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# Complementary Variable- and Person-Centered Approaches to the Dimensionality of Psychometric Constructs: Application to Psychological Wellbeing at Work



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## Abstract

**Purpose –** This study illustrates complementary variable- and person- centered approaches allowing for a more complete investigation of the dimensionality of psychometric constructs. Psychometric measures often assess conceptually-related facets of global overarching constructs based on the implicit or explicit assumption that these overarching constructs exist as global entities including conceptually-related specificities mapped by the facets. Proper variable- and person-centered methodologies are required to adequately reflect the dimensionality of these constructs.

**Design/methodology/approach –** We illustrate these approaches using employees' ($N$ = 1077) ratings of their psychological wellbeing at work.

**Findings –** The results supported the added value of the variable-centered approach proposed here, showing that employees' ratings of their own wellbeing simultaneously reflect a global overarching wellbeing construct, together with a variety of specific wellbeing dimensions. Similarly, the results show that anchoring person-centered analyses into these variable-centered results helps to achieve a more precise depiction of employees' wellbeing profiles.

**Implications –** The variable-centered bifactor exploratory structural equation modelling (ESEM) framework provides a way to fully explore these sources of psychometric multidimensionality. Similarly, whenever constructs are characterized by the coexistence of overarching constructs with specific dimensions, it becomes important to properly disaggregate these two components in person-centered analyses. In this context, person-centered analyses need to be clearly anchored in the results of preliminary variable-centered analyses.

**Originality/value –** Substantively, this study proposes an improved representation of employees' wellbeing at work. Methodologically, this study aims to pedagogically illustrate the application of recent methodological innovations to organizational researchers.



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

In psychological, organizational, and managerial research, measurement instruments are often designed to assess various facets of an overarching construct, such as performance, commitment, empowerment, justice or motivation. Although these facets are all grouped under one single overarching label, they are typically represented, in measurement models, as a series of distinct correlated factors. This phenomenon raises a series of potentially critical questions for many areas of organizational research: (a) whether these distinct facets really retain meaningful specificity over and above the assessment of the overarching construct assumed to underlie responses to the items forming the instrument, (b) whether this overarching construct exists as a global entity including specificities mapped by the facets, or alternatively, (c) whether these facets reflect distinct correlated dimensions without a common core. Unfortunately, for decades now, the confirmatory factor analytic (CFA) model has dominated research on the underlying structure of psychometric constructs in organizational research and, although some tests of the presence of an overarching construct may be provided by hierarchical CFA, these models include important restrictions that limit their usefulness when the goal is to conduct a complete investigation of the underlying dimensionality of psychometric constructs. Alternative variable- and person-centered approaches able to provide a more complete investigation of these issues remain underutilized in organizational research. Our objective is to present these approaches, and illustrate their usefulness using employees' ratings of their psychological wellbeing.

## Methodological Issues: The Dimensionality of Psychometric Constructs

### A Variable-Centered Perspective

CFA and its integration within the Structural Equation Modeling (SEM) framework clearly have had a major impact on organizational research. Indeed, CFA/SEM makes it possible to rely on a fully confirmatory approach to research, provides a way to systematically compare alternative a priori representations of the data based on rigorous and objective fit assessment procedures, and permits the assessment of relations that are corrected for measurement errors. However, CFA relies on the restrictive Independent Cluster Model (ICM), in which cross-loadings between items and non-target factors are assumed to be exactly zero, which has recently been shown to be unrealistic for many instruments (e.g., Marsh, Lüdtke et al., 2010; Marsh, Morin, Parker, & Kaur, 2014; Marsh, Muthén, et al., 2009; Morin, Marsh, & Nagengast, 2013). Translated into psychometric terms, this restriction forces each item to be associated with one, and only one, source of true score variance – represented by the factors. However, at the core of classical test theory lies the notion that the indicators (i.e., items) used in psychometric assessment naturally tend to include more than one source of true score variance (e.g., Nunnally & Bernstein, 1994), that is to represent more than one factor.

Classical test theory assumes that ratings include at least three sources of variance: random measurement error (typically assessed in analyses of reliability), construct-irrelevant sources of true score variance (typically assessed in analyses of validity), and construct-relevant sources of true score variance. For example, answers to a job aptitude test will be naturally influenced by the testing conditions (noise, light, etc.; random measurement error), by the true aptitude of the participant on specific test dimensions (e.g., coordination, dexterity; construct-relevant sources of true score variance), but also by the ability of the participant to understand the questions (construct-irrelevant sources of true score variance). However, should the test also include a vocabulary dimension, then this form of construct-irrelevant dimensionality in relation to the assessment of participants' dexterity or coordination becomes construct-relevant in the assessment of their vocabulary.

In the typical CFA model, random measurement error is naturally absorbed within the uniquenesses of the indicators while the construct-relevant source of true score variance is represented by the factor loadings linking the items to their latent construct. When a single factor is assessed, construct-irrelevant sources of true score variance will also be absorbed as part of the uniquenesses. However, whenever multiple conceptually-related constructs are assessed within the same model (such as in the above example of a job aptitude test assessing coordination, dexterity, and vocabulary), construct-irrelevant sources of true score variance depicting the true associations between the items and other constructs will have to be absorbed into other parts of the model when these additional associations are forced to be zero according to ICM-CFA assumptions. In practice, this "absorption" will typically lead to biased estimates of the model parameters (such as the factor correlations) through which these misspecifications are expressed. These observations led Morin, Arens, and Marsh (2016; also see Reise, 2012) to note the importance of relying on measurement models specifically designed to take into account the various 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. 3). Morin, Arens et al. (2016) distinguish two sources of construct-relevant multidimensionality, the presence of hierarchically-ordered and conceptually-related constructs, to which we now turn our attention.

**Hierarchically-Ordered Constructs**. The question to which we alluded in the opening section, regarding whether there is an overarching global construct (e.g., global psychological wellbeing, global intelligence) underlying the various subscales of an instrument (e.g., thriving, verbal abilities), refers to a first form of construct-relevant multidimensionality. In the ability testing example presented above, this form of construct relevant multidimensionality would reflect participants' overall level of job aptitude, over and above their specific levels of dexterity, coordination, and vocabulary. Two distinct approaches exist to model this second source of construct-relevant multidimensionality. The most typical approach relies on hierarchical (i.e., higher-order) factor models (e.g., Rindskopf & Rose, 1988). In hierarchical models, items define first-order factors, which are used to define a higher-order factor reflecting the variance that is shared among the first-order factors. Although intuitively appealing because they remain fully anchored in the ICM-CFA tradition, hierarchical models present one critical limitation. Indeed, hierarchical models 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 (i.e., its disturbance; e.g., Chen, West, & Sousa, 2006; Jenrich & Bentler, 2011; Reise, 2012). More precisely, the relation between an item and the higher-order factor is indirect, i.e., mediated by the first-order factor. This indirect effect is reflected as the product of (a) the item's first-order factor loading by (b) the loading of this first-order factor on the higher-order factor. This second term (b) is thus a constant for all items associated with a specific first-order factor. Similarly, the relation between an item and the disturbance of the first-order factor to which it is associated is also reflected by the product of this item's loadings on the first-order factor (a) and another constant representing the link between the first order factor and its disturbance (c). These implicit proportionality constraints imply that the ratio of global/specific variance (ab/ac) will be exactly the same for all items associated with a specific first-order factor (i.e., corresponding to b/c), and unlikely to hold in real life (Reise, 2012; Yung, Thissen, & McLeod, 1999).

Bifactor models provide an alternative to hierarchical models (Brunner, Nagy, & Wilhelm, 2012; Chen et al., 2006; Reise, 2012). In a *f*-factor bifactor model, one Global (G) factor (e.g., job aptitude) and *f*-1 Specific (S) factors (e.g., coordination, dexterity, vocabulary) are used to explain the covariance among a set of *n* items. In the CFA approach to bifactor models, each item's loading on the G-Factor and on one S-Factor are estimated while other loadings are constrained to be zero, and all factors are set to be orthogonal. Bifactor models thus partition the total covariance into a G component underlying all items, and *f*-1 S components reflecting the residual covariance not explained by the G-Factor[1]. Bifactor models thus 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 specificities (S-Factors) defined by the part of the items not explained by the G-Factor. Thus, bifactor models estimate co-existing and properly disaggregated global and specific constructs, but are able do so without imposing the restrictive proportionality constraints inherent in higher-order factor models.

**Conceptually-Related Constructs**. Items assessing psychometric constructs may also be expected to include another source of construct-relevant multidimensionality reflecting some degree of true score association with non-target constructs (Morin, Arens et al., 2016). In our example on aptitude testing, the idea that participants' vocabulary (one facet of the instrument) may influence responses to items designed to assess the other facets (e.g., dexterity, coordination) characterizes this second source of construct relevant multidimensionality. This source of construct-relevant multidimensionality is likely to be further reinforced in instruments assessing conceptually-related constructs, which describes the majority of psychometric instruments used in organizational research, and is particularly marked when the subscales forming an instrument all refer to a single overarching construct such as commitment, empowerment, justice, motivation, or wellbeing. We come back to these examples in a moment. When ICM-CFA models force these associations (i.e., cross-loadings) to be zero, the only way for them to be expressed is through the inflation of the factor correlations, in turn leading to biased estimates of the relations among constructs according to a variety of simulation studies (Asparouhov & Muthén, 2009; Sass & Schmitt, 2010; Schmitt & Sass, 2011) and studies of simulated data (Marsh et al., 2013; Morin, Arens et al., 2016) in which the true population value of the factor correlations are known beforehand (for a review see Asparouhov, Muthén, & Morin, 2015). Given that the meaning of a construct lies in the way it relates to other constructs, these results suggest that the exclusion of true cross-loadings may induce a fundamental bias in the definition of the constructs. Interestingly, these same studies show that when the true population model meets the ICM assumptions of CFA, relying on an exploratory factor analytic (EFA) model allowing for cross-loadings still provides unbiased estimated of factor correlations (Asparouhov et al., 2015).

This form of construct-relevant multidimensionality thus calls for EFA models allowing for the free estimation of cross-loadings between items and conceptually-related constructs. EFA has recently been integrated with CFA and SEM into an overarching exploratory structural equation modeling (ESEM) framework (Marsh et al., 2014; Morin et al., 2013), making possible the use of EFA factors in predictions, tests of measurement invariance, etc. Likewise, it is now possible to rely on a confirmatory approach to the estimation of EFA/ESEM models through the use of target rotation (Asparouhov & Muthén, 2009; Browne, 2001). Target rotation allows for the pre-specification of target loadings in a confirmatory manner, while cross-loadings are targeted to be as close to zero as possible. Furthermore, newly developed bifactor target rotation now makes it possible to estimate confirmatory bifactor-ESEM models (Reise, 2012; Reise, Moore, & Maydeu-Olivares, 2011).

Morin, Arens et al.'s (2016) framework for the identification of sources of construct-relevant multidimensionality involves the comparison of CFA, ESEM, bifactor-CFA, and bifactor-ESEM models. These models are illustrated in Figure 1. This comparison is critical given that excluding true cross-loadings present in the population model from a bifactor model has been shown to result in inflated estimates of the variance attributed to the G-Factor (i.e., as illustrated by inflated estimates of the indicators' loadings on the G-factor; Morin, Arens et al., 2016; Murray, & Johnson, 2013). Similarly, ignoring the presence of hierarchically-superior (global) constructs is also likely to result in inflated estimates of cross-loadings in ESEM, or inflated factor correlations in CFA (Morin, Arens et al., 2016). In other words, even when the objective is simply to assess the presence of an overarching global factor (bifactor model), ignoring cross-loadings is likely to result in biased estimates of this global factor which will be forced to absorb unmodelled cross-loadings. In the present study, our first objective is to illustrate the application of this *variable-centered* framework for the investigation of the dimensionality of psychometric constructs. ESEM and bifactor models have been extensively used in the social sciences (for reviews, see Marsh et al., 2014; Reise, 2012). However, applications of these models remain scarce in organizational research (e.g., ESEM: Abou-Shouk, Megicks, & Lim, 2013; Furnham, Guenole, Levine, & Chamorro-Premuzic, 2013; Bifactor: Furtner, Rauthmann, & Sachse, 2015; Gignac, 2006; Mészáros, Ádám, Szabó, Szigeti &, Urbán, 2014). Before moving on to the complementary person-centered framework, we now provide a few examples of well-known organizational constructs for which these approaches may be important.

**Dimensionality Issues in Typical Organizational Constructs.** Rather than the exception, we surmise that these dimensionality issues may be quite frequent in organizational research. To illustrate this assumption, we briefly present a few well-known constructs for which conceptual bases clearly support the application of the current framework. First, research on the organizational justice construct (Colquitt, 2001) alternatively proposed this construct to encompass a variety of conceptually-related facets (distributive, procedural, interpersonal, informational) or to form a single overarching construct (Ambrose, Wo, & Griffith, 2015). Interestingly, this second approach appears to be related to conceptual arguments highlighting the idea that individuals tend to experience fairness in a more holistic way (Hauenstein et al., 2001; Lind, 2001), which seems empirically supported by the observation that correlations between justice dimensions are typically over .50-.60 (Colquitt & Shaw, 2005; Hauenstein et al., 2001). These high factor correlations suggest that it might be important to explicitly allow for construct-relevant psychometric multidimensionality related to the assessment of conceptually-related dimensions. Similarly, the theoretical idea that justice perceptions do follow some kind of heuristic process suggest that it might be useful to rely on a model providing a way to explicitly test for the presence of this overarching construct in order to assess its contribution to relevant outcomes over and above the contribution of its specific facets (Ambrose & Arnaud, 2005).

Second, the psychological empowerment construct, defined by Spreitzer (1995) as an overarching construct expected to reflect a sense of job meaningfulness, feelings of competence, and perceptions of autonomy and impact, provides another example. As was the case for organizational justice, these facets of psychological empowerment are typically found to be highly correlated, and have been confirmed to reflect a global higher-order construct (Boudrias, Gaudreau & Laschinger, 2004, Spreitzer, 1995) which tends to more strongly relate to antecedents and outcomes than any of its dimensions (Seibert, Courtight & Wang, 2011). Although the Seibert et al. (2011) meta-analysis suggests that there is little evidence of discriminant validity for these specific dimensions, some recent evidence suggests that the dimensions do present theoretically meaningful and well-differentiated patterns of associations with a variety of external criteria (e.g., Boudrias, Morin & Lajoie, 2014). Clearly, the bifactor-ESEM framework represents a promising approach to simultaneously take into account the conceptually-related nature of psychological empowerment dimensions while also obtaining a direct estimate of the global overarching construct.

A third example suggests that a bifactor-ESEM approach may provide a way to reconcile diverging perspectives. Self-determination theory (SDT; Gagné & Deci, 2005) proposes that employees' engage in volitional behaviors for a variety of reasons, ranging from purely intrinsic motivation for inherently pleasurable behaviors, to purely extrinsic motivation for instrumental behaviors, with a variety of additional motivation types (e.g., internalized, introjected) occurring in between these two extremes. A key assumption of SDT is that these motivation types are ordered along a continuum reflecting employees' degree of relative autonomy, or self-determination. However, tests of this continuum structure have not been convincing (for reviews, see Chemolli & Gagné, 2014; Guay, Morin, Litalien, Valois, & Vallerand, 2015). To clarify these issues, Chemolli and Gagné (2014) tested this continuum structure based on the logic of higher-order CFA models (conducted within the item-response-theory framework), and failed to find support for the expected continuum structure. In contrast, Guay et al. (2015; also see Litalien, Morin, & Guay, 2015) argued that the conceptually-related nature of the motivation types required a proper control for cross-loadings, leading to biased estimates of factor correlations in the CFA context (and, in turn, of higher-order motivation factors estimated from CFA factor correlations). Using ESEM, these authors provided more convincing evidence in favor of the expected continuum structure. Interestingly, relying on a bifactor-ESEM model would provide a direct way to reconcile these two approaches, while providing a direct test of the motivation continuum.

Finally, we note that there might be situations for which the full bifactor-ESEM framework might not be desirable. For instance, the tripartite model of organizational commitment (Allen & Meyer, 1997) proposes that employees tend to remain members of their organization for three types of reasons: Because they enjoy it (affective commitment), because they feel a moral obligation to stay (normative commitment), or because they have too much to lose and limited alternatives (continuance commitment). Measuring these three commitment mindsets involves the assessment of constructs for which cross-loadings (i.e., ESEM) can be expected due to the fact that all dimensions refer to the same entity (i.e., the organization) and aim to explain the same outcome (i.e., staying). In contrast, these commitment mindsets are explicitly defined as distinct reasons for staying and, while they can combine for specific employees, they are unlikely to form a single overarching construct (i.e., bifactor). In contrast, alternative theoretical representations focus on affective commitment to a variety of work-related entities (e.g., supervisor, colleagues), for which it may be relevant to control for employees' global tendencies to commit in an affective manner, through a bifactor approach (Morin, Morizot, Boudrias & Madore, 2011). However, because this conception involves the assessment of dimensions related to clearly differentiated entities, an ESEM representation involving cross-loadings between factors presenting such a differentiated focus might not be as appropriate.

