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Running Head. Need Satisfaction Profiles

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Nicolas Gillet*, Département de Psychologie, Université de Tours, France
Alexandre J.S. Morin*, Substantive Methodological Synergy Research Laboratory, Department of Psychology, Concordia University, Canada
Frédéric Choisay, Département de Psychologie, Université de Tours, France
Evelyne Fouquereau, Département de Psychologie, Université de Tours, France

* The first two authors (N.G. & A.J.S.M.) contributed equally to this article and their order was determined at random: Both should thus be considered first authors.

Corresponding author
Nicolas Gillet,
Université de Tours,
UFR Arts et Sciences Humaines,
Département de psychologie,
3 rue des Tanneurs, 37041 Tours Cedex 1, France.
E-mail: nicolas.gillet@univ-tours.fr

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Abstract

This study examines how a global overarching need satisfaction construct, together with three specific dimensions (autonomy, competence, and relatedness needs satisfaction) combine within different profiles of workers among two independent samples (n = 1419 and n = 677). In addition, this research investigates the role of job demands and resources in the prediction of profile membership, and documents the relation between these profiles and maladaptive outcomes (anxiety and physical fatigue). The results revealed four distinct profiles. Job resources (e.g., participation, organizational support, work scheduling autonomy) predicted an increased likelihood of membership into the *Normative* profile in both samples. The *Globally Dissatisfied yet Moderately Autonomous* profile was also associated with the highest anxiety levels relative to all other profiles.

Key words: Psychological need satisfaction; Latent profiles; Bifactor; Job demands and resources; Burnout

The satisfaction of employees' psychological needs at work represents an important driver of work motivation, well-being, and performance (Deci, Olafsen, & Ryan, 2017). Self-determination theory (SDT; Deci & Ryan, 2000) proposes that the satisfaction of the needs for autonomy (the need to experience a sense of volition and psychological freedom), competence (the need to feel effective), and relatedness (the need to feel connected with others) is crucial to the emergence of self-determined goal-directed behaviors across domains, including work (Deci et al., 2017). While SDT has received strong support from variable-centered studies demonstrating the importance of psychological need satisfaction for employees' functioning, this support remains mainly focused on the isolated effect of each need, without considering the combined effects of autonomy, competence, and relatedness needs satisfaction. In a related way, despite the acknowledgement that individuals might be driven by a combination of multiple forms of needs satisfaction (e.g., Ferrand, Martinent, & Charry, 2015; Souesme, Martinent, & Ferrand, 2016), little is known about the typical configurations that characterize these combinations, the organizational factors involved in their emergence, and their effects on work-related outcomes.

Indeed, 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. In contrast, person-centered analyses, such as latent profile analyses (LPA), identify homogeneous subgroups (or profiles) of workers sharing similar configurations of psychological needs satisfaction. The present study adopts such a person-centered approach to identify naturally occurring profiles characterized by distinct configurations of need satisfaction, their determinants, and their outcomes, while also considering the extent to which results would generalize across two independent samples of employees. Indeed, from a more practical standpoint, the ability to rely on person-centered solutions as guides for the development of intervention strategies tailored at distinct profiles of employees (e.g., Meyer & Morin, 2016) is conditional on the ability to demonstrate that these profiles can be reliably identified across a variety of samples. More precisely, observing similarity means that generic interventions strategies (designed to select, promote, manage, help or support employees based on their profiles) can be developed and expected to generalize to different types of workers, which is a much more parsimonious approach than having to develop strategies targeting different types of profiles for distinct types of workers. More generally, the present research aims to illustrate the utility of innovative statistical procedures by showing how they may help to achieve an improved representation of employees' need satisfaction profiles.

We first reviewed prior studies examining the combined effects of need satisfaction using variable- and person-centered methodologies. Then, we referred to the construct validity of person-centered solutions in order to ascertain that the extracted profiles of participants are meaningful in their own right and can be expected to generalize across samples. Finally, we studied the links between need satisfaction profiles and a set of predictors (job demands and resources) and outcomes (anxiety and physical fatigue) to support a substantive interpretation of the identified profiles.

The Combined Effects of Need Satisfaction

SDT positions the psychological needs for autonomy, competence, and relatedness as essential nutriments for well-being (Deci & Ryan, 2000) and positive work outcomes, such as work engagement and job satisfaction (Huyghebaert, Gillet, Fernet et al., 2018). In contrast, when these needs are not satisfied, maladaptive outcomes, such as burnout, are expected (Trépanier, Fernet, & Austin, 2013). These conclusions hold across a variety of work settings (Gillet, Fouquereau, Forest, Brunault, & Colombat, 2012). SDT also states that all three needs must be fulfilled for psychological well-being to occur (Deci & Ryan, 2000). Thus, if only one or two of the three needs are satisfied, employees' functioning would be less optimal than when the three needs are satisfied. Despite evidence suggesting differential relations between the three needs and work outcomes (Trépanier, Fernet, & Austin, 2016), this hypothesis remains difficult to verify with variable-centered studies given the interrelated nature of the three needs (Bidee et al., 2017; Gillet, Lafrenière, Vallerand, Huart, & Fouquereau, 2014). Two approaches can be used to study these combined effects of psychological needs satisfaction: Variable-centered analyses of interactions or balance, and person-centered analyses of employees' profiles.

Variable-Centered Analyses

Variable-centered tests of interaction effects are designed to assess the extent to which the effects of a variable differ as a function of any other variable (e.g., Marsh, Hau, Wen, Nagengast, & Morin, 2013). In this approach, mutually reinforcing effects would be evidenced by the observation that the

effects of the satisfaction of each need would increase when the level of satisfaction of the other needs increases. In a first study of interactions effects, Vansteenkiste, Lens, Soenens, and Luyckx (2006) showed that the needs for autonomy, competence, and relatedness all predicted unique variance in students' psychological well-being, vitality, and depression. Autonomy need satisfaction also had a weaker positive effect on vitality and a weaker negative effect on depression when relatedness need satisfaction was high. Thus, as suggested by SDT, the experience of interpersonal intimacy and connection with others appeared to compensate for a lack of ability to function in a volitional manner. In addition, the positive relation between competence need satisfaction and vitality was found to be weaker among students with low levels of autonomy compared to those with high levels of autonomy. Thus, again in line with SDT, the ability to function in a volitional manner seemed to help students maximally benefit from high levels of competence need satisfaction. In a more recent study focusing on leisure activities among adults, Chang (2012) observed a similar mutually reinforcing positive interaction between autonomy and competence need satisfaction in the prediction of self-rated health.

Rather than focusing on interactions, Sheldon and Niemiec (2006) argued that understanding the combined effects of need satisfaction required the consideration of the extent to which the satisfaction of the three needs would be balanced with one another. They argued that two employees with the same global level of need satisfaction might present two very distinct need satisfaction profiles, based on the degree to which satisfaction level was similar across the three needs. Using an additional score reflecting the "balance" among the satisfaction of these three needs, their results showed that students who experienced a balanced level of need satisfaction tended to report higher levels of well-being than other students presenting the same global amount of need satisfaction but a more unbalanced profile. However, although Dysvik, Kuvaas, and Gagné (2013) reported similar effects of need balance in the prediction of workers' intrinsic motivation, they also found that need balance did not account for any additional variance in intrinsic motivation once the effects of need satisfaction levels and of their interactions were taken into account. When considering these results, it is important to note that both studies relied on an indirect measurement of need balance via the calculation of difference scores, known to be particularly sensitive to measurement errors (Edwards, 2002). An additional flaw of Dysvik et al.'s (2013) approach comes from the fact that they added the need balance difference score to a regression equation already incorporating the interactions effects. Yet, these interactions effects are known to incorporate an implicit representation of balance effects (e.g., Cheung, 2009; Edwards, 2009). This statistical redundancy could explain Dysvik et al.'s (2013) observation of the limited added-value of balance effects.

Interestingly, recent psychometric research on the structure of need satisfaction ratings has revealed a more direct way to measure of need balance. More precisely, despite the recognition that a complete assessment of psychological need satisfaction should tap into the needs of autonomy, competence, and relatedness (Bidee, Vantilborgh, Pepermans, Griep, & Hofmans, 2016; Knight, Patterson, Dawson, & Brown, 2017), high correlations are typically observed among ratings of autonomy, competence, and relatedness needs satisfaction (Bidee et al., 2017; Gillet et al., 2014). This observation has led many researchers to suggest that employees might experience need satisfaction in a more holistic manner (Huyghebaert, Gillet, Fernet et al., 2018) as a single overarching dimension (Gillet, Forest, Benabou, & Bentein, 2015; Gillet, Fouquereau, Huyghebaert, & Colombat, 2015; Jungert, Van den Broeck, Schreurs, & Osterman, 2018). More recently, studies relying on bifactor models have started to demonstrate that that need satisfaction ratings simultaneously reflect respondents' global levels of need satisfaction across all three needs as well as the more specific levels of satisfaction of their needs for competence, relatedness, and autonomy left unexplained by this global level (Sánchez-Oliva et al., 2017; Tóth-Király, Morin, Bőthe, Orosz, & Rigó, 2018). In a bifactor model (Chen, West, & Sousa, 2006), one Global (G) factor underlying the answers to all items (here reflecting balance in the satisfaction of all three needs) and a series of orthogonal Specific (S) factors (here reflecting the degree of imbalance associated with each need when compared to the others) explain the covariance among a set of items. This bifactor representation of need satisfaction has been supported in the work (Bidee et al., 2016; Sánchez-Oliva et al., 2017), educational (Gillet et al., 2018), sport (Brunet, Gunnell, Teixeira, Sabiston, & Bélanger, 2016), and general life (Tóth-Király et al., 2018) areas, and provides a way to simultaneously obtain a direct explicit estimate of the extent to which the satisfaction of all three needs is balanced for a specific individual (the global component), together with a non-redundant estimate of imbalance in the satisfaction of each need relative to all

others for a specific individual (i.e., expressed as deviations from that global level).

A Person-Centered Perspective

Person-centered analyses, such as LPA, are specifically designed to account for the presence of subpopulations characterized by different parameters (Meyer & Morin, 2016; Morin, 2016). LPA focus on the identification of subgroups characterized by distinct configurations, or profiles, on a set of variables, and are naturally suited to the consideration of the joint effects of variable combinations. More precisely, LPA provide a way to investigate how the various components of need satisfaction will be combined among different types of employees. However, no person-centered research on employees' need satisfaction profiles has so far been conducted in the work domain.

Of direct relevance to the present investigation, Morin and Marsh (2015; also see Morin, Boudrias et al., 2016, 2017) showed that whenever global constructs are assumed to co-exist with specific dimensions assessed from the same set of indicators, failure to control for this global tendency in the context of LPA may mistakenly result in the identification of profiles of employees differing from one another quantitatively (*level*) rather than qualitatively (*shape*). More precisely, these authors note that the identification of *level*-differentiated profiles (i.e., profiles characterized by matching levels across all indicators and differing from one another quantitatively) is generally taken as evidence against the meaningfulness of a person-centered solution, when compared to *shape*-differentiated profiles (i.e., profiles characterized by a qualitatively different configuration of indicators). However, just like ignoring co-existing global and specific constructs is likely to result in inflated factor correlations or cross-loadings in variable-centered analyses, this ignorance is likely to result in the erroneous estimation of *level*-differentiated profiles in LPA. These considerations appear to be particularly important to person-centered research focusing on need satisfaction given the aforementioned research evidence that employees ratings of need satisfaction do indeed tend to follow a bifactor structure encompassing both a global (need balance) and specific (need imbalance) components. Following Morin, Boudrias et al.'s (2016, 2017) recommendations, the need satisfaction profiles estimated in the present study will thus be estimated on the basis of factor scores taken from preliminary bifactor measurement models. According to these authors, this approach not only provides a way to achieve a better control for measurement errors than relying on scale scores (Skrondal & Laake, 2001), but it also provides a way to identify profiles differing on the basis of both the global and specific factors.

Despite the fact that no research has ever been done to estimate need satisfaction profiles in the work area, two recent person-centered studies of need satisfaction profiles have been conducted among geriatric populations. In the first of those studies, Souesme et al. (2016) identified three need satisfaction profiles among geriatric patients characterized by (1) low levels of autonomy and competence needs satisfaction, coupled with moderate levels of relatedness need satisfaction (low-moderate satisfaction profile), (2) high levels of relatedness need satisfaction, coupled with moderate levels of autonomy and competence needs satisfaction (high-moderate satisfaction profile), and (3) high levels of autonomy, competence, and relatedness needs satisfaction (high satisfaction profile). In the second study, Ferrand et al. (2015) similarly identified three need satisfaction profiles among hospitalized elderly people: (1) a high satisfaction profile, (2) a profile characterized by high levels of autonomy and competence needs satisfaction, coupled with moderate levels of relatedness need satisfaction, and (3) a low satisfaction profile.

This study is the first to estimate need satisfaction profiles in the work area, and the first do so while relying on factor scores taken from preliminary bifactor measurement models. Yet, recent person-centered results obtained in the geriatric area, coupled with variable-centered results related to the need balance perspective (Dysvik et al., 2013; Sheldon & Niemiec, 2006; Vansteenkiste et al., 2006), allow us to propose the following hypotheses:

Hypothesis 1. Employees' need satisfaction at work will be best represented by a relatively small number of profiles (i.e., between three and five).

Hypothesis 2. At least one profile reflecting employees' need satisfaction at work will be characterized by high and matching levels of need satisfaction across dimensions.

