: change in chi square calculated with the MPlus DIFFTEST function (Asparouhov & Muthén, 2006); * $p < 0.01$.

Table 2.

Standardized Parameter Estimates for the A Priori Bifactor-ESEM model with 6 S-Factors

	Harmony (λ)	Serenity (λ)	Involvement (λ)	Irritability (λ)	Anx./Dep. (λ)	Distance (λ)	G-Factor (λ)	Uniqueness
W11	**.495****	.142**	.159**	-.181**	.025	.024	.371**	.538**
W18	**.665****	.075**	-.138**	-.218**	.055*	.060*	.388**	.329**
W9	**.338****	.170**	.090**	.033	.142**	-.020	.628**	.433**
W10	**.313****	.286**	.107**	.005	.176**	.121**	.587**	.419**
W5	**.442****	.041	.066**	.083**	.072*	-.027	.607**	.417**
W12	**.273****	.246**	.404**	-.051	-.099*	.076	.293**	.598**
W21	**.326****	.141**	.084**	.134**	-.024	.016	.358**	.720**
W23	.021	**.464****	.007	.089**	-.038	.074**	.605**	.403**
W24	-.027	**.394****	.196**	.041	.16**	.347**	.629**	.261**
W22	.043*	**.483****	.028	.102**	.020	.230**	.685**	.231**
W25	.017	**.43****	.105**	.129**	.145**	.251**	.743**	.151**
W17	.082**	**.431****	.189**	-.059*	.072*	.173**	.518**	.464**
W4	.089**	**.369****	.107**	.091**	.078**	.148**	.672**	.356**
W15	.185**	**.670****	-.064**	.059*	-.201**	-.207**	.443**	.230**
W16	.076**	**.486****	-.016	-.241**	.076*	.059	.346**	.571**
W7	.154**	**.596****	.030	.031	-.318**	-.134**	.357**	.373**
W19	.093**	**.542****	-.155**	-.018	-.012	-.115**	.318**	.559**
W3	.049*	-.011	**.690****	.128**	-.043	.144**	.402**	.321**
W14	.079**	.084**	**.499****	.105**	.229**	-.315**	.592**	.224**
W20	.009	.131**	**.381****	.121**	.264**	-.409**	.638**	.179**
W6	.202**	.033	**.611****	-.010	-.043	.047	.456**	.372**
W2	.036	.079**	**.495****	.128**	.054*	.086**	.552**	.416**
D1	.118**	-.060*	.067**	**.585****	-.114**	.042	-.598**	.264**
D8	-.416**	.222**	.262**	**.354****	.059	.047	-.506**	.230**
D12	-.328**	.179**	.127**	**.410****	.066	-.025	-.543**	.376**
D5	.099**	-.019	.131**	**.493****	-.046	-.029	-.694**	.245**
D22	-.131**	.089**	-.038	**.309****	.304**	.110*	-.613**	.398**
D15	.166**	-.121**	-.033	**.412****	.075*	.032	-.722**	.259**
D2	-.138**	.115**	.144**	**.141****	.109**	.082**	-.680**	.447**

	Harmony (λ)	Serenity (λ)	Involvement (λ)	Irritability (λ)	Anx./Dep. (λ)	Distance (λ)	G-Factor (λ)	Uniqueness
D14	.226**	-.123**	.135**	.011	**.256****	-.003	-.810**	.194**
D13	.138**	-.086**	.028	-.046	**.324****	-.177**	-.689**	.360**
D20	.022	-.056**	.126**	.032	**.178****	-.019	-.858**	.211**
D16	.081**	-.022	.119**	-.018	**.174****	.095**	-.879**	.167**
D4	.131**	-.065**	.017	.089**	**.058**	-.023	-.783**	.354**
D21	.202**	-.211**	.132**	.097**	**.239****	.125**	-.706**	.317**
D10	.039	.085**	.169**	-.081**	**.075**	.140**	-.890**	.138**
D23	.089**	-.088**	-.027	.247**	**.382****	.145**	-.669**	.308**
D11	-.222**	.130**	.219**	-.029	**.292****	.032	-.761**	.219**
D19	.055**	.205**	-.241**	.063**	.054*	**.383****	-.744**	.190**
D9	.051*	.104**	-.006	-.032	.011	**.359****	-.792**	.323**
D7	.004	.168**	.092**	.084**	.004	**.248****	-.803**	.251**
D18	-.011	.180**	-.076**	.008	.152**	**.179****	-.738**	.362**
D17	.072**	.128**	-.266**	.066*	.301**	**.045**	-.745**	.256**
D6	.085**	.121**	-.039	.110**	.062**	**.308****	-.748**	.307**
D3	.121**	.145**	-.137**	.017	-.109**	**.241****	-.736**	.334**

Notes. [a] The full labels of all items used in this analysis and their correspondence to items labels reported in this Table are fully disclosed in the online supplements (Tables S1 and S2); ESEM = Exploratory structural equation modelling; λ = Standardized factor loading; * $p < 0.05$; ** $p < 0.01$

Table 3.

Fit Indices from Alternative Person-Centered Models (1, 2R, 3).

Model	LL	#fp	Scaling	AIC	CAIC	BIC	ABIC	Entropy	aLMR	BLRT
Model 1: Latent Profiles Models, Estimated from ESEM Factor Scores.										
1 Profile	-9582.186	12	0.9835	19188.372	19261.768	19249.768	19211.651	Na	Na	Na
2 Profiles	-8824.415	25	1.0896	17826.740	17851.740	17826.740	17747.329	0.784	≤ 0.001	≤ 0.001
3 Profiles	-8556.433	38	1.1562	17188.867	17421.290	17383.290	17262.585	0.832	≤ 0.001	≤ 0.001
4 Profiles	-8430.853	51	1.2011	16963.705	17275.641	17224.641	17062.643	0.821	0.0237	≤ 0.001
5 Profiles	-8353.019	64	1.1318	16834.038	17225.487	17161.487	16958.196	0.844	≤ 0.001	≤ 0.001
6 Profiles	-8301.394	77	1.1326	16756.789	17227.751	17150.751	16906.166	0.792	0.013	≤ 0.001
7 Profiles	-8276.509	90	1.1842	16733.018	17283.494	17193.494	16907.615	0.784	0.024	≤ 0.001
8 Profiles	-8226.763	103	1.1857	16659.525	17289.514	17186.514	16859.342	0.741	1.000	≤ 0.001
Model 2R. Latent Profiles Models, Estimated from Bifactor-ESEM Factor Scores.										
1 Profile	-10761.253	14	1.0796	21550.505	21636.135	21622.135	21577.665	Na	Na	Na
2 Profiles	-10652.302	29	1.7569	21362.604	21539.980	21510.980	21418.863	0.423	0.489	≤ 0.001
3 Profiles	-10552.280	44	1.1217	21192.560	21461.682	21417.682	21277.919	0.513	≤ 0.001	≤ 0.001
4 Profiles	-10467.400	59	1.3009	21052.801	21413.668	21354.668	21167.259	0.612	0.316	≤ 0.001
5 Profiles	-10394.507	74	1.2739	20937.014	21389.627	21315.627	21080.571	0.660	0.490	≤ 0.001
6 Profiles	-10351.563	89	1.1391	20881.126	21425.485	21336.485	21053.783	0.657	0.012	≤ 0.001
7 Profiles	-10309.254	104	1.1931	20826.508	21462.613	21358.613	21028.264	0.621	0.271	0.250
8 Profiles	-10274.291	119	1.0792	20786.582	21514.433	21395.433	21017.437	0.649	0.124	≤ 0.001
Model 3: Factor Mixture Models, Estimated from ESEM Factor Scores.										
1 Profile	-8506.688	18	1.0374	17049.376	17159.471	17141.471	17084.295	Na	Na	Na
2 Profiles	-8433.532	31	1.0920	16929.064	17118.672	17087.672	16989.203	0.579	≤ 0.001	≤ 0.001
3 Profiles	-8375.114	44	1.0818	16838.227	17107.349	17063.349	16923.586	0.719	0.003	≤ 0.001
4 Profiles	-8325.178	57	1.0818	16764.355	17112.990	17055.990	16874.933	0.623	0.022	≤ 0.001
5 Profiles	-8289.957	70	1.2230	16719.914	17148.062	17078.062	16855.711	0.618	0.560	≤ 0.001
6 Profiles	-8253.720	83	0.0092	16673.440	17181.101	17098.101	16834.457	0.663	0.018	≤ 0.001
7 Profiles	-8236.887	96	1.3830	16665.773	17252.947	17156.947	16852.010	0.664	0.227	0.429
8 Profiles	-8205.650	109	1.1800	16629.301	17295.988	17186.988	16840.757	0.710	0.2340	≤ 0.001

Notes. ESEM = Exploratory structural equation modelling; LL = Model loglikelihood; #fp = number of free parameters; SF: scaling factor of the robust Maximum Likelihood estimator; AIC = Akaïke Information Criterion; CAIC = Consistent AIC; BIC = Bayesian Information Criterion; ABIC = sample-size Adjusted BIC; ALMR: Adjusted Lo-Mendell-Rubin Likelihood Ratio Test; BLRT = Bootstrap Likelihood Ratio Test

Online supplements for

Further Reflections on Disentangling Shape and Level Effects in Person-Centered Analyses: An Illustration Exploring the Dimensionality of Psychological Health.

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 an external website (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 if you deem it useful. We developed these materials mostly to provide additional technical information and to keep the main manuscript from becoming needlessly long.

Table S1.

Item Labels for the Psychological Wellbeing Subscales (Gilbert et al., 2011).

Item Code	English Version	French Version
Harmony		
W5	I feel that others love me and appreciate me	Je me sens aimé et apprécié
W9	I smile easily	J'ai facilement un beau sourire
W10	I am true to myself, natural at all the times	Je suis égal à moi-même, naturel, en toutes circonstances
W11	I am able to concentrate on and listen to my colleagues	Je suis à l'écoute de mes collègues de travail
W12	I am curious and interested in all sorts of things	Je suis curieux, je m'intéresse à toutes sortes de choses
W18	I get along well with my colleagues	Je suis en bon terme avec mes collègues de travail
W21	I have a good sense of humor, I easily make my colleagues laugh	J'ai beaucoup d'humour, je fais facilement rire mes collègues de travail
Serenity		
W4	I feel emotionally balanced.	Je me sens équilibré émotionnellement
W7	I want to participate in my favorite activities and past-times outside of work	J'ai le goût de pratiquer mes loisirs et activités préférés en dehors du travail
W15	My life is well-balanced between my family, personal and professional activities	J'ai un équilibre entre mes activités professionnelles, familiales et personnelles
W16	I am quite calm	Je suis plutôt calme et posé
W17	I am able to find answers to my problems without trouble	Je trouve facilement des solutions à mes problèmes
W19	I work at a normal pace, not doing anything excessively	Je travaille avec modération, en évitant de tomber dans les excès
W22	I feel good, at peace with myself	Je suis bien dans ma peau, en paix avec moi-même
W23	I feel healthy and in top shape	Je me sens en santé, en pleine forme
W24	I am able to face difficult situations in a positive way	Je sais affronter positivement les situations difficiles
W25	My moral is good	J'ai un bon moral)
Involvement		
W2	I feel satisfied with what I am able to accomplish, I feel proud of myself	Je suis satisfait de mes réalisations, je suis fier de moi
W3	I have lots of "get up and go", I take on lots of project	Je suis fonceur, j'entreprends plein de choses
W6	I have goals and ambitions	J'ai des buts, des ambitions
W14	I find my work exciting and I want to enjoy every moment of it	Je trouve mon travail excitant et j'ai envie d'en profiter
W20	I have the impression of really enjoying my work to the fullest	J'ai l'impression de vraiment apprécier mon travail

Table S2.

Item Labels for the Psychological Distress Subscale (Gilbert et al., 2011).