**A Complementary Person-Centered Perspective**

The approaches reviewed so far, together with the data analytic approaches typically used in organizational research (e.g., multiple regression, SEM) are variable-centered analyses. Variable-centered analyses operate under the assumption that all participants are drawn from a single population for which a single set of "average" parameters can be estimated. Complementary person-centered analyses, which relax this assumption by considering the possibility that the sample might include multiple subpopulations characterized by different sets of parameters, may also be used to explore the dimensionality of psychometric constructs. The key difference between variable-centered factor analyses reviewed so far and person-centered latent profile analyses[2] is that "*the common factor model decomposes the covariances to highlight relationships among the variables, whereas the latent profile model decomposes the covariances to highlight relationships among individuals*" (Bauer & Curran, 2004, p. 6). Factor analyses group variables, whereas latent profile analyses (LPA) group persons (Lubke & Muthén, 2005). LPA thus result in a typology in which participants are classified into qualitatively and quantitatively distinct subpopulations (or profiles) based on their specific configuration on a set of indicators. For example, a typology of organizational commitment would classify employees into groups so that those within a group present a similar configuration of commitment mindsets that is qualitatively and quantitatively distinct from the configuration observed in other groups (e.g., Meyer, Morin, & Vandenberghe, 2015).

**Disentangling Shape versus Level Effects in Latent Profile Analyses.** In theory, the difference between person- and variable-centered analyses is straightforward. In practice however differentiating between these two approaches is complicated by the fact that a LPA model including *k* distinct latent profiles and a common factor model including *k-1* latent factors are 'equivalent' in terms of having identical covariance implications (Bauer & Curran, 2004; Steinley & McDonald, 2007). Spurious latent profiles might also emerge when none exist to compensate for violations of the model distributional assumptions, most of which are impossible to empirically assess in practice (e.g., Bauer, 2007). Variable- and person- centered analyses are thus considered as complementary approaches, as both provide alternative views of the same reality. It is important to emphasize this complementarity of approaches as, given that both are equivalent models, it is unlikely that one approach will add to the other in terms of statistical predictive value (Morin, Morizot, et al., 2011). In this regard, the person-centered approach appears to fit more naturally with managers' tendencies to categorize employees, provides a more holistic representation of employees as whole persons, and may be more suitable to the detection of complex interactions among multiple variables (Meyer & Morin, 2016).

A key issue in assessing the value of a person-centered solution is whether the profiles present qualitative (*shape*) differences (i.e., present different configurations on the profile indicators), rather than only quantitative (*level*) differences (i.e., with one profile simply presenting a higher level than the other on the profile indicators) (Bauer, 2007; Morin & Marsh, 2015). The idea behind this criterion is that *level*-differentiated profiles would be better represented by a variable-centered approach. However, the *shape* versus *level* distinction is also highly informative when the objective of the study is to assess whether the dimensions present in an instrument reflect an underlying global construct (in which case the profiles will present *level* differences), or whether there is value in considering them as distinct from one another (in which case the profiles will present *shape* differences).

However, when there is reason to expect that a global construct co-exists with specific dimensions assessed from the same set of indicators (e.g., based on variable-centered results), it becomes critical to control for this generic tendency shared across all dimensions (e.g., global job aptitude) before identifying patterns of relative strength and weaknesses on these dimensions. Failure to control for this global tendency makes the identification of qualitatively distinct profiles harder since strong *level* effects tend to create equally strong quantitative differences between profiles. For example, Morin, Morizot et al. (2011) estimated profiles of employees' affective commitment to a variety of work-related entities while controlling for their global tendency to affectively commit to any entity. Morin and Marsh (2015) extended this approach in order to estimate profiles of strengths and weaknesses in terms of teaching effectiveness, while controlling for global levels of effectiveness (i.e., the presence of good and poor teachers). Their results showed that controlling for global levels of effectiveness was necessary for the estimation of well-differentiated profiles of specific strengths and weaknesses over and above these global levels of effectiveness.

Morin and Marsh (2015) contrasted the efficacy of four models to control for global levels of competencies shared across indicators. These four models are illustrated in Figure 2a. Model 1 was simply a comparison benchmark for the other models and involved the estimation of a simple LPA including no control for *level* effects shared by profile indicators. Model 2 was also a LPA, but this model included a higher-order dimension reflecting *level* effects as an additional profile indicator. Model 3 was a factor mixture analysis (FMA; Lubke & Muthén, 2005) where a continuous latent factor representing *level* effects was estimated from the profile indicators, so that the latent profiles were estimated from the residual covariance not explained by this global factor. This model explicitly disentangles *shape* (i.e., the profiles) and *level* (i.e., the factor) effects, estimating both components (i.e., the profiles and the global factor) from the covariance left unexplained by the other component. However, because both components are simultaneously estimated, the global factor does not absorb all *level* effects, only the portion left unexplained by the profiles. Model 4 forces the extraction of all *level* effects from the estimated latent profiles. In this model, all indicators are regressed on a higher-order dimension representing *level* effects, and profiles are estimated from the residuals of these predictions reflecting the part of the indicators not explained by the higher-order dimension. Morin and Marsh (2015) showed that Model 3 achieved the clearest disaggregation of *shape* and *level* effects while being in line with theoretical expectations. Still this model resulted in a loss of classification accuracy, potentially due to the exclusion of valuable *level* information from the profiles.

**Alternative Approaches to Disentangle Shape from Level in LPA.** Although promising, Morin and Marsh's (2015) approach presents limitations that become evident in light of the aforementioned discussion of the alternative variable-centered approaches available to guide the investigation of the dimensionality of psychometric constructs. To understand these limitations, it is important to note that Morin and Marsh (2015) used factor scores saved from preliminary measurement models as profile indicators. LPA are usually estimated using scale scores (i.e., using the sum or average of the items as profile indicators). Although latent variables controlled for measurement error (i.e., models where the items are used to estimate latent factors, which are used as profile indicators) provide a stronger control for the biasing effects of measurement errors (Bollen, 1989), applications of fully latent (starting at the item level) profile models are few (e.g., Morin, Scalas, & Marsh, 2015). Indeed, given their complexity, these models often fail to converge on proper solutions. An alternative is to rely on factor scores saved from preliminary measurement models (Kam, Morin, Meyer, & Topolnytsky, 2016; Morin & Marsh, 2015). Factor scores do not explicitly control for measurement error. However, by giving more weight to items with lower levels of measurement errors, they still provide a partial control for measurement errors (Morin, Meyer, Creusier, & Biétry, 2016; Skrondal & Laake, 2001).

Morin and Marsh's (2015) Models 1 and 3 relied on factor scores saved from a preliminary first-order ESEM model, whereas Models 2 and 4 relied on factor scores saved from a higher-order ESEM model. From our previous discussion of the proportionality constraints characteristic of higher-order factor models, a limitation of this approach in regards to Model 2 and 4 should be obvious. Morin and Marsh's (2015) Model 3 is also characterized by similar proportionality constraints given that the continuous latent factor incorporated to control for global *level* effects is itself estimated from the first-order factors scores used as profile indicators. However, another characteristic of higher-order factor models makes them even more problematic when the objective is to save factor scores for subsequent analyses (Models 2 and 4): The higher-order factor score is psychometrically redundant with the first-order factors scores. More precisely, in higher-order models, the first-order factors include both the part of the variance in ratings that is explained by the higher-order factor ($\sigma_h^2$), as well as the part of the variance in ratings that is specific to the first-order factor ($\sigma_{fx}^2$). This specificity ($\sigma_{fx}^2$) is absorbed as part of the first-order factors' disturbances, and thus treated as a form of measurement error in higher-order models, but remain included in first-order factor scores ($\sigma_h^2$+ $\sigma_{fx}^2$). Thus, a model including both first- and higher- order factor scores is likely to suffer from multicollinearity (because both include $\sigma_{fx}^2$), which may explain the poor performance of Models 2 and 4.

Furthermore, even though Model 3 presents similarities with a bifactor model (i.e., both include a global factor to estimate specific factors or profiles controlled for this global tendency), it also presents another key limitation. Indeed, for identification purposes, the mean of the latent factor included in Model 3 needs to be constrained to equality across profiles. Thus, a strong assumption of Model 3 is that all profiles present similar average levels on this global factor. In practical terms, this means that the average level of the global construct (e.g., global teaching effectiveness) is assumed to be the same in all profiles. Model 4 also relied on a similar assumption.

The reliance on preliminary bifactor (CFA or ESEM) models to generate factor scores is likely to solve these limitations whenever ratings can be assumed to reflect some overarching global tendencies in addition to more specific dimensions. For instance, the estimation of Model 2 based on factor scores taken from a bifactor model (rather than from a higher-order factor model) would have allowed for the direct estimation of profiles differing from one another on properly disaggregated *shape* versus *level* effects. In sum, bifactor factor scores provide a way to estimate profiles without losing any *level* information, as the G-factor factor scores can be directly integrated to the estimation process as an additional profile indicator without inducing any redundancy. This model thus provides a way to disaggregate *shape* and *level* effects within the profile indicators themselves. In this study, we thus propose, and illustrate, a revised version of Morin and Marsh (2015) framework illustrated in Figure 2b. This revised framework involves the estimation of three distinct models, two of which (Models 1 and 3) remain equivalent to Morin and Marsh (2015) models. Thus, Model 1 remains identical to Morin and Marsh (2015) Model 1, and serves as comparison benchmark for the other models. Model 2 is similar to Morin and Marsh (2015) Model 2, but rather than relying on factor scores taken from a hierarchical model, it relies on factor scores taken from a bifactor model. Model 3 remains identical to Morin and Marsh (2015) Model 3, and also serves as a comparison benchmark for Model 2. Because Morin and Marsh (2015) showed that this model proved to be the most efficient in their study, we felt that it was important to contrast this model with the revised Model 2. No correspondence for Morin and Marsh (2015) Model 4 was necessary given that S-Factors taken from a bifactor model are already controlled for global tendencies reflected in the G-Factor, and that the performance of Model 4 estimated from hierarchical factor scores was already shown to be suboptimal in Morin and Marsh (2015). To illustrate this framework, we use employees' ratings of their psychological wellbeing at work. Because no analysis should be disconnected from substantive theory and expectations, we now briefly review relevant substantive issues.

**Substantive Application: The Dimensionality of Psychological Wellbeing at Work.**

It is now recognized that a complete assessment of psychological health at work needs to include an assessment of the positive aspects of individuals' functioning, namely their psychological wellbeing (Boudrias et al., 2011; Massé et al., 1998). This conclusion is based on empirical evidence that different psychological wellbeing measures (e.g., positive affect, engagement) assess something more than the opposite of distress measures (e.g., negative affect, burnout), to which they provide relevant complementary information (Barbier, Peters & Hansez 2009; Gonzalez-Roma, Schaufeli, Bakker & Llorets, 2006; Keyes, 2005; Massé et al., 1998). Yet, efforts to operationalize psychological wellbeing have often defined it as the antithesis of mental illness. For instance, Keyes (2005) defined wellbeing as characterized by hedonia (vs. ahedonia) and positive functioning (vs. impairment). In this approach, individuals who "flourish" (e.g., Huppert & So, 2013) report not only the absence of impairment but also display high levels of enjoyment and functioning. This perspective integrates two theoretical approaches taken to conceptualize and measure psychological wellbeing (e.g., Ryan & Deci, 2001): Hedonic (positive emotions) and eudaimonic (positive functioning).

In the hedonic approach, psychological wellbeing is seen as driven by a quest for rewards/pleasure and the avoidance of negative experiences, and occurs when one has a high level of positive affect, a low level of negative affect, and a high level of life satisfaction (e.g., Diener, 2000). In comparison, the eudaimonic approach proposes that psychological wellbeing is derived from the assessment that ones' life situation is meaningful and provides opportunity for self-expression (e.g., Ryff & Keyes, 1995). Theorizing psychological wellbeing within the eudaimonic approach has led to further distinctions between personal, versus social, components of eudaimonic wellbeing. However, so far, research has not been clear regarding the distinctiveness of these theoretical components of wellbeing. For instance, Keyes, Shmotkin and Ryff (2002) showed significant overlap between measures of hedonic and eudaimonic wellbeing (r =.45 between the two factors, as well as many cross-loading for eudaimonic indicators). Similarly, Gallagher, Lopez, and Preacher (2009) found that hedonic wellbeing, as well as the personal and social components of eudaimonic wellbeing displayed very high latent correlations across two distinct samples of midlife adults ($r$ = .69 to .85) and students ($r$ = .78 to .92). Furthermore, their results also demonstrated that a higher-order factor solution also represented a viable alternative. Keyes (2005) results similarly supported a higher-order solution underlying these same three components. In sum, this research clearly suggests that psychological wellbeing encompasses conceptually-related dimensions of an underlying global construct, rather than orthogonal facets. However, one question that remains is whether sufficient specificity exists in these components once the global overarching construct is properly taken into account, something that can be systematically assessed though the variable- and person- centered framework described above.

Rather than relying solely on a top-down theoretical approach to define psychological wellbeing, other researchers have relied on a more inductive approach to identify its key dimensions (Dagenais-Desmarais & Savoie, 2012; Massé et al., 1998). This line of research asks respondents to identify critical incidents and natural manifestations of wellbeing in order to develop measures that are more meaningful to participants. Specifying "work" as the focal domain, Dagenais-Desmarais & Savoie (2012) used such an inductive approach to develop the measure of psychological wellbeing at work, which forms the basis of the present investigation. The interest of contextualizing wellbeing within the work domain is anchored in research showing that patterns and levels of wellbeing varies across life contexts (Gilbert, Savoie & Dagenais-Desmarais, 2011; Page & Vella-Brodrick, 2009; Warr, 1990).

In their research, Dagenais-Desmarais and Savoie (2012) identified 80 manifestations of psychological wellbeing at work. These manifestations were then used to develop a questionnaire that was submitted to 1080 workers. Their results revealed five dimensions presenting a high level of similarity to Ryff (1989; Ryff & Keyes, 1995) conception of psychological wellbeing, rooted in the eudaimonic approach: (1) *Interpersonal fit at work*, or experiences of positive interpersonal relationships at work; (2) *Thriving at work*, or feelings that one's job is significant, interesting and fulfilling; (3) *Feelings of competency*, or the impression of having the aptitudes required to perform efficiently with mastery in one's job; (4) *Perceived recognition at work*, or feelings of being personally appreciated within one's workplace; (5) *Desire for involvement at work*, or a desire for increased involvement in, and contribution to, the organization's functioning and success. The correlations between the five factors range from .36 to .67 (M = .53), and results revealed that a higher-order factor explained 63.4% of the variance present in the first-order factors. It is interesting to note that these results parallel those reported by Ryff & Keyes (1995) using their similar, but non-contextualized, measure of psychological wellbeing ($r$ = -.24 to .85; M = .51; and support for a higher-order model), and since replicated in many different contexts (Ryff, 2014). A general factor of psychological wellbeing is therefore highly plausible (Springer, Hauser & Freese, 2006). However, additional results show that the first-order dimensions do present differentiated patterns of relationships with outcomes, suggesting their complementarity as measures of wellbeing (Ryff & Singer, 2006). Again, this suggests the need for a proper reassessment of the underlying dimensionality of the psychological wellbeing construct.

So far, research on psychological wellbeing at work has been mainly variable-centered. We could only locate one study that investigated profiles of employees' psychological wellbeing at work. Relying on LPA, Biétry and Creusier (2015) found five profiles of employees defined based on four indicators of wellbeing (positive relationships with colleagues, positive relationships with manager, satisfaction with the physical environment, satisfaction pertaining to work-life balance). The profiles were identified as: (1) Deficient wellbeing (24%, all dimensions below average); (2) Normative wellbeing (41%, all dimensions average); (3) Organizational wellbeing (18.5%, high scores for relationships with manager and satisfaction with the physical environment); (4) Complete wellbeing (4%, all dimensions above average); (5) Social wellbeing (12%, high score for relationships with colleagues). These authors concluded that psychological wellbeing at work was too complex to be summarized by a single score. However, their results also show that at least three of their profiles differed from one another mainly based on *level* differences, suggesting the need to replicate this research using methods that allow for a more proper disaggregation of *shape* and *level* effects.