Hypothesis 3. Additional profiles reflecting employees' need satisfaction at work will be characterized by well-differentiated configurations of need satisfaction across indicators.

A Construct-Validation Perspective

As noted by Morin, Meyer, Creusier, and Biétry (2016), it is critical to systematically assess the construct validity of person-centered solutions in order to ascertain that the extracted profiles of participants

are meaningful in their own right and can be expected to generalize across samples. A way to address these issues is the demonstration that the identified profiles have heuristic and theoretical values, which is best illustrated by the identification of well-differentiated relations between the identified profiles and a series of theoretically-relevant predictors and outcomes, and that they can reliably be replicated across samples (Marsh, Lüdtke, Trautwein, & Morin, 2009; Morin, 2016).

Generalizability. Person-centered evidence is cumulative in nature, and requires an accumulation of results obtained within distinct samples to differentiate the core subset of profiles that systematically emerges, the peripheral profiles that only emerges in specific situations, and the even less frequent set of profiles that simply reflects random sampling variations (e.g., Morin, 2016; Solinger, Van Olffen, Roe, & Hofmans, 2013). In the absence of prior person-centered research on need satisfaction profiles at work, it appeared particularly critical for this study to assess the extent to which the identified profiles would generalize across two distinct samples of participants.

Hypothesis 4. The identified profiles reflecting employees' need satisfaction at work will be replicated across two distinct samples of employees.

Job Demands and Resources. According to the job demands-resources model (Bakker & Demerouti, 2007), a health impairment process is activated by excessive demands that lead to physical and psychological health problems. Job demands refer to those aspects of a job that require sustained physical and/or psychological effort, therefore resulting in physiological and/or psychological costs. In contrast, job resources may help to enhance employees' well-being and to reduce psychological health difficulties as they contribute to achieving goals, reducing the costs associated with job demands, and stimulating personal growth. The effects of job demands (e.g., mental load, workload, role ambiguity) and resources (e.g., information, participation, perceived colleagues support, perceived organizational support, work scheduling autonomy, task identity, and significance) have been examined in relation to burnout, work engagement, and organizational commitment (Bakker, Demerouti, & Sanz-Vergel, 2014; Brauchli, Schaufeli, Jenny, Füllemann, & Bauer, 2013). This influence has been shown to occur through personal resources (Xanthopoulou, Bakker, Demerouti, & Schaufeli, 2007), equity (Hu, Schaufeli, & Taris, 2013) or recovery (Kinnunen, Feldt, Siltaloppi, & Sonnentag, 2011). Attention has also been paid to the effects of job demands and resources on need satisfaction (Gillet, Fouquereau et al., 2015; Trépanier et al., 2015). Fernet, Austin, Trépanier, and Dussault (2013) showed that employees' perceptions of role ambiguity negatively predicted their competence need satisfaction.

Despite the well-documented importance of job demands and resources in the work context (Alarcon, 2011), to the best of our knowledge, no person-centered research has examined the effects of job demands and resources on employees' need satisfaction profiles. We thus leave as an open research question the exact differential role of job demands and resources in need satisfaction profiles. However, prior variable-centered studies (Fernet et al., 2013; Trépanier et al., 2015) suggest that job demands and resources should predict membership into need satisfaction profiles. More specifically, higher job demands should predict a higher likelihood of membership into the profiles characterized by lower levels of autonomy, competence, and relatedness needs satisfaction. In contrast, higher job resources should predict a higher likelihood of membership into the profiles characterized by higher levels of autonomy, competence, and relatedness needs satisfaction (Trépanier et al., 2015). Nevertheless, because of the demonstrated benefits of need balance (Dysvik et al., 2013; Sheldon & Niemiec, 2006; Vansteenkiste et al., 2006), we also expect that higher job resources and lower job demands should predict a higher likelihood of membership into the profiles in which there is a balance across the three needs (i.e., with high levels of global need satisfaction and low specific levels of imbalance in the satisfaction of the needs for autonomy, competence, and relatedness).

Outcomes of Profile Membership. The present study also seeks to assess relations between the need satisfaction profiles and employees' levels of job anxiety and physical fatigue. These two outcome variables were retained based on previous research showing that they present significant associations with employees' need satisfaction (Huyghebaert, Gillet, Lahiani, Dubois-Fleury, & Fouquereau, 2018; Trépanier et al., 2013). Previous variable-centered research has shown need satisfaction to be associated with a variety of desirable outcomes (e.g., lower anxiety and burnout; see Deci et al., 2017). In addition, numerous studies (Trépanier et al., 2016) report well-differentiated relations between each need and work outcomes. However, research also leads to divergent conclusions regarding the relative importance of each need in the prediction of outcomes. For instance, Sheldon and Niemiec's (2006) results suggest that moderate levels of autonomy need satisfaction are

not necessarily harmful when combined with equally moderate levels of competence and relatedness needs satisfaction among undergraduate students. In addition, autonomy need satisfaction was less strongly related to well-being when relatedness need satisfaction was high (Vansteenkiste et al., 2006). Given that all of these previous results stem from variable-centered research, we leave as an open research question the exact differential nature of the associations between the need satisfaction profiles and employees' levels of anxiety and physical fatigue. Yet, these previous variable-centered results still allow us to expect that the profile characterized by the highest levels of autonomy, competence, and relatedness needs satisfaction would be associated with the lowest levels of anxiety and physical fatigue. Likewise, the profile characterized by the lowest levels of autonomy, competence, and relatedness needs satisfaction should similarly be associated with the highest levels of anxiety and physical fatigue. Finally, a profile characterized by differentiated scores across specific needs, attesting to need imbalance (e.g., high specific levels of autonomy coupled with low specific levels of competence and relatedness) should be associated with higher levels of anxiety and physical fatigue than a profile characterized by matching levels across all indicators (i.e., high levels on the global need satisfaction factors coupled with low levels of imbalance evidenced by average scores on the specific autonomy, competence, and relatedness factors).

Method

Participants and Procedure

Sample 1. This study was conducted in the French Air Force. Soldiers received information about the study via the intranet network of the French Air Force, and were then sent an e-mail inviting them to complete an online survey. Each soldier also received a letter explaining the study's purposes, a consent form stressing that participation was voluntary, and a link to the online survey. A sample of 580 contract and 839 career soldiers (1107 men and 312 women) participated in this study. Respondents were aged between 20 and 62 years (M = 36.61, SD = 8.06), had an average tenure of 16.29 years (SD = 8.44) in the French Air Force and of 3.56 years (SD = 3.26) in their position.

Sample 2. Research assistants distributed a paper-based questionnaire to a convenience sample of 677 workers (309 men; 367 women; 1 participant did not indicate his/her gender) from organizations (e.g., public hospitals, industries, sales, and services) located in France. In each organization, participants received a survey packet including the questionnaire, a cover letter explaining the study's purposes, and a consent form stressing that participation was anonymous and voluntary. Questionnaires took approximately 20 minutes to complete. Completed questionnaires were returned to the research assistants. Respondents were aged between 18 and 61 years (M = 37.56, SD = 12.79), had an average tenure of 10.19 years (SD = 10.66) in their organization and of 6.65 years (SD = 8.11) in their position. A total of 557 participants were full-time workers (82.3%). Thirty-eight participants (5.6%) had no diploma, 211 completed vocational training (31.2%), 187 completed high school (27.6%), 231 completed university (34.1%), and 10 did not indicate their education level (1.5%).

Measures

***Need Satisfaction*.** Need satisfaction was measured with fifteen items from a measure initially developed in French by Gillet, Rosnet, and Vallerand (2008). In the present study, these items were contextualized with the referent "At work…", and were rated on a 7-point scale ranging from 1 (strongly disagree) to 7 (strongly agree). Five items assessed the need for competence (α in Sample 1 = .85; α in Sample 2 = .86; e.g., "I feel like I am able to meet the demands of the tasks that I have to perform"), five items referred to the need for autonomy (α in Samples 1 and 2 = .89; e.g., "I have the opportunity to make decisions about the tasks that I have to perform"), and five items measured the need for relatedness (α in Sample 1 = .83; α in Sample 2 = .80; e.g., "I get along well with the people whom I interact with"). Previous studies showed good psychometric properties for this scale in work settings (e.g., Gillet et al., 2012).

***Job demands and resources (Sample 1: Predictors)*.** Mental load (4 items, α = .87; e.g., "Do you have to give continuous attention to your work?"), workload (4 items, α = .85; e.g., "Do you have too much work to do?"), role ambiguity (4 items, α = .81; e.g., "Do you know exactly for what you are responsible and which areas are not your responsibility?", reversed item), information (4 items, α = .85; e.g., "Does your work give you the opportunity to check on how well you are doing your work?"), participation (4 items, α = .88; e.g., "Can you participate in decisions affecting issues related to your work?"), and perceived colleagues support (4 items, α = .90; e.g., "Can you count on your colleagues when you encounter difficulties in your work?") were measured with six subscales from a measure

developed and validated in French by Lequeurre, Gillet, Ragot, and Fouquereau (2013). Responses were provided on a 7-point response scale ranging from 1 (never) to 7 (always).

Job resources (Sample 2: Predictors). Work scheduling autonomy (3 items, α = .73; e.g., "The job allows me to plan how I do my work"), task identity (4 items, α = .78; e.g., "The job allows me to complete work I start"), and significance (4 items, α = .78; e.g., "The job has a large impact on people outside the organization") were measured via scales from the French version of the Work Design Questionnaire (Bigot et al., 2014; Morgeson & Humphrey, 2006). Items were rated on a 7-point scale (1- strongly disagree to 7- strongly agree).

Perceived organizational support (Sample 2: Predictor). Perceived organizational support was assessed using 8 items (α = .87; e.g., "My organization really cares about my well-being") from the French version (Gillet, Colombat, Michinov, Pronost, & Fouquereau, 2013; Gillet, Huart, Colombat, & Fouquereau, 2013) of Eisenberger, Huntington, Hutchison, and Sowa's (1986) measure. All items were rated on a 1 (strongly disagree) to 7 (strongly agree) response scale.

Anxiety (Sample 2: Outcome). A 5-item subscale (α = .85) from the French version (Gillet, Fouquereau, Lafrenière, & Huyghebaert, 2016) of the Job-Anxiety-Scale (Linden, Muschalla, & Olbrich, 2008) was employed (e.g., "Colleagues or family have already told me that I am worrying too much about my work") to assess anxiety. Participants responded to items on a 7-point Likert-scale ranging from 1 (totally disagree) and 7 (totally agree).

Physical fatigue (Sample 2: Outcome). Physical fatigue was assessed with 6 items (α = .92; e.g., "I feel tired") from the French version (Sassi & Neveu, 2010) of the Shirom and Melamed's (2006) burnout measure. Responses were provided on a 7-point scale (1- never to 7- always).

Analyses

Preliminary Analyses

Mixture models (including LPA) are often estimated using mean or sum scores as profile indicators. Although latent factors controlled for measurement errors (i.e., models where the items are used to estimate factors, themselves used as profile indicators) provide a stronger approach (e.g., Bollen, 1989), fully-latent mixture models are rarely seen (e.g., Morin, Scalas, & Marsh, 2015). Indeed, given their computational complexity, it is often impossible to estimate fully-latent mixture models. An alternative, which is becoming more frequent recently, is to rely on factor scores saved from preliminary measurement models (e.g., Gillet, Morin, & Reeve, 2017; Kam, Morin, Meyer, & Topolnytsky, 2016). Factor scores do not explicitly control for measurement errors the way latent variables do, but provide a partial control for measurement errors by giving more weight to items presenting lower residuals (Skrondal & Laake, 2001), and preserve the nature of the measurement model (i.e., measurement invariance and bifactor structure) better than scale scores (Morin, Meyer et al., 2016). This is the approach taken in the present study for profile indicators, predictors, and outcomes.

In addition, given the aforementioned mounting evidence regarding the superiority of a bifactor representation of need satisfaction ratings (Sánchez-Oliva et al., 2017; Tóth-Király et al., 2018), first-order and bifactor models were systematically contrasted. As expected, our results supported the superiority of a bifactor representation of need satisfaction ratings. Yet, for comparison purposes, factor scores from preliminary first-order and bifactor measurement models were used as inputs for the analyses. These factor scores were saved from multi-group models of measurement invariance (Millsap, 2011) to ensure the comparability of the results across samples. Extensive details on these measurement models, their measurement invariance, and composite reliability are reported in the online supplements. All analyses relied on Mplus 8.0's (Muthén & Muthén, 2017) robust maximum likelihood (MLR) estimator, and Full Information Maximum Likelihood (FIML; Enders, 2010) to handle missing responses (Sample 1: 0%; Sample 2: 0.00-1.62%).

Person-Centered Analyses

LPA were first estimated separately in each sample using the need satisfaction factor scores as profile indicators to verify whether the same number of profiles would be extracted in both samples (e.g., Morin & Wang, 2016). In each sample, we examined solutions including 1 to 8 latent profiles in which the means of the need satisfaction factor scores were freely estimated in all profiles. Despite the advantages of models in which the indicators' variances are also freely estimated in all profiles (Morin, Maïano et al., 2011), these models tended to converge on improper solutions or not at all. This suggests the inadequacy of these models and their overparameterization, and the superiority of our more

parsimonious models (Chen, Bollen, Paxton, Curran, & Kirby, 2001). LPA were conducted using 5000 random sets of start values, 1000 iterations, and retaining the 200 best solutions for final optimization (Hipp & Bauer, 2006). The procedure used to determine the optimal number of profiles, as well as the similarity in the profile solutions across samples, is described in the online supplements.