Item Code	English Version	French Version
Irritability		
D1	I am aggressive about everything and nothing	Je suis agressif pour tout et pour rien
D2	I stay away from others as much as possible	J'ai tendance à m'isoler, à me couper du monde
D5	I am very touchy, I get angry about any comment directed at me	Je suis facilement irritable, je réagis plutôt mal et/ou avec colère aux commentaires qu'on me fait
D8	I am at odds with my colleagues	Je suis en conflit avec mes collègues de travail
D12	I am arrogant and even rude towards my colleagues	Je suis arrogant et même " bête " avec mes collègues de travail
D15	I have no patience	Je perds patience facilement).
D22	I am less receptive to the ideas and opinions of others	J'ai tendance à être moins réceptif aux idées (opinions) de mes collègues de travail
Anxiety/Depression		
D4	I have difficulty facing my problems	J'éprouve de la difficulté à faire face à mes problèmes
D10	I feel sad	Je me sens triste
D11	I have the impression that no one loves me	J'ai l'impression que personne ne m'aime
D13	I lack self-confidence	Je manque de confiance en moi
D14	I feel preoccupied and uneasy	Je me sens préoccupé, anxieux
D16	I feel depressed or « down in the dumps »	Je me sens déprimé, ou " down "
D20	I feel ill at ease with myself	Je me sens mal dans ma peau
D21	I feel stressed and under pressure	Je me sens stressé, sous pression
D23	I have difficulty concentrating on anything	J'éprouve de la difficulté à me concentrer sur quoi que ce soit
Distance		
D3	I have the impression that I messed up my career	J'ai l'impression d'avoir raté ma carrière
D6	I don't feel like doing anything more	Je n'ai plus le goût de faire quoi que ce soit de plus
D7	I feel belittled, diminished	Je me sens dévalorisé, je me sens diminué
D9	I feel like throwing everything to the wind, quitting	J'ai envie de tout lâcher, de tout abandonner
D17	I generally lack initiative and drive	Je manque d'initiative en général, je suis moins fonceur
D18	I feel useless	J'ai le sentiment d'être inutile
D19	I feel that I am not interested anymore in my work	Je me sens désintéressé par mon travail

Table S3.

Standardized Parameter Estimates for the A Priori 6-Factor ICM-CFA and ESEM Solutions

	ESEM solution							ICM-CFA solution	
Item[a]	Harmony (λ)	Serenity (λ)	Involvement (λ)	Irritability (λ)	Anx./Dep. (λ)	Distance (λ)	Uniqueness	λ	Uniqueness
W11	**.534****	.130**	.138**	-.215**	.155**	.051	.555**	.565**	0.681**
W18	**.732****	.086**	-.141**	-.300**	.102**	.096**	.327**	.557**	0.690**
W9	**.413****	.284**	.185**	-.087**	.001	-.130**	.447**	.808**	0.347**
W10	**.370****	.405**	.199**	-.134**	.035	.042	.438**	.786**	0.383**
W5	**.537****	.130**	.165**	-.005	-.091**	-.143**	.434**	.763**	0.417**
W12	**.293****	.212**	.361**	.009	.048	.108**	.665**	.508**	0.742**
W21	**.382****	.191**	.119**	.138**	-.108**	-.019	.723**	.492**	0.758**
W23	.054*	**.620****	.048**	.017	-.241**	.022	.407**	.779**	0.393**
W24	.002	**.562****	.349**	-.171**	-.131**	.263**	.276**	.799**	0.362**
W22	.087**	**.664****	.129**	-.032	-.282**	.166**	.238**	.869**	0.245**
W25	.065**	**.635****	.273**	-.076**	-.214**	.143**	.178**	.918**	0.157**
W17	.102**	**.536****	.223**	-.163**	.004	.137**	.469**	.708**	0.499**
W4	.144**	**.529****	.215**	-.044	-.175**	.047	.368**	.831**	0.309**
W15	.203**	**.804****	-.245**	.221**	-.106**	-.185**	.262**	.705**	0.502**
W16	.062*	**.571****	-.082**	-.316**	.168**	.091**	.581**	.530**	0.720**
W7	.164**	**.672****	-.167**	.222**	-.171**	-.083**	.480**	.615**	0.622**
W19	.090**	**.664****	-.252**	.010	.028	-.091**	.566**	.504**	0.746**
W3	.103**	-.038	**.802****	.108**	-.093**	.050	.343**	.629**	0.605**
W14	.132**	.165**	**.600****	.017	.243**	-.509**	.223**	.855**	0.270**
W20	.061**	.256**	**.480****	.017	.238**	-.626**	.186**	.894**	0.200**
W6	.253**	-.008	**.674****	-.023	.010	-.012	.411**	.708**	0.499**
W2	.095**	.137**	**.627****	.043	-.095**	-.055*	.421**	.767**	0.411**
D1	.113**	-.131**	.039	**.867****	-.139**	.115**	.263**	.730**	0.467**
D8	-.497**	.214**	.225**	**.500****	.122**	.085*	.322**	.611**	0.627**
D12	-.396**	.178**	.086*	**.578****	.105*	.010	.378**	.657**	0.568**
D5	.065**	-.117**	.063**	**.770****	.075**	.076**	.254**	.813**	0.339**
D22	-.169**	.100**	-.040	**.379****	.317**	.122**	.461**	.755**	0.430**
D15	.143**	-.199**	-.066**	**.617****	.149**	.113**	.273**	.867**	0.249**
D2	-.226**	.029	.062*	**.271****	.335**	.213**	.448**	.770**	0.407**

	ESEM solution							ICM-CFA solution	
Item[a]	Harmony (λ)	Serenity (λ)	Involvement (λ)	Irritability (λ)	Anx./Dep. (λ)	Distance (λ)	Uniqueness	λ	Uniqueness
D14	.160**	-.283**	.043*	.129**	**.649****	.141**	.194**	.859**	0.261**
D13	.070**	-.197**	-.064**	.030	**.707****	-.074**	.366**	.725**	0.474**
D20	-.071**	-.209**	.009	.175**	**.564****	.137**	.213**	.886**	0.215**
D16	-.017	-.187**	.000	.108**	**.570****	.288**	.168**	.912**	0.168**
D4	.062*	-.213**	-.105**	.269**	**.375****	.148**	.362**	.806**	0.351**
D21	.164**	-.343**	.116**	.180**	**.454****	.215**	.328**	.781**	0.389**
D10	-.082**	-.108**	.004	.072**	**.534****	.392**	.168**	.904**	0.182**
D23	.051*	-.109**	-.005	.299**	**.426****	.161**	.402**	.767**	0.412**
D11	-.342**	.033	.123**	.036	**.659****	.159**	.220**	.790**	0.375**
D19	-.022	.151**	-.352**	.181**	.171**	**.580****	.200**	.836**	0.302**
D9	-.042	-.035	-.125**	.087**	.265**	**.599****	.232**	.863**	0.256**
D7	-.097**	.032	-.037	.251**	.290**	**.477****	.263**	.857**	0.265**
D18	-.102**	.107**	-.196**	.114**	.402 **	**.354****	.363**	.797**	0.364**
D17	-.002	.108**	-.367**	.163**	.497**	**.161****	.285**	.822**	0.324**
D6	.012	.026	-.133**	.246**	.236**	**.498****	.308**	.825**	0.320**
D3	.039	.012	-.292**	.198**	.137**	**.495****	.351**	.784**	0.385**

Notes. [a] The full labels of all items used in this analysis and their correspondence to items labels reported in this Table are fully disclosed in the online supplements (Tables S1 and S2); ICM = Independent cluster model; CFA = Confirmatory factor analysis; ESEM = Exploratory structural equation modeling; λ = Standardized factor loading; * $p < 0.05$; ** $p < 0.01$

Table S4.

Latent Factor Correlations for the 6-Factor ICM-CFA (Over the Diagonal) and ESEM (Under the Diagonal) Solutions

	Harmony	Serenity	Involvement	Irritability	Anx./Dep.	Distance
Harmony		.762**	.693**	-.644**	-.616**	-.591**
Serenity	.272**		.623**	-.568**	-.722**	-.539**
Involvement	.189**	.358**		-.457**	-.545**	-.724**
Irritability	-.314**	-.368**	-.269**		.859**	.812**
Anx./Dep.	-.295**	-.385**	-.326**	.570**		.896**
Distance	-.228**	-.267**	-.215**	.403**	.439**	