## Method

### Sample and Procedure

A total of 39 Hong Kong schools, including 20 primary schools and 19 secondary schools located across all educational regions in Hong Kong, agreed to participate in this study. All teachers from these schools had the possibility to complete the questionnaire and a total of 1077 ($M_{age}$ = 39.15, $SD$ =

9.40; 67% female) individually consented to participate and completed the wellbeing questionnaire. Of those teachers, 495 (46%) teach in primary schools and 582 (54%) teach in secondary schools. On average, they have been teaching for 13.54 years (1 to 40 years, *SD* = 9.16) and in their schools for 9.37 years (1 to 38 years, *SD* = 7.91).

**Measure**

Psychological wellbeing at work was assessed using the five dimensions from Dagenais-Desmarais and Savoie (2012) instrument: (1) *Interpersonal fit at work* (5 items; α = .894; e.g., "I value the people I work with"); (2) *Thriving at work* (5 items; α = .914; e.g., "I find my job exciting"); (3) *feelings of competency* (5 items; α = .884; e.g., "I know I am capable of doing my job"); (4) *perceived recognition at work* (5 items; α = .880; e.g., "I feel that my work is recognized"); (5) *desire for involvement at work* (5 items; α = .806; e.g., "I want to take initiative in my work"). Items were rated on a seven-point Likert scale (1-strongly disagree to 7-strongly agree).

**Analyses**

**Variable-Centered Analyses.** Measurement models were estimated using Mplus 7.2 (Muthén & Muthén, 2014) robust weight least square estimator using diagonal weight matrices (WLSMV) and taking into account teachers' nesting within schools with the Mplus design-based correction of standard errors (Asparouhov, 2005). The choice to rely on WLSMV estimation is linked to the fact that this estimator is more 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, see the online supplements for more details on WLSMV estimation).

Participants responses to the instrument were successfully represented according to the four models (CFA, bifactor-CFA, ESEM, and bifactor-ESEM) presented in Figure 1. In the CFA model, each item was only allowed to load on the factor it was assumed to measure and no cross-loadings on other factors were allowed. This model included five correlated factors representing the previously described subscales (Interpersonal Fit, Thriving, Competency, Recognition, Involvement). In the ESEM model, the same set of five factors were represented using a confirmatory oblique target rotation (Asparouhov & Muthén, 2009; Browne, 2001), where 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 five S-Factors corresponding to the a priori wellbeing factors, with no cross-loadings allowed across 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 (e.g., Chen et al., 2006; Reise, 2012). Finally, in B-ESEM, the same set of five S-Factor and one G-Factor were estimated using orthogonal bi-factor target rotation (Reise, 2012; Reise et al., 2011). In this model, all items were allowed to define a G-Factor, while the five S-Factors were defined from the same pattern of target and non-target factor loadings as in ESEM.

Given the known oversensitivity of the chi-square test of exact fit to sample size and minor model misspecifications (e.g., Marsh, Hau, & Grayson, 2005), we also relied on goodness-of-fit indices to describe the fit of the alternative models: 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, Hau, & Wen, 2004; Marsh et al., 2005; Yu, 2002), values greater than .90 and .95 for the CFI and TLI respectively are considered to be indicative of adequate and excellent fit to the data, while values smaller than .08 or .06 for the RMSEA respectively support acceptable and excellent model fit. With WLSMV, $\chi^2$ values are not exact, but adjusted to obtain a correct *p* value. This explains why $\chi^2$ and CFI can be nonmonotonic with model complexity. Although the performance of this index has been studied far less, and because it has been found to perform well in context of WLSMV estimation for which it has been specifically developed, the weighted root-mean-square residual (WRMR) will also be reported, with values under 1 taken to indicate satisfactory fit to the data (Yu, 2002). In the comparison of nested models, typical interpretation guidelines suggest that models differing from one another by less than .01 on the CFI and TLI, or .015 on the RMSEA, can be considered to provide an equivalent level of fit to the data (e.g., Chen, 2007; Cheung & Rensvold, 2002). No such guideline is available yet for the WRMR.

However, it is important to reinforce that goodness-of-fit is only one of the multiple sources of information to consider in the comparison of these alternative models. As noted above, each of these models is relatively efficient at absorbing unmodelled construct-relevant multidimensionality (e.g., Asparouhov et al., 2016; Morin, Arens et al., 2016; Murray, & Johnson, 2013). Thus, unmodelled cross-loadings could typically result in inflated CFA factor correlations, or inflated bifactor-CFA estimates of the loadings on the G-factor. Similarly, an unmodelled G-factor could result in inflated CFA factor correlations, or inflated ESEM cross-loadings. Previous research shows that a close examination of parameter estimates and theoretical conformity is often required to select the best alternative among a series of possibly similarly fitting models (Marsh, Liem, et al., 2011; Marsh, Nagengast, et al., 2011; Morin, Arens et al., 2016). As suggested by Morin, Arens et al. (2016), the application of this framework should start with a comparison of alternative CFA and ESEM measurement models. Assuming that the factors remain well-defined by strong target factor loadings in both models, the key comparison point is related to the factor correlations. Based on statistical evidence that ESEM results in more exact estimates of factor correlations when cross-loadings are present in the population model but unbiased estimates otherwise (Asparouhov et al., 2016), the observation of a distinct pattern of factor correlations in ESEM versus CFA represents evidence in favor of the ESEM measurement model. Otherwise, the CFA model might be preferred on the basis of its greater parsimony. Naturally, observing large and theoretically hard to explain cross-loadings may also reveal some problems at the item level and suggest the need to revisit the instrument.

Once the decision has been made to retain a CFA or ESEM representation of the data, the second comparison involves contrasting the retained CFA or ESEM model with its bifactor counterpart (bifactor-CFA or bifactor-ESEM). Here, the key comparisons are related to the presence of a G-factor well-defined by strong, and theoretically-meaningful factor loadings. Similarly, in relation to the ESEM versus bifactor-ESEM comparison, the observation of multiple large cross-loadings in the ESEM model that are reduced in the bifactor-ESEM model provides strong evidence in favor of the bifactor representation (Morin, Arens, et al., 2016). It is important to reinforce that, although this process might appear to be somewhat data driven, theory and expectations should remain the driving force behind these comparisons. For instance, if there are no reasons to expect that the items might reflect the presence of an overarching global construct, such as in the tripartite representation of commitment to the organization example provided above, then it might not be theoretically-meaningful to pursue a bifactor representation of the data. Similarly, when the various dimensions cannot be argued to reflect conceptually-related constructs, such as in the multifoci representation of affective commitment example provided above, then it might not be theoretically-meaningful to pursue an ESEM representation of the data. Still, contrasting these alternative models may remain particularly useful to identify measurement problems located at the item level in new measurement instruments through the free estimation of all cross-loadings (Morin & Maïano, 2011). Similarly, the identification of an unexpected global factor may either suggest the presence of important response biases, or potentially suggest the need to revise one’s theoretical expectations.

**Person-Centered Analyses.** LPA and FMA were used to extract profiles based on their levels of wellbeing as a function of the three parameterization illustrated in Figure 2b. Factor scores saved from the final retained first-order (CFA or ESEM) and bifactor (CFA or ESEM) models in standardized units ($M$ = 0, $SD$ = 1) from the first stage were used as profile indicators. These analyses were conducted using Mplus 7.2 (Muthén & Muthén, 2014) MLR estimator, using 10,000 random starts, 1000 iterations for these random starts and the 500 best retained for final stage optimization (Hipp & Bauer, 2006; McLachlan & Peel, 2000). All reported models converged on a replicated solution and can be assumed to reflect a “real” maximum likelihood. For each parameterization, models with 1 to 8 latent profiles were estimated with the indicators’ (wellbeing factor scores) intercepts and residuals freely estimated in all profiles (Morin, Maïano, et al., 2011; Peugh & Fan, 2013). However, for FMA (Model 3), these models converged on improper solutions (negative variance estimates, non-positive definite Fisher Information matrix, etc.) or failed to converge. This suggests the inadequacy of these models (Bauer & Curran, 2003; Chen, Bollen, Paxton, Curran, & Kirby, 2001), which may have been overparameterized, and the superiority of more parsimonious models. For Model 3, variances of the indicators were thus constrained to invariance across profiles.

Model 1 is a classical LPA model, using factor scores saved from the best fitting first-order (CFA or ESEM) model as profile indicators. Model 2 is also a classical LPA model, but using factor scores saved from the best fitting bifactor (CFA or ESEM) model as profile indicators. Finally, Model 3 is a FMA, using factor scores saved from the best fitting first-order (CFA or ESEM) model as profile indicators. In this model, a global continuous latent factor, specified as invariant across profiles, was included to to reflect global *level* effects shared among profile indicators. Although we contrast these three models in order to illustrate their impact on substantive interpretations, we reinforce that researchers do not need to embark on this extensive comparison process. Rather, our key rationale is that the decision of which model to retain should be anchored in the results of the variable-centered analyses conducted before on the same data. Thus, whenever variable-centered analyses converge on a CFA or ESEM representation of the data, then Model 1 should be retained. In contrast, whenever variable-centered analyses converge on a bifactor-CFA or bifactor-ESEM representation of the data, then Model 2 should be retained. For reasons presented above, Model 3 does not appear to represent a desirable alternative for most research contexts, unless there is some reason to seek the estimation of profiles presenting the same average level on the global overarching construct. Similarly, whenever latent profiles are estimated based on observed single-indicator measures (e.g., objective indicators of physiological health such as respiratory or cardiovascular) that do not lend themselves to preliminary psychometric investigations, then Model 3 may represent a viable alternative to achieve a disaggregation of *shape* and *level* effects.

In mixture models, deciding how many profiles to retain is guided by an examination of the theoretical meaning and conformity of the extracted profiles (Marsh, Lüdtke, Trautwein, & Morin, 2009; Muthén, 2003), as well as the statistical adequacy of the solution (e.g., absence of negative variance estimates; Bauer & Curran, 2004). A number of statistical tests and indices are also available to guide this decision process (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, Mendel and Rubin's (2001) 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. The aLMR and BLRT compare a *k*-class model with a *k-1*-class model. A significant *p* value indicates that the *k-1*-class model should be rejected in favor of a *k*-class model. Simulation studies indicate that four of these indicators (CAIC, BIC, ABIC, and BLRT) are particularly effective and that when the indicators fail to retain the optimal model, the ABIC and BLRT tend to overestimate the number of classes, whereas the BIC, CAIC, and aLMR tend to underestimate it (Nylund et al., 2007; Peugh & Fan, 2013; Tein, Coxe, & Cham, 2013; Tofighi & Enders, 2008; Tolvanen, 2007; Yang, 2006). However, these tests are variations of tests of statistical significance, heavily influenced by sample size (Marsh, Lüdtke et al., 2009), so that with sufficiently large sample sizes, these indicators may keep on suggesting the addition of profiles without ever reaching a minimum. In these cases, information criteria should be graphically presented through "elbow plots" illustrating the gains associated with additional profiles (Morin, Maïano, et al., 2011; Petras & Masyn, 2010). In these plots, the point after which the slope flattens out indicates the optimal number of profiles. Finally, the entropy indicates the precision with which the cases are classified into the various profiles. Although the entropy should not be used to determine the optimal number of profiles (Lubke & Muthén, 2007), it provides a useful summary of the classification accuracy. The entropy varies from 0 to 1, with higher values indicating less classification errors.

In LPA and FMA, it is possible to control for the non-independence of the observations due to teachers' nesting within schools (Asparouhov, 2005). However, this correction precludes calculation of the BLRT. Because ignoring nesting has been shown not to affect decisions regarding the number of profiles present in the data in LPA (Chen, Kwok, Luo, & Willson, 2010), class enumeration was conducted without controlling for nesting. However, because failure to control nesting can impact standard errors and classification accuracy, the final retained models were re-estimated while correcting for teachers' nesting within schools so that all parameter estimates reported in this study are corrected for the nesting structure of the data. Annotated Mplus input codes for all variable- and person-centered models used in the current study are provided in the online supplements.

## Results

**Variable-Centered Analyses**

Table 1 presents the goodness-of-fit indices of the various models. Both the CFA and bifactor-CFA provide a satisfactory degree of fit to the data according to the CFI (.971 and .972) and TLI (.968 and .966), but not the RMSEA (.094 and .096) or the WRMR (2.848 and 2.775). 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 (.988 and 992) and TLI (.981 and .986), as well as an acceptable level of fit to the data according to the RMSEA (.072 and .063). The WRMR only reached an acceptable level of fit (.933) with the bifactor-ESEM solution. 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 meaningless (i.e., weakly defined through low factor loadings). If this was the case, then the ESEM model could represent a viable alternative.

However, as noted above, model selection should always be conditional on a detailed examination of the parameter estimates and theoretical conformity. Following Morin, Arens et al.'s (2016) recommendations, we first compare the CFA and ESEM solutions to investigate the presence of construct-relevant psychometric multidimensionality due to the presence of 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 available in Table S1 of the online supplements. With the exception of three items presenting weak target factor loadings in ESEM (Recognition 5: $\lambda$ =.036; Involvement 2: $\lambda$ = .080; Involvement 4: $\lambda$ = .168), the five a priori constructs appear to be well defined through high target factor loadings in both CFA ($\lambda$ = .371 to .929; $M$ = .819) and ESEM ($\lambda$ = .342 to .866; $M$ = .611). A noteworthy difference is that the estimated factor correlations are much lower in ESEM ($|r|$ = .313 to .632; $M$ = .452) than CFA ($|r|$ = .764 to .917; $M$ = .834), suggesting that ESEM results in a clearer differentiation between the factors. Simulation studies clearly show that ESEM tends to provide a better representation of the true factor correlations when cross-loadings are present in the population model, yet unbiased estimates of these correlations when no cross-loadings are present in the population model (e.g., Asparouhov et al., 2015). In this context, the observation that factor correlations are reduced clearly argues in favor of ESEM. Furthermore, the fact that the correlations remain high in ESEM suggests that a global overarching construct may be present in ratings of wellbeing. The presence of many high cross-loadings in ESEM ($|\lambda|$ = .001 to .507; $M$ = .158) also suggests the presence of an unmodeled overarching construct. Out of 100 cross-loadings, only 13 are non-significant, whereas 12 are between |.200| and |.300|, 7 are between |.300| and |.400|, and 7 are over |.400|. It is noteworthy that the three weaker items from ESEM (Recognition 5; Involvement 2 and 4) present elevated cross-loadings on multiple factors, suggesting that they may be more potent indicators of the global wellbeing construct than of their specific factors.

**ESEM versus Bifactor-ESEM.** The bifactor-ESEM solution provides the highest level of fit to the data of all models considered here, and the only solution for which WRMR values are in the acceptable range. The parameter estimates from this model are reported in Table 2. These results reveal a G-Factor well-defined by strong and positive loadings from most items ($\lambda$ =.308 to .857, $M$ = .743). In particular, the three weaker items from the ESEM solution (Recognition 5; Involvement 2 and 4) all present high loadings on this G-Factor (.768, .804, .824), lower loadings on their S-Factors (-.112, .138, .230) and substantially reduced cross-loadings when compared to ESEM. This observation confirms our assertion that these items represent clearer indicators of global wellbeing than of their specific factors. Over and above this G-Factor, all S-Factors retain at least some specificity once the G-Factor is taken into account in the model ($\lambda$ = -.112 to .556; $M$ = .337). More precisely, although the items defining these S-Factors present a weaker association with their S-Factor than with the G-Factor, the Interpersonal Fit ($\lambda$ = .237 to .528; $M$ = .391), Thriving ($\lambda$ = .303 to .420; $M$ = .355), and Competency ($\lambda$ = .036 to .556; $M$ = .390) S-Factors remain relatively well-defined by a majority of items. In contrast, the Recognition ($\lambda$ = -.112 to .380; $M$ = .205) and Involvement ($\lambda$ = .138 to .535; $M$ = .344) S-Factors are more weakly defined (i.e., by a minority of items). However, although not defined as strongly as the other S-Factors, it should be kept in mind that all target loadings on these S-Factors remain significant, supporting the need to control for this content specificity in the model. The fact that these S-Factors retain less specificity than the other factors does not signify that this specificity is not meaningful especially when modelled using an approach that explicitly controls for both measurement error and associations with the global wellbeing construct. Finally, the superiority of the bifactor-ESEM solution is also apparent from the substantially reduced cross-loadings ($|\lambda|$ = .001 to .317; $M$ = .081) relative to ESEM: Only 7 cross-loadings remained between |.200| and |.300|, 1 between |.300| and |.400|, and 0 over |.400|.