Predictors and Outcomes of Profile Membership

The results reported in the online supplements supported the similarity of the profiles estimated (in terms of number, structure, and size) across samples. This most "similar" profile was retained in order to test associations between the profiles, predictors, and outcomes in order to ensure the comparability of results. Because predictors and outcomes differed across samples, separate models had to be estimated. To ensure that the final, most similar, LPA solution remained unchanged by the addition of predictors and outcomes (Diallo, Morin, & Lu, 2017; Marsh et al., 2009; Morin, Morizot, Boudrias, & Madore, 2011), sample-specific solutions aligned with the final retained multi-group solution were defined using the manual three-step approach described by Asparouhov and Muthén (2014; also see Morin & Litalien, 2017). Multinomial logistic regressions were conducted separately in each sample to test the relations between the predictors and profile membership. In Sample 2, outcomes were also incorporated into the final solution. Outcome levels were contrasted using a model-based approach proposed by Lanza, Tan, and Bray (2013) and implemented through the Auxiliary (DCON) function (Asparouhov & Muthén, 2014). Predictors and outcomes were incorporated to these models as factors scores saved from preliminary measurement models estimated separately in each sample. In these models, each predictor and outcome was defined as a simple correlated CFA factor. One a priori correlated uniqueness was added to the model estimated in Sample 2 to account for the negative wording of two of the perceived organizational support items (Marsh, Scalas, & Nagengast, 2010). In both samples, these preliminary measurement models resulted in an acceptable level of model fit (CFI/TLI $\geq$ .90; RMSEA $\leq$ .06). Parameter estimates from these preliminary measurement models are reported in Tables S5 (Sample 1) and S6 (Sample 2) of the online supplements, and the correlations among all variables used in both samples are reported in Table S7 (Sample 1) and S8 (Sample 2) of these online supplements. It is interesting to note that estimates of composite reliability obtained in these preliminary measurement models were fully satisfactory for all variables (Sample 1: ω = .819 to .910; Sample 2: ω = .749 to .918).

Results

Latent Profile Solutions

In line with Hypothesis 1, the class enumeration procedure and tests of profile similarity described in the online supplement supported a solution including four profiles per sample for the LPA solution based on bifactor factor scores. These profiles presented the same structure and relative sizes across samples, thus supporting Hypothesis 4. However, within-profile variation on the relatedness S-factor, but not on the other factors, were found to be slightly higher in Sample 2. For comparison purposes, the 4-profile solution was also retained for models based on first-order factor scores, and tests of profile similarity conducted on this solutions converged on identical conclusions. These models were thus retained for interpretation, and are graphically illustrated in Figures 1 (bifactor) and 2 (first-order). As noted above, these solutions were characterized by the same profile structure and size across samples. Parameter estimates from these models are reported in Table S11 of the online supplements. As expected, the solution based on first-order factor scores resulted in substantively uninteresting profiles presenting almost pure *level* differences, revealing a very small profile characterized by extremely low levels of need satisfaction (Profile 1: 1.44%), two large profiles characterized by average (Profile 2: 40.35%) or high (Profile 4: 41.02%) levels of need satisfaction, and one moderately large profile characterized by low levels of need satisfaction (17.18%). In contrast, the solution based on bifactor factor scores resulted in profiles presenting clear *shape* differences. This observation is aligned with Morin, Boudrias et al.'s (2016, 2017) observation that relying on bifactor factor scores helps to extract profiles that can differ from one another both in terms of this global construct (here the global level of need satisfaction), but also based on their specific levels of autonomy, competence, and relatedness needs satisfaction. For this reason, we retained the LPA solution based on bifactor factor scores as our final solution. For this solution, the results also reveal a high level of classification accuracy of participants into their most likely profile in both samples (reported in Table S12 of the online supplements), varying from 82.3% to 94.7% in Sample 1, and from 72.1% to 94.1% in Sample 2.

The solution obtained when using bifactor factor scores is illustrated in Figure 1. A first noteworthy observation lies in the identification of a *Normative* profile (Profile 1), representing 77.13% of the employees. The label *Normative* was retained to reflect the fact that this profile not only characterized the majority of employees, but also reflected a subpopulation of employees whose global levels of need satisfaction are slightly above average (about .3 SD higher than the sample average), whereas their specific levels of autonomy, competence, and relatedness satisfaction are similarly close to the average. The identification of such a profile suggested that the basic psychological needs of most employees tended to be globally met at work and to display a strong level of balance across each of the three needs. In contrast, the remaining profiles were characterized not only by moderately low (Profile 2) to very low (Profiles 3 and 4) global levels of need satisfaction, but also by a strong imbalance in the degree of satisfaction of each specific need. Thus, members of Profile 2 were characterized by very low levels of satisfaction of their specific need for autonomy, but by moderately high levels of satisfaction of their specific needs for competence and relatedness. This *Globally Dissatisfied yet Moderately Competent and Connected* profile characterized 11.87% of the employees. In contrast, members of Profile 3 were characterized by low levels of satisfaction of their specific needs for autonomy and competence, but by very high levels of satisfaction of their specific need for relatedness. This *Globally Dissatisfied yet Highly Connected* profile characterized 3.34% of the employees. Finally, members of Profile 4 were characterized by very low levels of satisfaction of their specific need for relatedness, but by average to moderately high levels of satisfaction of their specific needs for autonomy and competence. This *Globally Dissatisfied yet Moderately Autonomous* profile characterized 7.66% of the employees. More generally, these results supported Hypotheses 2 and 3.

Predictors of Profile Membership. Associations between predictors and profile membership are reported in Table 1. Before considering specific results, it is noteworthy that these predictors, when taken together, were able to achieve a statistically significant differentiation between all pairs of profiles. More precisely, in Sample 1, mental load predicted an increased likelihood of membership in the *Globally Dissatisfied yet Moderately Competent and Connected* profile (2) relative to all other profiles. Role ambiguity predicted an increased likelihood of membership into the *Globally Dissatisfied yet Moderately Competent and Connected* (2) and *Globally Dissatisfied yet Highly Connected* (3) profiles relative to the *Normative* (1) one. In contrast, the ability to participate in decisions predicted an increased likelihood of membership into the *Normative* (1) and *Globally Dissatisfied yet Moderately Autonomous* (4) profiles relative to the *Globally Dissatisfied yet Moderately Competent and Connected* (2) and *Globally Dissatisfied yet Highly Connected* (3) profiles. Perceptions of colleagues support predicted an increased likelihood of membership into all profiles relative to the *Globally Dissatisfied yet Moderately Autonomous* (4) profile. Finally, workload and information were unrelated to profile membership.

In Sample 2, perceptions of organizational support predicted an increased likelihood of membership into the *Normative* (1) and *Globally Dissatisfied yet Moderately Competent and Connected* (2) profiles relative to the *Globally Dissatisfied yet Moderately Autonomous* (4) profile. This predictor was also associated with an increased likelihood of membership into the *Normative* (1) profile relative to the *Globally Dissatisfied yet Moderately Competent and Connected* (2) profile. Work scheduling autonomy predicted an increased likelihood of membership into the *Normative* (1) profile relative to all other profiles, whereas neither task identity nor significance presented any statistically significant association with the likelihood of profile membership.

Outcomes of Profile Membership. The associations between profile membership and the outcomes obtained in Sample 2 are reported in Table 2. These analyses reveal that the highest anxiety levels were associated with the *Globally Dissatisfied yet Moderately Autonomous* profile (4) relative to all other profiles, which could not be differentiated from one another in terms of anxiety. In contrast, levels of physical fatigue were the highest in the *Globally Dissatisfied yet Moderately Autonomous* (4) and *Globally Dissatisfied yet Highly Connected* (3) profiles, which could not be differentiated from one another, followed by the *Globally Dissatisfied yet Moderately Competent and Connected* profile (2), with the lowest levels observed among the *Normative* profile (1).

Discussion

Relying on a recent bifactor operationalization of need satisfaction at work (Sánchez-Oliva et al., 2017), we sought to identify profiles of employees characterized by distinct configurations of need satisfaction. To do so, we relied on a proper disaggregation of employees' ratings of their global levels

of need satisfaction from more specific ratings of imbalance related to the satisfaction of the need for autonomy, competence, and relatedness relative to this global level of need satisfaction.

Characteristics of Need Satisfaction Profiles

Morin, Boudrias et al. (2016, 2017) demonstrated the importance of adopting a proper variable-centered measurement model as a starting point for person-centered analyses. Importantly, they showed that failure to take into account construct-relevant psychometric multidimensionality related to the presence of a bifactor measurement structure could lead to the estimation of latent profiles in which *shape* differences are minimized and *level* differences artificially inflated. Indeed, when profiles were estimated based on first-order factor scores, the results revealed profiles presenting almost pure *level* differences (similar to results previously reported in the geriatric context by Ferrand et al., 2015). In contrast, when the profiles were estimated based on bifactor factor scores, our results revealed much clearer *shape* differences. More precisely, our results revealed four well-differentiated need satisfaction profiles: (a) *Normative*; (b) *Globally Dissatisfied yet Moderately Competent and Connected*; (c) *Globally Dissatisfied yet Highly Connected*; and (d) *Globally Dissatisfied yet Moderately Autonomous*. The identification of a large (77.1%) *Normative* profile is interesting and suggests that, for the majority of the sample, global levels of need satisfaction remain satisfactory and balanced with the specific needs (autonomy, competence, and relatedness). This result is well-aligned with the results from Morin, Boudrias et al. (2016, 2017) who also identified the presence of a dominant *normative* profile characterized by moderate levels of well-being (2017) or psychological health (2016) across indicators. Apart from this profile characterized by balanced levels of need satisfaction across specific needs and a slightly above average level of global need satisfaction, it is interesting to note that all other profiles are characterized both by discrepant levels of need satisfaction across needs, and by low global levels of need satisfaction, supporting Sheldon and Niemiec's (2006) assertion of the importance of achieving balanced levels of need satisfaction.

Generally, these profiles support the value of a finer-grained representation of need satisfaction incorporating both the global extent to which all three needs are met, and the specificity associated with each need over and above this global level (need imbalance, expressed as deviations from the global level), rather than simply focusing on a global score of need satisfaction (Vansteenkiste et al., 2006). Importantly, our results also showed that these profiles presented a well-differentiated pattern of associations with the two outcomes considered in this study (i.e., anxiety and physical fatigue).

Effects of Need Satisfaction Profiles on Work Outcomes

To better understand the meaning and the psychological processes involved in these profiles, it is helpful to consider their associations with the two outcomes considered in this study. Specifically, the lowest levels of physical fatigue were observed in the *Normative* (1) profile, which was the profile characterized by the highest global level of need satisfaction, coupled with the most balanced need satisfaction profile. Based on prior theoretical developments (Sheldon & Niemiec, 2006) and results (Sánchez-Oliva et al., 2017; Tóth-Király et al., 2018), this result demonstrates the key role of employees' need satisfaction balance in the prediction of work outcomes.

One might wonder about the non-significant differences between the *Normative* profile and the *Globally Dissatisfied yet Moderately Competent and Connected* and *Globally Dissatisfied yet Highly Connected* ones in terms of anxiety. Similarly, the *Globally Dissatisfied yet Moderately Autonomous* profile appeared to be the least desirable one from an outcomes perspective. When we compare these three globally dissatisfied profiles, it is interesting to note that the least desirable one is associated with the lowest levels of relatedness need satisfaction, whereas both the *Globally Dissatisfied yet Moderately Competent and Connected* and *Globally Dissatisfied yet Highly Connected* profiles present high levels of relatedness need satisfaction. These results thus suggest that high levels of relatedness need satisfaction could somehow help to buffer the negative effects of low global levels of need satisfaction. This interpretation is consistent with the theoretically positive role ascribed to relatedness need satisfaction (Vansteenkiste et al., 2006), and the idea that relatedness need satisfaction leads to positive outcomes by helping the internalization process of work-related rules and regulations (Dysvik et al., 2013). Managers should thus focus their efforts in helping to increase relatedness need satisfaction, prior to any other needs, among globally dissatisfied workers.

Finally, the *Globally Dissatisfied yet Moderately Competent and Connected* profile was associated with lower levels of physical fatigue than the *Globally Dissatisfied yet Highly Connected* profile. It is noteworthy that the key difference between these two profiles appears to lie in the

achievement of a more balanced level of need satisfaction across at least two of the needs (competence and relatedness) in the first of these profiles. This result thus suggests that competence need satisfaction might also be helpful, particularly in combination with relatedness need satisfaction. This observation is aligned with the results from previous studies showing that employees who believe in their capabilities to organize and execute their job tasks display lower levels of burnout (Consiglio, Borgogni, Alessandri, & Schaufeli, 2013). Employees with high levels of competence need satisfaction persevere when faced with difficulties and tend to interpret demands as challenges rather than hindrances or uncontrollable events. They have also optimistic feelings about their performance and their own personal achievements (Ventura, Salanova, & Llorens, 2015). It thus appears to be better for globally dissatisfied employees to find a way to satisfy their specific need for competence, as doing so may contribute to preserve their emotional resources (Hobfoll, 1989).