* $p < 0.05$; ** $p < 0.01$

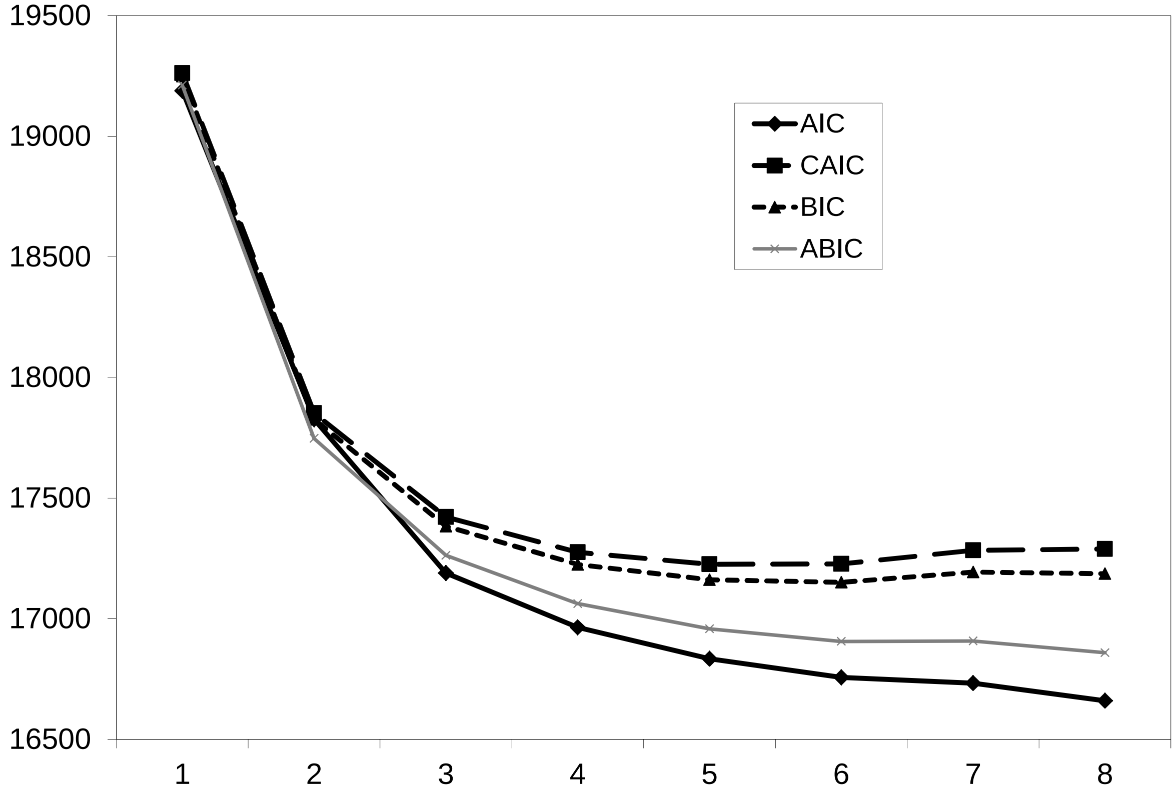

Figure S1. Elbow Plot for Model 1

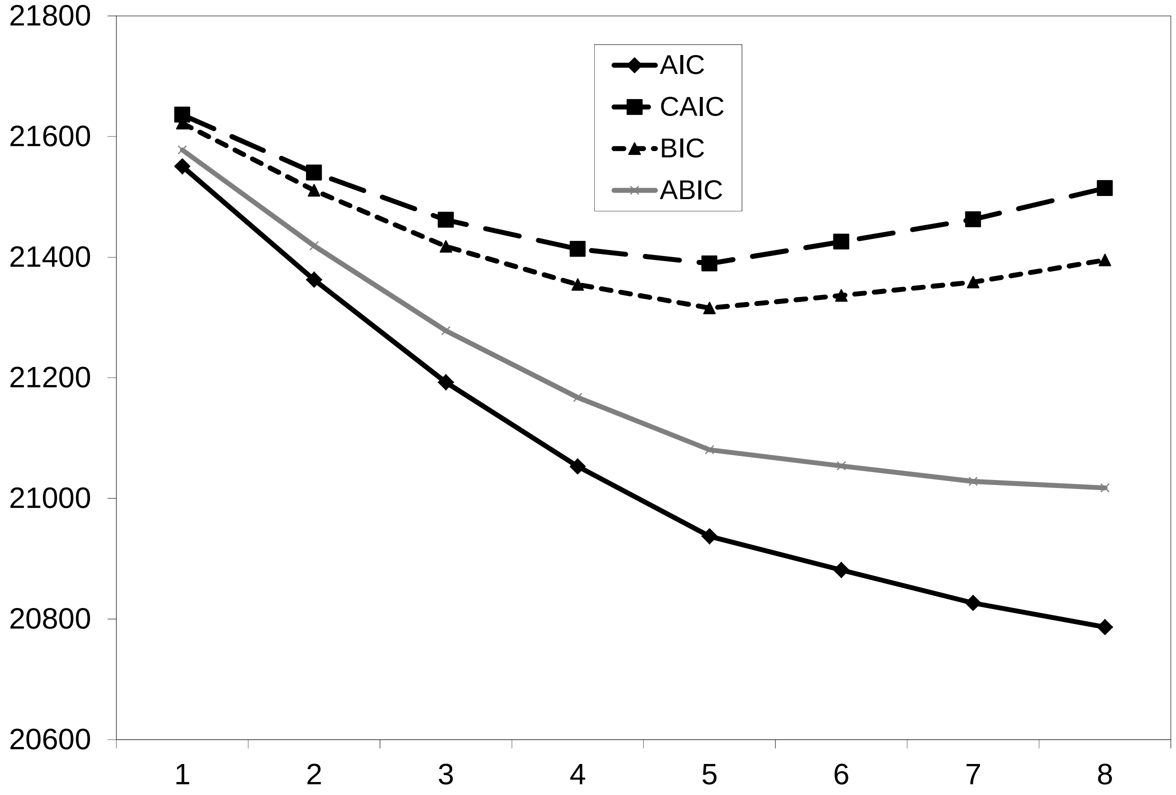

Figure S2. Elbow Plot for Model 2R

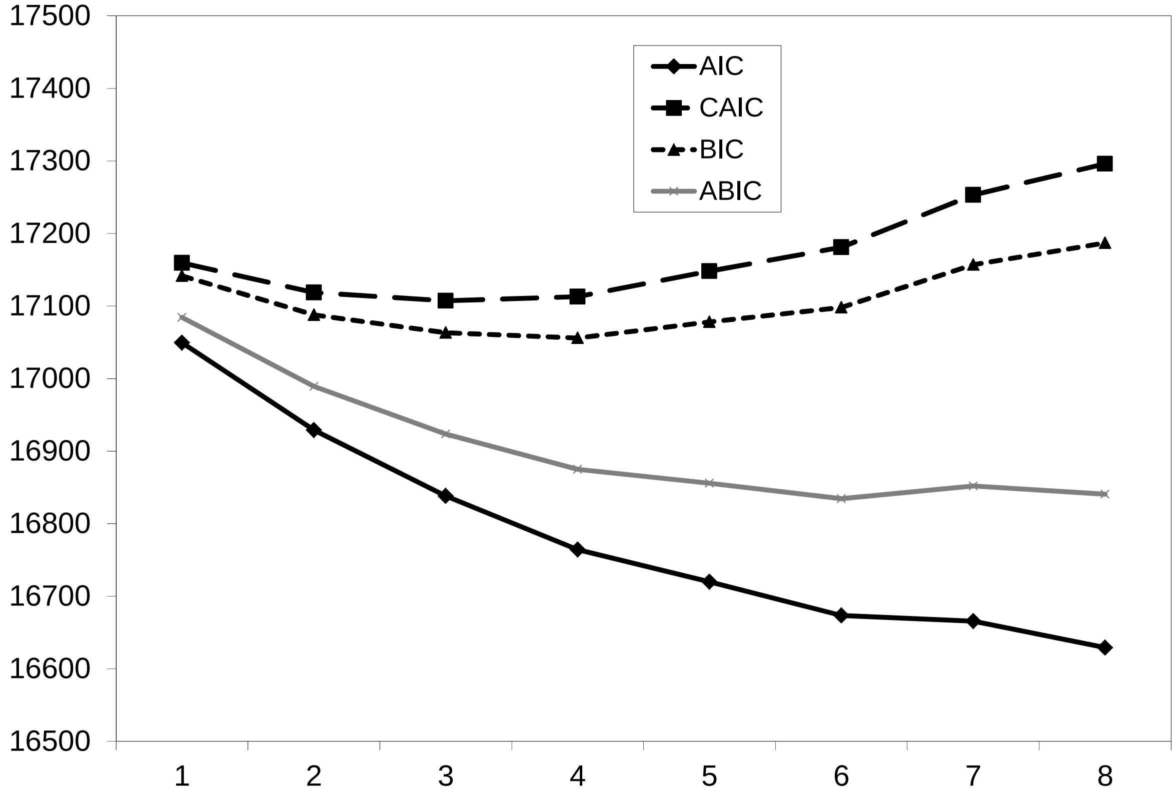

Figure S3. Elbow Plot for Model 3

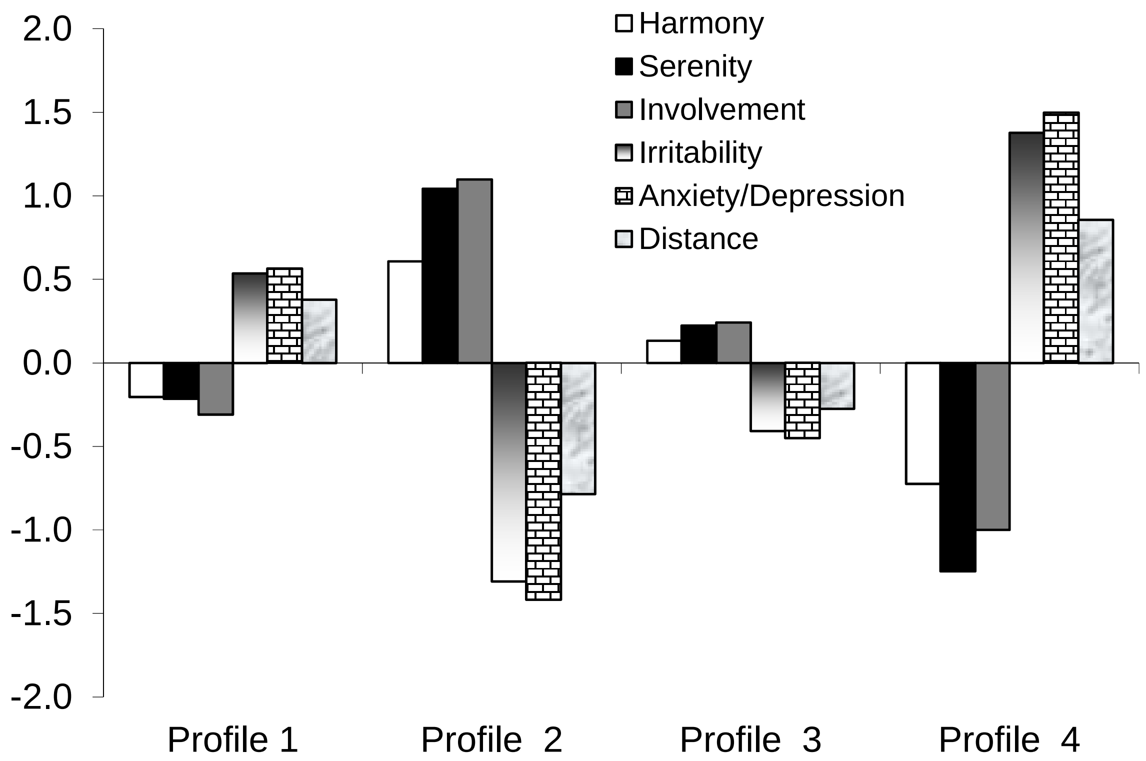

Figure S4. *Results from the Latent Profile Model (Model 1)*

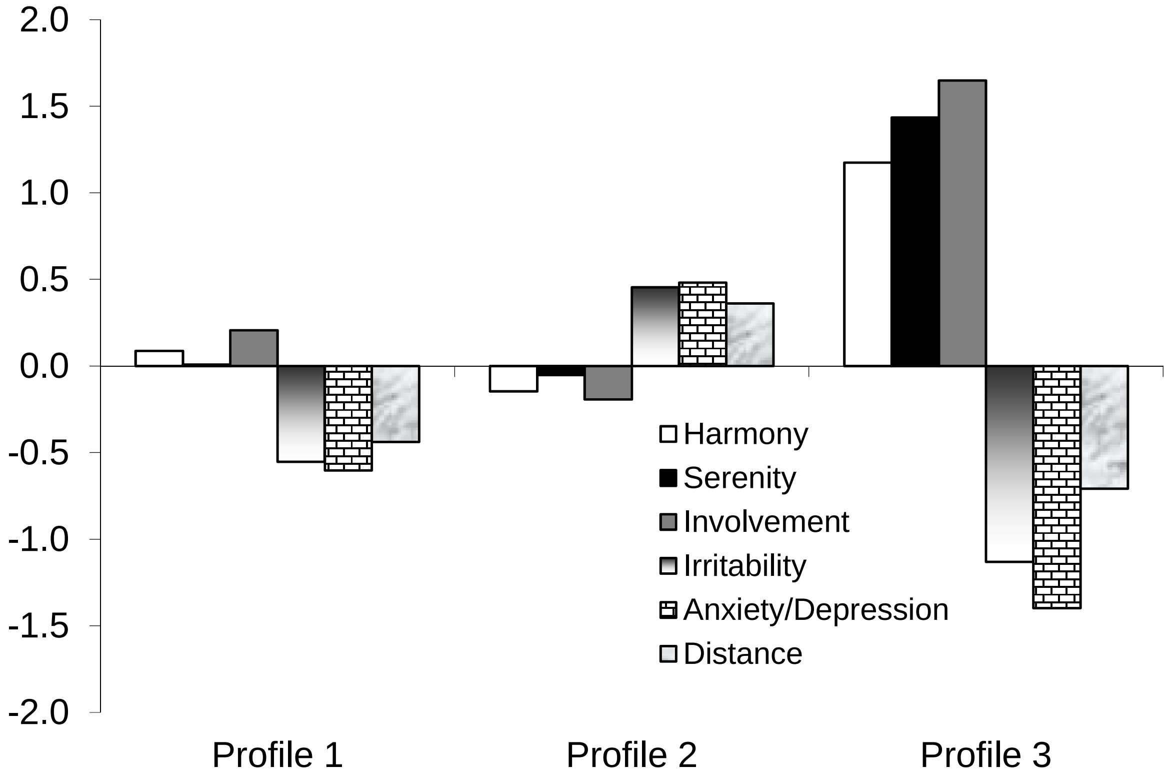

Figure S5. *Results from the Factor Mixture Model (Model 3)*

Title: ICM-CFA

! The following statement is used to identify the data file. Here, the data file is labelled BESEM.dat.
Data:
file = BESEM.dat;
! The variables names function identifies all variables in the data set, in order of appearance.
! The usevar command identifies the variables used in the analysis.
! The categorical command identifies the variables that are ordered-categorical
Variable:
names = ID Count be_2 be_3 be_4 be_5 be_6 be_7 be_9 be_10 be_11 be_12 be_14 be_15 be_16 be_17 be_18 be_19 be_20 be_21 be_22 be_23 be_24 be_25 det_1 det_2 det_3 det_4 det_5 det_6 det_7 det_8 det_9 det_10 det_11 det_12 det_13 det_14 det_15 det_16 det_17 det_18 det_19 det_20 det_21 det_22 det_23;
usevar = be_2 be_3 be_4 be_5 be_6 be_7 be_9 be_10 be_11 be_12 be_14 be_15 be_16 be_17 be_18 be_19 be_20 be_21 be_22 be_23 be_24 be_25 det_1 det_2 det_3 det_4 det_5 det_6 det_7 det_8 det_9 det_10 det_11 det_12 det_13 det_14 det_15 det_16 det_17 det_18 det_19 det_20 det_21 det_22 det_23;
Categorical = be_2 be_3 be_4 be_5 be_6 be_7 be_9 be_10 be_11 be_12 be_14 be_15 be_16 be_17 be_18 be_19 be_20 be_21 be_22 be_23 be_24 be_25 det_1 det_2 det_3 det_4 det_5 det_6 det_7 det_8 det_9 det_10 det_11 det_12 det_13 det_14 det_15 det_16 det_17 det_18 det_19 det_20 det_21 det_22 det_23;
! The missing functions clarifies which missing code is used
! The idvariable function identifies participants' unique identifier,
missing = all (-9999);
IDVARIABLE = ID;
! The next section defines the analysis. Here WLSMV estimation is used with the Theta
! Parameterization, allowing for the estimation of loadings, thresholds and uniquenesses.
Analysis:
ESTIMATOR = WLSMV;
PARAMETERIZATION=THETA;
! The next section defines the model. An ICM-CFA model is specified with 6 factors (labelled BHAR, BSER, BIMP, DIRR, DANX, DDES) defined by their respective items (with the BY command)
! All loadings and intercepts are freely estimated (*), so that factor means are fixed to 0 by default
! and factor variance fixed to 1 (@1).
Model:
BHAR BY be_1* be_18 be_9 be_10 be_5 be_12 be_21;
BSER BY be_23* be_24 be_22 be_25 be_17 be_4 be_15 be_16 be_7 be_19;
BIMP BY be_3* be_14 be_20 be_6 be_2;
DIRR BY det_1* det_8 det_12 det_5 det_22 det_15 det_2;
DANX BY det_14* det_13 det_20 det_16 det_4 det_21 det_10 det_23 det_11;
DDES BY det_19* det_9 det_7 det_18 det_17 det_6 det_3;
BHAR@1; BSER@1; BIMP@1; DIRR@1; DANX@1; DDES@1 ;
! To save factor scores in a file named WBCFA.dat
SAVEDATA:
FILE IS WBCFA.dat;
FORMAT IS FREE;
SAVE = FSCORES;
! Specific sections of output are requested.
Output: sampstat standardized SVALUES stdyx tech4;