**Person-Centered Analyses**

The goodness-of-fit indices associated with the alternative models are reported in Table S2 from the online supplements. The information criteria continue to improve when latent profiles are added for each of the alternative models, with the exception of the CAIC and BIC which reach a minimum at 6 profiles for Model 2. Similarly, the BLRT remains significant across most comparisons, except for Model 2 where it supports the 6-profile solution. Finally, the aLMR, an indicator with a known tendency for under-extraction, supports the 2-profile solution for Models 2 and 3, and the 4-profile solution for Model 1. In accordance with previous recommendations, we thus relied on elbow plots to help in the selection of the final solution (e.g., Morin, Maïano et al., 2011; Petras & Masyn, 2010). These elbow plots are reported in figures S1 to S3 of the online supplements. For Models 1 and 2, these plots showed a relatively clear plateau at 4 profiles, after which improvement in fit becomes minimal. Examination of these 4-profile solutions shows them to be fully proper and interpretable. Examination of adjacent 3- and 5-profile solutions confirmed the added value of the 4-profile solutions compared to the 3-profile solutions, and the lack of added value of the 5-profile solutions which resulted in the estimation of additional very small profiles (3.7% for Model 1 and 0.6% for Model 2) that brought no new information to the model (i.e., had the same *shape* as other profiles). The 4-profile solutions were thus retained for Models 1 and 2.

The results are not as clear for Model 3. Looking at the elbow plots reveals that additional profiles beyond the first one bring only limited additional information to the model, with no clear plateau. An approximate plateau can be found around 2 profiles (supporting the aLMR), and another one can be found around 4 profiles. However, examination of these alternative solutions shows that each additional profile beyond the first one only characterizes a very small minority of participants, with the dominant profile always corresponding to over 90% of the participants. Furthermore, the results show that this dominant profile presents average levels on all indicators, with high levels of within profile variability, while the remaining profiles present diverging levels on the indicators, but always corresponding to 5% or less of the sample. For illustrative purposes, the 2-profile solution is graphed in Figure S4 of the online supplements, with the first profile describing 5.6% of the sample, compared to 94.4% for the second profile. Taken together, these FMA results thus support a single profile solution, suggesting that wellbeing levels are best represented along a single, variable-centered continuum, which contradicts the results from our previous variable-centered analyses showing that significant specificity remained in the S-Factors once the global wellbeing G-Factor was taken into account. More importantly, these results suggest that the apparent superiority of the FMA approach suggested by Morin and Marsh (2015) may not hold in all situations. In particular, this model may pose problem when the construct is known to follow a bifactor structure so that extracting *level* effects as part of the profile-estimation process (rather than as part of factor-score estimation) may leave too little residual specificity in the S-Factors to form meaningful profiles. This model was thus not retained, and will not be further discussed. We now turn our attention to Models 1 and 2.

**Results from Model 1**. Results from the four-profile solution retained for Model 1 (i.e., using LPA estimated form the ESEM factor scores) are represented in Figure 3. In this solution, profiles 1, 3, and 4 appear mainly differentiated in terms of *level*, with limited *shape* differences. Thus, at least at first sight, this solution appears to support the idea that psychological wellbeing at work is best represented as a single underlying dimension. However, some *shape*-related differences also appear, suggesting that models in which global levels of psychological wellbeing are more properly controlled might be preferable, especially given previously reported variable-centered results showing the superiority of a bifactor representation. More specifically, Profile 1 is characterized by high levels of wellbeing on most indicators, particularly on Recognition and Involvement, followed by Interpersonal Fit, with slightly lower levels on Thriving and Competence. These results thus describe employees' who perceive having a high level of interpersonal fit to their workplace, where they seek to be involved, and feel recognized for it. This "Well-Integrated" profile remains relatively small, and describes 6.4% of the sample. Profile 2 is also relatively small, characterizing 4.1% of the sample, but presents even clearer *shape* differences. This profile presents relatively low levels of Interpersonal Fit, Competence and Thriving, while presenting a high level of Involvement and average level of Recognition. This "Ill-Adjusted Extrinsically-Driven" profile thus describes employees with a lower global level of wellbeing at work, who do not feel that they possess the required competencies, that they fit with others, and that they thrive at work, while maintaining a high level of involvement for which they perceive receiving at least some level of moderate recognition. Profile 3 presents low levels on all dimensions. This "Ill-Adjusted" profile is also the largest, and characterizes 54.4% of the sample. Finally, Profile 4 is similar to Profile 1, but much larger (35.1%), and presents high levels of wellbeing on most indicators. However, compared with Profile 1, this profile is dominated by the Interpersonal Fit, Competence and Thriving dimensions, with slightly lower levels of Recognition and Involvement. This "Thriving in the job" profile also characterizes employees with a high level of wellbeing at work. However, although we interpreted the minimal *shape*-related differences between these profiles, these differences remain minimal. Indeed, apart from minimal shape-related differences between profiles 1 and 4, profiles 1, 3 and 4 differ from one another mainly based on their global levels of wellbeing, and profile 2 is the only one presenting a clearly distinct configuration.

**Results from Model 2**. Results from the four-profile solution retained for Model 2 are represented in Figure 4. In this solution, profiles present much clearer *shape* differences, with the G-Factor indicator providing a clear pointer of the global level of psychological wellbeing present in each profile. This solution thus supports, and enriches, the conclusions from the previous variable-centered analyses, showing that a global underlying psychological wellbeing dimension does coexist with meaningful subscale specificity. In this solution, Profile 1 represents a more realistic representation of the dominant profile than Model 1, corresponding to the majority of employees (59.4%). This "Normative" profile presents a globally average level of psychological wellbeing at work, with no specific dimensions showing any dominance over the others. In contrast, the remaining profiles present well-differentiated configuration of wellbeing indicators. Thus, Profile 2 characterizes a substantial proportion of the sample (29.2%) presenting an average level of global wellbeing (based on the G-factor indicators), but a moderately high level of Competence, a moderately low level of Recognition and Involvement, and close average levels of Interpersonal Fit and Thriving. Thus, employees corresponding to this "Intrinsically-Driven" profile appear relatively confident in their ability to do their job well, but do not seek increased levels of organizational involvement, perhaps due to a perceived lack of recognition. In this profile, there is an apparent imbalance between the level of competence brought in the job by the employees, and the level of recognition received from the organization. This imbalance may explain why the global level of wellbeing remains slightly below average in this profile. Interestingly, this profile presents a high level of similarity to Profile 4 (i.e. "Thriving in the job") from Model 1 once global *level* effects are extracted from it.

The third profile is smaller, corresponding to 6.6% of the sample, and includes employees presenting a very low level of global wellbeing. These individuals feel that they receive a high level of recognition at work, for which they apparently want to reciprocate through a desire for involvement. While this could fuel some extrinsically-driven thriving at work, the fact that two critical basic needs (Gagné & Deci, 2005) for competence and relatedness (i.e., Interpersonal Fit) do not seem to be fulfilled for these employees may explain why the global score of psychological wellbeing is so low in this profile. Overall, this "Ill-Adjusted Extrinsically-Driven" profile seems to correspond to Profile 2 from Model 1 once global levels of wellbeing are properly extracted. Finally, Profile 4 is also smaller (4.8%) and describes employees with a very high level of global wellbeing at work. In addition to this, these "Well-Integrated" employees also present an average (i.e., satisfactory, without being higher than average) level of Competence, moderate levels of Interpersonal Fit and feelings of Thriving, and a high level of Involvement and Perceived Recognition. This profile seems to be characterized by an advantageous balance between what employees brings to the organization, and the recognition they receive from it. Further, intrinsic needs for competence and relatedness seem to be correctly met in order for these employees to thrive and perceive their work as meaningful. This profile seems to correspond well to Profile 1 from Model 1, once level effects are properly extracted.

This correspondence of results for at least 3 out of 4 profiles between Model 1 and 2 is highly informative and shows that relying on alternative ways of representing shape and level effects in latent profile solution may bring a different perspective on the same results. Thus, in this study, both models revealed a "Well-Integrated" profile (Profile 1 in Model 1, and Profile 4 in Model 2) corresponding to approximately 5% of the sample, in line with Biétry and Creusier's (2015) results. Both models also revealed an "Intrinsically-Driven/Thriving on the Job" profile (Profile 4 from Model 1 and Profile 2 from Model 2) corresponding roughly to one third of the employees. Finally, both models reveal a small "Ill-Adjusted Extrinsically-Driven" profile (Profile 2 from Model 1 and Profile 3 from Model 2) corresponding to approximately 5% of the sample. However, these results also show that there is a risk of misinterpretation coming from using profile indicators from a suboptimal measurement model in that the conclusions from Model 1 suggested that a majority of employees (54.4%) presented "Ill-Adjusted" profile, which is not in line results from our wellbeing literature review. In contrast, Model 2, based on more properly defined profile indicators, revealed that the dominant profile (59.4%) rather corresponds to a "Normative" profile with moderate levels on all wellbeing indicators, again in line with Biétry and Creusier's (2015) results.

## Discussion

### An Integrated Variable- and Person- Centered Approach

This study aimed to present, extend, and illustrate a framework of broad relevance to managerial, psychological, and organizational research, which often relies on multidimensional measures of specific complementary dimensions of global underlying constructs. Although theoretical frameworks used to guide research applications often explicitly or implicitly posit that such global overarching constructs exist, practical applications often simply ignore these global overarching construct to focus on the dimensions, typically represented as correlated factors, and ignore the fact that test items may often reflect multiple conceptually-related dimensions. Doing so creates the risk of converging on biased estimates of the key relations among 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, and that items may provide a valid reflection of multiple constructs. Alternatively, when this shared variance becomes too important, a typical solution is to collapse all dimensions into a single measure of the overarching construct, resulting in a loss of information regarding the specific dimensions. In this study, we proposed an integrated methodological framework for the investigation of the underlying dimensionality of psychometric constructs relying, in sequence, on a combination of variable-centered and person-centered analyses.

**On the Importance of Preliminary Measurement Models**. The application of this framework starts with a variable-centered approach based on the integration of CFA, bifactor, and ESEM models (Morin, Arens, et al., 2016; Reise, 2012), which provides a way to systematically assess the presence of two distinct sources of construct-relevant psychometric multidimensionality potentially present in psychometric measures. These two sources are related to the hierarchical and conceptually-related nature of the constructs. The first source of construct-relevant multidimensionality can be identified by the comparison of classical correlated factor models with bifactor models, while the second source can be identified by a comparison of ESEM and CFA models. Previous research shows that ignoring these sources of construct-relevant multidimensionality, when they are present in the data, lead to inflated estimates of the factor correlations, resulting in potentially severe multicollinearity (Asparouhov & Muthén, 2009; Marsh et al., 2013; Morin, Arens et al., 2016; Sass & Schmitt, 2010; Schmitt & Sass, 2011). Research has also shown that ignoring any one of these two sources of construct-relevant multidimensionality (i.e., ignoring cross-loadings or the global construct) may lead to inflated estimates of the other source of multidimensionality (i.e., inflated loadings on the global factor or inflated cross-loadings; Morin, Arens et al., 2016; Murray, & Johnson, 2013), reinforcing the need to combine these two comparisons in the overarching bifactor-ESEM framework.

As advocated by Morin, Arens et al. (2016), the first step in the application of this variable-centered framework is to compare the results from of CFA and ESEM models to assess the presence of construct-relevant multidimensionality due to the assessment of conceptually-related constructs. In this comparison, the observation of better fit indices and substantially reduced factor correlations in ESEM relative to CFA, coupled with small or easy to explain cross-loadings and factors that remain properly defined argue in favor of ESEM (e.g., Marsh et al., 2013, 2014; Morin et al., 2013). In particular, observing multiple cross-loadings of a reasonable magnitude (≥ .10-.20, or even .30) in ESEM solution suggests that a global construct might be present in the data. Contrary to common misconceptions, these cross-loadings, as long as they remain reasonably small (e.g., smaller than the target loading), should not be seen as tainting the meaning of the latent factors themselves (Morin, Arens et al., 2016). Indeed, according to the reflective logic of factor analyses, the factors are seen as influencing the indicators rather than the reverse. Thus, keeping in mind that the true meaning of constructs lies in the way they relate to other constructs, it seems that including these cross-loadings rather allows for the factors to be estimated using all of the available information present at the item level (Asparouhov, Muthén, & Morin, 2015). Nevertheless, the demonstrated superiority of an ESEM measurement model in recovering true population values for the factor correlations and the idea that cross-loadings should not be seen as tainting the meaning of the factors (e.g., Asparouhov et al., 2015) should not be taken as a justification to retain poorly written items, nor as a rationale to stop striving for the development of conceptually "clean" items providing a clear reflection of a single construct. Rather, it simply recognizes that when conceptually-related constructs are assessed, reasonably small cross-loadings (.10, .20, perhaps even .30) can be expected to occur as a reflection of the conceptual relatedness of the various constructs. However, items presenting large and unexpected cross-loadings, or weak loadings on their target factors, should still be called into question and possibly eliminated or at least targeted for revision (for an example of this process, see Morin & Maïano, 2011).

As long as there are reasons to expect that a global construct might be present, the second step involves a comparison of a classical correlated factor model (ESEM or CFA, based on the conclusions from the first step), with a bifactor (CFA or ESEM) representation of the data. Over and above the observation of better-fit indices associated with the bifactor model, a key argument in favor of the bifactor representation is the observation of a well-defined G-factor. It is not as critical for the S-factors to be equally well-defined, and these may be included sometimes only to control for residual specificities shared among a subset of indicators. Still, a proper bifactor representation should typically result in at least some well-defined S-factors. Finally, whenever both sources of construct relevant multidimensionality are present in the data, a bifactor-ESEM representation of the data should be seriously considered. It is critical to understand that we are not arguing for the systematic application of this complete framework to any psychometric measure in a purely data-driven manner. Rather, we argue that each component of this framework needs to be anchored in the clear a priori expectation that each of these two sources of construct-relevant multidimensionality is likely to be present in the measure under investigation. Still, the application of this complete framework to any other measure may reveal unexpected results, which we argue will need to be interpreted as such.

**A Proper Representation of Shape and Level Effects in Person-Centered Analyses**. A critical advantage of relying on a bifactor representation of the data becomes obvious whenever this initial psychometric measurement model is used in subsequent analyses. In this context, the adoption of a bifactor model makes it possible to explicitly represent this global overarching construct, while simultaneously taking into account the specific information brought to the model by the specific dimensions. In this article, we demonstrated this advantage in the context of person-centered analyses. Person-centered analyses represent another complementary framework for exploring the inherent dimensionality of psychometric constructs. In person-centered research, a clear implicit assumption is that 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 little heuristic value and would be better represented by a variable-centered approach (Morin & Marsh, 2015). However, as noted above, psychological, organizational, and managerial research often focuses on multidimensional constructs for which equally strong *level* and *shape* effects can be present.

In the present study, we proposed that person-centered methodologies could be considered as a complementary framework for the exploration of the inherent multidimensionality of psychometric constructs. More precisely, the observation of *level*-differentiated profiles suggests the presence of an overarching construct underlying the various dimensions used in the latent profile model, and possibly the need to revisit the preliminary variable-centered measurement model underlying these dimensions to obtain a more exact person-centered representation of the data. Addressing this issue, Morin and

Marsh (2015) proposed a person-centered framework specifically designed to achieve a more proper disaggregation of shape versus level effects in latent profile analyses. However, as we discussed above, two of the models they considered relied on factor scores saved from a higher-order factor model, thus introducing redundancy in the latent profile model. Indeed, first-order factors scores taken from a higher-order factor model, in contrast to factor scores taken from a bifactor model, are not properly disaggregated from the variance explained by the higher-order factor – which may explain the suboptimal performance of Morin and Marsh's (2015) Models 2 and 4. In addition, the FMA model (Model 3) recommended by these authors was also based on a higher-order factor logic, relying on the estimation of a global factor directly from the first-order factor scores, and thus also relied on strict implicit proportionality constraints that may not hold in real life settings (Chen et al,. 2006; Jenrich & Bentler, 2011; Reise, 2012). This FMA model was also anchored in the very strict assumption that all profiles present similar average levels on this global factor. In this context, it is perhaps not surprising to note that this model did not perform as well in the current study as in Marsh and Morin's (2015) study – suggesting that it may not be equally well-suited to all situations. Importantly, in the current study, the conclusions reached from this model were clearly not aligned to the results from the alternative models, or to the results from the variable-centered analyses, which clearly supported the co-existence of a global overarching construct with specific dimensions.