More generally, and as mentioned above, these results confirm that specific needs tend to present well-differentiated relations with outcomes when global levels of need satisfaction are considered. They point out the importance of exploring synergistic relations between the three needs and argue for the added-value of jointly considering the global and specific levels of need satisfaction. However, our results suggest that some of the compensatory effects described above are limited to one outcome (anxiety) without generalizing to the other one (physical fatigue). Sánchez-Oliva et al. (2017) demonstrated the nomological validity of global (balance) and specific (imbalance) ratings of need satisfaction in relation to burnout components (emotional exhaustion, depersonalization, and professional efficacy). Their findings revealed that global levels of need balance were negatively associated to all burnout components. They also showed that specific levels of imbalance in the satisfaction of the need for competence (S-factor: having one's need for competence satisfied more than one's global levels of need satisfaction) were negatively related to depersonalization, and positively related to professional efficacy, whereas imbalance in relatedness need satisfaction was negatively related to emotional exhaustion. No such effects were found in relation to imbalance in autonomy need satisfaction. Such results suggest that the combined effects of global and specific levels of need satisfaction may differ as a function of the outcomes under study. This observation reinforces the importance for future research to consider a broader range of desirable (e.g., organizational citizenship behaviors, organizational commitment) and undesirable (e.g., workaholism, work-family conflict) outcomes in order to better understand the mechanisms at play in explaining these differential effects. In addition, future studies should examine how the effects of balance in need satisfaction change as a function of the imbalance related to autonomy, competence, and relatedness.

Predictors of Employees' Need Satisfaction Profiles

The present study was finally designed to investigate the role of job demands and resources in the prediction of profile membership. To our knowledge, no research has yet considered the factors that contribute to the development of employees' need satisfaction profiles. The present results first showed that job demands such as role ambiguity predicted a decreased likelihood of membership into the *Normative* profile, while job resources (e.g., participation, organizational support, work scheduling autonomy) predicted an increased likelihood of membership into this profile. This finding is in line with research showing that job demands tend to be associated with lower levels of need satisfaction (Gillet, Fouquereau et al., 2015; Trépanier et al., 2015) and negative outcomes (Bakker et al., 2014) given that they negatively relate to equity (Hu et al., 2013) and recovery (Kinnunen et al., 2011). In contrast, job resources are associated with higher levels of need satisfaction (Fernet et al., 2013) and positive outcomes (Brauchli et al., 2013) as they have positive influence on employees' recovery experiences (Kinnunen et al., 2011). Furthermore, perceptions of organizational and colleagues support also predicted a decreased likelihood of membership into the least desirable *Globally Dissatisfied yet Moderately Autonomous* profile when compared to the other globally dissatisfied profiles characterized by higher levels of relatedness need satisfaction. This result is in line with past studies showing that perceived organizational and colleagues support foster relatedness need satisfaction as they tend to be associated with lower interpersonal conflicts at work (Eisenberger & Stinglhamber, 2011). Other investigations also demonstrated that perceived organizational and colleagues support tended to positively relate to psychological need satisfaction (Gillet et al., 2012).

Limitations and Directions for Future Research

The present study has limitations. First, we used self-report measures that can be impacted by social desirability and self-report biases. We thus encourage researchers to conduct additional research

using more objective turnover data as well as informant-reported (e.g., supervisor) measures of performance as ultimate outcomes. Second, although our treatment of some variables as predictors or outcomes was based on theoretical considerations (e.g., Deci et al., 2017), our design did not allow us to rule out the possibility of reverse causality, reciprocal influence, or spurious associations. Future longitudinal research should devote more attention to the identification of the true directionality of the associations among predictors, outcomes, and profiles. It would also be important for future research to better consider the mechanisms involved in both the formation and consequences of need satisfaction profiles. Third, future studies may contribute to the literature by adopting a longitudinal design and addressing the joint issues of within-person and within-sample profile stability (Gillet et al., 2017; Kam et al., 2016). More precisely, it would be interesting to examine whether the need satisfaction profiles identified in the current study change in terms of number, structure, variability, size, and outcomes across time (within-sample stability) and whether membership into the different need satisfaction profiles remain stable (within-person stability). Future research may also consider the possible mechanisms at play in explaining these potential profile transitions. Furthermore, it would be interesting for further studies to examine whether a profile characterized by high levels of global need satisfaction balance and low specific levels of imbalance in the satisfaction of the needs for autonomy, competence, and relatedness presents the greatest levels of stability over time. Fourth, we only considered job demands and resources as possible predictors of need satisfaction profiles. It would be interesting for future research to consider a more diversified set of determinants of need satisfaction profiles (e.g., proactive personality, job crafting, organizational culture, transformational leadership). Finally, our reliance on a sample of soldiers (Sample 1) and a convenience sample of workers (Sample 2) makes it hard to assess the extent to which these samples can be considered to be representative of more general populations of workers. It would remain important for future research to rely on more diversified (in terms of cultures, languages, and professions) and representative samples.

Practical Implications

From a practical perspective, our results suggest that managers should be particularly attentive to employees displaying low global levels of need satisfaction, and especially to those who also display low levels of relatedness need satisfaction (*Globally Dissatisfied yet Moderately Autonomous*) as these workers appeared to be particularly at risk for a variety of work difficulties, including anxiety and fatigue. Interestingly, our results revealed that perceiving high levels of organizational and colleagues support was associated with a lower likelihood of membership into that least desirable profile. Therefore, practitioners and human resources managers should try to promote organizational and colleagues support in the workplace in order to increase employees' need satisfaction and reduce their psychological health difficulties. Among ways to achieve this objective, top management might promote a supportive culture, for instance, by providing employees the resources or materials they need to perform their job effectively, by reducing work overload, and by promoting justice and fairness in terms of policy implementation and rewards distribution (Eisenberger & Stinglhamber, 2011). Recently, Gonzalez-Morales, Kernan, Becker, and Eisenberger (2018) also developed and provided evidence for the efficacy of a brief support training program including four basic strategies (i.e., benevolence, sincerity, fairness, and experiential processing). Finally, in order to foster a climate of support among colleagues, managers may implement informal mentoring activities, as well as help to organize informal social events aiming to encourage the development of stronger social ties (Newman, Thanacoody, & Hui, 2012). In the existing literature, numerous studies have also shown that autonomy-supportive behaviors were positively related to psychological need satisfaction (Gillet et al., 2012). Thus, having managers displaying higher levels of autonomy-supportive behaviors could be associated with higher levels of need satisfaction among employees.

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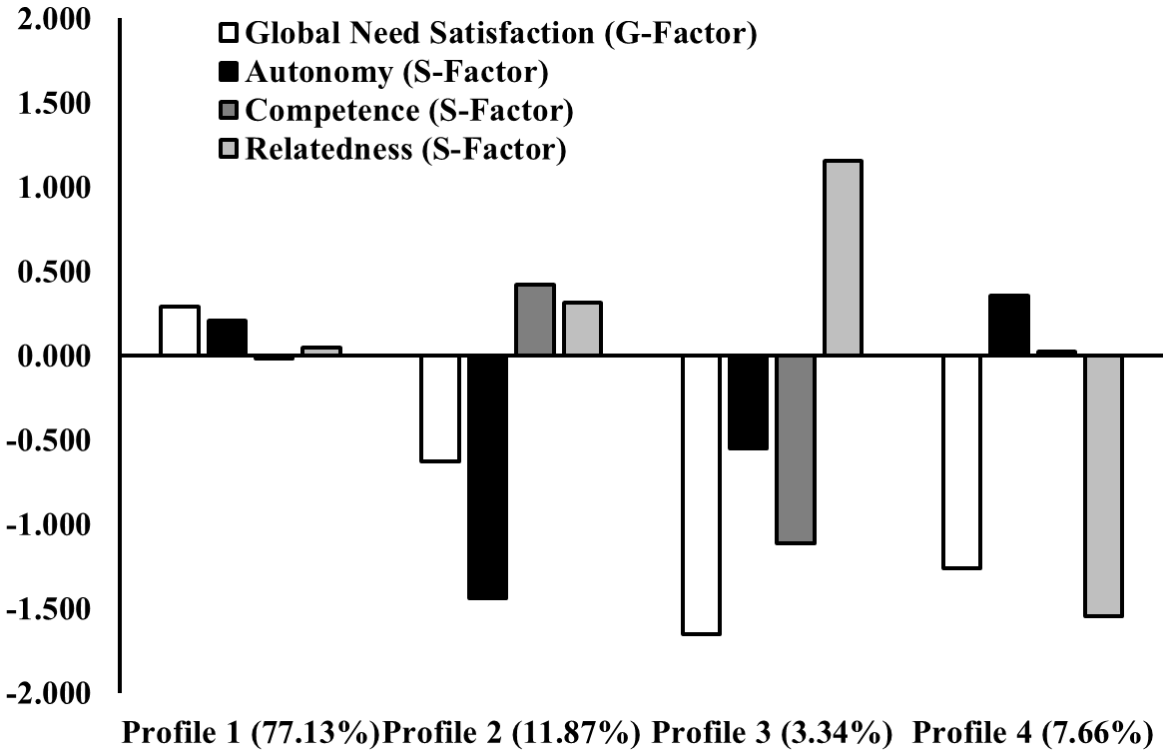

Figure 1. Final 4-Profile Solution Based on Bifactor Factor Scores

Note. The global need satisfaction G-factor reflects respondents' global levels of balance in the satisfaction of all three needs; The specific autonomy, relatedness, and competence S-factors reflect imbalance in the satisfaction of all three needs when compared to the others (specific levels of need satisfaction left unexplained by the G-factor); Profile indicators are estimated from factor scores with a *M* of 0 and a *SD* of 1; Profile 1: Normative profile; Profile 2: Globally Dissatisfied yet Moderately Competent and Connected profile; Profile 3: Globally Dissatisfied yet Highly Connected profile; and Profile 4: Globally Dissatisfied yet Moderately Autonomous profile.

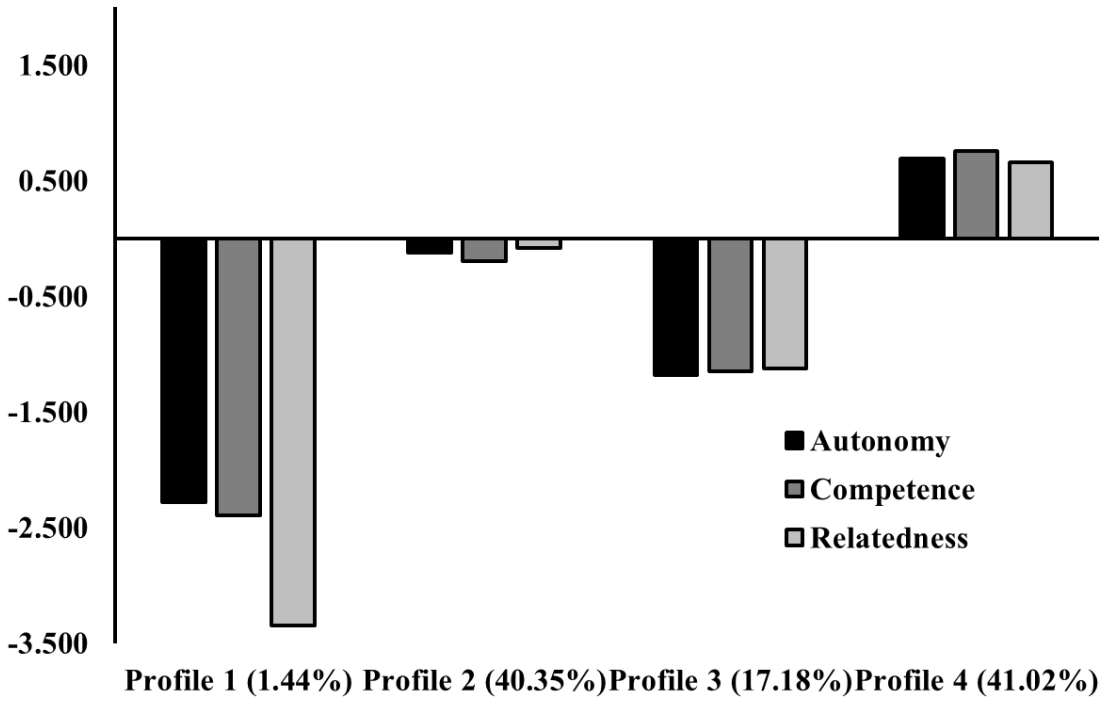

Figure 2. Comparison 4-Profile Solution Based on First-Order Factor Scores
Note. Profile indicators are estimated from factor scores with a *M* of 0 and a *SD* of 1.