Title: Bifactor CFA

```
! Previously presented sections of inputs are skipped to focus only on differences from prior models.
! A bifactor CFA model is specified with the same 6 specific factors
! All items are also used to define a global factor G.
model:
G BY be_24*  be_2 be_3 be_4 be_5 be_6 be_7 be_9 be_10
    be_11 be_12 be_14 be_15 be_16 be_17 be_18 be_19 be_20 be_21
    be_22 be_23  be_25
    det_1 det_2 det_3 det_4 det_5 det_6 det_7 det_9 det_8 det_10
    det_11 det_12 det_13 det_14 det_15 det_16 det_17 det_18 det_19 det_20 det_21
    det_22 det_23;
  BHAR BY be_11* be_18 be_9 be_10 be_5 be_12 be_21;
  BSER BY be_23* be_24 be_22 be_25 be_17 be_4 be_15 be_16 be_7 be_19;
  BIMP BY be_3* be_14 be_20 be_6 be_2;
  DIRR BY det_1* det_8 det_12 det_5 det_22 det_15 det_2;
  DANX BY det_14* det_13 det_20 det_16 det_4 det_21 det_10 det_23 det_11;
  DDES BY det_19* det_9 det_7 det_18 det_17 det_6 det_3;
 G@1;  BHAR@1; BSER@1;  BIMP@1;  DIRR@1;  DANX@1;  DDES@1 ;
! All factors are specified as orthogonal, with their correlations (WITH) constrained to be 0 (@0).
G WITH BHAR@0 BSER@0  BIMP@0  DIRR@0  DANX@0  DDES@0 ;
BHAR WITH BSER@0  BIMP@0  DIRR@0  DANX@0  DDES@0 ;
BSER WITH  BIMP@0  DIRR@0  DANX@0  DDES@0 ;
BIMP WITH  DIRR@0  DANX@0  DDES@0 ;
DIRR WITH  DANX@0  DDES@0 ;
DANX WITH DDES@0 ;
SAVEDATA:
FILE IS WBBIF.dat;
FORMAT IS FREE;
SAVE = FSCORES;
```

Title: ESEM

```
! Previously presented sections of inputs are skipped to focus only on differences from prior models.
! The Analysis section is adjusted to request target oblique rotation.
Analysis:
ESTIMATOR = WLSMV;
ROTATION = TARGET;
PARAMETERIZATION=THETA;
! An ESEM model is specified with target oblique rotation.
! The 6 factors are defined respectively with main loadings from their respective items
! In addition to these main loadings, all other cross-loadings are estimated but targeted
! to be as close to 0 as possible (~0). Factors forming a single set of ESEM factors (with cross-
! loadings between factors) are indicated by using the same label in parenthesis after * (*1).
model:
  BHAR BY be_11 be_18 be_9 be_10 be_5 be_12 be_21
  be_23~0 be_24~0 be_22~0 be_25~0 be_17~0 be_4~0 be_15~0 be_16~0 be_7~0 be_19~0
  be_3~0 be_14~0 be_20~0 be_6~0 be_2~0
  det_1~0 det_8~0 det_12~0 det_5~0 det_22~0 det_15~0 det_2~0
  det_14~0 det_13~0 det_20~0 det_16~0 det_4~0 det_21~0 det_10~0 det_23~0 det_11~0
  det_19~0 det_9~0 det_7~0 det_18~0 det_17~0 det_6~0 det_3~0 (*1);
  BSER BY be_23 be_24 be_22 be_25 be_17 be_4 be_15 be_16 be_7 be_19
  be_11~0 be_18~0 be_9~0 be_10~0 be_5~0 be_12~0 be_21~0
  be_3~0 be_14~0 be_20~0 be_6~0 be_2~0
  det_1~0 det_8~0 det_12~0 det_5~0 det_22~0 det_15~0 det_2~0
  det_14~0 det_13~0 det_20~0 det_16~0 det_4~0 det_21~0 det_10~0 det_23~0 det_11~0
  det_19~0 det_9~0 det_7~0 det_18~0 det_17~0 det_6~0 det_3~0 (*1);
  BIMP BY be_3 be_14 be_20 be_6 be_2
  be_11~0 be_18~0 be_9~0 be_10~0 be_5~0 be_12~0 be_21~0
  be_23~0 be_24~0 be_22~0 be_25~0 be_17~0 be_4~0 be_15~0 be_16~0 be_7~0 be_19~0
  det_1~0 det_8~0 det_12~0 det_5~0 det_22~0 det_15~0 det_2~0
  det_14~0 det_13~0 det_20~0 det_16~0 det_4~0 det_21~0 det_10~0 det_23~0 det_11~0
  det_19~0 det_9~0 det_7~0 det_18~0 det_17~0 det_6~0 det_3~0 (*1);
  DIRR BY det_1 det_8 det_12 det_5 det_22 det_15 det_2
  be_11~0 be_18~0 be_9~0 be_10~0 be_5~0 be_12~0 be_21~0
  be_23~0 be_24~0 be_22~0 be_25~0 be_17~0 be_4~0 be_15~0 be_16~0 be_7~0 be_19~0
  be_3~0 be_14~0 be_20~0 be_6~0 be_2~0
  det_14~0 det_13~0 det_20~0 det_16~0 det_4~0 det_21~0 det_10~0 det_23~0 det_11~0
  det_19~0 det_9~0 det_7~0 det_18~0 det_17~0 det_6~0 det_3~0 (*1);
  DANX BY det_14 det_13 det_20 det_16 det_4 det_21 det_10 det_23 det_11
  be_11~0 be_18~0 be_9~0 be_10~0 be_5~0 be_12~0 be_21~0
  be_23~0 be_24~0 be_22~0 be_25~0 be_17~0 be_4~0 be_15~0 be_16~0 be_7~0 be_19~0
  be_3~0 be_14~0 be_20~0 be_6~0 be_2~0
  det_1~0 det_8~0 det_12~0 det_5~0 det_22~0 det_15~0 det_2~0
  det_19~0 det_9~0 det_7~0 det_18~0 det_17~0 det_6~0 det_3~0 (*1);
  DDES BY det_19 det_9 det_7 det_18 det_17 det_6 det_3
  be_11~0 be_18~0 be_9~0 be_10~0 be_5~0 be_12~0 be_21~0
  be_23~0 be_24~0 be_22~0 be_25~0 be_17~0 be_4~0 be_15~0 be_16~0 be_7~0 be_19~0
  be_3~0 be_14~0 be_20~0 be_6~0 be_2~0
  det_1~0 det_8~0 det_12~0 det_5~0 det_22~0 det_15~0 det_2~0
  det_14~0 det_13~0 det_20~0 det_16~0 det_4~0 det_21~0 det_10~0 det_23~0 det_11~0  (*1);
SAVEDATA:
FILE IS WBESEM.dat;
FORMAT IS FREE;
SAVE = FSCORES;
```

Title: Bifactor ESEM

```
! Previously presented sections of inputs are skipped to focus only on differences from prior models.
! The Analysis section is adjusted to request orthogonal bifactor target rotation.
Analysis:
ESTIMATOR = WLSMV;
ROTATION = TARGET (orthogonal);
! In this model, a global factor is also defined through main loadings from all items, and is included in
! the same set of ESEM factors as the 6 specific factors.
model:
  G BY be_2 be_3 be_4 be_5 be_6 be_7 be_9 be_10
    be_11 be_12 be_14 be_15 be_16 be_17 be_18 be_19 be_20 be_21
    be_22 be_23 be_24 be_25
    det_1 det_2 det_3 det_4 det_5 det_6 det_7 det_9 det_8 det_10
    det_11 det_12 det_13 det_14 det_15 det_16 det_17 det_18 det_19 det_20 det_21
    det_22 det_23 (*1);
  BHAR BY be_11 be_18 be_9 be_10 be_5 be_12 be_21
  be_23~0 be_24~0 be_22~0 be_25~0 be_17~0 be_4~0 be_15~0 be_16~0 be_7~0 be_19~0
  be_3~0 be_14~0 be_20~0 be_6~0 be_2~0
  det_1~0 det_8~0 det_12~0 det_5~0 det_22~0 det_15~0 det_2~0
  det_14~0 det_13~0 det_20~0 det_16~0 det_4~0 det_21~0 det_10~0 det_23~0 det_11~0
  det_19~0 det_9~0 det_7~0 det_18~0 det_17~0 det_6~0 det_3~0 (*1);
  BSER BY be_23 be_24 be_22 be_25 be_17 be_4 be_15 be_16 be_7 be_19
  be_11~0 be_18~0 be_9~0 be_10~0 be_5~0 be_12~0 be_21~0
  be_3~0 be_14~0 be_20~0 be_6~0 be_2~0
  det_1~0 det_8~0 det_12~0 det_5~0 det_22~0 det_15~0 det_2~0
  det_14~0 det_13~0 det_20~0 det_16~0 det_4~0 det_21~0 det_10~0 det_23~0 det_11~0
  det_19~0 det_9~0 det_7~0 det_18~0 det_17~0 det_6~0 det_3~0 (*1);
  BIMP BY be_3 be_14 be_20 be_6 be_2
  be_11~0 be_18~0 be_9~0 be_10~0 be_5~0 be_12~0 be_21~0
  be_23~0 be_24~0 be_22~0 be_25~0 be_17~0 be_4~0 be_15~0 be_16~0 be_7~0 be_19~0
  det_1~0 det_8~0 det_12~0 det_5~0 det_22~0 det_15~0 det_2~0
  det_14~0 det_13~0 det_20~0 det_16~0 det_4~0 det_21~0 det_10~0 det_23~0 det_11~0
  det_19~0 det_9~0 det_7~0 det_18~0 det_17~0 det_6~0 det_3~0 (*1);
  DIRR BY det_1 det_8 det_12 det_5 det_22 det_15 det_2
  be_11~0 be_18~0 be_9~0 be_10~0 be_5~0 be_12~0 be_21~0
  be_23~0 be_24~0 be_22~0 be_25~0 be_17~0 be_4~0 be_15~0 be_16~0 be_7~0 be_19~0
  be_3~0 be_14~0 be_20~0 be_6~0 be_2~0
  det_14~0 det_13~0 det_20~0 det_16~0 det_4~0 det_21~0 det_10~0 det_23~0 det_11~0
  det_19~0 det_9~0 det_7~0 det_18~0 det_17~0 det_6~0 det_3~0 (*1);
  DANX BY det_14 det_13 det_20 det_16 det_4 det_21 det_10 det_23 det_11
  be_11~0 be_18~0 be_9~0 be_10~0 be_5~0 be_12~0 be_21~0
  be_23~0 be_24~0 be_22~0 be_25~0 be_17~0 be_4~0 be_15~0 be_16~0 be_7~0 be_19~0
  be_3~0 be_14~0 be_20~0 be_6~0 be_2~0
  det_1~0 det_8~0 det_12~0 det_5~0 det_22~0 det_15~0 det_2~0
  det_19~0 det_9~0 det_7~0 det_18~0 det_17~0 det_6~0 det_3~0 (*1);
  DDES BY det_19 det_9 det_7 det_18 det_17 det_6 det_3
  be_11~0 be_18~0 be_9~0 be_10~0 be_5~0 be_12~0 be_21~0
  be_23~0 be_24~0 be_22~0 be_25~0 be_17~0 be_4~0 be_15~0 be_16~0 be_7~0 be_19~0
  be_3~0 be_14~0 be_20~0 be_6~0 be_2~0
  det_1~0 det_8~0 det_12~0 det_5~0 det_22~0 det_15~0 det_2~0
  det_14~0 det_13~0 det_20~0 det_16~0 det_4~0 det_21~0 det_10~0 det_23~0 det_11~0  (*1);
SAVEDATA:
FILE IS WBESEMBIF.dat;
FORMAT IS FREE; SAVE = FSCORES;
```