**The Complementarity and Connections between Variable- and Person-Centered Analyses**. Our results supported the importance of adopting a proper variable-centered measurement model as a starting point to person-centered analyses. Indeed, our results showed the advantages of using factor scores estimated from a bifactor-ESEM model as a starting point to the estimation of profiles when the objective is to obtain profiles based on properly disaggregated *shape* versus *level* effects. In the current study, this person-centered model proved superior to the alternative models in providing a more easily interpretable solution that was fully in line with the conclusions from the variable-centered analyses regarding the co-existence of global and specific constructs. Although the results from Models 1 (based on ESEM factor scores) and 2 (based on bifactor-ESEM factor scores) presented similarities, the results from Model 2 had a greater heuristic value. The ability to estimate profiles differing from one another based on both the global and specific dimensions also provided valuable information to enrich their description. Furthermore, this model also provided a more realistic representation of the data, based on convergence with previous research (see discussion below) showing the greater realism of having a dominant "normative" profile, rather than a dominant "Ill-Adjusted" profile.

In the current study, we systematically contrasted the results obtained from Models 1 to 3 for purposes of demonstrating the proposed person-centered framework and of illustrating the impact of each type of model on the substantive interpretation of the results. However, in terms of practical applications, our recommendation is much simpler: Person-centered analyses should be directly anchored into the results from the preliminary variable-centered analyses. Thus, whenever the final retained variable-centered model corresponds to either a CFA or ESEM representation of the data, Model 1 (a LPA based on factor scores taken from the final CFA or ESEM model) should be retained. Alternatively, whenever the final retained variable-centered model corresponds to a bifactor-CFA or bifactor-ESEM representation of the data, then Model 2 (a LPA based on factor scores taken from the final bifactor-CFA or bifactor-ESEM model) should be retained. We leave as an open research question whether there are research contexts for which it might be desirable to pursue Model 3 (Factor Mixture model). Clearly, the superiority of this model identified in the Morin and Marsh (2015) study did not generalize to the present application, and future research conducted within the statistical area should aim to clarify the conditions under which this model might prove to be useful. Based on our own experience and understanding of these models, we surmise that Model 3 may be potentially useful when preliminary measurement models are found to satisfactorily meet the assumptions of higher-order factor models. This model may also be appropriate when there are reasons to seek the estimation of profiles presenting the same average level on the global overarching *level* effects. Finally, Model 3 may prove to be an interesting alternative to Model 2 when profiles are estimated with on single-indicator measures for which preliminary measurement models cannot be estimated.

**Substantive Implications for the Study of Psychological Wellbeing at Work**

**A Variable-Centered Representation of the Psychological Wellbeing Construct**. This study supported the superiority of a bifactor-ESEM representation of answers provided to the psychological wellbeing questionnaire considered in this study. This result reveals the presence of construct-relevant multidimensionality related to the existence of a global overarching psychological wellbeing construct underlying responses to the complete set of items included in this questionnaire, as well as to the assessment of conceptually-related facets of psychological wellbeing. The observation of the first of these two sources of construct-relevant multidimensionality is consistent with the theoretical conceptions of psychological wellbeing as driven by a single global underlying dimension (Dagenais-Desmarais & Savoie, 2012; Keyes, 2002; Massé et al., 1998). Yet, our results supported that the dimensions covered in this instrument retained some degree of meaningful specificity once this global overarching construct is taken into account in the model. These results suggest that future studies of psychological wellbeing at work would do well to consider the variable-centered framework proposed in the current study as a way to properly represent the psychological wellbeing construct.

**A Person-Centered Representation of the Psychological Wellbeing Construct**. Our results also reinforced the importance of adopting a proper variable-centered measurement model as a starting point to person-centered analyses. The results from LPA analyses conducted on the factor scores from the ESEM model were contrasted to those obtained from the bifactor-ESEM model, which yielded a different yet complementary perspective on the nature of employees' profiles of psychological wellbeing. On the one hand, the LPA model estimated from ESEM factor scores (Model 1) revealed profiles differing from one another mainly based on level-differences, although a closer examination revealed that they also presented shape-related differences once global levels of psychological wellbeing were extracted. As such, the alternative model estimated from bifactor-ESEM factor scores (Model 2) provide a clearer disaggregation of *shape* and *level* effect that both contributed to the interpretation of the profiles. This finding supports variable-centered results in showing that meaningful specificity remained in the wellbeing dimensions once global levels of wellbeing were taken into account. The ability to directly integrate a global indicator of psychological wellbeing to the model while allowing levels on this indicator to differ across profiles enriched their interpretation.

**A New Taxonomy of Employees' Profiles of Psychological Wellbeing**. Once global levels of psychological wellbeing were taken into account, three of the four profiles were highly similar across these two solutions. Various theoretical perspectives could help us to shed some light on the meaning of these three distinct profiles. For instance, SDT proposes that levels of psychological wellbeing and more intrinsic forms of motivation at work are fostered by individuals' satisfaction of their basic psychological needs for relatedness, competence, and autonomy (Gagné & Deci, 2005). We postulate that the fulfillment of these needs should lead individuals to develop higher levels of psychological wellbeing components such as perceived interpersonal fit (through the satisfaction of the need for relatedness), feelings of being competent (through the satisfaction of the need for competence), and impressions of thriving in their job (through the satisfaction of the need for autonomy). The remaining dimensions, perceived recognition and desire for involvement, seem to be governed by more external (or less intrinsic) forms of regulations. In the current study, one of the profiles ("Intrinsically-Driven/Thriving on the Job") is characterized by a far more intrinsic orientation at work, that is reflected by high levels of interpersonal fit, thriving, and competence, but lower levels of recognition and involvement. In contrast, another profile ("Ill-Adjusted Extrinsically-Driven") appears to present a more extrinsic orientation to work, being dominated by high levels of recognition and involvement, but lower levels of interpersonal fit and thriving, suggesting that at least basic needs for relatedness and autonomy are not fulfilled for these employees. Not surprisingly, and as predicted by SDT, employees' global levels of psychological wellbeing appear to be much higher (closer to average) for the more intrinsically driven profile, and well below average for the extrinsically-driven profile.

It appears that the greatest global levels of wellbeing at work are achieved when both intrinsic and external sources of influence are combined, as in the "Well-Integrated" profile. Although this observation is not fully consistent with SDT, it can still be argued that recognition may contribute to the satisfaction of the need for relatedness, especially when combined with perceived interpersonal fit at work, and that a *desire* for involvement, especially when anchored in competence and thriving, is typically rooted in autonomy to enact his desire. However, other theoretical perspectives can help to refine our understanding of this "Well-Integrated" profile. For instance, the Effort-Reward Imbalance

(ERI) model (Sigriest, 1996) suggests that higher levels of wellbeing will be achieved when there is a balance between the efforts made and the rewards obtained by the employees. Interestingly, this model has proved to be particularly effective in predicting poor psychological health, particularly in service-related professions, as well as in other samples of Chinese teachers (e.g., Cass, Faragher & Cooper, 2003; Loerbroks et al., 2014). In light of the ERI model, it is particularly interesting to note that the "Intrinsically-Driven/Thriving on the Job" profile shows the lowest desire to get involved at work in Model 2. This suggests some form of imbalance between competence levels that employees' bring to the job (high in this profile) in comparison with the level of recognition obtained (low in this profile). Thus, although intrinsic needs appear to be met in this profile, this imbalance may explain why the global level of psychological wellbeing observed in this profile remains average. In contrast, in the "Well-Integrated" profile, there is a greater level of balance between involvement and recognition, and competence, albeit lower, remains at a satisfactory average level. Future research should aim to investigate the extent to which the profiles identified in the present study will replicate in new samples and more diversified cultures, devoting a particular attention to whether global levels of wellbeing appear to react to the balance between intrinsic and extrinsic factors (Chan, 2009).

Perhaps even more interesting is the fourth profile, whose meaning differed across Model 1 and 2, reinforcing the need to estimate profiles using indicators defined based on proper preliminary measurement model. Indeed, when using factor scores saved from a preliminary ESEM model, the dominant profile (54.4%) appeared to be "Ill-Adjusted", characterized by low levels on all indicators. In contrast, when using the factor scores from the bifactor-ESEM, the dominant profile presented a far more realistic "Normative" profile, characterized by average levels of wellbeing. The results from this second model are more in line with Keyes' (2005) observation that around 50% of individuals present a moderate level of wellbeing (also see Biétry & Creusier, 2015), whereas only 7% tend to present severe deficiencies in wellbeing (an estimate consistent with the relative size of the "Ill-Adjusted Extrinsically-Driven" profile identified in the current study). These estimates are also consistent with international statistics on work satisfaction indicating that only 8% of employees, on average, present low levels of work satisfaction (Souza-Posa & Souza-Poza, 2000). Similarly, while the teaching profession is known to be demanding (Johnson et al., 2005), research in this area also shows that teachers' levels of psychological wellbeing tend to remain, on the average, in the moderate range (Chan, 2009; López, Bolaño, Mariño, & Pol, 2010; Pisanti, Gagliardi, Razzino, & Bertini, 2003; Vercambre, Brosselin, Gilbert, Nerrière, & Kovess-Masféty, 2009). Similarly, the relative prevalence of the other profiles also appears in line with the results from prior research, showing that very high levels of psychological wellbeing remain relatively rare (e.g., Biétry & Creusier, 2015; Keyes, 2005).

**Generalizability**. Although this similarity with previous estimates is comforting, it is important to keep in mind that the present study was conducted within the Hong Kong teaching profession, which limits the generalization of the current results to other countries, and reinforces the need for replications in more diverse groups of employees, from a more diverse set of countries and professions. Indeed, although the Hong Kong teaching profession is generally described as highly stressful (Lau, Yuen, & Chan, 2005), with heavy teaching loads, forced downsizing of schools and potential staff redundancies (Titus & Ora, 2005), it also presents a very low rate of teacher turnover when compared to other countries. Cultural differences may play a role. Indeed, collectivistic cultures, particularly those anchored in a strong Confucian tradition, tend to define wellbeing more in terms of meaningfulness and contribution to the collectivity, than as a quest for happiness and self-expression (e.g., Chan, 2009; Loerbroks et al., 2014; Suh & Khoo, 2008). For this reason, it remains possible that the specific (im)balance between intrinsic and extrinsic orientations observed in the current set of profiles might have been influenced by this cultural context, where perhaps interpersonal fit, recognition and involvement may be potentially more important than in Western cultures. Future research should thus explore cultural influences on profile structure and development.

Over and above the need to specifically consider the extent to which the current results are specific to the Hong Kong teaching profession, cross-validation represents a particularly critical issue for person-centered analyses. Indeed, as noted earlier in the introduction, variable-, and person-, centered analyses provided complementary, and potentially equivalent, views of the same reality (Bauer, 2007; Bauer & Curran, 2004; Steinley & McDonald, 2007). To support a substantive interpretation of the profiles as representing meaningful subgroups of participants, it is thus critical embark on a process of construct validation to demonstrate that the profiles: (a) have heuristic and theoretical value, (b) are meaningful relation with relevant covariates, and (c) generalize to new samples (Marsh et al., 2009; Morin, Morizot, et al., 2011). Arguably, evidence of construct validity is built on an accumulation of studies (e.g., Meyer & Morin, 2016), from which it becomes possible to identify core profiles emerging with regularity across samples, as well as a set of peripheral profiles emerging less regularly (Solinger, Van Olffen, Roe & Hofmans, 2013). In order to systematically, and quantitatively, assess the extent to which a variable-centered model generalizes to new samples of participants, researchers can rely on the well-established measurement invariance framework (Millsap, 2011), which can easily be extended to bifactor-ESEM measurement model (Morin, Arens, et al. 2016). A similar approach has recently been proposed to guide the systematic investigation of the similarity of profile solutions across samples, and can easily be transposed to the models presented in the current study (Morin, Meyer et al., 2016).

## Conclusion

This study aimed to present, and illustrate, complementary variable- and person- centered approaches for the investigation of construct-relevant psychometric multidimensionality. Our results illustrated, using data on employees' levels of psychological wellbeing at work, that when there are reasons to expect measures to assess specific complementary dimensions of global underlying constructs, researchers would do well to adopt a methodological framework similar to the one proposed here. As the examples presented in our introduction suggested, we surmise that this situation might be quite frequent. In this context, the framework presented here provides researchers with a way to achieve a clearer understanding of the structure of psychological, organizational, or managerial constructs, while relying on complementary variable- (global versus specific constructs) and person-centered (*level* versus *shape* effects) approaches. Using this framework allowed us to present an apparently more complete variable- and person-centered representation of the psychological wellbeing at work construct, well aligned with the results from prior research. Yet, future research is needed to test the extent to which our results generalize across samples, types of employees, and cultures.

## Endnotes

[1] This partitioning is made possible by the orthogonality of the factors, which forces the covariance shared among all items to be fully absorbed into the G-factor, while the S-factors represent the covariance shared among a subset of items but not with the others. Similar models in which the specific factors are allowed to correlate thus allow some of the variance shared among multiple sets of items to be modelled separately from the global factor, importantly changing the meaning of the model. Such non-orthogonal models are typically used to incorporate methodological controls in a model rather than to estimate meaningful G- and S- Factors. In one such example, the global factor has been proposed to control for responses tendencies shared across all items (Podsakoff, MacKenzie, & Podsakoff, 2003), albeit with limited success based on the demonstration that meaningful information was still absorbed into this global "method" factor (Richardson, Simmering, & Sturman, 2009). More typically, this approach is used to represent a global trait factor assessed by multiple sources of information (i.e. multi-trait-multi-method) represented by the specific factors (Eid, 2000).

[2] The person-centered approach presented in the present study focuses on latent profile analyses rather than more common cluster analyses. Readers interested in a comparison of both methods are referred to Meyer and Morin (2016), Morin, Morizot et al. (2011), and Vermunt and Magidson (2002).

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**Table 1**

Fit Results from the Alternative Measurement Models for the Wellbeing Scale

| | $\chi^2$ | df | CFI | TLI | RMSEA | RMSEA 90% CI | WRMR |
|---|---|---|---|---|---|---|---|
| CFA | 2776.358* | 265 | 0.971 | 0.968 | 0.094 | 0.091; 0.097 | 2.848 |
| Bifactor-CFA | 2714.437* | 250 | 0.972 | 0.966 | 0.096 | 0.092; 0.099 | 2.775 |
| ESEM | 1221.967* | 185 | 0.988 | 0.981 | 0.072 | 0.068; 0.076 | 1.206 |
| Bifactor ESEM | 864.907* | 165 | 0.992 | 0.986 | 0.063 | 0.059; 0.067 | 0.933 |

*Notes.* CFA = Confirmatory factor analysis; ESEM = Exploratory structural equation modeling; $\chi^2$ = 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; WRMR = weighted root-mean-square residual; * $p < .01$.

**Table 2.**

Standardized Parameter Estimates (Loadings λ; Residuals; correlations) for the A Priori Bifactor-ESEM Solution

| | Fit (λ) | Thriving (λ) | Competency (λ) | Recognition (λ) | Involvement (λ) | G-Factor | Residual (1-$R^2$) |
|---|---|---|---|---|---|---|---|
| Interpersonal Fit 1 [a] | **0.496 *** | 0.030 | 0.091 * | -0.100 * | 0.075 * | 0.661 * | 0.293* |
| Interpersonal Fit 2 | **0.528 *** | 0.119 * | -0.103 * | 0.053 * | 0.070 * | 0.697 * | 0.203* |
| Interpersonal Fit 3 | **0.353 *** | -0.177 * | -0.095 * | 0.065 * | -0.105 * | 0.763 * | 0.237* |
| Interpersonal Fit 4 | **0.342 *** | -0.027 | 0.007 | 0.097 * | 0.001 | 0.829 * | 0.186* |
| Interpersonal Fit 5 | **0.237 *** | -0.175 * | -0.051 * | 0.232 * | -0.116 * | 0.782 * | 0.231* |
| Thriving 1 | -0.026 | **0.303 *** | -0.111 * | 0.277 * | 0.317 * | 0.707 * | 0.219* |
| Thriving 2 | 0.037 * | **0.413 *** | 0.085 * | -0.045 * | 0.045 * | 0.786 * | 0.199* |
| Thriving 3 | 0.037 * | **0.420 *** | 0.009 | -0.093 * | 0.026 | 0.790 * | 0.189* |
| Thriving 4 | -0.058 * | **0.333 *** | -0.047 * | -0.118 * | -0.023 | 0.826 * | 0.187* |
| Thriving 5 | -0.128 * | **0.306 *** | -0.066 * | 0.112 * | 0.058 * | 0.809 * | 0.216* |
| Competency 1 | 0.052 * | -0.025 * | **0.556 *** | -0.074 * | 0.062 * | 0.736 * | 0.137* |
| Competency 2 | -0.083 * | 0.048 * | **0.492 *** | 0.028 * | 0.040 * | 0.784 * | 0.131* |
| Competency 3 | 0.005 | -0.016 | **0.538 *** | 0.159 * | 0.072 * | 0.554 * | 0.372* |
| Competency 4 | -0.125 * | -0.094 * | **0.328 *** | -0.116 * | 0.001 | 0.784 * | 0.240* |
| Competency 5 | -0.049 * | -0.030 * | **0.036 *** | 0.012 | -0.089 * | 0.847 * | 0.269* |
| Recognition 1 | 0.023 | 0.008 | -0.100 * | **0.346 *** | -0.074 * | 0.848 * | 0.144* |
| Recognition 2 | 0.015 | 0.093 * | -0.093 * | **0.380 *** | 0.004 | 0.789 * | 0.216* |
| Recognition 3 | 0.020 | -0.100 * | 0.168 * | **0.130 *** | -0.160 * | 0.857 * | 0.185* |
| Recognition 4 | 0.288 * | 0.015 | 0.237 * | **0.280 *** | -0.044 * | 0.707 * | 0.281* |
| Recognition 5 | 0.067 * | 0.077 * | -0.025 | **-0.112 *** | -0.065 * | 0.768 * | 0.382* |
| Involvement 1 | -0.011 | 0.148 * | 0.261 * | -0.106 * | **0.292 *** | 0.681 * | 0.350* |
| Involvement 2 | -0.016 | 0.012 | -0.115 * | -0.210 * | **0.138 *** | 0.804 * | 0.277* |
| Involvement 3 | -0.034 * | 0.130 * | 0.099 * | 0.149 * | **0.524 *** | 0.643 * | 0.262* |
| Involvement 4 | -0.009 | 0.011 | -0.080 * | -0.221 * | **0.230 *** | 0.824 * | 0.213* |
| Involvement 5 | 0.065 * | 0.037 | -0.007 | -0.032 | **0.535 *** | 0.308 * | 0.612* |

***Notes***. [a] Exact item labels are available in Dagenais-Desmarais and Savoie's (2011) appendix; ESEM = Exploratory structural equation modeling; * $p < 0.01$.