Table 1

Results from Multinomial Logistic Regressions for the Effects of the Predictors on Profile Membership

	Latent Profile 1 vs. 4		Latent Profile 2 vs. 4		Latent Profile 3 vs. 4	
	Coef. (SE)	OR	Coef. (SE)	OR	Coef. (SE)	OR
Sample 1						
Mental Load	.190 (.354)	1.209	.881 (.428)*	2.414	-.018 (.454)	.982
Workload	-.390 (.369)	.677	-.576 (.430)	.562	-.075 (.471)	.928
Information	-.257 (.359)	.774	-.014 (.455)	.986	-.313 (.487)	.731
Participation	.555 (.411)	1.743	-1.485 (.515)**	.226	-2.166 (.557)**	.115
Colleagues Support	2.184 (.398)**	8.883	2.176 (.558)**	8.811	1.983 (.523)**	7.263
Role Ambiguity	-.459 (.339)	.632	-.045 (.384)	.956	.319 (.431)	1.375
Sample 2						
Scheduling Autonomy	.815 (.300)**	2.259	-.289 (.343)	.749	-1.092 (.829)	.336
Significance	.343 (.254)	1.410	.194 (.269)	1.215	-.255 (.455)	.775
Task Identity	.224 (.283)	1.251	.377 (.271)	1.457	.601 (.392)	1.824
Organizational Support	1.396 (.284)**	4.039	.555 (.277)*	1.742	.802 (.491)	2.230
	Latent Profile 1 vs. 3		Latent Profile 2 vs. 3		Latent Profile 1 vs. 2	
	Coef. (SE)	OR	Coef. (SE)	OR	Coef. (SE)	
Sample 1						
Mental Load	.207 (.345)	1.230	.899 (.363)*	2.457	-.692 (.229)**	.501
Workload	-.315 (.402)	.730	-.501 (.426)	.606	.185 (.208)	1.203
Information	.056 (.396)	1.058	.299 (.422)	1.349	-.243 (.238)	.784
Participation	2.721 (.498)**	15.196	.680 (.524)	1.974	2.041 (.276)**	7.698
Colleagues Support	.201 (.346)	1.223	.193 (.384)	1.213	.008 (.281)	1.008
Role Ambiguity	-.778 (.310)*	.459	-.364 (.318)	.695	-.414 (.200)*	.661
Sample 2						
Scheduling Autonomy	1.907 (.810)*	6.733	.803 (.860)	2.232	1.104 (.295)**	3.016
Significance	.598 (.455)	1.818	.449 (.497)	1.567	.149 (.270)	1.161
Task Identity	-.377 (.381)	.686	-.224 (.397)	.799	-.152 (.272)	.859
Organizational Support	.594 (.444)	1.811	-.247 (.453)	.781	.841 (.209)**	2.319

Note: **: $p < .01$; *: $p < .05$. SE: standard error of the coefficient; OR: odds ratio; the coefficients and OR reflects the effects of the predictors on the likelihood of membership into the first listed profile relative to the second listed profile; predictors are factor scores with mean of 0 and a standard deviation of 1; Profile 1: Normative profile; Profile 2: Globally Dissatisfied yet Moderately Competent and Connected profile; Profile 3: Globally Dissatisfied yet Highly Connected profile; and Profile 4: Globally Dissatisfied yet Moderately Autonomous profile.

Table 2

Associations between Profile Membership and the Outcomes (Sample 2)

	Profile 1 M [CI]	Profile 2 M [CI]	Profile 3 M [CI]	Profile 4 M [CI]	Summary of Differences ($p \leq .05$)
Anxiety	-.069 [-.145; .007]	.019 [-.179; .217]	-.051 [-.461; .359]	.756 [.440; 1.072]	4 > 1 = 2 = 3
Physical fatigue	-.138 [-.216; -.060]	.255 [.049; .461]	.746 [.311; 1.181]	.756 [.476; 1.036]	3 = 4 > 2 > 1

Note. M: mean; CI: 95% confidence interval; outcomes are estimated from factor scores with mean of 0 and a standard deviation of 1; Profile 1: Normative profile; Profile 2: Globally Dissatisfied yet Moderately Competent and Connected profile; Profile 3: Globally Dissatisfied yet Highly Connected profile; and Profile 4: Globally Dissatisfied yet Moderately Autonomous profile.

Online Supplemental Materials for:

A Person-Centered Representation of Basic Need Satisfaction Balance at Work

Authors' note:

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

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

Need Satisfaction Measurement Models

Brief Introduction to the Bifactor Exploratory Structural Equation Modeling Framework and Applicability to the Study of Need Satisfaction

When assessing the structure of responses obtained to typical psychometric measures, the confirmatory factor analysis (CFA) approach provides a way to assess the extent to which our a priori representations match the structure of responses obtained on an instrument, and even to compare alternative representations of the data based on objective fit assessment procedures. However, CFA relies on the independent cluster assumption that the latent constructs are unidimensional. More precisely, CFA assumes that ratings obtained on any indicator reflect, or correspond, to scores on a single factor. This assumption has recently been shown to be overly stringent, and often unrealistic, for many psychometric measures (e.g., Marsh, Morin, Parker, & Kaur, 2014). Morin and colleagues (Morin, Arens, & Marsh, 2016; Morin, Arens, Tran, & Caci, 2016) note that when conceptually-related constructs (e.g., autonomy, competence, and relatedness) are assessed within the same instrument, construct-relevant psychometric multidimensionality needs to be explicitly taken into account. Construct-relevant psychometric multidimensionality refers to additional sources of true score variance depicting associations between the items and non-target constructs that, when forcefully ignored in CFA, lead to biased parameter estimates (Asparouhov, Muthén, & Morin, 2015; Morin, Arens. & Marsh, 2016).

A first source of construct-relevant psychometric multidimensionality is particularly relevant to the need satisfaction construct and refers to the assessment of coexisting global and specific constructs. For instance, in the current debate regarding whether need satisfaction is best represented as a single global construct (Gillet, Fouquereau, Forest, Brunault, & Colombat, 2012) or as conceptually-distinct subscales (Trépanier, Fernet, & Austin, 2013, 2016), a third option exists according to which need satisfaction might exist as a global entity reflecting commonalities among ratings of autonomy, competence, and relatedness needs satisfaction, which themselves may include specificity unexplained by this global entity. Huyghebaert et al.'s (2018) higher-order results support the idea that ratings of autonomy, competence, and relatedness needs satisfaction are conceptually-related dimensions of an overarching global need satisfaction construct. However, one remaining question is whether sufficient specificity exists in the three needs (autonomy, competence, and relatedness) once the global construct is taken into account.

Psychometrically, two distinct approaches can be used to study this question. The most typical of these approaches relies on hierarchical models (e.g., Huyghebaert et al., 2018). In hierarchical models, ratings on specific indicators are used to define first-order factors (autonomy, competence, and relatedness), which are themselves used to define a higher-order factor (global need satisfaction). However, hierarchical models suffer from one important limitation: They rely on a stringent proportionality constraint according to which the ratio of variance explained by the global factor relative to that explained by the specific factors is forced to be exactly the same for all items associated with a specific first-order factor (Morin, Arens, & Marsh, 2016). Bifactor models provide a more flexible alternative not constrained by this unrealistic proportionality constraint (Chen, West, & Sousa, 2006). In a *f*-factor bifactor model, one Global (G) factor (psychological need satisfaction) and *f-1* orthogonal Specific (S) factors (autonomy, competence, and relatedness needs satisfaction) are used to explain the covariance among a set of *n* items. Bifactor models directly test the presence of a global unitary construct underlying the answers to all items (G-Factor) and whether this global construct co-exists with meaningful specificities (S-Factors) not explained by the G-Factor. Thus, bifactor models provide a way to simultaneously consider both the forest (i.e., the presence of a global level of need satisfaction) and the trees (i.e., the specificities associated with ratings of autonomy, competence, and relatedness needs satisfaction) (Tóth-Király, **Morin,** Bőthe, Orosz, & Rigó, 2018).

A second source of construct-relevant psychometric multidimensionality likely to be present in measures of need satisfaction occurs when items designed to assess one specific construct present some degree of true score association with non-target constructs (Morin, Arens, & Marsh, 2016; Morin, Arens, Tran, & Caci, 2016). For instance, workers' levels of autonomy need satisfaction may influence responses to items designed to assess their levels of competence or relatedness needs satisfaction due in part to the naturally imperfect nature of these ratings, but also to the fact that need satisfaction dimensions are interrelated conceptually (Bidee et al., 2017; Gillet, Lafrenière, Vallerand, Huart, & Fouquereau, 2014). This form of construct-relevant multidimensionality calls for exploratory

factor analyses (EFA) allowing for the free estimation of cross-loadings between items and conceptually-related constructs. EFA has recently been integrated with CFA and structural equation modeling into the exploratory structural equation modeling (ESEM) framework (Morin, Marsh, & Nagengast, 2013), making it possible to consider that items tend to present at least some degree of valid association with more than one conceptually-related construct (Morin, Arens, & Marsh, 2016; Morin, Arens, Tran, & Caci, 2016). In particular, statistical research evidence (for a review, see Asparouhov et al., 2015) shows that excluding cross-loadings even as small as .100 tends to result in inflated estimates of the G-factor in bifactor-CFA or of factor correlations in CFA, whereas incorporating unnecessary cross-loadings has been shown not to result in estimation biases.

When we focus on the needs for autonomy, competence and relatedness or on closely related constructs, emerging research tends to support the value of a bifactor-CFA approach, but without systematically considering bifactor-ESEM solutions. Thus, in the sport area, Brunet, Gunnell, Teixeira, Sabiston, and Bélanger (2016) supported a bifactor-CFA representation of participants' satisfaction of their needs for competence, autonomy, and relatedness. Gillet et al. (2018) reported similar results in the educational area, while Bidee, Vantilborgh, Pepermans, Griep, and Hofmans' (2016) results also supported this approach in the work area. Fewer studies have considered the more comprehensive bifactor-ESEM framework. Thus, in the sport area, Myers, Martin, Ntoumanis, Celimli, and Bartholomew (2014) demonstrated the usefulness of a bifactor-ESEM approach when considering participants' levels of need thwarting. In a more comprehensive study focusing on ratings of global (rather than domain-specific) levels of need fulfillment (combining ratings of need satisfaction and frustration), Tóth-Király et al. (2018) similarly showed the value of a bifactor-ESEM approach in a series of two independent studies. To our knowledge, a single study (Sánchez-Oliva et al., 2017) has tested, and supported the added value, of a bifactor-ESEM representation of employees' ratings of their need satisfaction at work.

Measurement Models: Estimation

All measurement models were estimated using Mplus 8 (Muthén & Muthén, 2017) robust Maximum Likelihood (MLR) estimator, which provides parameter estimates, standard errors, and goodness-of-fit that are robust to the non-normality of the response scales used in the present study (Finney & DiStefano, 2013). These models were estimated with Full Information Maximum Likelihood (FIML; Enders, 2010) to handle the few missing responses present at the item level (Sample 1: 0%; Sample 2: 0.00-1.62%).

CFA, bifactor-CFA, ESEM, and bifactor-ESEM representations of participants' ratings of need satisfaction at work were separately estimated in each sample following Morin et al.'s (Morin, Arens, & Marsh, 2016; Morin, Boudrias et al., 2016, 2017) recommendations. In CFA, each item was only allowed to load on the factor it was assumed to measure and no cross-loadings were allowed. This model included three correlated factors representing autonomy, competence, and relatedness. In ESEM, the same set of three factors was represented using a confirmatory oblique target rotation (Browne, 2001). Target rotation makes it possible to freely estimate all main loadings while constraining all cross-loadings to be as close to zero as possible. In bifactor-CFA, all items were allowed to simultaneously load on one G-factor reflecting global levels of need satisfaction, and on three S-factors corresponding to specific levels of autonomy, competence, and relatedness. No cross-loadings were allowed between the S-factors, and all factors were specified as orthogonal in line with bifactor assumptions (e.g., Morin, Arens, & Marsh, 2016). Bifactor-ESEM estimated the same G- and S-factors as the bifactor-CFA solution, allowing for the free estimation of cross-loadings between the S-factors using an orthogonal bifactor target rotation (Reise, Moore, & Maydeu-Olivares, 2011).

Given the oversensitivity of the chi-square test to sample size and minor misspecifications (Marsh, Hau, & Grayson, 2005), we relied on goodness-of-fit indices to describe the fit of the models: The comparative fit index (CFI), the Tucker-Lewis index (TLI), and the root mean square error of approximation (RMSEA) with its 90% confidence interval. According to typical interpretation guidelines (e.g., Marsh et al., 2005), 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. In the comparison of nested models (such as in tests of measurement invariance), typical 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 (Cheung & Rensvold, 2002).

As noted by Morin and colleagues (Morin, Arens, & Marsh, 2016; Morin, Boudrias et al., 2016, 2017), fit indices are not sufficient to guide the selection of the optimal model. Indeed, each of these alternative models is able to absorb sources of construct-relevant multidimensionality left unmodelled, thus hiding sources of misfit behind apparently similarly fitting models (e.g., Asparouhov et al., 2015; Morin, Arens, & Marsh, 2016). Unmodelled cross-loadings tend to result in inflated factor correlations in CFA, or inflated G-factor loadings in bifactor-CFA. Likewise, an unmodelled G-factor tends to produce inflated factor correlations in CFA, or inflated cross-loadings in ESEM. Thus, an examination of parameter estimates and theoretical conformity is required to select the best alternative. As suggested by Morin and colleagues (Morin, Arens, & Marsh, 2016; Morin, Boudrias et al., 2016, 2017), model comparison should always start by contrasting CFA and ESEM solutions. Here, statistical evidence shows that ESEM provides more exact estimates of factor correlations when cross-loadings are present in the population model while remaining unbiased otherwise (Asparouhov et al., 2015). For this reason, and as long as the factors remain well-defined, the observation of a distinct pattern of factor correlations should be taken as support for the ESEM solution. The second step involves contrasting the retained CFA or ESEM solution with a bifactor alternative. Here, the key elements supporting a bifactor model are the observation of: (1) an improved level of fit to the data; (2) a well-defined G-factor; and (3) at least some reasonably well-defined S-factors. The observation of multiple cross-loadings higher than .100 or .200 in ESEM that are reduced in bifactor-ESEM represents an additional source of evidence in favor of the bifactor solution (Morin, Arens, & Marsh, 2016; Morin, Arens, Tran, & Caci, 2016). For all models, we thus report standardized parameter estimates, and composite reliability coefficients associated with each of the a priori factors are calculated from the model standardized parameters using McDonald (1970) omega (ω):

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

where $|\lambda_i|$ are the standardized factor loadings in absolute values, and δi, the item uniquenesses.