TITLE: Configural Invariance

```
! Previously presented sections of inputs are skipped to focus only on differences from prior models.
! We present models of invariance testing based on the final Bifactor-ESEM solution.
! For a first order ESEM model, simply take out references to the G factor, and orthogonal rotation.
! In the variable section, the grouping function is used to define the levels of the grouping variable.
Variable:
 GROUPING is Count (1=CAN 2=FRA);
MODEL:
! In the model section, the first section is used to define the global model (and the model used in the
! first group. With WLSMV estimation, the loadings and thresholds are constrained to be invariant
! by default, the uniquenesses and variances are by default fixed to 1 in the first group and free in
! the other, the means are by default fixed to 0 in the first group and free in the other. In this model,
! the only required specification are for the loadings, and thresholds. For configural invariances, all
! thresholds are freely estimated in all groups, save for the first one for each variable, and the second
! one for a referent indicator selected for each factor. There are one less thresholds than answer
! categories.
  G BY be_2 be_3 be_4 be_5 be_6 be_7 be_9 be_10  be_11
    be_12 be_14 be_15 be_16 be_17 be_18 be_19 be_20 be_21 be_22 be_23
    be_24 be_25  det_1 det_2 det_3 det_4 det_5 det_6 det_7 det_9 det_8 det_10 det_11 det_12
    det_13 det_14 det_15 det_16 det_17 det_18 det_19 det_20 det_21 det_22 det_23 (*1);
  BHAR BY be_11 be_18 be_9 be_10 be_5 be_12 be_21
  be_23~0 be_24~0 be_22~0 be_25~0 be_17~0 be_4~0 be_15~0 be_16~0 be_7~0 be_19~0
  be_3~0 be_14~0 be_20~0 be_6~0 be_2~0
  det_1~0 det_8~0 det_12~0 det_5~0 det_22~0 det_15~0 det_2~0
  det_14~0 det_13~0 det_20~0 det_16~0 det_4~0 det_21~0 det_10~0 det_23~0 det_11~0
  det_19~0 det_9~0 det_7~0 det_18~0 det_17~0 det_6~0 det_3~0 (*1);
  BSER BY be_23 be_24 be_22 be_25 be_17 be_4 be_15 be_16 be_7 be_19
  be_11~0 be_18~0 be_9~0 be_10~0 be_5~0 be_12~0 be_21~0
  be_3~0 be_14~0 be_20~0 be_6~0 be_2~0
  det_1~0 det_8~0 det_12~0 det_5~0 det_22~0 det_15~0 det_2~0
  det_14~0 det_13~0 det_20~0 det_16~0 det_4~0 det_21~0 det_10~0 det_23~0 det_11~0
  det_19~0 det_9~0 det_7~0 det_18~0 det_17~0 det_6~0 det_3~0 (*1);
  BIMP BY be_3 be_14 be_20 be_6 be_2
  be_11~0 be_18~0 be_9~0 be_10~0 be_5~0 be_12~0 be_21~0
  be_23~0 be_24~0 be_22~0 be_25~0 be_17~0 be_4~0 be_15~0 be_16~0 be_7~0 be_19~0
  det_1~0 det_8~0 det_12~0 det_5~0 det_22~0 det_15~0 det_2~0
  det_14~0 det_13~0 det_20~0 det_16~0 det_4~0 det_21~0 det_10~0 det_23~0 det_11~0
  det_19~0 det_9~0 det_7~0 det_18~0 det_17~0 det_6~0 det_3~0 (*1);
  DIRR BY det_1 det_8 det_12 det_5 det_22 det_15 det_2
  be_11~0 be_18~0 be_9~0 be_10~0 be_5~0 be_12~0 be_21~0
  be_23~0 be_24~0 be_22~0 be_25~0 be_17~0 be_4~0 be_15~0 be_16~0 be_7~0 be_19~0
  be_3~0 be_14~0 be_20~0 be_6~0 be_2~0
  det_14~0 det_13~0 det_20~0 det_16~0 det_4~0 det_21~0 det_10~0 det_23~0 det_11~0
  det_19~0 det_9~0 det_7~0 det_18~0 det_17~0 det_6~0 det_3~0 (*1);
  DANX BY det_14 det_13 det_20 det_16 det_4 det_21 det_10 det_23 det_11
  be_11~0 be_18~0 be_9~0 be_10~0 be_5~0 be_12~0 be_21~0
  be_23~0 be_24~0 be_22~0 be_25~0 be_17~0 be_4~0 be_15~0 be_16~0 be_7~0 be_19~0
  be_3~0 be_14~0 be_20~0 be_6~0 be_2~0
  det_1~0 det_8~0 det_12~0 det_5~0 det_22~0 det_15~0 det_2~0
  det_19~0 det_9~0 det_7~0 det_18~0 det_17~0 det_6~0 det_3~0 (*1);
  DDES BY det_19 det_9 det_7 det_18 det_17 det_6 det_3
  be_11~0 be_18~0 be_9~0 be_10~0 be_5~0 be_12~0 be_21~0
  be_23~0 be_24~0 be_22~0 be_25~0 be_17~0 be_4~0 be_15~0 be_16~0 be_7~0 be_19~0
  be_3~0 be_14~0 be_20~0 be_6~0 be_2~0
  det_1~0 det_8~0 det_12~0 det_5~0 det_22~0 det_15~0 det_2~0
```

```
  det_14~0 det_13~0 det_20~0 det_16~0 det_4~0 det_21~0 det_10~0 det_23~0 det_11~0  (*1);
[be_4$2]; [be_5$2]; [be_6$2]; [be_7$2]; [be_9$2]; [be_10$2]; [be_12$2]; [be_14$2];
[be_15$2]; [be_16$2]; [be_17$2]; [be_18$2]; [be_19$2]; [be_20$2]; [be_21$2]; [be_22$2];
[be_24$2]; [be_25$2]; [det_1$2]; [det_2$2]; [det_3$2]; [det_4$2]; [det_6$2]; [det_7$2];
[det_8$2]; [det_9$2]; [det_10$2]; [det_11$2];  [det_12$2]; [det_13$2];  [det_15$2];  [det_16$2];
[det_17$2];  [det_18$2];  [det_20$2];  [det_21$2];  [det_22$2];  [det_23$2]; [be_2$3];[be_3$3];
[be_4$3];[be_5$3]; [be_6$3]; [be_7$3]; [be_9$3]; [be_10$3]; [be_11$3]; [be_12$3]; [be_14$3];
[be_15$3]; [be_16$3]; [be_17$3]; [be_18$3]; [be_19$3]; [be_20$3]; [be_21$3]; [be_22$3];
[be_23$3]; [be_24$3]; [be_25$3]; [det_1$3]; [det_2$3]; [det_3$3]; [det_4$3]; [det_5$3];
[det_6$3]; [det_7$3]; [det_8$3]; [det_9$3]; [det_10$3]; [det_11$3];  [det_12$3]; [det_13$3];
[det_14$3]; [det_15$3];  [det_16$3];  [det_17$3];  [det_18$3];  [det_19$3];  [det_20$3];
[det_21$3]; [det_22$3];  [det_23$3]; [be_2$4];[be_3$4]; [be_4$4];[be_5$4]; [be_6$4]; [be_7$4];
[be_9$4]; [be_10$4]; [be_11$4]; [be_12$4]; [be_14$4]; [be_15$4]; [be_16$4];
[be_17$4]; [be_18$4]; [be_19$4]; [be_20$4]; [be_21$4]; [be_22$4]; [be_23$4]; [be_24$4];
[be_25$4];[det_1$4]; [det_2$4]; [det_3$4]; [det_4$4]; [det_5$4]; [det_6$4]; [det_7$4]; [det_8$4];
[det_9$4]; [det_10$4]; [det_11$4]; [det_12$4]; [det_13$4];  [det_14$4]; [det_15$4];  [det_16$4];
[det_17$4];  [det_18$4];  [det_19$4];  [det_20$4];  [det_21$4];  [det_22$4];  [det_23$4];
! the next section is used to describe how the model estimated in the second group differs from the
! model estimated in the first group.
! Here, statements about loadings and thresholds are included to relax the default invariance.
! In doing so, variances will be automatically set to 1 in the second group.
MODEL FRA:
  G BY be_2 be_3 be_4 be_5 be_6 be_7 be_9 be_10  be_11
    be_12 be_14 be_15 be_16 be_17 be_18 be_19 be_20 be_21 be_22 be_23
    be_24 be_25  det_1 det_2 det_3 det_4 det_5 det_6 det_7 det_9 det_8 det_10 det_11 det_12
    det_13 det_14 det_15 det_16 det_17 det_18 det_19 det_20 det_21 det_22 det_23 (*1);
 BHAR BY be_11 be_18 be_9 be_10 be_5 be_12 be_21
  be_23~0 be_24~0 be_22~0 be_25~0 be_17~0 be_4~0 be_15~0 be_16~0 be_7~0 be_19~0
  be_3~0 be_14~0 be_20~0 be_6~0 be_2~0
  det_1~0 det_8~0 det_12~0 det_5~0 det_22~0 det_15~0 det_2~0
  det_14~0 det_13~0 det_20~0 det_16~0 det_4~0 det_21~0 det_10~0 det_23~0 det_11~0
  det_19~0 det_9~0 det_7~0 det_18~0 det_17~0 det_6~0 det_3~0 (*1);
  BSER BY be_23 be_24 be_22 be_25 be_17 be_4 be_15 be_16 be_7 be_19
  be_11~0 be_18~0 be_9~0 be_10~0 be_5~0 be_12~0 be_21~0
  be_3~0 be_14~0 be_20~0 be_6~0 be_2~0
  det_1~0 det_8~0 det_12~0 det_5~0 det_22~0 det_15~0 det_2~0
  det_14~0 det_13~0 det_20~0 det_16~0 det_4~0 det_21~0 det_10~0 det_23~0 det_11~0
  det_19~0 det_9~0 det_7~0 det_18~0 det_17~0 det_6~0 det_3~0 (*1);
  BIMP BY be_3 be_14 be_20 be_6 be_2
  be_11~0 be_18~0 be_9~0 be_10~0 be_5~0 be_12~0 be_21~0
  be_23~0 be_24~0 be_22~0 be_25~0 be_17~0 be_4~0 be_15~0 be_16~0 be_7~0 be_19~0
  det_1~0 det_8~0 det_12~0 det_5~0 det_22~0 det_15~0 det_2~0
  det_14~0 det_13~0 det_20~0 det_16~0 det_4~0 det_21~0 det_10~0 det_23~0 det_11~0
  det_19~0 det_9~0 det_7~0 det_18~0 det_17~0 det_6~0 det_3~0 (*1);
  DIRR BY det_1 det_8 det_12 det_5 det_22 det_15 det_2
  be_11~0 be_18~0 be_9~0 be_10~0 be_5~0 be_12~0 be_21~0
  be_23~0 be_24~0 be_22~0 be_25~0 be_17~0 be_4~0 be_15~0 be_16~0 be_7~0 be_19~0
  be_3~0 be_14~0 be_20~0 be_6~0 be_2~0
  det_14~0 det_13~0 det_20~0 det_16~0 det_4~0 det_21~0 det_10~0 det_23~0 det_11~0
  det_19~0 det_9~0 det_7~0 det_18~0 det_17~0 det_6~0 det_3~0 (*1);
  DANX BY det_14 det_13 det_20 det_16 det_4 det_21 det_10 det_23 det_11
  be_11~0 be_18~0 be_9~0 be_10~0 be_5~0 be_12~0 be_21~0
  be_23~0 be_24~0 be_22~0 be_25~0 be_17~0 be_4~0 be_15~0 be_16~0 be_7~0 be_19~0
  be_3~0 be_14~0 be_20~0 be_6~0 be_2~0
  det_1~0 det_8~0 det_12~0 det_5~0 det_22~0 det_15~0 det_2~0
```

```
  det_19~0 det_9~0 det_7~0 det_18~0 det_17~0 det_6~0 det_3~0 (*1);
  DDES BY det_19 det_9 det_7 det_18 det_17 det_6 det_3
  be_11~0 be_18~0 be_9~0 be_10~0 be_5~0 be_12~0 be_21~0
  be_23~0 be_24~0 be_22~0 be_25~0 be_17~0 be_4~0 be_15~0 be_16~0 be_7~0 be_19~0
  be_3~0 be_14~0 be_20~0 be_6~0 be_2~0
  det_1~0 det_8~0 det_12~0 det_5~0 det_22~0 det_15~0 det_2~0
  det_14~0 det_13~0 det_20~0 det_16~0 det_4~0 det_21~0 det_10~0 det_23~0 det_11~0  (*1);
[be_4$2]; [be_5$2]; [be_6$2]; [be_7$2]; [be_9$2]; [be_10$2]; [be_12$2]; [be_14$2];
[be_15$2]; [be_16$2]; [be_17$2]; [be_18$2]; [be_19$2]; [be_20$2]; [be_21$2]; [be_22$2];
[be_24$2]; [be_25$2]; [det_1$2]; [det_2$2]; [det_3$2]; [det_4$2]; [det_6$2]; [det_7$2];
[det_8$2]; [det_9$2]; [det_10$2]; [det_11$2];  [det_12$2]; [det_13$2];  [det_15$2];  [det_16$2];
[det_17$2];  [det_18$2];  [det_20$2];  [det_21$2];  [det_22$2];  [det_23$2]; [be_2$3];[be_3$3];
[be_4$3];[be_5$3]; [be_6$3]; [be_7$3]; [be_9$3]; [be_10$3]; [be_11$3]; [be_12$3]; [be_14$3];
[be_15$3]; [be_16$3]; [be_17$3]; [be_18$3]; [be_19$3]; [be_20$3]; [be_21$3]; [be_22$3];
[be_23$3]; [be_24$3]; [be_25$3]; [det_1$3]; [det_2$3]; [det_3$3]; [det_4$3]; [det_5$3];
[det_6$3]; [det_7$3]; [det_8$3]; [det_9$3]; [det_10$3]; [det_11$3];  [det_12$3]; [det_13$3];
[det_14$3]; [det_15$3];  [det_16$3];  [det_17$3];  [det_18$3];  [det_19$3];  [det_20$3];
[det_21$3]; [det_22$3];  [det_23$3]; [be_2$4];[be_3$4]; [be_4$4];[be_5$4]; [be_6$4]; [be_7$4];
[be_9$4]; [be_10$4]; [be_11$4]; [be_12$4]; [be_14$4]; [be_15$4]; [be_16$4];
[be_17$4]; [be_18$4]; [be_19$4]; [be_20$4]; [be_21$4]; [be_22$4]; [be_23$4]; [be_24$4];
[be_25$4];[det_1$4]; [det_2$4]; [det_3$4]; [det_4$4]; [det_5$4]; [det_6$4]; [det_7$4]; [det_8$4];
[det_9$4]; [det_10$4]; [det_11$4]; [det_12$4]; [det_13$4];  [det_14$4]; [det_15$4];  [det_16$4];
[det_17$4];  [det_18$4];  [det_19$4];  [det_20$4];  [det_21$4];  [det_22$4];  [det_23$4];
! The following function is used to request DIFFTEST for chi square difference tests.
SAVEDATA:
DIFFTEST = conf.dat;
```