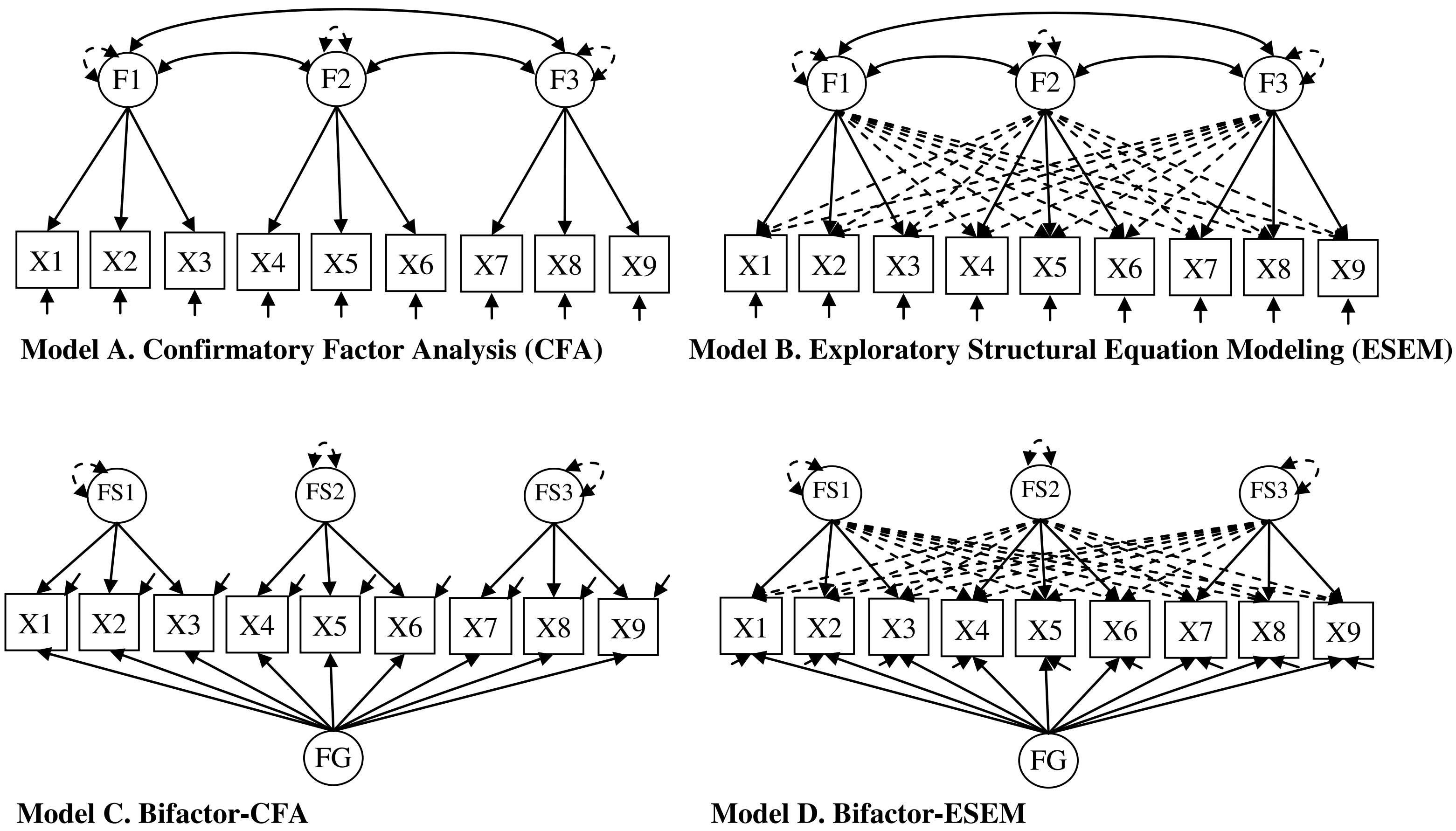
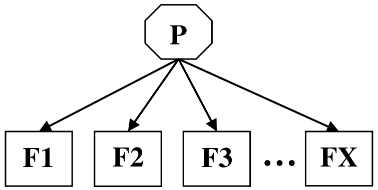
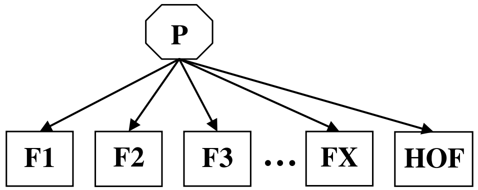


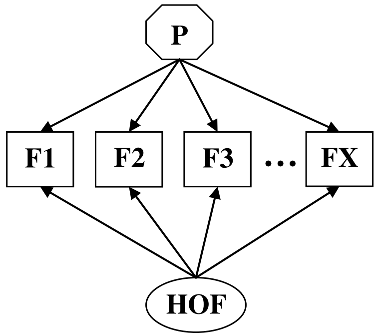

**Figure 1.** *Alternative Variable-Centered Models Discussed and Estimated in this Study.*
Note. X1-X9 = Items; F1-F3: CFA or ESEM factors; FS1-FS3: Specific factors from a Bifactor-CFA or Bifactor-ESEM model; GF: Global factor from a Bifactor-CFA or Bifactor-ESEM model; Ovals represent latent factors and squares represent observed variables; full unidirectional arrows linking ovals and squares represent factor loadings; dotted unidirectional arrows linking ovals and squares represent the cross-loadings; full unidirectional arrows linked to the items represent the item uniquenesses; bidirectional arrows linking the ovals are factor covariances/correlations; bidirectional arrows connecting a single oval are factor variances.



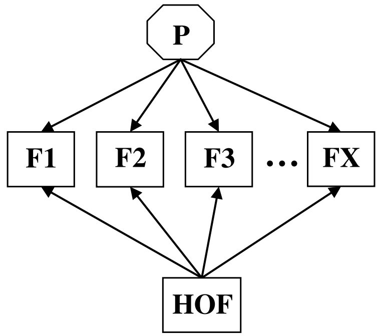

**Model 1**: Latent Profile Analysis (LPA)




**Model 2**: LPA Incorporating a Higher-Order Factor as Indicator

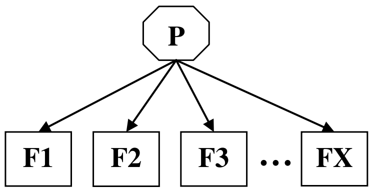



**Model 3**: Factor Mixture Analysis

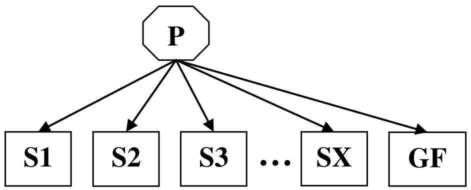



**Model 4**: LPA Incorporating a Higher-Order Factor as Control

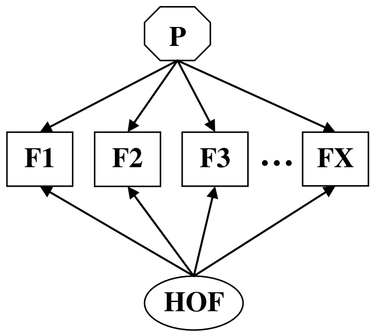
**Figure 2a.** Person-Centered Models Proposed in Morin and Marsh (2015)




**Model 1**: Latent Profile Analysis (LPA)




**Model 2 Revised**: LPA Incorporating Global- and Specific- Factors as Indicators




**Model 3**: Factor Mixture Analysis

**Figure 2b.** Revised Person-Centered Models Estimated in the Present Study

**Figure 2.** *Alternative Person-Centered Models Discussed and Estimated in this Study.*
**Note**. Squares represent observed variables (i.e., profile indicators); ovals represent continuous latent variables (i.e., factors); octagons represent categorical latent variables (i.e., profiles); F1-FX represent first-order factor scores used as profile indicators in the present study; HOF represents a higher-order factor score (square) or latent factor (oval); S1-SX represent specific factor scores from a bifactor model; GF represents a global factor score from a bifactor model; P represent the categorical latent variable reflecting the profiles.

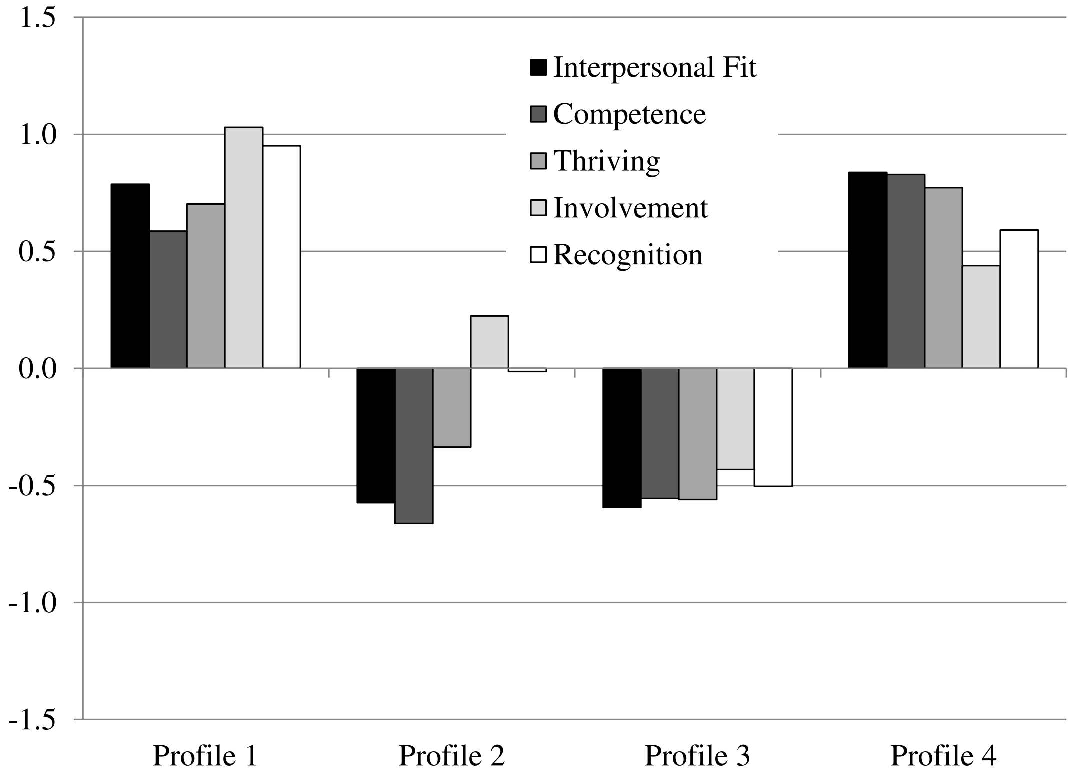



**Figure 3.** *Results from the Latent Profiles Models based on First-Order Factor Scores (Model 1)*

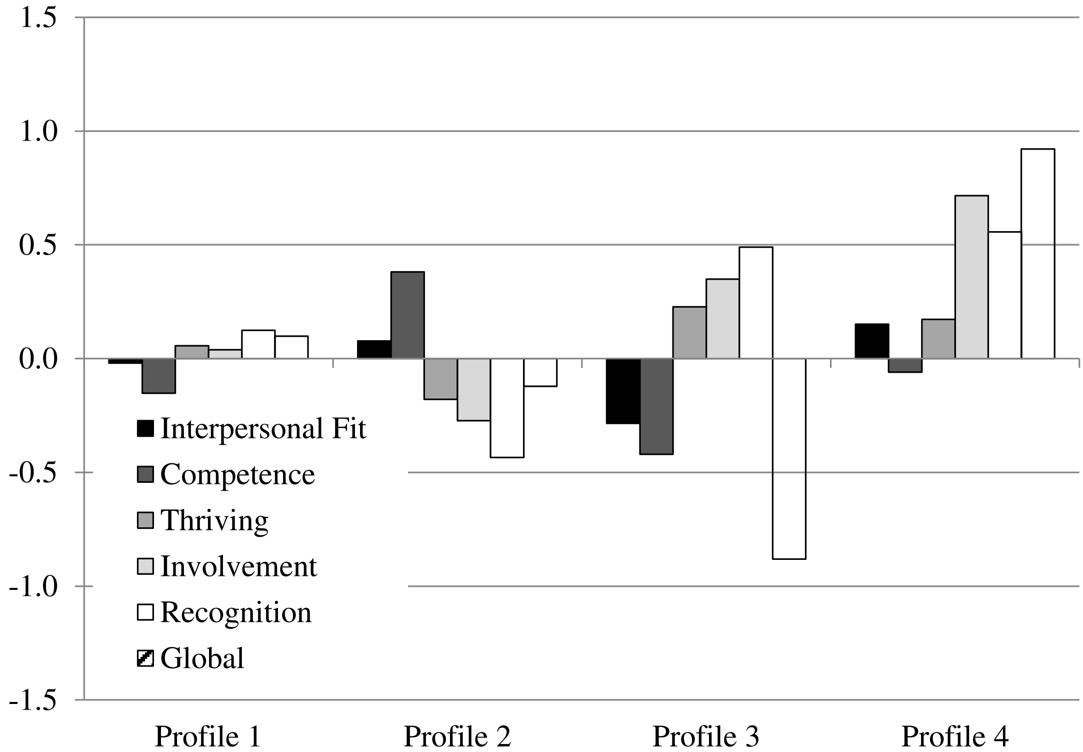



**Figure 4.** *Results from the Latent Profiles Models based on Bifactor Factor Scores (Model 2)*

**Online Supplements:**

# Complementary Variable- and Person-Centered Approaches to the Dimensionality of Psychometric Constructs: Application to Psychological Wellbeing at Work

**Additional Information about WLSMV Estimation.**

Measurement models were estimated using Mplus 7.2 (Muthén & Muthén, 2014) robust weight least square estimator using diagonal weight matrices (WLSMV) and taking into account teachers' nesting within schools with the Mplus design-based correction of standard errors (Asparouhov, 2005). The choice to rely on WLSMV estimation is linked to the fact that this estimator is more 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, 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 (Bandalos, 2014; Beauducel & Herzberg, 2006; Finney & DiStephano, 2013; Flora & Curran, 2004; Lei, 2009; Lubke & Muthén, 2004; Rhemtulla, Brosseau-Liard, & Savalei, 2012). It should be kept in mind that a key limitation of WLSMV, when compared to ML/MLR estimation has to do with the reliance on a slightly less efficient way of handling missing data (Asparouhov & Muthén, 2010), which is not an issue here in light of the very low level of missing data present: No participant had more than one missing response (only 12 participants had a missing response), and no item had more than 3 missing responses.