Measurement Models: Results

Table S1 presents the goodness-of-fit indices of the measurement models estimated in both samples. Parameter estimates for all solutions obtained in Sample 1 are reported in Table S2, whereas those obtained in Sample 2 are reported in Table S3 of the online supplements. The CFA model failed to achieve an acceptable level of fit in both samples according to the TLI, as well as to the CFI and RMSEA in Sample 2. Both the bifactor-CFA and ESEM models achieved an acceptable, and comparable, level of fit in both samples according to all goodness-of-fit indices. Finally, the bifactor-ESEM model achieved an excellent level of fit to the data in both samples according to all goodness-of-fit indices, and a substantial increase in model fit relative to both the bifactor-CFA (Sample 1: ΔCFI = +.024; ΔTLI = +.018; ΔRMSEA = -.009; Sample 2: ΔCFI = +.033; ΔTLI = +.032; ΔRMSEA = -.015) and ESEM (Sample 1: ΔCFI = +.027; ΔTLI = +.036; ΔRMSEA = -.016; Sample 2: ΔCFI = +.018; ΔTLI = +.021; ΔRMSEA = -.010) results in both samples. Based on this statistical information, the bifactor-ESEM solution should be retained. However, as noted above, model selection needs to be based on a complete examination of the parameter estimates and theoretical conformity. Thus, we first compare the CFA and ESEM solutions, before comparing the ESEM and bifactor-ESEM solutions.

ESEM versus CFA. Parameter estimates for the CFA and ESEM solutions are very similar in Samples 1 and 2, and reveal factors that are well-defined by strong factor loadings and satisfactory estimates of composite reliability in Samples 1 (CFA: λ = .602 to .895, M_λ = .740, ω = .839 to .888; ESEM: λ = .310 to .994, M_λ = .680, ω = .822 to .875) and 2 (CFA: λ = .503 to .849, M_λ = .746, ω = .829 to .893; ESEM: λ = .469 to .985, M_λ = .711, ω = .819 to .889). When we look more carefully at the ESEM solution, despite the fact that multiple cross-loadings are small and non-statistically significant (17 out of 30 possible cross loadings in both samples), multiple cross-loadings remain relatively strong (8 cross-loadings are between .100 and .200 in Sample 1 and 7 in Sample 2, and 3 cross-loadings are higher than .200 in Sample 1 and 2 in Sample 2). Although the presence of cross-loadings reinforces the need to incorporate this source of construct-relevant psychometric multidimensionality to the model, they also suggest that a global factor might be needed. Examination of the factor correlations associated with both of these solutions (see Table S4 of the online supplements) similarly reinforce the need to incorporate cross-loadings to the model, as these are somewhat reduced smaller in ESEM (Sample 1: r = .586 to .690; Sample 2: r = .568 to .605) relative to CFA (Sample 1: r = .564 to .618; Sample 2: r = .529 to .575) in both samples.

ESEM versus Bifactor-ESEM. The bifactor-ESEM results reveal a G-Factor well-defined by

strong and positive loadings from most items in both samples (Sample 1: λ = .451 to .788; M_λ = .621, ω = .937; Sample 2: λ = .264 to .798; M_λ = .578, ω = .929). Over and above this G-Factor, most items associated with the relatedness (Sample 1: λ = .381 to .619; M_λ = .465, ω = .696; Sample 2: λ = .514 to .622; M_λ = .487, ω = .711) and competence (Sample 1: λ = .169 to .677, M_λ = .438, ω = .703; Sample 2: λ = .337 to .712, M_λ = .502, ω = .758) S-factors retain a satisfactory level of specificity. In contrast, the autonomy S-factor appears to be more weakly defined by a majority of items (Sample 1: λ = .006 to .607, M_λ = .292; Sample 2: λ = .093 to .855, M_λ = .413), suggesting that autonomy ratings mainly define participants' global levels of need satisfaction. Still, the fact that this S-Factor retains less specificity than the other S-factors does not signify that this specificity is not meaningful, especially when models using an approach that explicitly controls for measurement errors and associations with the global need satisfaction construct. Indeed, this S-factor appears to retain at least some amount of specificity as illustrated by non-negligible estimates of composite reliability (Sample 1: ω = .595; Sample 2: ω = .760). Finally, the superiority of the bifactor-ESEM solution is also apparent from the observation of reduced cross-loadings (no cross-loadings higher than .200 remain in the solution, and 7 cross-loadings between .100 and .200 remain in Sample 1 and 5 in Sample 2).

Measurement Invariance. The bifactor-ESEM solution was retained in both samples and used for tests of measurement invariance. However, in order to be able to compare LPA solutions estimated based on first-order, relative to bifactor, factor scores, we also retained the ESEM solution. These tests were conducted in the following sequence (Millsap, 2011): (a) configural invariance, (b) weak invariance (loadings), (c) strong invariance (loadings, intercepts), (d) strict invariance (loadings, intercepts, uniquenesses), (e) invariance of the latent variances-covariances (loadings, intercepts, uniquenesses, variances-covariances), and (f) latent means invariance (loadings, intercepts, uniquenesses, variances-covariances, latent means). The results from the tests of measurement invariance realized on these two solutions are reported in the bottom of Table S1, and support the complete measurement invariance of both solutions (i.e., none of the changes in fit indices exceeded the recommended guidelines). Factors scores for the person-centered analyses were extracted from the model of complete measurement invariance for both solutions. Although only strict measurement invariance is required to ensure that measurement of the constructs remains equivalent across samples for models based on factor scores (Millsap, 2011), there are advantages to saving factors scores from a model of complete measurement invariance, which provides measures which are directly comparable across samples based on a mean of 0 and a SD of 1.

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Class Enumeration Procedure and Tests of Profile Similarity

To determine the optimal number of profiles, multiple sources of information need to be considered, including the substantive meaningfulness, theoretical conformity, and statistical adequacy of the solutions (Marsh et al., 2009; Morin, 2016; Muthén, 2003). In addition, statistical indices are available to support this decision (McLachlan & Peel, 2000): (i) the Akaïke Information Criterion (AIC), (ii) the Consistent AIC (CAIC), (iii) the Bayesian Information Criterion (BIC), (iv) the sample-size Adjusted BIC (ABIC), (v) the standard and adjusted Lo, Mendell and Rubin's (2001) Likelihood Ratio Tests (LMR/aLMR; as these tests typically yield the same conclusions, we only report the aLMR), and (vi) 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 (Henson, Reise, & Kim, 2007; Nylund, Asparouhov, & Muthén, 2007; Peugh & Fan, 2013; Tein, Coxe, & Cham, 2013; Tofighi & Enders, 2008), while the AIC and LMR/ALMR should not be used in the class enumeration process as they respectively tend to over- and under-extract incorrect number of profiles (Diallo, Morin, & Lu, 2016, 2017; Henson et al., 2007; Nylund et al., 2007; Peugh & Fan, 2013; Tofighi & Enders, 2008). These indicators will thus be reported only in order to ensure a complete disclosure, but will not be used to select the optimal number of profiles. It should be noted that these tests remain heavily influenced by sample size (Marsh et al., 2009), so that with sufficiently large samples, they may keep on suggesting the addition of profiles without reaching a minimum. In this situation, the point at which these indicators appear to reach a plateau can be used as an additional indicator to inform the selection of the optimal solution (Morin, Maïano et al., 2011). Finally, the entropy indicates the precision with which the cases are classified into the various profiles. The entropy should not be used to determine the optimal number of profiles (Lubke & Muthén, 2007), but summarizes the classification accuracy (0 to 1), with higher values indicating greater accuracy.

Once the optimal number of profiles has been selected in each sample, we integrated the two retained LPA solutions (one per sample) into a single multi-group LPA model allowing for systematic tests of profile similarity. These tests were conducted following the sequential strategy proposed by Morin, Meyer et al. (2016) for tests of profile similarity across multiple groups: (a) *configural* similarity (i.e., same number of profiles); (b) *structural* similarity (i.e., same within-profile mean levels on the profile indicators); (c) *dispersion* similarity (i.e., same within-profile variance of the profile indicators); and (d) *distributional* similarity (i.e., same relative size of the profiles). The fit of these models can be compared using the aforementioned information criteria. Morin, Meyer et al. (2016) also suggest that at least two indices out of the CAIC, BIC, and ABIC should be lower for the more "similar" model for the hypothesis of profile similarity to be supported.

The fit indices of the LPAs estimated from bifactor factor scores separately in both samples are reported in the top (Sample 1) and middle (Sample 2) sections of Table S9 of these online supplements, and the elbow plots associated with these results are presented in Figure S1 of the online supplements. Comparable results for models estimated based on first-order factor scores are reported in Table S10 and Figure S2 of the online supplements. In Sample 1, all indices kept on suggesting the addition of profiles. In Sample 2, the ABIC and BLRT kept on suggesting the addition of profiles, whereas the CAIC and BIC respectively supported 5 and 7 profiles. The elbow plots associated with these solutions attain a first point of inflexion after 3 profiles, although this inflexion point was not as marked in Sample 1. Based on these observations, we carefully examined solutions including 3 to 6 profiles in both samples. This examination showed that all solutions were fully proper statistically and characterized by a very high level of similarity across samples. Furthermore, this examination revealed that moving from 3 to 4 profiles resulted in the addition of a meaningfully different profile to the solution in both samples, whereas moving from 4 to 5, or from 5 to 6, profiles simply resulted in the arbitrary division of one profile into very small ($\leq$ 1%) and similar profiles. The 4-profile solution was thus retained in both samples, supporting its *configural* similarity. For comparison purposes, the 4-profile solution was also retained for models based on first-order factor scores.

A multigroup LPA of *configural* similarity, including 4 profiles per sample, was then estimated. The fit indices from all multigroup LPAs are reported in the bottom section of Table S9, and support the *structural* similarity of the profiles across samples based on the observation of reduced CAIC, BIC, and ABIC value associated with this solution, but not the *dispersion* similarity of the profiles as

this model results in higher values on all information criteria. A careful examination of the results revealed that scores on the relatedness S-factors presented slightly higher within-profile variability in Sample 2 (suggesting that profiles estimated in Sample 2 were slightly less "homogenous" in terms of relatedness than those estimated in Sample 1). We thus estimated an additional model of partial *dispersion* similarity in which equality constraints across samples were relaxed on the variances of the relatedness S-factor. Relative to the model of *configural* similarity, this model resulted in lower values on the CAIC and BIC, supporting the partial *dispersion* similarity of this solution across samples. Finally, we estimated a model of *distributional* similarity by constraining the size of the latent profiles to be equal across samples. Compared with the model of partial *dispersion* similarity, this model resulted in lower values on the CAIC, BIC, and ABIC, thereby supporting the *distributional* similarity of the solution. Comparable results for the models based on first-order factors scores are reported in Table S10 of the online supplements, and converge on identical conclusions.

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Table S1

Goodness-of-Fit Statistics of the Alternative Measurement Models

Description	χ^2 (*df*)	CFI	TLI	RMSEA	90% CI	$\Delta\chi^2$	Δdf	ΔCFI	ΔTLI	ΔRMSEA
Sample 1										
CFA	979.760 (87)*	.879	.854	.085	[.080; .090]	-		-	-	-
ESEM	429.566 (63)*	.950	.917	.064	[.058; .070]	-		-	-	-
B-CFA	417.993 (75)*	.953	.935	.057	[.052; .062]	-		-	-	-
B-ESEM	220.066 (51)*	.977	.953	.048	[.042; .055]	-		-	-	-
Sample 2										
CFA	433.125 (87)*	.907	.887	.077	[.070; .084]	-		-	-	-
ESEM	217.273 (63)*	.958	.931	.060	[.052; .069]	-		-	-	-
B-CFA	288.387 (75)*	.943	.920	.065	[.057; .073]	-		-	-	-
B-ESEM	138.295 (51)*	.976	.952	.050	[.040; .060]	-		-	-	-
Measurement Invariance (ESEM)										
Configural invariance	653.437 (126)*	.953	.922	.063	[.058; .068]	-		-	-	-
Weak invariance	736.488 (162)*	.949	.934	.058	[.054; .062]	86.476*	36	-.004	+.012	-.005
Strong invariance	816.271 (174)*	.943	.931	.059	[.055; .063]	89.543*	12	-.006	-.003	+.001
Strict invariance	889.155 (189)*	.938	.931	.059	[.056; .063]	72.190*	15	-.005	.000	.000
Latent variance-covariance invariance	904.863 (195)*	.937	.932	.059	[.055; .063]	16.558	6	-.001	+.001	.000
Latent means invariance	921.547 (198)*	.936	.932	.059	[.055; .063]	17.680*	3	-.001	.000	.000
Measurement Invariance (Bifactor-ESEM)										
Configural invariance	365.506 (102)*	.977	.952	.050	[.044; .055]	-		-	-	-
Weak invariance	437.711 (146)*	.974	.963	.044	[.039; .048]	85.549*	44	-.003	+.011	-.006
Strong invariance	513.819 (157)*	.968	.958	.047	[.042; .051]	93.742*	11	-.006	-.005	+.003
Strict invariance	624.997 (172)*	.960	.951	.050	[.046; .054]	109.213*	15	-.008	-.007	+.003
Latent variance-covariance invariance	626.248 (182)*	.961	.954	.048	[.044; .052]	14.659	10	+.001	+.003	-.002
Latent means invariance	644.032 (186)*	.959	.954	.048	[.044; .053]	18.856*	4	-.002	.000	.000

Note. * $p < .01$; χ^2: robust chi-square test of exact fit; *df*: degrees of freedom; CFI: comparative fit index; TLI: Tucker-Lewis index; RMSEA: root mean square error of approximation; 90% CI: 90% confidence interval; Δ: change in fit relative to the preceding model in the sequence.

