A Multilevel Person-Centered Perspective on the Role of Job Demands and Resources for Employees' Job Engagement and Burnout Profiles

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Abstract

The present study first examined the configurations, or profiles, taken by distinct global and specific facets of job engagement and burnout (by relying on a bifactor operationalization of these constructs) among a nationally representative sample of Canadian Defence employees (n = 13,088; nested within 65 work units). The present study also adopted a multilevel perspective to investigate the role of job demands (work overload and role ambiguity), as well as individual (psychological empowerment), workgroup (interpersonal justice), supervisor (transformational leadership), and organizational (organizational support) resources in the prediction of profile membership. Latent profile analyses revealed five profiles of employees: *Burned-Out/Disengaged* (7.13%), *Burned-Out/Involved* (12.13%), *Engaged* (18.14%), *Engaged/Exhausted* (15.50%), and *Normative* (47.10%). The highest levels of turnover intentions were observed in the *Burned-Out/Disengaged* profile, and the lowest in the *Engaged* profile. Employees' perceptions of job demands and resources were also associated with profile membership across both levels, although the effects of psychological empowerment were more pronounced than the effects of job demands and resources related to the workgroup, supervisor, and organization. Individual level effects were also more pronounced than effects occurring at the work unit level, where shared perceptions of work overload and organizational support proved to be the key shared drivers of profile membership.

Key words: Job engagement; burnout; latent profiles; multilevel; psychological empowerment; job demands and resources

According to Kahn (1990), job engagement occurs when employees' personal resources are actively channeled toward the realization of their work. High levels of job engagement facilitate the accomplishment of organizationally valued behaviors, support behaviors that are more focused and vigilant, and help workers meet the emotional demands of their roles (Kahn, 1990). Job engagement is a precursor of desirable outcomes for the organization (e.g., lower turnover intentions, better performance; Rich et al., 2010) and the employee (e.g., higher job satisfaction; Haynie et al. 2016). Conversely, burnout is characterized by high levels of emotional exhaustion and negative attitudes toward work (Maslach et al., 2001). Employees suffering from burnout feel disillusioned, helpless, irritated, and worn-out. They have lost connection with their work and distance themselves mentally and emotionally from their work activities (Leiter & Maslach, 2016). Burnout is associated with high levels of turnover intentions (Cheng et al., 2016) and depressive symptoms (Hatch et al., 2019).

Despite abundant research (Bakker & Demerouti, 2017; Laughman et al., 2016) supporting the benefits associated with job engagement components (physical, cognitive, and emotional; Rich et al., 2010) and the undesirable outcomes of burnout components (emotional exhaustion and disengagement; Demerouti et al., 2010), little is known about their combined impact (Mäkikangas et al., 2017). Two very distinct, yet complementary, types of analyses can help to better comprehend this combined impact. On the one hand, variable-centered analyses can help to understand the nature of associations between a subset of variables and other subsets of variables. Unfortunately, these analyses are unable to reveal a clear picture of the combined effect of more than two or three variables. On the other hand, person-centered analyses consider the configurations taken by a set of variables among discrete subpopulations, or profiles, of employees.

In the present study, we rely on person-centered analyses (i.e., latent profile analyses – LPA) to identify the configurations of burnout and job engagement among different profiles of employees in a way that would be impossible to achieve using variable-centered analyses. More precisely, the resulting profiles would represent discrete subpopulations of employees characterized by qualitatively distinct configurations of burnout and job engagement (e.g., such as a profile of employees experiencing high levels of burnout coupled with low levels of job engagement, a profile characterized by high levels of engagement coupled with high levels of emotional exhaustion, or even a profile dominated by specific dimensions of burnout and/or job engagement). This approach helps to achieve a more integrative, or holistic, understanding of the reality of job engagement and burnout profiles as it is truly experienced among employees, and in a way that shares clear connections with our (i.e., researchers, managers, and practitioners) tendency to think of employees as members of discrete categories (Zyphur, 2009). More precisely, whereas a nomothetic variable-centered approach considers job engagement and burnout components as separate interrelated constructs, a more idiographic person-centered approach rather focuses on how all of these components are experienced together by different types of employees (Marsh et al., 2009; Meyer & Morin, 2016).