Asparouhov, T., & Muthén, B.O. (2010). *Weighted Least Square estimation with missing data*. www.statmodel.com/download/GstrucMissingRevision.pdf

Bandalos, D.L. (2014). Relative performance of categorical diagonally weighted least squares and robust maximum likelihood estimation. *Structural Equation Modeling*, *21*, 102-116.

Beauducel, A., & Herzberg, P. Y. (2006). On the Performance of Maximum Likelihood Versus Means and Variance Adjusted Weighted Least Squares Estimation in CFA. *Structural Equation Modeling*, *13*, 186-203.

Finney, S.J., & DiStefano, C. (2013). Non-normal and categorical data in structural equation modeling. In G.R. Hancock & R.O. Mueller (Eds), *Structural Equation Modeling: A Second Course*, *2nd edition* (pp. 439-492). Greenwich, CO: IAP.

Flora, D.B. & Curran, P.J. (2006). An Empirical Evaluation of Alternative Methods of Estimation for Confirmatory Factor Analysis With Ordinal Data. *Psychological Methods*, *9,* 466-491.

Finney, S.J., & DiStefano, C. (2013). Non-normal and categorical data in structural equation modeling. In G.R. Hancock & R.O. Mueller (Eds), *Structural Equation Modeling: A Second Course*, *2nd edition* (pp. 439-492). Greenwich, CO: IAP.

Flora, D.B. & Curran, P.J. (2006). An Empirical Evaluation of Alternative Methods of Estimation for Confirmatory Factor Analysis With Ordinal Data. *Psychological Methods*, *9,* 466-491.

Lei, P.-W. (2009). Evaluating estimation methods for ordinal data in structural Equation modeling. *Quality & Quantity*, *43*, 495-507.

Lubke, G., & Muthén, B. (2004). Applying multigroup confirmatory factor models for continuous outcomes to likert scale data complicates meaningful group comparisons. *Structural Equation Modeling*, *11*, 514-34.

Rhemtulla, M., Brosseau-Liard, P.E., & Savalei, V. (2012). When can categorical variables be treated as continuous? A cmparison of robust continuous and categorical SEM estimation methods under suboptimal conditions. *Psychological Methods, 17*, 354-373.

**Table S1.**

Standardized Parameter Estimates (Loadings λ; Residuals; correlations) for the A Priori CFA and ESEM Solutions

| | ESEM | | | | | | CFA | |
|---|---|---|---|---|---|---|---|---|
| | Fit (λ) | Thriving (λ) | Competency (λ) | Recognition (λ) | Involvement (λ) | Residual (1-$R^2$) | λ | Residual (1-$R^2$) |
| Interpersonal Fit 1[a] | **0.850 *** | -0.130 * | 0.075 * | -0.137 * | 0.199 * | 0.294* | 0.770* | 0.406* |
| Interpersonal Fit 2 | **0.866 *** | 0.002 | -0.203 * | 0.070 * | 0.205 * | 0.235* | 0.808* | 0.347* |
| Interpersonal Fit 3 | **0.781 *** | -0.017 | 0.021 | 0.201 * | -0.119 * | 0.244* | 0.833* | 0.306* |
| Interpersonal Fit 4 | **0.686 *** | 0.017 | 0.083 * | 0.195 * | 0.074 * | 0.184* | 0.929* | 0.137* |
| Interpersonal Fit 5 | **0.566 *** | -0.011 | 0.093 * | 0.410 * | -0.119 * | 0.240* | 0.859* | 0.263* |
| Thriving 1 | 0.005 | **0.422 *** | -0.135 * | 0.393 * | 0.458 * | 0.206* | 0.807* | 0.349* |
| Thriving 2 | 0.095 * | **0.516 *** | 0.190 * | 0.081 * | 0.207 * | 0.265* | 0.873* | 0.237* |
| Thriving 3 | 0.126 * | **0.600 *** | 0.115 * | 0.043 * | 0.181 * | 0.245* | 0.870* | 0.244* |
| Thriving 4 | 0.068 * | **0.690 *** | 0.148 * | 0.073 * | 0.069 * | 0.202* | 0.880* | 0.226* |
| Thriving 5 | -0.068 * | **0.627 *** | 0.089 * | 0.313 * | 0.152 * | 0.216* | 0.878* | 0.229* |
| Competency 1 | 0.100 * | -0.098 * | **0.858 *** | -0.026 | 0.156 * | 0.141* | 0.867* | 0.248* |
| Competency 2 | -0.097 * | 0.078 * | **0.818 *** | 0.139 * | 0.136 * | 0.133* | 0.906* | 0.179* |
| Competency 3 | -0.076 * | -0.217 * | **0.747 *** | 0.197 * | 0.190 * | 0.376* | 0.676* | 0.543* |
| Competency 4 | 0.029 | 0.189 * | **0.715 *** | 0.025 | -0.015 | 0.259* | 0.848* | 0.282* |
| Competency 5 | 0.186 * | 0.347 * | **0.342 *** | 0.230 * | -0.105 * | 0.276* | 0.899* | 0.192* |
| Recognition 1 | 0.221 * | 0.264 * | 0.058 * | **0.597 *** | -0.036 * | 0.147* | 0.885* | 0.217* |
| Recognition 2 | 0.146 * | 0.270 * | 0.001 | **0.598 *** | 0.083 * | 0.217* | 0.844* | 0.287* |
| Recognition 3 | 0.220 * | 0.128 * | 0.478 * | **0.351 *** | -0.149 * | 0.184* | 0.882* | 0.222* |
| Recognition 4 | 0.425 * | -0.181 * | 0.295 * | **0.347 *** | 0.107 * | 0.309* | 0.791* | 0.374* |
| Recognition 5 | 0.334 * | 0.390 * | 0.184 * | **0.036** | -0.046 | 0.380* | 0.785* | 0.383* |
| Involvement 1 | 0.047 * | 0.220 * | 0.435 * | -0.085 * | **0.379 *** | 0.347* | 0.776* | 0.398* |
| Involvement 2 | 0.339 * | 0.507 * | 0.131 * | -0.107 * | **0.080 *** | 0.292* | 0.834* | 0.305* |
| Involvement 3 | 0.005 | 0.193 * | 0.148 * | 0.154 * | **0.567 *** | 0.323* | 0.744* | 0.447* |
| Involvement 4 | 0.313 * | 0.454 * | 0.175 * | -0.102 * | **0.168 *** | 0.278* | 0.866* | 0.250* |
| Involvement 5 | 0.146 * | 0.074 * | -0.046 | -0.126 * | **0.529 *** | 0.676* | 0.371* | 0.862* |

***Factor correlations (CFA: Over the diagonal; ESEM: Under the diagonal)***

| | Interpersonal Fit | Thriving | Competency | Recognition | Involvement |
|---|---|---|---|---|---|
| Interpersonal Fit | | 0.775* | 0.764* | 0.917* | 0.773* |
| Thriving | 0.630* | | 0.799* | 0.874* | 0.907* |
| Competency | 0.632* | 0.547* | | 0.866* | 0.845* |
| Recognition | 0.524* | 0.396* | 0.434* | | 0.815* |
| Involvement | 0.331* | 0.354* | 0.360* | 0.313* | |

***Notes***. [a] Exact item labels are available in Dagenais-Desmarais and Savoie's (2011) appendix; CFA = Confirmatory factor analysis; ESEM = Exploratory structural equation modeling; * $p < 0.01$.

**Table S2.**

Fit Indices from Alternative Person-Centered Models 1 to 3.

| Model | LL | #fp | SF | AIC | CAIC | BIC | ABIC | Entropy | aLMR | BLRT |
|---|---|---|---|---|---|---|---|---|---|---|
| Latent profiles models (Model 1) | | | | | | | | | | |
| 1 Profile | -7258.061 | 10 | 1.099 | 14536.123 | 14595.942 | 14585.942 | 14554.180 | Na | Na | Na |
| 2 Profiles | -6355.820 | 21 | 1.435 | 12753.641 | 12879.262 | 12858.262 | 12791.561 | 0.861 | ≤ 0.001 | ≤ 0.001 |
| 3 Profiles | -5628.817 | 32 | 1.285 | 11321.634 | 11513.056 | 11481.056 | 11379.417 | 0.910 | ≤ 0.001 | ≤ 0.001 |
| 4 Profiles | -5156.591 | 43 | 1.487 | 10399.182 | 10656.406 | 10613.406 | 10476.829 | 0.918 | ≤ 0.001 | ≤ 0.001 |
| 5 Profiles | -4895.440 | 54 | 1.681 | 9898.881 | 10221.905 | 10167.905 | 9996.390 | 0.930 | 0.076 | ≤ 0.001 |
| 6 Profiles | -4670.136 | 65 | 1.554 | 9470.272 | 9859.098 | 9794.098 | 9587.645 | 0.885 | ≤ 0.001 | ≤ 0.001 |
| 7 Profiles | -4437.856 | 76 | 1.719 | 9027.713 | 9482.340 | 9406.340 | 9164.949 | 0.879 | 0.325 | ≤ 0.001 |
| 8 Profiles | -4332.084 | 87 | 1.615 | 8838.167 | 9358.595 | 9271.595 | 8995.266 | 0.882 | 0.240 | ≤ 0.001 |
| Latent profiles models incorporating global &specific factors (Model 2) | | | | | | | | | | |
| 1 Profile | -8141.740 | 12 | 1.833 | 16307.479 | 16379.262 | 16367.262 | 16329.148 | Na | Na | Na |
| 2 Profiles | -7415.539 | 25 | 1.566 | 14881.079 | 15030.627 | 15005.627 | 14926.222 | 0.761 | ≤ 0.001 | ≤ 0.001 |
| 3 Profiles | -6922.869 | 38 | 3.006 | 13921.739 | 14149.052 | 14111.052 | 13990.357 | 0.819 | 0.591 | ≤ 0.001 |
| 4 Profiles | -6402.631 | 51 | 1.256 | 12907.261 | 13212.340 | 13161.340 | 12999.354 | 0.841 | ≤ 0.001 | ≤ 0.001 |
| 5 Profiles | -6288.709 | 64 | 1.263 | 12705.418 | 13088.261 | 13024.261 | 12820.985 | 0.864 | 0.004 | ≤ 0.001 |
| 6 Profiles | -6187.745 | 77 | 1.188 | 12529.490 | 12990.099 | 12913.099 | 12668.532 | 0.801 | 0.189 | ≤ 0.001 |
| 7 Profiles | -6159.630 | 90 | 1.199 | 12499.260 | 13037.634 | 12947.634 | 12661.777 | 0.791 | 0.075 | 0.087 |
| 8 Profiles | -6114.470 | 103 | 1.184 | 12434.940 | 13051.079 | 12948.079 | 12620.931 | 0.783 | 0.203 | 0.238 |
| Factor mixture models (Model 3) | | | | | | | | | | |
| 1 Profile | -6024.329 | 15 | 1.707 | 12078.658 | 12168.387 | 12153.387 | 12105.744 | Na | Na | Na |
| 2 Profiles | -5890.318 | 21 | 2.008 | 11822.637 | 11948.257 | 11927.257 | 11860.557 | 0.955 | 0.031 | ≤ 0.001 |
| 3 Profiles | -5806.970 | 27 | 2.197 | 11667.939 | 11829.452 | 11802.452 | 11716.694 | 0.945 | 0.240 | ≤ 0.001 |
| 4 Profiles | -5744.202 | 33 | 2.176 | 11554.405 | 11751.809 | 11718.809 | 11613.994 | 0.947 | 0.349 | ≤ 0.001 |
| 5 Profiles | -5693.789 | 39 | 1.911 | 11465.577 | 11698.873 | 11659.873 | 11536.001 | 0.940 | 0.219 | ≤ 0.001 |
| 6 Profiles | -5647.099 | 45 | 1.976 | 11384.198 | 11653.385 | 11608.385 | 11465.456 | 0.942 | 0.923 | ≤ 0.001 |
| 7 Profiles | -5601.445 | 51 | 1.987 | 11304.889 | 11609.968 | 11558.968 | 11396.982 | 0.945 | 0.368 | ≤ 0.001 |
| 8 Profiles | -5573.900 | 57 | 1.970 | 11261.799 | 11602.769 | 11545.769 | 11364.726 | 0.935 | 0.513 | ≤ 0.001 |