TITLE: Weak (Loadings) Invariance

```
! Previously presented sections of inputs are skipped to focus only on differences from prior models.
! In the analysis section, we specify that we want a chi square difference test based on the DIFFTEST
! file saved with the previous model in the sequence.
ANALYSIS:
DIFFTEST = conf.dat;
MODEL:
  G BY be_2 be_3 be_4 be_5 be_6 be_7 be_9 be_10  be_11
    be_12 be_14 be_15 be_16 be_17 be_18 be_19 be_20 be_21 be_22 be_23
    be_24 be_25  det_1 det_2 det_3 det_4 det_5 det_6 det_7 det_9 det_8 det_10 det_11 det_12
    det_13 det_14 det_15 det_16 det_17 det_18 det_19 det_20 det_21 det_22 det_23 (*1);
  BHAR BY be_11 be_18 be_9 be_10 be_5 be_12 be_21
  be_23~0 be_24~0 be_22~0 be_25~0 be_17~0 be_4~0 be_15~0 be_16~0 be_7~0 be_19~0
  be_3~0 be_14~0 be_20~0 be_6~0 be_2~0
  det_1~0 det_8~0 det_12~0 det_5~0 det_22~0 det_15~0 det_2~0
  det_14~0 det_13~0 det_20~0 det_16~0 det_4~0 det_21~0 det_10~0 det_23~0 det_11~0
  det_19~0 det_9~0 det_7~0 det_18~0 det_17~0 det_6~0 det_3~0 (*1);
  BSER BY be_23 be_24 be_22 be_25 be_17 be_4 be_15 be_16 be_7 be_19
  be_11~0 be_18~0 be_9~0 be_10~0 be_5~0 be_12~0 be_21~0
  be_3~0 be_14~0 be_20~0 be_6~0 be_2~0
  det_1~0 det_8~0 det_12~0 det_5~0 det_22~0 det_15~0 det_2~0
  det_14~0 det_13~0 det_20~0 det_16~0 det_4~0 det_21~0 det_10~0 det_23~0 det_11~0
  det_19~0 det_9~0 det_7~0 det_18~0 det_17~0 det_6~0 det_3~0 (*1);
  BIMP BY be_3 be_14 be_20 be_6 be_2
  be_11~0 be_18~0 be_9~0 be_10~0 be_5~0 be_12~0 be_21~0
  be_23~0 be_24~0 be_22~0 be_25~0 be_17~0 be_4~0 be_15~0 be_16~0 be_7~0 be_19~0
  det_1~0 det_8~0 det_12~0 det_5~0 det_22~0 det_15~0 det_2~0
  det_14~0 det_13~0 det_20~0 det_16~0 det_4~0 det_21~0 det_10~0 det_23~0 det_11~0
  det_19~0 det_9~0 det_7~0 det_18~0 det_17~0 det_6~0 det_3~0 (*1);
  DIRR BY det_1 det_8 det_12 det_5 det_22 det_15 det_2
  be_11~0 be_18~0 be_9~0 be_10~0 be_5~0 be_12~0 be_21~0
  be_23~0 be_24~0 be_22~0 be_25~0 be_17~0 be_4~0 be_15~0 be_16~0 be_7~0 be_19~0
  be_3~0 be_14~0 be_20~0 be_6~0 be_2~0
  det_14~0 det_13~0 det_20~0 det_16~0 det_4~0 det_21~0 det_10~0 det_23~0 det_11~0
  det_19~0 det_9~0 det_7~0 det_18~0 det_17~0 det_6~0 det_3~0 (*1);
  DANX BY det_14 det_13 det_20 det_16 det_4 det_21 det_10 det_23 det_11
  be_11~0 be_18~0 be_9~0 be_10~0 be_5~0 be_12~0 be_21~0
  be_23~0 be_24~0 be_22~0 be_25~0 be_17~0 be_4~0 be_15~0 be_16~0 be_7~0 be_19~0
  be_3~0 be_14~0 be_20~0 be_6~0 be_2~0
  det_1~0 det_8~0 det_12~0 det_5~0 det_22~0 det_15~0 det_2~0
  det_19~0 det_9~0 det_7~0 det_18~0 det_17~0 det_6~0 det_3~0 (*1);
  DDES BY det_19 det_9 det_7 det_18 det_17 det_6 det_3
  be_11~0 be_18~0 be_9~0 be_10~0 be_5~0 be_12~0 be_21~0
  be_23~0 be_24~0 be_22~0 be_25~0 be_17~0 be_4~0 be_15~0 be_16~0 be_7~0 be_19~0
  be_3~0 be_14~0 be_20~0 be_6~0 be_2~0
  det_1~0 det_8~0 det_12~0 det_5~0 det_22~0 det_15~0 det_2~0
  det_14~0 det_13~0 det_20~0 det_16~0 det_4~0 det_21~0 det_10~0 det_23~0 det_11~0  (*1);
[be_4$2]; [be_5$2]; [be_6$2]; [be_7$2]; [be_9$2]; [be_10$2]; [be_12$2]; [be_14$2];
[be_15$2]; [be_16$2]; [be_17$2]; [be_18$2]; [be_19$2]; [be_20$2]; [be_21$2]; [be_22$2];
[be_24$2]; [be_25$2]; [det_1$2]; [det_2$2]; [det_3$2]; [det_4$2]; [det_6$2]; [det_7$2];
[det_8$2]; [det_9$2]; [det_10$2]; [det_11$2];  [det_12$2]; [det_13$2];  [det_15$2];  [det_16$2];
[det_17$2];  [det_18$2];  [det_20$2];  [det_21$2];  [det_22$2];  [det_23$2]; [be_2$3];[be_3$3];
[be_4$3];[be_5$3]; [be_6$3]; [be_7$3]; [be_9$3]; [be_10$3]; [be_11$3]; [be_12$3]; [be_14$3];
[be_15$3]; [be_16$3]; [be_17$3]; [be_18$3]; [be_19$3]; [be_20$3]; [be_21$3]; [be_22$3];
[be_23$3]; [be_24$3]; [be_25$3]; [det_1$3]; [det_2$3]; [det_3$3]; [det_4$3]; [det_5$3];
```

```
[det_6$3]; [det_7$3]; [det_8$3]; [det_9$3]; [det_10$3]; [det_11$3]; [det_12$3]; [det_13$3];
[det_14$3]; [det_15$3]; [det_16$3]; [det_17$3]; [det_18$3]; [det_19$3]; [det_20$3];
[det_21$3]; [det_22$3]; [det_23$3]; [be_2$4];[be_3$4]; [be_4$4];[be_5$4]; [be_6$4]; [be_7$4];
[be_9$4]; [be_10$4]; [be_11$4]; [be_12$4]; [be_14$4]; [be_15$4]; [be_16$4];
[be_17$4]; [be_18$4]; [be_19$4]; [be_20$4]; [be_21$4]; [be_22$4]; [be_23$4]; [be_24$4];
[be_25$4];[det_1$4]; [det_2$4]; [det_3$4]; [det_4$4]; [det_5$4]; [det_6$4]; [det_7$4]; [det_8$4];
[det_9$4]; [det_10$4]; [det_11$4]; [det_12$4]; [det_13$4]; [det_14$4]; [det_15$4]; [det_16$4];
[det_17$4]; [det_18$4]; [det_19$4]; [det_20$4]; [det_21$4]; [det_22$4]; [det_23$4];
! The loadings are invariant by default (and variances freely estimated), so only statements to request
! the free estimation of the thresholds are required.
MODEL FRA:
[be_4$2]; [be_5$2]; [be_6$2]; [be_7$2]; [be_9$2]; [be_10$2]; [be_12$2]; [be_14$2];
[be_15$2]; [be_16$2]; [be_17$2]; [be_18$2]; [be_19$2]; [be_20$2]; [be_21$2]; [be_22$2];
[be_24$2]; [be_25$2]; [det_1$2]; [det_2$2]; [det_3$2]; [det_4$2]; [det_6$2]; [det_7$2];
[det_8$2]; [det_9$2]; [det_10$2]; [det_11$2]; [det_12$2]; [det_13$2]; [det_15$2]; [det_16$2];
[det_17$2]; [det_18$2]; [det_20$2]; [det_21$2]; [det_22$2]; [det_23$2]; [be_2$3];[be_3$3];
[be_4$3];[be_5$3]; [be_6$3]; [be_7$3]; [be_9$3]; [be_10$3]; [be_11$3]; [be_12$3]; [be_14$3];
[be_15$3]; [be_16$3]; [be_17$3]; [be_18$3]; [be_19$3]; [be_20$3]; [be_21$3]; [be_22$3];
[be_23$3]; [be_24$3]; [be_25$3]; [det_1$3]; [det_2$3]; [det_3$3]; [det_4$3]; [det_5$3];
[det_6$3]; [det_7$3]; [det_8$3]; [det_9$3]; [det_10$3]; [det_11$3]; [det_12$3]; [det_13$3];
[det_14$3]; [det_15$3]; [det_16$3]; [det_17$3]; [det_18$3]; [det_19$3]; [det_20$3];
[det_21$3]; [det_22$3]; [det_23$3]; [be_2$4];[be_3$4]; [be_4$4];[be_5$4]; [be_6$4]; [be_7$4];
[be_9$4]; [be_10$4]; [be_11$4]; [be_12$4]; [be_14$4]; [be_15$4]; [be_16$4];
[be_17$4]; [be_18$4]; [be_19$4]; [be_20$4]; [be_21$4]; [be_22$4]; [be_23$4]; [be_24$4];
[be_25$4];[det_1$4]; [det_2$4]; [det_3$4]; [det_4$4]; [det_5$4]; [det_6$4]; [det_7$4]; [det_8$4];
[det_9$4]; [det_10$4]; [det_11$4]; [det_12$4]; [det_13$4]; [det_14$4]; [det_15$4]; [det_16$4];
[det_17$4]; [det_18$4]; [det_19$4]; [det_20$4]; [det_21$4]; [det_22$4]; [det_23$4];
SAVEDATA:
DIFFTEST = load.dat;
```