Table S2

Standardized Factor Loadings (λ) and Uniquenesses (δ) in Sample 1

	CFA		B-CFA			ESEM				B-ESEM				
Items	λ	δ	G-λ	S-λ	δ	Λ	λ	λ	δ	G-λ	S-λ	S-λ	S-λ	δ
Autonomy														
Item 1	.654	.572	.697	*.068*	.510	**.505**	*.039*	.172	.584	**.741**	***.006***	-.131	-.123	.418
Item 2	.686	.530	.778	*-.002*	.394	**.423**	.103	.300	.485	**.788**	***-.009***	-.056	*.016*	.375
Item 3	.813	.340	.776	.252	.335	**.701**	.078	.071	.368	**.780**	**.243**	*-.035*	-.081	.324
Item 4	.850	.277	.650	.624	.187	**.940**	*.023*	-.150	.231	**.649**	**.607**	*.037*	-.047	.207
Item 5	.895	.199	.725	.575	.144	**.989**	*-.016*	-.096	.137	**.720**	**.596**	*-.005*	-.041	.126
ω	.888			.596		.875					.595			
Competence														
Item 1	.780	.391	.525	.661	.288	-.114	**.921**	*-.040*	.305	**.551**	-.054	**.620**	.053	.307
Item 2	.788	.410	.645	.378	.441	*.049*	**.588**	.184	.439	**.648**	*-.052*	**.366**	.112	.432
Item 3	.763	.608	.493	.339	.642	.090	**.485**	*.089*	.633	**.469**	*.093*	**.357**	.143	.624
Item 4	.602	.504	.749	.149	.417	.406	**.310**	.143	.445	**.715**	.140	**.169**	*.050*	.439
Item 5	.703	.350	.552	.676	.238	*-.046*	**.994**	-.152	.222	**.568**	*.009*	**.677**	*-.003*	.219
ω	.854			.705			.842					.703		
Relatedness														
Item 1	.706	.501	.571	.425	.494	.085	*-.037*	**.696**	.475	**.598**	-.076	*-.042*	**.396**	.478
Item 2	.788	.379	.535	.630	.317	*-.045*	*-.049*	**.868**	.336	**.551**	-.064	*.008*	**.619**	.309
Item 3	.763	.418	.540	.527	.430	*-.020*	.114	**.679**	.448	**.534**	*.005*	.131	**.525**	.422
Item 4	.602	.638	.448	.391	.646	*.061*	*-.019*	**.569**	.649	**.451**	*-.003*	*.010*	**.381**	.652
Item 5	.703	.505	.561	.400	.526	*.018*	.207	**.538**	.515	**.546**	*-.002*	.173	**.406**	.507
ω	.839		.934	.700				.822		.937			.696	

Note: CFA: confirmatory factor analysis; ESEM: exploratory factor analyses; G: global factor estimated as part of a bifactor model; S: specific factor estimated as part of a bifactor model; λ: factor loading; δ: item uniqueness; ω: omega coefficient of model-based composite reliability; target ESEM and B-ESEM factor loadings are indicated in bold; non-significant parameters ($p \geq .05$) are marked in italics.

Table S3

Standardized Factor Loadings (λ) and Uniquenesses (δ) in Sample 2

	CFA		B-CFA			ESEM				B-ESEM				
Items	λ	δ	G-λ	S-λ	δ	λ	λ	λ	δ	G-λ	S-λ	S-λ	S-λ	δ
Autonomy														
Item 1	.793	.371	.670	.376	.409	**.720**	*.030*	*.059*	.409	**.721**	**.313**	-.077	-.070	.372
Item 2	.714	.491	.767	*.115*	.399	**.501**	.119	.218	.478	**.765**	***.093***	*-.041*	*.008*	.404
Item 3	.840	.295	.731	*.368*	.330	**.765**	.102	*-.011*	.332	**.798**	***.286***	*-.066*	-.163	.250
Item 4	.755	.429	.502	.689	.273	**.879**	*-.079*	*-.077*	.354	**.464**	**.855**	*.046*	*.077*	.046
Item 5	.849	.280	.658	.594	.213	**.914**	*-.036*	*-.024*	.219	**.677**	***.517***	*-.039*	*-.027*	.272
ω	.893			.739		.889					.760			
Competence														
Item 1	.795	.367	.533	.610	.343	-.059	**.837**	*.001*	.347	**.537**	*-.029*	**.597**	*.056*	.352
Item 2	.824	.321	.617	.517	.352	*-.021*	**.763**	.094	.345	**.616**	-.084	**.516**	*.076*	.342
Item 3	.610	.628	.521	*.302*	.637	*.046*	**.469**	.163	.633	**.471**	*.031*	**.349**	.155	.631
Item 4	.699	.511	.667	.285	.474	.338	**.494**	*.004*	.461	**.623**	*.169*	**.337**	*.024*	.469
Item 5	.819	.329	.505	.727	.217	-.086	**.985**	-.128	.229	**.519**	-.050	**.712**	*-.015*	.221
ω	.867			.747			.862					.758		
Relatedness														
Item 1	.730	.468	.493	.564	.439	*.028*	-.110	**.786**	.448	**.518**	*-.024*	*-.057*	**.532**	.445
Item 2	.843	.290	.590	.628	.258	*-.035*	-.068	**.940**	.215	**.615**	*-.082*	*-.023*	**.622**	.227
Item 3	.699	.512	.556	.403	.529	*.045*	.177	**.544**	.526	**.532**	*.006*	.166	**.415**	.517
Item 4	.503	.746	.279	.438	.731	*-.013*	*.001*	**.486**	.770	**.264**	*.086*	.098	**.439**	.721
Item 5	.714	.490	.570	.410	.507	*.056*	.143	**.581**	.501	**.551**	*.019*	.135	**.425**	.497
ω	.829		.925	.708				.819		.929			.711	

Note: CFA: Confirmatory factor analysis; ESEM: exploratory factor analyses; G: global factor estimated as part of a bifactor model; S: specific factor estimated as part of a bifactor model; λ: factor loading; δ: item uniqueness; ω: omega coefficient of model-based composite reliability; Target ESEM and B-ESEM factor loadings are indicated in bold; Non-significant parameters ($p \geq .05$) are marked in italics.

Table S4

Latent Factor Correlations for the CFA and ESEM Solutions

	CFA			ESEM		
	Autonomy	Competence	Relatedness	Autonomy	Competence	Relatedness
Sample 1						
Autonomy	-			-		
Competence	.681	-		.605	-	
Relatedness	.586	.690	-	.564	.618	-
Sample 2						
Autonomy	-			-		
Competence	.573	-		.529	-	
Relatedness	.568	.605	-	.529	.575	-

Note. CFA: confirmatory factor analysis; ESEM: exploratory structural equation modeling; All correlations are statistically significant ($p < .01$)

Table S5

Standardized Factor Loadings (λ), Uniquenesses (δ), and Latent Correlations for the Predictors (Sample 1)

	Mental Load		Workload		Information		Participation		Colleagues Support		Role Ambiguity	
Items	λ	δ	λ	δ	λ	δ	λ	δ	λ	δ	λ	δ
Item 1	.791	.375	.765	.414	.647	.582	.853	.272	.794	.370	.816	.334
Item 2	.745	.445	.839	.297	.880	.226	.876	.233	.903	.185	.802	.356
Item 3	.775	.399	.757	.427	.849	.280	.843	.290	.793	.370	.712	.493
Item 4	.855	.270	.707	.500	.700	.511	.685	.530	.890	.208	.572	.673
ω	.871		.852		.855		.889		.910		.819	

Correlations	1	2	3	4	5	6
1. Mental Load	--					
2. Workload	.565	--				
3. Information	.244	*.058*	--			
4. Participation	.199	.136	.643	--		
5. Colleagues Support	.181	*-.037*	.329	.264	--	
6. Role Ambiguity	-.295	*.037*	-.563	-.461	-.485	--

Note: λ: factor loading; δ: item uniqueness; Non-significant parameters ($p \geq .05$) are marked in italics

Table S6

Standardized Factor Loadings (λ), Uniquenesses (δ), and Latent Correlations for the Predictors and Outcomes (Sample 2)

	Scheduling Autonomy		Meaning.		Task Identity		Organizational Support		Anxiety		Physical exhaustion	δ
Items	λ	δ	λ	δ	λ	δ	λ	δ	λ	δ	λ	
Item 1	.624	.611	.678	.540	.574	.670	.788	.380	.681	.537	.722	.479
Item 2	.836	.302	.684	.531	.456	.792	.876	.232	.707	.500	.689	.526
Item 3	.650	.577	.692	.521	.817	.333	.865	.253	.637	.595	.864	.254
Item 4			.704	.505	.932	.131	.768	.410	.811	.342	.693	.519
Item 5							.491	.759	.858	.263	.933	.129
Item 6							.446	.801			.919	.155
Item 7							.569	.676				
Item 8							.590	.652				
ω	.749		.784		.800		.875		.859		.918	

Correlations	1	2	3	4	5	6
1. Scheduling Autonomy	--					
2. Meaningfulness	.465	--				
3. Task Identity	.587	.427	--			
4. Organizational Support	.454	.280	.355	--		
5. Anxiety	-.142	.094	-.127	-.308	--	
6. Physical exhaustion	-.329	*-.074*	-.189	-.381	.508	--

Note: λ: factor loading; δ: item uniqueness; Non-significant parameters ($p \geq .05$) are marked in italics

Table S7

Correlations between Variables (Sample 1)

	1.	2.	3.	4.	5.	6.	7.	8.	9.	10.
1. Global Need Sat.										
2. Autonomy Need Sat.	.164**									
3. Competence Need Sat.	.123**	-.048								
4. Relatedness Need Sat.	.111**	-.156**	-.015							
5. Mental Load	.199**	-.030	.163**	.062*						
6. Workload	-.002	.079**	.092**	-.029	.628**					
7. Information	.548**	.171**	.069**	.036	.272**	.067*				
8. Participation	.631**	.350**	.044	-.083**	.223**	.150**	.702**			
9. Colleagues Support	.500**	-.021	.012	.497**	.199**	-.041	.361**	.288**		
10. Role Ambiguity	-.605**	-.122**	-.139**	-.179**	-.331**	.035	-.632**	-.517**	-.538**	

Note. * $p < .05$; ** $p < .01$; All variables are estimated from factor scores with mean of 0 and a standard deviation of 1.

Table S8

Correlations between Variables (Sample 2)

	1.	2.	3.	4.	5.	6.	7.	8.	9.	10.
1. Global Need Sat.										
2. Autonomy Need Sat.	.130**									
3. Competence Need Sat.	.020	-.223**								
4. Relatedness Need Sat.	.094*	-.157**	-.044							
5. Scheduling Autonomy	.630**	.255**	-.024	.008						
6. Meaningfulness	.437**	.165**	.076*	.095*	.545**					
7. Task Identity	.466**	.102**	.082*	.102**	.657**	.486**				
8. Organizational Support	.645**	.049	-.085*	.134**	.508**	.318**	.386**			
9. Anxiety	-.226**	.123**	.006	-.187**	-.164**	.106**	-.140**	-.339**		
10. Physical exhaustion	-.349**	-.014	-.016	-.045	-.363**	-.081*	-.203**	-.406**	.551**	

Note. * $p < .05$; ** $p < .01$; All variables are estimated from factor scores with mean of 0 and a standard deviation of 1.

Table S9

Results from the Latent Profile Analysis Models Based on Bifactor Factor Scores

Model	LL	#fp	Scaling	AIC	CAIC	BIC	ABIC	Entropy	aLMR	BLRT
Sample 1										
1 Profile	-7105.777	8	1.359	14227.553	14277.615	14269.615	14244.202	Na	Na	Na
2 Profiles	-6979.487	13	1.431	13984.973	14066.324	14053.324	14012.027	.822	< .001	< .001
3 Profiles	-6838.413	18	1.830	13712.826	13825.465	13807.465	13750.285	.836	.045	< .001
4 Profiles	-6764.281	23	1.597	13574.563	13718.490	13695.490	13622.427	.862	.006	< .001
5 Profiles	-6706.400	28	1.822	13468.801	13644.016	13616.016	13527.070	.845	.372	< .001
6 Profiles	-6662.617	33	1.732	13391.233	13597.738	13564.738	13459.908	.861	.254	< .001
7 Profiles	-6620.208	38	1.763	13316.416	13554.209	13516.209	13395.496	.865	.334	< .001
8 Profiles	-6579.989	43	1.435	13245.978	13515.060	13472.060	13335.464	.875	.001	< .001
Sample 2										
1 Profile	-3565.035	8	1.250	7146.070	7190.212	7182.212	7156.811	Na	Na	Na
2 Profiles	-3496.188	13	1.280	7018.377	7090.107	7077.107	7035.830	.814	< .001	< .001
3 Profiles	-3437.179	18	1.450	6910.357	7009.675	6991.675	6934.523	.848	.014	< .001
4 Profiles	-3416.410	23	1.560	6878.820	7005.726	6982.726	6909.699	.832	.354	< .001
5 Profiles	-3391.439	28	1.450	6838.879	6993.373	6965.373	6876.470	.856	.087	< .001
6 Profiles	-3374.842	33	1.454	6815.683	6997.767	6964.767	6859.988	.859	.554	< .001
7 Profiles	-3357.359	38	1.341	6790.718	7000.390	6962.390	6841.736	.842	.247	< .001
8 Profiles	-3343.728	43	1.281	6773.456	7010.716	6967.716	6831.186	.828	.198	< .001
Profile Similarity Across Samples										
Configural Similarity	-11499.300	47	1.566	23092.600	23605.046	23558.046	23208.723	.902	Na	Na
Structural Similarity	-11530.075	31	1.476	23122.151	23328.232	23297.232	23198.742	.904	Na	Na
Dispersion Similarity	-11553.180	27	1.489	23160.360	23339.850	23312.850	23227.069	.903	Na	Na
Partial Dispersion Similarity	-11535.653	28	1.462	23127.307	23313.445	23285.445	23196.486	.903	Na	Na
Distribution Similarity	-11538.054	25	1.526	23126.108	23293.303	23267.303	23187.875	.903	Na	Na

Note: LL: Model LogLikelihood; #fp: Number of free parameters; Scaling: Scaling factor associated with MLR loglikelihood estimates; AIC: Akaïke Information Criteria; CAIC: Constant AIC; BIC: Bayesian Information Criteria; ABIC: Sample-size adjusted BIC; aLMR: Adjusted Lo-Mendel-Rubin likelihood ratio test; BLRT: Bootstrap Likelihood Ratio Test.