***Notes***. 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

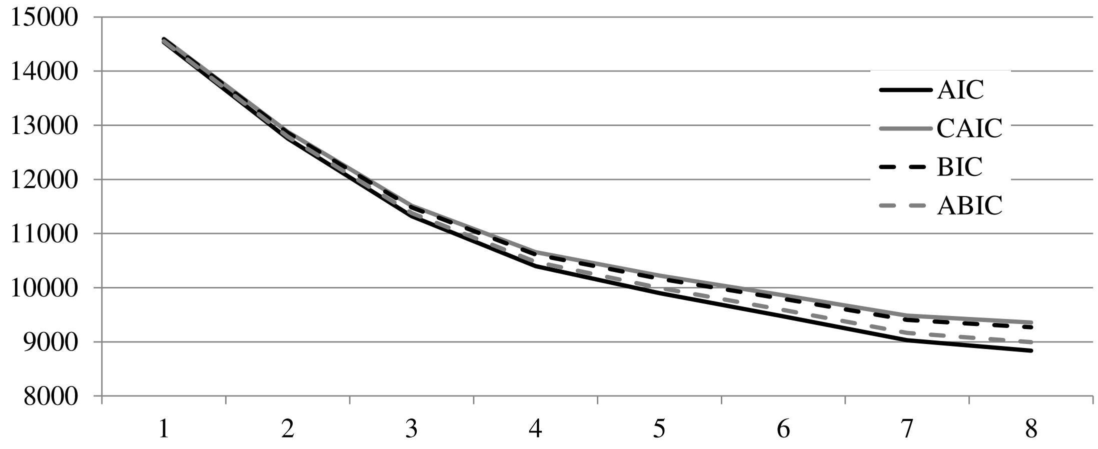



**Figure S1.** Elbow plot of the information criteria for Model 1.

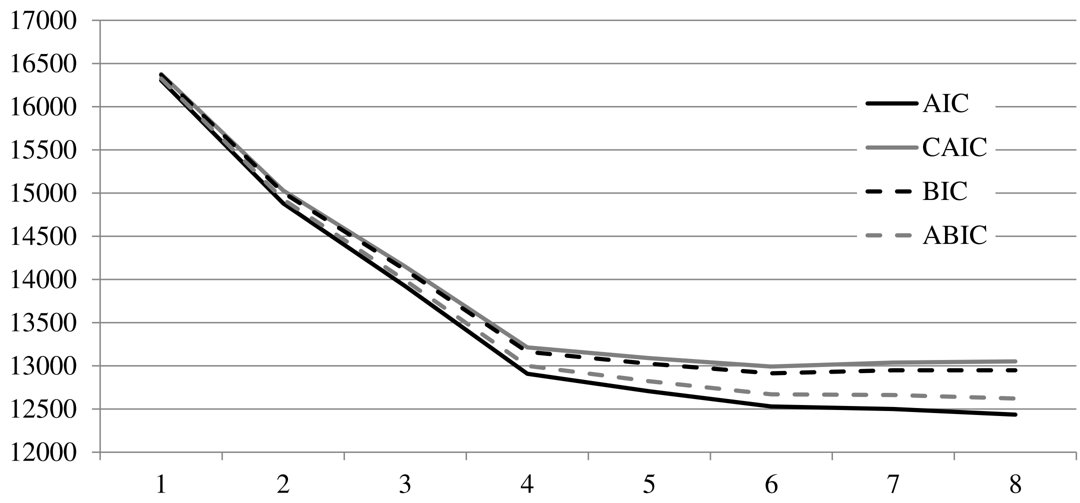



**Figure S2.** Elbow plot of the information criteria for Model 2.

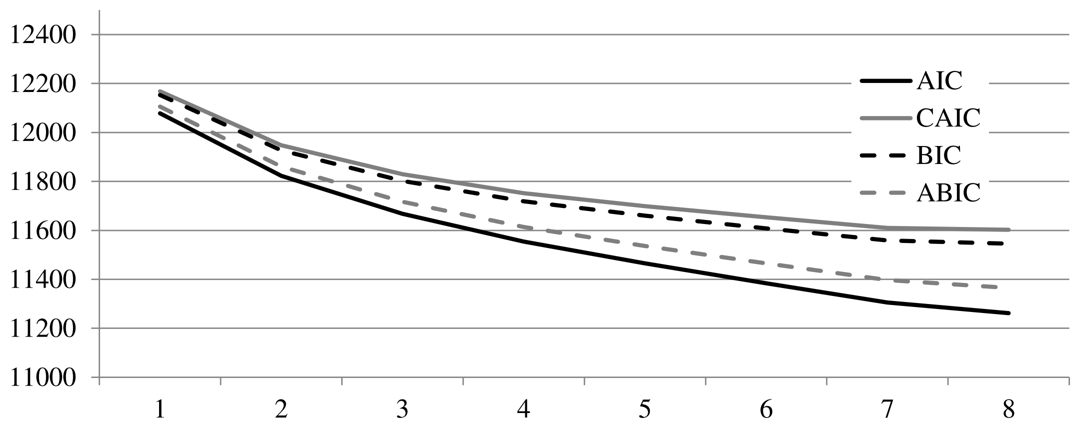



**Figure S3.** Elbow plot of the information criteria for Model 3.

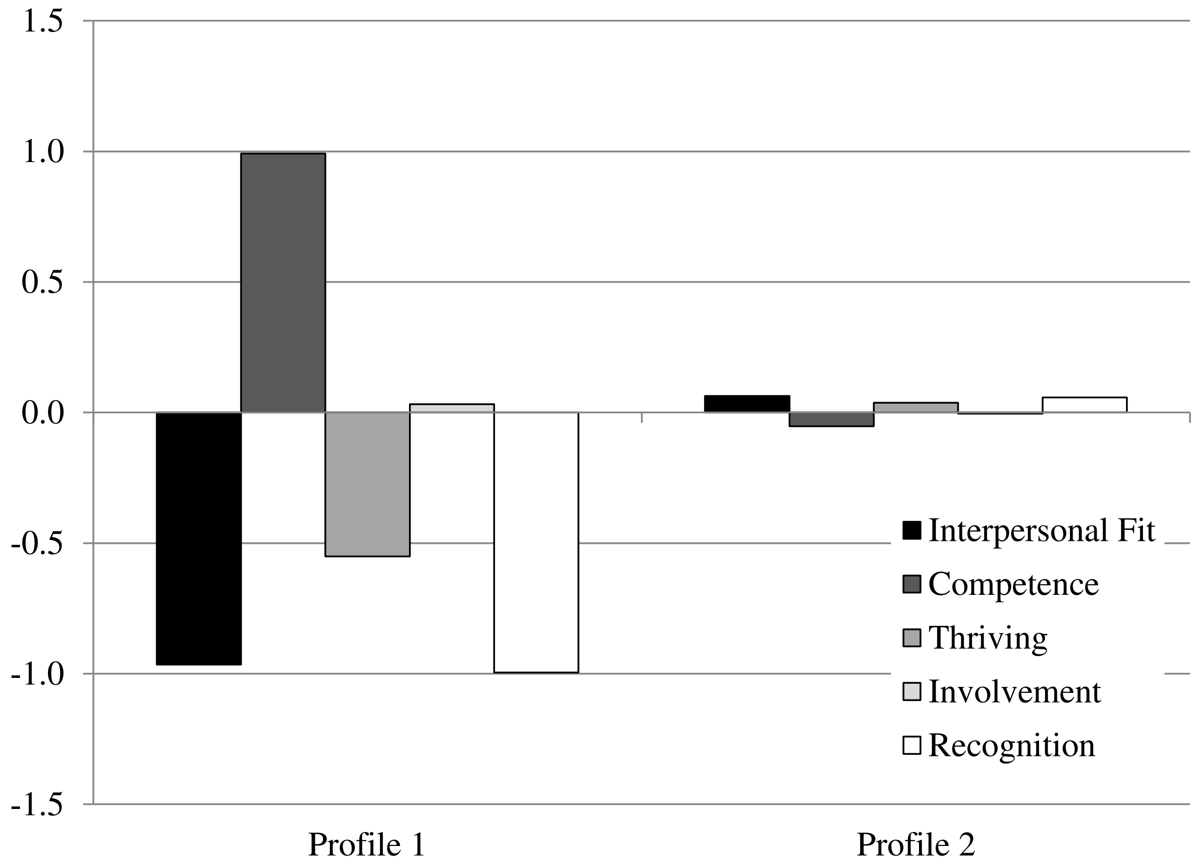



**Figure S4.** *Results from the Factor Mixture Models (Model 3)*

**Title: ICM-CFA**

```
! The following statement is used to identify the data file. Here, the data file is labelled BESEM.dat.
Data:
file = WBglob.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 SCHOOL IFW1 IFW2 IFW3 IFW4 IFW5 TAW1 TAW2 TAW3 TAW4 TAW5 FOC1
FOC2 FOC3 FOC4 FOC5 PRW1 PRW2 PRW3 PRW4 PRW5 DIW1 DIW2 DIW3 DIW4 DIW5;
usevar =  IFW1 IFW2 IFW3 IFW4 IFW5 TAW1 TAW2 TAW3 TAW4 TAW5 FOC1
FOC2 FOC3 FOC4 FOC5 PRW1 PRW2 PRW3 PRW4 PRW5 DIW1 DIW2 DIW3 DIW4 DIW5;
Categorical =  IFW1 IFW2 IFW3 IFW4 IFW5 TAW1 TAW2 TAW3 TAW4 TAW5 FOC1
FOC2 FOC3 FOC4 FOC5 PRW1 PRW2 PRW3 PRW4 PRW5 DIW1 DIW2 DIW3 DIW4 DIW5;
! The missing functions clarifies which missing code is used
! The idvariable function identifies participants' unique identifier,
! The cluster function identifies the nesting structure (here, the code identifies school membership)
missing = all (-9999);
IDVARIABLE = ID;
CLUSTER = SCHID;
! The next section defines the analysis. Here WLSMV estimation is used
! Type = complex provides correction for the nesting structure
Analysis:
TYPE = COMPLEX;
ESTIMATOR = WLSMV;
! The next section defines the model. An ICM-CFA model is specified with 5 factors (labelled FIT,
! THRIV, COMP, RECOG, INVO) 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:
FIT BY IFW1* IFW2 IFW3 IFW4 IFW5 ;
THRIV BY TAW1* TAW2 TAW3 TAW4 TAW5 ;
COMP BY FOC1* FOC2 FOC3 FOC4 FOC5 ;
RECOG BY PRW1* PRW2 PRW3 PRW4 PRW5 ;
INVO BY DIW1* DIW2 DIW3 DIW4 DIW5;
FIT@1;
THRIV@1;
COMP@1;
RECOG@1;
INVO@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 changes in the MODEL section.
! A bifactor CFA model is specified with the same 5 specific factors
! All items are also used to define a global factor G.
model:
G BY IFW1*  IFW2 IFW3 IFW4 IFW5
TAW1 TAW2 TAW3 TAW4 TAW5 FOC1 FOC2 FOC3 FOC4 FOC5 PRW1 PRW2
PRW3 PRW4 PRW5 DIW1 DIW2 DIW3 DIW4 DIW5 ;
FIT BY IFW1* IFW2 IFW3 IFW4 IFW5 ;
THRIV BY TAW1* TAW2 TAW3 TAW4 TAW5 ;
COMP BY FOC1* FOC2 FOC3 FOC4 FOC5 ;
RECOG BY PRW1* PRW2 PRW3 PRW4 PRW5 ;
INVO BY DIW1* DIW2 DIW3 DIW4 DIW5;
G@1;
FIT@1;
THRIV@1;
COMP@1;
RECOG@1;
INVO@1;
! All factors are specified as orthogonal, with their correlations (WITH) constrained to be 0 (@0).
G WITH FIT@0 THRIV@0 COMP@0  RECOG@0  INVO@0;
FIT WITH THRIV@0 COMP@0  RECOG@0  INVO@0;
THRIV WITH  COMP@0  RECOG@0  INVO@0;
COMP WITH  RECOG@0  INVO@0;
RECOG WITH  INVO@0;

SAVEDATA:
FILE IS WBBIF.dat;
FORMAT IS FREE;
SAVE = FSCORES;
```

**Title: ESEM**

```
! The Analysis section is adjusted to request target oblique rotation.
Analysis:
TYPE = COMPLEX;
ESTIMATOR = WLSMV;
ROTATION = TARGET;
! An ESEM model is specified with target oblique rotation.
! The 5 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:

FIT BY IFW1 IFW2 IFW3 IFW4 IFW5
TAW1~0 TAW2~0 TAW3~0 TAW4~0 TAW5~0
FOC1~0 FOC2~0 FOC3~0 FOC4~0 FOC5~0
PRW1~0 PRW2~0 PRW3~0 PRW4~0 PRW5~0
DIW1~0 DIW2~0 DIW3~0 DIW4~0 DIW5~0 (*1);

THRIV BY IFW1~0 IFW2~0 IFW3~0 IFW4~0 IFW5~0
TAW1 TAW2 TAW3 TAW4 TAW5
FOC1~0 FOC2~0 FOC3~0 FOC4~0 FOC5~0
PRW1~0 PRW2~0 PRW3~0 PRW4~0 PRW5~0
DIW1~0 DIW2~0 DIW3~0 DIW4~0 DIW5~0 (*1);

COMP BY IFW1~0 IFW2~0 IFW3~0 IFW4~0 IFW5~0
TAW1~0 TAW2~0 TAW3~0 TAW4~0 TAW5~0
FOC1 FOC2 FOC3 FOC4 FOC5
PRW1~0 PRW2~0 PRW3~0 PRW4~0 PRW5~0
DIW1~0 DIW2~0 DIW3~0 DIW4~0 DIW5~0 (*1);

RECOG BY IFW1~0 IFW2~0 IFW3~0 IFW4~0 IFW5~0
TAW1~0 TAW2~0 TAW3~0 TAW4~0 TAW5~0
FOC1~0 FOC2~0 FOC3~0 FOC4~0 FOC5~0
PRW1 PRW2 PRW3 PRW4 PRW5
DIW1~0 DIW2~0 DIW3~0 DIW4~0 DIW5~0 (*1);

INVO BY IFW1~0 IFW2~0 IFW3~0 IFW4~0 IFW5~0
TAW1~0 TAW2~0 TAW3~0 TAW4~0 TAW5~0
FOC1~0 FOC2~0 FOC3~0 FOC4~0 FOC5~0
PRW1~0 PRW2~0 PRW3~0 PRW4~0 PRW5~0
DIW1 DIW2 DIW3 DIW4 DIW5 (*1);


SAVEDATA:
FILE IS WBESEM.dat;
FORMAT IS FREE;
SAVE = FSCORES;
```

**Title: Bifactor ESEM**

```
! The Analysis section is adjusted to request orthogonal bifactor target rotation.
Analysis:
TYPE = COMPLEX;
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 five specific factors.
model:
G BY IFW1 IFW2 IFW3 IFW4 IFW5
TAW1 TAW2 TAW3 TAW4 TAW5
FOC1 FOC2 FOC3 FOC4 FOC5
PRW1 PRW2 PRW3 PRW4 PRW5
DIW1 DIW2 DIW3 DIW4 DIW5 (*1);

FIT BY IFW1 IFW2 IFW3 IFW4 IFW5
TAW1~0 TAW2~0 TAW3~0 TAW4~0 TAW5~0
FOC1~0 FOC2~0 FOC3~0 FOC4~0 FOC5~0
PRW1~0 PRW2~0 PRW3~0 PRW4~0 PRW5~0
DIW1~0 DIW2~0 DIW3~0 DIW4~0 DIW5~0 (*1);

THRIV BY IFW1~0 IFW2~0 IFW3~0 IFW4~0 IFW5~0
TAW1 TAW2 TAW3 TAW4 TAW5
FOC1~0 FOC2~0 FOC3~0 FOC4~0 FOC5~0
PRW1~0 PRW2~0 PRW3~0 PRW4~0 PRW5~0
DIW1~0 DIW2~0 DIW3~0 DIW4~0 DIW5~0 (*1);

COMP BY IFW1~0 IFW2~0 IFW3~0 IFW4~0 IFW5~0
TAW1~0 TAW2~0 TAW3~0 TAW4~0 TAW5~0
FOC1 FOC2 FOC3 FOC4 FOC5
PRW1~0 PRW2~0 PRW3~0 PRW4~0 PRW5~0
DIW1~0 DIW2~0 DIW3~0 DIW4~0 DIW5~0 (*1);

RECOG BY IFW1~0 IFW2~0 IFW3~0 IFW4~0 IFW5~0
TAW1~0 TAW2~0 TAW3~0 TAW4~0 TAW5~0
FOC1~0 FOC2~0 FOC3~0 FOC4~0 FOC5~0
PRW1 PRW2 PRW3 PRW4 PRW5
DIW1~0 DIW2~0 DIW3~0 DIW4~0 DIW5~0 (*1);

INVO BY IFW1~0 IFW2~0 IFW3~0 IFW4~0 IFW5~0
TAW1~0 TAW2~0 TAW3~0 TAW4~0 TAW5~0
FOC1~0 FOC2~0 FOC3~0 FOC4~0 FOC5~0
PRW1~0 PRW2~0 PRW3~0 PRW4~0 PRW5~0
DIW1 DIW2 DIW3 DIW4 DIW5 (*1);

SAVEDATA:
FILE IS WBESEMBIF.dat;
FORMAT IS FREE;
SAVE = FSCORES;
```

**Title: Latent Profile Analysis (Model 1)**

```
Data:
FILE IS WBESEM.dat;
Variable:
names = ID SCHOOL FIT THRIV COMP RECOG INVO;
usevar =  FIT THRIV COMP RECOG INVO;
missing = all (-9999);
IDVARIABLE = ID;
! The cluster function needs to be taken out at first to obtain BLRT.
CLUSTER = SCHID;
! The classes function specifies the number of profile to estimate.
CLASSES = c (4);
! In the analysis section, type = mixture is specified to conduct latent profile analyses and
! complex to control for nesting.
! 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 COMPLEX;
ESTIMATOR = MLR;
process = 3;
STARTS = 10000 500;
STITERATIONS = 1000;
! 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%
FIT THRIV COMP  RECOG INVO ;
[FIT THRIV COMP  RECOG INVO ];

%c#1%
FIT THRIV COMP  RECOG INVO;
[FIT THRIV COMP  RECOG INVO ];

%c#2%
FIT THRIV COMP  RECOG INVO;
[FIT THRIV COMP  RECOG INVO ];

%c#3%
FIT THRIV COMP  RECOG INVO;
[FIT THRIV COMP  RECOG INVO ];

%c#4%
FIT THRIV COMP  RECOG INVO;
[FIT THRIV COMP  RECOG INVO ];
! Specific sections of output are requested. Add 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 2)**

```
Data:
FILE IS WBESEMBIF.dat;
Variable:
names = ID SCHOOL FIT THRIV COMP RECOG INVO G;
usevar =  FIT THRIV COMP RECOG INVO G;
missing = all (-9999);
IDVARIABLE = ID;
CLUSTER = SCHID;
CLASSES = c (4);
ANALYSIS:
TYPE = MIXTURE COMPLEX;
ESTIMATOR = MLR;
process = 3;
STARTS = 10000 500;
STITERATIONS = 1000;
model:
%OVERALL%
FIT THRIV COMP  RECOG INVO G;
[FIT THRIV COMP  RECOG INVO G];
%c#1%
FIT THRIV COMP  RECOG INVO G;
[FIT THRIV COMP  RECOG INVO G];
%c#2%
FIT THRIV COMP  RECOG INVO G;
[FIT THRIV COMP  RECOG INVO G];
%c#3%
FIT THRIV COMP  RECOG INVO G;
[FIT THRIV COMP  RECOG INVO G];
%c#4%
FIT THRIV COMP  RECOG INVO G;
[FIT THRIV COMP  RECOG INVO G];
output: sampstat standardized stdyx TECH1 TECH2 TECH4
 MOD (1.0) SVALUES;! TECH11 TECH14;
```

**Title: Factor Mixture Analysis (Model 3)**

```
Data:
FILE IS WBESEM.dat;
Variable:
names = ID SCHOOL FIT THRIV COMP RECOG INVO;
usevar =  FIT THRIV COMP RECOG INVO;
missing = all (-9999);
IDVARIABLE = ID;
CLUSTER = SCHID;
CLASSES = c (2);
ANALYSIS:
TYPE = MIXTURE COMPLEX;
ESTIMATOR = MLR;
process = 3;
STARTS = 10000 500;
STITERATIONS = 1000;
! 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.
%OVERALL%
G BY FIT* THRIV COMP  RECOG INVO ;
G@1;
[G@0];
FIT THRIV COMP  RECOG INVO ;
[FIT THRIV COMP  RECOG INVO ];
%c#1%
! Because indicator variances had to be constrained to equality across profiles, the class specific
! statements for the variances were taken our using !
! FIT THRIV COMP  RECOG INVO;
[FIT THRIV COMP  RECOG INVO ];
%c#2%
! FIT THRIV COMP  RECOG INVO;
[FIT THRIV COMP  RECOG INVO ];
```