TITLE: Strong (Loadings, Thresholds) Invariance

```
! Previously presented sections of inputs are skipped to focus only on differences from prior models.
ANALYSIS:
DIFFTEST = load.dat;
 MODEL:
 G BY be_2 be_3 be_4 be_5 be_6 be_7 be_9 be_10  be_11
  be_12 be_14 be_15 be_16 be_17 be_18 be_19 be_20 be_21 be_22 be_23
  be_24 be_25  det_1 det_2 det_3 det_4 det_5 det_6 det_7 det_9 det_8 det_10 det_11 det_12
  det_13 det_14 det_15 det_16 det_17 det_18 det_19 det_20 det_21 det_22 det_23 (*1);
 BHAR BY be_11 be_18 be_9 be_10 be_5 be_12 be_21
 be_23~0 be_24~0 be_22~0 be_25~0 be_17~0 be_4~0 be_15~0 be_16~0 be_7~0 be_19~0
 be_3~0 be_14~0 be_20~0 be_6~0 be_2~0
 det_1~0 det_8~0 det_12~0 det_5~0 det_22~0 det_15~0 det_2~0
 det_14~0 det_13~0 det_20~0 det_16~0 det_4~0 det_21~0 det_10~0 det_23~0 det_11~0
 det_19~0 det_9~0 det_7~0 det_18~0 det_17~0 det_6~0 det_3~0 (*1);
 BSER BY be_23 be_24 be_22 be_25 be_17 be_4 be_15 be_16 be_7 be_19
 be_11~0 be_18~0 be_9~0 be_10~0 be_5~0 be_12~0 be_21~0
 be_3~0 be_14~0 be_20~0 be_6~0 be_2~0
 det_1~0 det_8~0 det_12~0 det_5~0 det_22~0 det_15~0 det_2~0
 det_14~0 det_13~0 det_20~0 det_16~0 det_4~0 det_21~0 det_10~0 det_23~0 det_11~0
 det_19~0 det_9~0 det_7~0 det_18~0 det_17~0 det_6~0 det_3~0 (*1);
 BIMP BY be_3 be_14 be_20 be_6 be_2
 be_11~0 be_18~0 be_9~0 be_10~0 be_5~0 be_12~0 be_21~0
 be_23~0 be_24~0 be_22~0 be_25~0 be_17~0 be_4~0 be_15~0 be_16~0 be_7~0 be_19~0
 det_1~0 det_8~0 det_12~0 det_5~0 det_22~0 det_15~0 det_2~0
 det_14~0 det_13~0 det_20~0 det_16~0 det_4~0 det_21~0 det_10~0 det_23~0 det_11~0
 det_19~0 det_9~0 det_7~0 det_18~0 det_17~0 det_6~0 det_3~0 (*1);
 DIRR BY det_1 det_8 det_12 det_5 det_22 det_15 det_2
 be_11~0 be_18~0 be_9~0 be_10~0 be_5~0 be_12~0 be_21~0
 be_23~0 be_24~0 be_22~0 be_25~0 be_17~0 be_4~0 be_15~0 be_16~0 be_7~0 be_19~0
 be_3~0 be_14~0 be_20~0 be_6~0 be_2~0
 det_14~0 det_13~0 det_20~0 det_16~0 det_4~0 det_21~0 det_10~0 det_23~0 det_11~0
 det_19~0 det_9~0 det_7~0 det_18~0 det_17~0 det_6~0 det_3~0 (*1);
 DANX BY det_14 det_13 det_20 det_16 det_4 det_21 det_10 det_23 det_11
 be_11~0 be_18~0 be_9~0 be_10~0 be_5~0 be_12~0 be_21~0
 be_23~0 be_24~0 be_22~0 be_25~0 be_17~0 be_4~0 be_15~0 be_16~0 be_7~0 be_19~0
 be_3~0 be_14~0 be_20~0 be_6~0 be_2~0
 det_1~0 det_8~0 det_12~0 det_5~0 det_22~0 det_15~0 det_2~0
 det_19~0 det_9~0 det_7~0 det_18~0 det_17~0 det_6~0 det_3~0 (*1);
 DDES BY det_19 det_9 det_7 det_18 det_17 det_6 det_3
 be_11~0 be_18~0 be_9~0 be_10~0 be_5~0 be_12~0 be_21~0
 be_23~0 be_24~0 be_22~0 be_25~0 be_17~0 be_4~0 be_15~0 be_16~0 be_7~0 be_19~0
 be_3~0 be_14~0 be_20~0 be_6~0 be_2~0
 det_1~0 det_8~0 det_12~0 det_5~0 det_22~0 det_15~0 det_2~0
 det_14~0 det_13~0 det_20~0 det_16~0 det_4~0 det_21~0 det_10~0 det_23~0 det_11~0  (*1);
! Nothing is required in the group specific statement.
MODEL FRA:

SAVEDATA:
DIFFTEST = thre.dat;
```

TITLE: Strict (Loadings, Thresholds, Uniquenesses) Invariance

```
! Previously presented sections of inputs are skipped to focus only on differences from prior models.
ANALYSIS:
DIFFTEST = thre.dat;
MODEL:
  G BY be_2 be_3 be_4 be_5 be_6 be_7 be_9 be_10  be_11
    be_12 be_14 be_15 be_16 be_17 be_18 be_19 be_20 be_21 be_22 be_23
    be_24 be_25  det_1 det_2 det_3 det_4 det_5 det_6 det_7 det_9 det_8 det_10 det_11 det_12
    det_13 det_14 det_15 det_16 det_17 det_18 det_19 det_20 det_21 det_22 det_23 (*1);
  BHAR BY be_11 be_18 be_9 be_10 be_5 be_12 be_21
  be_23~0 be_24~0 be_22~0 be_25~0 be_17~0 be_4~0 be_15~0 be_16~0 be_7~0 be_19~0
  be_3~0 be_14~0 be_20~0 be_6~0 be_2~0
  det_1~0 det_8~0 det_12~0 det_5~0 det_22~0 det_15~0 det_2~0
  det_14~0 det_13~0 det_20~0 det_16~0 det_4~0 det_21~0 det_10~0 det_23~0 det_11~0
  det_19~0 det_9~0 det_7~0 det_18~0 det_17~0 det_6~0 det_3~0 (*1);
  BSER BY be_23 be_24 be_22 be_25 be_17 be_4 be_15 be_16 be_7 be_19
  be_11~0 be_18~0 be_9~0 be_10~0 be_5~0 be_12~0 be_21~0
  be_3~0 be_14~0 be_20~0 be_6~0 be_2~0
  det_1~0 det_8~0 det_12~0 det_5~0 det_22~0 det_15~0 det_2~0
  det_14~0 det_13~0 det_20~0 det_16~0 det_4~0 det_21~0 det_10~0 det_23~0 det_11~0
  det_19~0 det_9~0 det_7~0 det_18~0 det_17~0 det_6~0 det_3~0 (*1);
  BIMP BY be_3 be_14 be_20 be_6 be_2
  be_11~0 be_18~0 be_9~0 be_10~0 be_5~0 be_12~0 be_21~0
  be_23~0 be_24~0 be_22~0 be_25~0 be_17~0 be_4~0 be_15~0 be_16~0 be_7~0 be_19~0
  det_1~0 det_8~0 det_12~0 det_5~0 det_22~0 det_15~0 det_2~0
  det_14~0 det_13~0 det_20~0 det_16~0 det_4~0 det_21~0 det_10~0 det_23~0 det_11~0
  det_19~0 det_9~0 det_7~0 det_18~0 det_17~0 det_6~0 det_3~0 (*1);
  DIRR BY det_1 det_8 det_12 det_5 det_22 det_15 det_2
  be_11~0 be_18~0 be_9~0 be_10~0 be_5~0 be_12~0 be_21~0
  be_23~0 be_24~0 be_22~0 be_25~0 be_17~0 be_4~0 be_15~0 be_16~0 be_7~0 be_19~0
  be_3~0 be_14~0 be_20~0 be_6~0 be_2~0
  det_14~0 det_13~0 det_20~0 det_16~0 det_4~0 det_21~0 det_10~0 det_23~0 det_11~0
  det_19~0 det_9~0 det_7~0 det_18~0 det_17~0 det_6~0 det_3~0 (*1);
  DANX BY det_14 det_13 det_20 det_16 det_4 det_21 det_10 det_23 det_11
  be_11~0 be_18~0 be_9~0 be_10~0 be_5~0 be_12~0 be_21~0
  be_23~0 be_24~0 be_22~0 be_25~0 be_17~0 be_4~0 be_15~0 be_16~0 be_7~0 be_19~0
  be_3~0 be_14~0 be_20~0 be_6~0 be_2~0
  det_1~0 det_8~0 det_12~0 det_5~0 det_22~0 det_15~0 det_2~0
  det_19~0 det_9~0 det_7~0 det_18~0 det_17~0 det_6~0 det_3~0 (*1);
  DDES BY det_19 det_9 det_7 det_18 det_17 det_6 det_3
  be_11~0 be_18~0 be_9~0 be_10~0 be_5~0 be_12~0 be_21~0
  be_23~0 be_24~0 be_22~0 be_25~0 be_17~0 be_4~0 be_15~0 be_16~0 be_7~0 be_19~0
  be_3~0 be_14~0 be_20~0 be_6~0 be_2~0
  det_1~0 det_8~0 det_12~0 det_5~0 det_22~0 det_15~0 det_2~0
  det_14~0 det_13~0 det_20~0 det_16~0 det_4~0 det_21~0 det_10~0 det_23~0 det_11~0  (*1);
! With WLSMV, the uniquenesses are by default constrained to 1 in the first group, and free in the
! other groups. To constrain them to invariance, they need to be fixed to 1 in the remaining groups.
MODEL FRA:
be_2-det_23@1;
SAVEDATA:
DIFFTEST = uniq.dat;
```

```
TITLE: Variance-Covariance (Loadings, Thresholds, Uniquenesses, Var.-Covar.) Invariance
! Previously presented sections of inputs are skipped to focus only on differences from prior models.
ANALYSIS: DIFFTEST = uniq.dat;
MODEL:
  G BY be_2 be_3 be_4 be_5 be_6 be_7 be_9 be_10  be_11
    be_12 be_14 be_15 be_16 be_17 be_18 be_19 be_20 be_21 be_22 be_23
    be_24 be_25  det_1 det_2 det_3 det_4 det_5 det_6 det_7 det_9 det_8 det_10 det_11 det_12
    det_13 det_14 det_15 det_16 det_17 det_18 det_19 det_20 det_21 det_22 det_23 (*1);
  BHAR BY be_11 be_18 be_9 be_10 be_5 be_12 be_21  be_23~0 be_24~0 be_22~0
  be_25~0 be_17~0 be_4~0 be_15~0 be_16~0 be_7~0 be_19~0 be_3~0 be_14~0 be_20~0
  be_6~0 be_2~0  det_1~0 det_8~0 det_12~0 det_5~0 det_22~0 det_15~0 det_2~0
  det_14~0 det_13~0 det_20~0 det_16~0 det_4~0 det_21~0 det_10~0 det_23~0 det_11~0
  det_19~0 det_9~0 det_7~0 det_18~0 det_17~0 det_6~0 det_3~0 (*1);
  BSER BY be_23 be_24 be_22 be_25 be_17 be_4 be_15 be_16 be_7 be_19 be_11~0 be_18~0
  be_9~0 be_10~0 be_5~0 be_12~0 be_21~0 be_3~0 be_14~0 be_20~0 be_6~0
  be_2~0det_1~0 det_8~0 det_12~0 det_5~0 det_22~0 det_15~0 det_2~0
  det_14~0 det_13~0 det_20~0 det_16~0 det_4~0 det_21~0 det_10~0 det_23~0 det_11~0
  det_19~0 det_9~0 det_7~0 det_18~0 det_17~0 det_6~0 det_3~0 (*1);
  BIMP BY be_3 be_14 be_20 be_6 be_2 be_11~0 be_18~0 be_9~0 be_10~0 be_5~0
  be_12~0 be_21~0 be_23~0 be_24~0 be_22~0 be_25~0 be_17~0 be_4~0 be_15~0
  be_16~0 be_7~0 be_19~0 det_1~0 det_8~0 det_12~0 det_5~0 det_22~0 det_15~0 det_2~0
  det_14~0 det_13~0 det_20~0 det_16~0 det_4~0 det_21~0 det_10~0 det_23~0 det_11~0
  det_19~0 det_9~0 det_7~0 det_18~0 det_17~0 det_6~0 det_3~0 (*1);
  DIRR BY det_1 det_8 det_12 det_5 det_22 det_15 det_2
  be_11~0 be_18~0 be_9~0 be_10~0 be_5~0 be_12~0 be_21~0
  be_23~0 be_24~0 be_22~0 be_25~0 be_17~0 be_4~0 be_15~0 be_16~0 be_7~0 be_19~0
  be_3~0 be_14~0 be_20~0 be_6~0 be_2~0
  det_14~0 det_13~0 det_20~0 det_16~0 det_4~0 det_21~0 det_10~0 det_23~0 det_11~0
  det_19~0 det_9~0 det_7~0 det_18~0 det_17~0 det_6~0 det_3~0 (*1);
  DANX BY det_14 det_13 det_20 det_16 det_4 det_21 det_10 det_23 det_11 be_11~0 be_18~0
  be_9~0 be_10~0 be_5~0 be_12~0 be_21~0 be_23~0 be_24~0 be_22~0 be_25~0 be_17~0
  be_4~0 be_15~0 be_16~0 be_7~0 be_19~0 be_3~0 be_14~0 be_20~0 be_6~0 be_2~0
  det_1~0 det_8~0 det_12~0 det_5~0 det_22~0 det_15~0 det_2~0
  det_19~0 det_9~0 det_7~0 det_18~0 det_17~0 det_6~0 det_3~0 (*1);
  DDES BY det_19 det_9 det_7 det_18 det_17 det_6 det_3 be_11~0 be_18~0 be_9~0
  be_10~0 be_5~0 be_12~0 be_21~0 be_23~0 be_24~0 be_22~0 be_25~0
  be_17~0 be_4~0 be_15~0 be_16~0 be_7~0 be_19~0 be_3~0 be_14~0 be_20~0 be_6~0 be_2~0
  det_1~0 det_8~0 det_12~0 det_5~0 det_22~0 det_15~0 det_2~0
  det_14~0 det_13~0 det_20~0 det_16~0 det_4~0 det_21~0 det_10~0 det_23~0 det_11~0  (*1);
! These statements are used to request invariance constraint on the unrotated factor covariances
! (because the rotation is orthogonal, the rotated covariances are all 0). Correlations are specified
! with WITH, and when parameters are estimated to be invariant when they share the same label in
! parentheses (g1, etc.). Here these labels are only used in the global section of the model, and thus
! will be imposed in all groups, thus constraining unrotated covariances to be invariant.
G WITH BHAR  BSER BIMP DIRR DANX DDES (g1-g6);
BHAR WITH BSER BIMP DIRR DANX DDES (a1-a5);
BSER WITH BIMP DIRR DANX DDES (a6-a9); BIMP WITH DIRR DANX DDES (a10-a12);
DIRR WITH DANX DDES (a13-a14); DANX WITH DDES (a15);
MODEL FRA:
be_2-det_23@1;
! To override the default that freely estimates the variances in the remaining groups, they need to be
constrained back to 1 for invariance purposes.
G@1; BHAR@1;BSER@1;BIMP@1;DIRR@1;DANX@1;DDES@1;
SAVEDATA: DIFFTEST = varcov.dat;
```