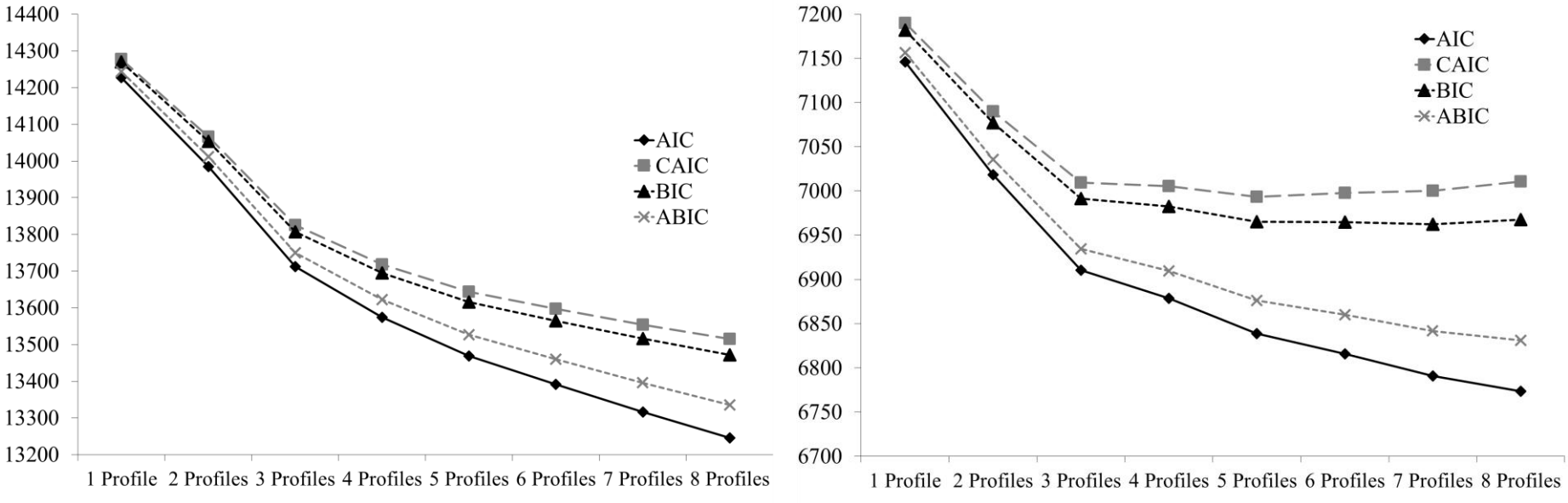

Figure S1
Elbow Plot of the Value of the Information Criteria for Solutions Including Different Number of Latent Profiles (Based on Bifactor Factor Scores) in Samples 1 (Left) and 2 (Right)

Table S10

Results from the Latent Profile Analysis Models Based on First-Order Factor Scores

Model	LL	#fp	Scaling	AIC	CAIC	BIC	ABIC	Entropy	aLMR	BLRT
Sample 1										
1 Profile	-5758.199	6	1.346	11528.398	11565.945	11559.945	11540.885	Na	Na	Na
2 Profiles	-5092.163	10	1.658	10204.326	10266.903	10256.903	10225.137	.826	< .001	< .001
3 Profiles	-4885.859	14	2.182	9799.718	9887.326	9873.326	9828.853	.834	.092	< .001
4 Profiles	-4786.464	18	3.425	9608.929	9721.567	9703.567	9646.388	.795	.632	< .001
5 Profiles	-4730.134	22	1.791	9504.269	9641.938	9619.938	9550.052	.828	.016	< .001
6 Profiles	-4646.537	26	1.585	9345.074	9507.774	9481.774	9299.181	.796	.026	< .001
7 Profiles	-4590.702	30	1.500	9241.403	9429.135	9399.135	9303.835	.817	.021	< .001
8 Profiles	-4451.514	34	1.418	9171.028	9383.790	9349.790	9241.784	.828	.002	< .001
Sample 2										
1 Profile	-2816.042	6	1.169	5644.085	5677.191	5671.191	5652.140	Na	Na	Na
2 Profiles	-2552.962	10	1.492	5125.923	5181.100	5171.100	5139.349	.783	< .001	< .001
3 Profiles	-2470.071	14	1.513	4968.141	5045.389	5031.389	4986.937	.731	.020	< .001
4 Profiles	-2420.567	18	1.519	4877.133	4976.451	4958.451	4901.299	.766	.044	< .001
5 Profiles	-2394.261	22	1.534	4832.522	4953.911	4931.911	4862.058	.771	.137	< .001
6 Profiles	-2369.969	26	1.757	4791.939	4935.398	4909.398	4826.845	.787	.544	< .001
7 Profiles	-2353.952	30	1.434	4767.904	4933.434	4903.434	4808.181	.756	.115	< .001
8 Profiles	-2338.689	34	1.405	4745.378	4932.979	4898.979	4791.025	.787	.338	< .001
Profile Similarity Across Samples										
Configural Similarity	-8525.640	37	2.432	17125.280	17371.248	17334.248	17216.695	.857		
Structural Similarity	-8565.203	25	1.782	17180.407	17346.602	17321.602	17242.174	.843		
Dispersion Similarity	-8576.950	22	1.812	17197.900	17344.152	17322.152	17252.255	.841		
Partial Dispersion Similarity	-8572.473	23	1.741	17190.945	17343.845	17320.845	17247.771	.844		
Distribution Similarity	-8576.834	20	1.847	17193.668	17326.624	17306.624	17243.082	.815		

Note: LL: Model LogLikelihood; #fp: Number of free parameters; Scaling: Scaling factor associated with MLR loglikelihood estimates; AIC: Akaïke Information Criteria; CAIC: Constant AIC; BIC: Bayesian Information Criteria; ABIC: Sample-size adjusted BIC; aLMR: Adjusted Lo-Mendel-Rubin likelihood ratio test; BLRT: Bootstrap Likelihood Ratio Test.

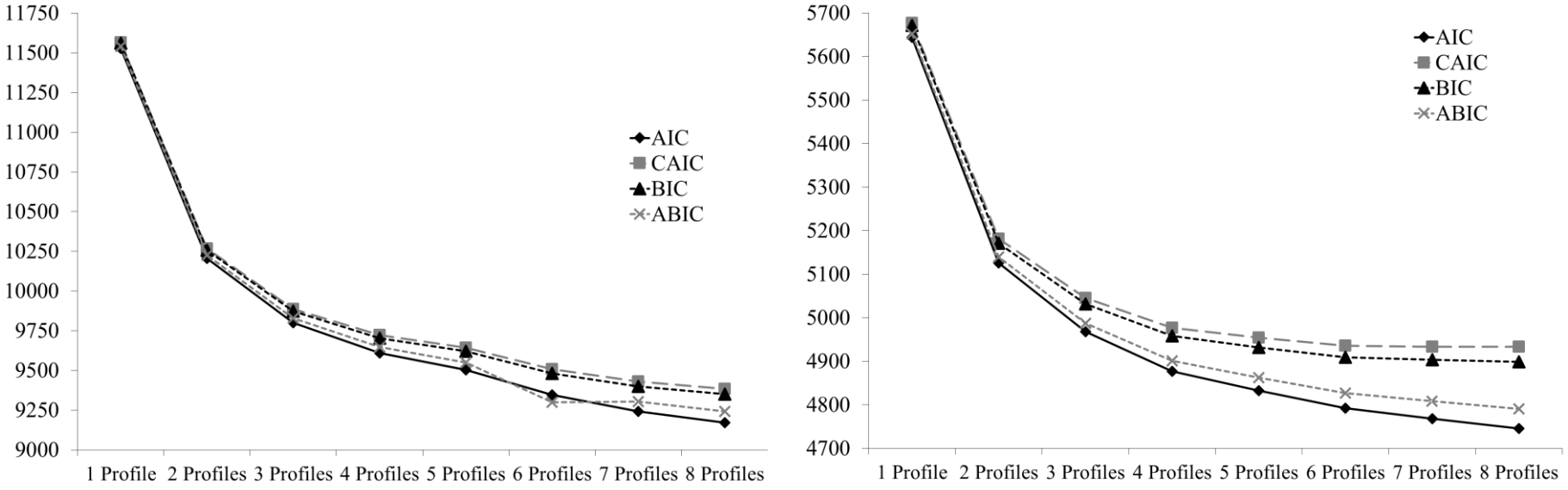

Figure S2
Elbow Plot of the Value of the Information Criteria for Solutions Including Different Number of Latent Profiles (Based on First-Order Factor Scores) in Samples 1 (Left) and 2 (Right)

Table S11

Detailed Parameter Estimates from the Final LPA Solutions (Distributional Similarity with Partial Dispersion Similarity)

	Profile 1 Mean [CI]	Profile 2 Mean [CI]	Profile 3 Mean [CI]	Profile 4 Mean [CI]	Variance [CI]
Bifactor Factor Scores					
Global Need Satisfaction	.293 [.227; .359]	-.625 [-.796; -.455]	-1.649 [-1.858; -1.440]	-1.261 [-1.577; -.945]	.560 [.492; .628]
Autonomy	.209 [.173; .246]	-1.436 [-1.573; -1.298]	-.552 [-.794; -.311]	.356 [.144; .568]	.377 [.336; .419]
Competence	-.019 [-.061; .023]	.420 [.259; .582]	-1.111 [-1.746; -.476]	.022 [-.236; .280]	.703 [.644; .761]
Relatedness	.051 [.002; .100]	.315 [.165; .465]	1.157 [.872; 1.442]	-1.543 [-1.914; -1.171]	Sample 1: .385 [.324; .447] Sample 2: .592 [.510; .675]
First-Order Factor Scores					
Autonomy	-2.280 [-2.716; -1.844]	-.124 [-.308; .059]	-1.177 [-1.346; -1.008]	.695 [.619; .772]	.407 [.358; .457]
Competence	-2.396 [-3.173; -1.618]	-.196 [-.341; -.052]	-1.144 [-1.331; -.958]	.757 [.656; .857]	.348 [.312; .384]
Relatedness	-3.350 [-4.197; -2.502]	-.078 [-.217; .060]	-1.123 [-1.367; -.878]	.659 [.586; .731]	Sample 1: .282 [.239; .326] Sample 2: .366 [.297; .435]

Note. CI = 95% confidence interval. The profile indicators are estimated from factor scores with mean of 0 and a standard deviation of 1; Profile 1 (Bifactor): *Normative* profile; Profile 2 (Bifactor): *Globally Dissatisfied yet Moderately Competent and Connected* profile; Profile 3 (Bifactor): *Globally Dissatisfied yet Highly Connected* profile; Profile 4 (Bifactor): *Globally Dissatisfied yet Moderately Autonomous* profile.

Table S12

Classification Accuracy: Average Probability of Membership into Each Latent Profile (Column) as a Function of the Most Likely Profile Membership (Row)

	Profile 1	Profile 2	Profile 3	Profile 4
Sample 1 (Bifactor)				
Profile 1	.947	.026	.007	.020
Profile 2	.112	.844	.031	.013
Profile 3	.063	.088	.849	0
Profile 4	.157	.015	.005	.823
Sample 2 (Bifactor)				
Profile 1	.941	.028	.007	.025
Profile 2	.120	.844	.024	.012
Profile 3	.108	.137	.721	.033
Profile 4	.164	.033	.007	.796
Sample 1 (First-Order)				
Profile 1	.917	0	.083	0
Profile 2	0	.831	.058	.112
Profile 3	.006	.103	.891	0
Profile 4	0	.125	0	.875
Sample 2 (First-Order)				
Profile 1	.926	0	.074	0
Profile 2	0	.830	.054	.116
Profile 3	.010	.104	.886	0
Profile 4	0	.109	0	.891

Note. The profile indicators are estimated from factor scores with mean of 0 and a standard deviation of 1; Profile 1 (Bifactor): *Normative* profile; Profile 2 (Bifactor): *Globally Dissatisfied yet Moderately Competent and Connected* profile; Profile 3 (Bifactor): *Globally Dissatisfied yet Highly Connected* profile; Profile 4 (Bifactor): *Globally Dissatisfied yet Moderately Autonomous* profile.