TITLE: Latent Means (Loadings, Thresholds, Uniq., Var.-Covar., Means) Invariance

! Previously presented sections of inputs are skipped to focus only on differences from prior models.

```
ANALYSIS: DIFFTEST = varcov.dat;
MODEL:
 G BY be_2 be_3 be_4 be_5 be_6 be_7 be_9 be_10  be_11
  be_12 be_14 be_15 be_16 be_17 be_18 be_19 be_20 be_21 be_22 be_23
  be_24 be_25  det_1 det_2 det_3 det_4 det_5 det_6 det_7 det_9 det_8 det_10 det_11 det_12
  det_13 det_14 det_15 det_16 det_17 det_18 det_19 det_20 det_21 det_22 det_23 (*1);
 BHAR BY be_11 be_18 be_9 be_10 be_5 be_12 be_21  be_23~0 be_24~0 be_22~0
 be_25~0 be_17~0 be_4~0 be_15~0 be_16~0 be_7~0 be_19~0 be_3~0 be_14~0 be_20~0
 be_6~0 be_2~0  det_1~0 det_8~0 det_12~0 det_5~0 det_22~0 det_15~0 det_2~0
 det_14~0 det_13~0 det_20~0 det_16~0 det_4~0 det_21~0 det_10~0 det_23~0 det_11~0
 det_19~0 det_9~0 det_7~0 det_18~0 det_17~0 det_6~0 det_3~0 (*1);
 BSER BY be_23 be_24 be_22 be_25 be_17 be_4 be_15 be_16 be_7 be_19 be_11~0 be_18~0
 be_9~0 be_10~0 be_5~0 be_12~0 be_21~0 be_3~0 be_14~0 be_20~0 be_6~0
 be_2~0det_1~0 det_8~0 det_12~0 det_5~0 det_22~0 det_15~0 det_2~0
 det_14~0 det_13~0 det_20~0 det_16~0 det_4~0 det_21~0 det_10~0 det_23~0 det_11~0
 det_19~0 det_9~0 det_7~0 det_18~0 det_17~0 det_6~0 det_3~0 (*1);
 BIMP BY be_3 be_14 be_20 be_6 be_2 be_11~0 be_18~0 be_9~0 be_10~0 be_5~0
 be_12~0 be_21~0 be_23~0 be_24~0 be_22~0 be_25~0 be_17~0 be_4~0 be_15~0
 be_16~0 be_7~0 be_19~0 det_1~0 det_8~0 det_12~0 det_5~0 det_22~0 det_15~0 det_2~0
 det_14~0 det_13~0 det_20~0 det_16~0 det_4~0 det_21~0 det_10~0 det_23~0 det_11~0
 det_19~0 det_9~0 det_7~0 det_18~0 det_17~0 det_6~0 det_3~0 (*1);
 DIRR BY det_1 det_8 det_12 det_5 det_22 det_15 det_2
 be_11~0 be_18~0 be_9~0 be_10~0 be_5~0 be_12~0 be_21~0
 be_23~0 be_24~0 be_22~0 be_25~0 be_17~0 be_4~0 be_15~0 be_16~0 be_7~0 be_19~0
 be_3~0 be_14~0 be_20~0 be_6~0 be_2~0
 det_14~0 det_13~0 det_20~0 det_16~0 det_4~0 det_21~0 det_10~0 det_23~0 det_11~0
 det_19~0 det_9~0 det_7~0 det_18~0 det_17~0 det_6~0 det_3~0 (*1);
 DANX BY det_14 det_13 det_20 det_16 det_4 det_21 det_10 det_23 det_11 be_11~0 be_18~0
 be_9~0 be_10~0 be_5~0 be_12~0 be_21~0 be_23~0 be_24~0 be_22~0 be_25~0 be_17~0
 be_4~0 be_15~0 be_16~0 be_7~0 be_19~0 be_3~0 be_14~0 be_20~0 be_6~0 be_2~0
 det_1~0 det_8~0 det_12~0 det_5~0 det_22~0 det_15~0 det_2~0
 det_19~0 det_9~0 det_7~0 det_18~0 det_17~0 det_6~0 det_3~0 (*1);
 DDES BY det_19 det_9 det_7 det_18 det_17 det_6 det_3 be_11~0 be_18~0 be_9~0
 be_10~0 be_5~0 be_12~0 be_21~0 be_23~0 be_24~0 be_22~0 be_25~0
 be_17~0 be_4~0 be_15~0 be_16~0 be_7~0 be_19~0 be_3~0 be_14~0 be_20~0 be_6~0 be_2~0
 det_1~0 det_8~0 det_12~0 det_5~0 det_22~0 det_15~0 det_2~0
 det_14~0 det_13~0 det_20~0 det_16~0 det_4~0 det_21~0 det_10~0 det_23~0 det_11~0  (*1);
G WITH BHAR  BSER BIMP DIRR DANX DDES (g1-g6);
BHAR WITH BSER BIMP DIRR DANX DDES (a1-a5);
BSER WITH BIMP DIRR DANX DDES (a6-a9); BIMP WITH DIRR DANX DDES (a10-a12);
DIRR WITH DANX DDES (a13-a14); DANX WITH DDES (a15);
MODEL FRA:
be_2-det_23@1;
G@1; BHAR@1;BSER@1;BIMP@1;DIRR@1;DANX@1;DDES@1;
! To override the default that freely estimates the means in the remaining groups, they need to be constrained back to 0 for invariance purposes.
 [G@0];[BHAR@0];[BSER@0];[BIMP@0];[DIRR@0];[DANX@0];[DDES@0];
SAVEDATA:
DIFFTEST = mean.dat;
! This section is to request the extraction of facto scores
FILE IS WBBIFESEMfscores.dat;
SAVE = Fscores;
```

Title: Latent Profile Analysis (Model 1)

```
Data:
FILE IS WBESEMfscores.dat;
Variable:
names = ID BHAR BSER BIMP DIRR DANX DDES;
usevar =  BHAR BSER BIMP DIRR DANX DDES;
missing = all (-9999);
IDVARIABLE = ID;
! The classes function specifies the number of profile to estimate.
CLASSES = c (5);
! In the analysis section, type = mixture is specified to conduct latent profile analyses
! The process function specifies the number of processors to use to speed up the calculation
! The starts functions indicates the number of random starts, followed by the number retained
! for final stage optimization.
! The stiterations function specifies the number of iterations.
ANALYSIS:
TYPE = MIXTURE;
ESTIMATOR = MLR;
process = 3;
STARTS = 5000 300;
STITERATIONS = 200;
! the model section the %OVERALL% section describes the global relations estimated among the
! constructs, and profile specific statements (here %c#1% to %c#4%)
! The profile specific sections request that the means (indicated by the name of the variable
! between brackets []) and variances (indicated simply by the names of the variables) of the indicators
! be freely estimated in all profiles.
model:
%OVERALL%
BHAR BSER BIMP DIRR DANX DDES;
[BHAR BSER BIMP DIRR DANX DDES];
%c#1%
BHAR BSER BIMP DIRR DANX DDES;
[BHAR BSER BIMP DIRR DANX DDES];
%c#2%
BHAR BSER BIMP DIRR DANX DDES;
[BHAR BSER BIMP DIRR DANX DDES];
%c#3%
BHAR BSER BIMP DIRR DANX DDES;
[BHAR BSER BIMP DIRR DANX DDES];
%c#4%
BHAR BSER BIMP DIRR DANX DDES;
[BHAR BSER BIMP DIRR DANX DDES];
%c#5%
BHAR BSER BIMP DIRR DANX DDES;
[BHAR BSER BIMP DIRR DANX DDES];
! Specific sections of output are requested. Tech11 and Tech14 to obtain ALMR and BLRT.
output: sampstat standardized stdyx TECH1 TECH2 TECH4
 MOD (1.0) SVALUES TECH11 TECH14;
```

Title: Latent Profile Analysis (Model 2R)

```
Data:
FILE IS WBBIFESEMfscores.dat;
Variable:
names = ID G BHAR BSER BIMP DIRR DANX DDES;
usevar =  G BHAR BSER BIMP DIRR DANX DDES;
missing = all (-9999);
IDVARIABLE = ID;
CLASSES = c (5);
ANALYSIS:
TYPE = MIXTURE;
ESTIMATOR = MLR;
process = 3;
STARTS = 5000 300;
STITERATIONS = 200;
model:
%OVERALL%
G BHAR BSER BIMP DIRR DANX DDES;
[G BHAR BSER BIMP DIRR DANX DDES];
%c#1%
G BHAR BSER BIMP DIRR DANX DDES;
[G BHAR BSER BIMP DIRR DANX DDES];
%c#2%
G BHAR BSER BIMP DIRR DANX DDES;
[G BHAR BSER BIMP DIRR DANX DDES];
%c#3%
G BHAR BSER BIMP DIRR DANX DDES;
[G BHAR BSER BIMP DIRR DANX DDES];
%c#4%
G BHAR BSER BIMP DIRR DANX DDES;
[G BHAR BSER BIMP DIRR DANX DDES];
%c#5%
G BHAR BSER BIMP DIRR DANX DDES;
[G BHAR BSER BIMP DIRR DANX DDES];
output: sampstat standardized stdyx TECH1 TECH2 TECH4
 MOD (1.0) SVALUES;! TECH11 TECH14;
```

Title: Factor Mixture Analysis (Model 3)

```
Data:
WBESEMfscores.dat;
Variable:
names = ID BHAR BSER BIMP DIRR DANX DDES;
usevar =  BHAR BSER BIMP DIRR DANX DDES;
missing = all (-9999);
IDVARIABLE = ID;
CLASSES = c (3);
ANALYSIS:
TYPE = MIXTURE;
ESTIMATOR = MLR;
process = 3;
STARTS = 5000 300;
STITERATIONS = 200;
! Compared to previous models, we now introduce a factor model in the %OVERALL% section
! This factor is labeled G, and defined by all indicators. All loadings are freely (*),
! which requires its variance to be fixed to 1 (@1). The factor means also needs to be fixed to 0.
Model:
%OVERALL%
G BY BHAR* BSER BIMP DIRR DANX DDES;
G@1; [G@0];
BHAR BSER BIMP DIRR DANX DDES;
[BHAR BSER BIMP DIRR DANX DDES];
%c#1%
BHAR BSER BIMP DIRR DANX DDES;
[BHAR BSER BIMP DIRR DANX DDES];
%c#2%
BHAR BSER BIMP DIRR DANX DDES;
[BHAR BSER BIMP DIRR DANX DDES];
%c#3%
BHAR BSER BIMP DIRR DANX DDES;
[BHAR BSER BIMP DIRR DANX DDES];
output: sampstat standardized stdyx TECH1 TECH2 TECH4
 MOD (1.0) SVALUES TECH11 TECH14;
```