Emerging person-centered research has started to look at how job engagement and burnout components combine within specific individuals (Abós et al., 2019; Mäkikangas et al., 2012, 2014, 2017; Moeller et al., 2018; Salmela-Aro et al., 2019; see Table S1 in the online supplements for an overview of the profiles identified in these studies, as well as their associations with a variety of predictors and outcomes). However, no research has done so while considering the specificity of all theoretical facets of job engagement, or by simultaneously considering employees' global and specific levels of job engagement (physical, cognitive, and emotional; e.g., Gillet et al., 2020c) and burnout (emotional exhaustion and disengagement; Isoard-Gautheur et al., 2018). Information is thus lacking regarding the nature of employees' job engagement and burnout configurations based on a complete theoretical coverage of the inherent multidimensionality of both constructs.

To inform this issue, this study documents the job engagement and burnout configurations that best characterize members of a large-scale representative sample of Canadian Defence personnel, while accounting for the multidimensionality of job engagement and burnout. In doing so, the present study emphasizes the importance of adopting a finer-grained representation of job engagement and burnout by simultaneously considering their global and specific components. This more refined perspective helps us to better understand the unique, and complementary, role played by each specific facet of burnout and job engagement beyond the role played by employees' global levels of burnout and job engagement. This approach should help us to uncover whether profiles defined by more, or less, balanced configurations of burnout and job engagement across components may carry greater, or lower, levels of risk for exposed employees. For instance, despite the generally assumed positive effects of job engagement, is it possible for some highly engaged employees to also come to experience higher than expected levels of emotional exhaustion? Alternatively, is job engagement enough to limit employees' risk of turnover intentions, or would these benefits be maximized only for employees presenting some specific combinations of burnout and job engagement components?

This study also documents the construct validity (Muthén, 2003) of these profiles by considering their associations with job demands and resources (work overload, role ambiguity, interpersonal justice, transformational leadership, organizational support, and psychological empowerment), and turnover intentions. From a practical perspective, this study should help provide improved guidance for managers seeking to nurture, preserve, and improve the psychological health among different types of employees (Zyphur, 2009). For instance, by documenting the implications of these profiles for employees' turnover intentions, this study should help organizations to determine which profiles should be prioritized from an intervention perspective. Likewise, understanding how different types of job demands and resources contribute to the emergence of these different types of profiles should also provide guidance in relation to the identification of actionable levers of intervention. Importantly, a unique contribution of this study would be to examine these associations from a multilevel perspective. This multilevel perspective will allow us to verify whether, and how, the effects of employees' perceptions of job demands and resources on their likelihood of profile membership would differ across the individual versus group levels of analyses, leading to a clearer understanding of the role played by employees' shared perceptions of the job demands and resources present in their work unit, once properly disaggregated from their individual perceptions of these same job demands and resources.

A Multidimensional Representation of Burnout and Job Engagement

It is recognized that an assessment of job engagement should tap into the physical, cognitive, and emotional facets of this construct (Rich et al., 2010), just like an assessment of burnout should at least tap into its emotional exhaustion and disengagement components (Demerouti et al., 2003). It has also been proposed that employees might experience job engagement and burnout in a more holistic manner as a function of two overarching dimensions (Alfes et al., 2013; Cheng et al., 2016). This global approach is supported by high correlations among ratings of physical, cognitive, and emotional job engagement (Shuck & Reio, 2014), and among ratings of emotional exhaustion and disengagement (Demerouti et al., 2010). Research has also shown that a higher-order representation of job engagement relates more strongly to antecedents and outcomes than its first-order components (Shuck et al., 2017). However, research has also revealed well-differentiated associations between distinct components of job engagement and burnout, and a variety of outcomes, thus supporting the existence of conceptually distinct components of job engagement (Shuck et al., 2017) and burnout (Collie et al., 2018).

These options are not mutually exclusive as burnout might also exist as a global entity (i.e., burnout) reflecting commonalities among ratings of emotional exhaustion and disengagement, themselves including specificity unexplained by this global burnout entity (Barcza-Renner et al., 2016; Isoard-Gautheur et al., 2018). Likewise, job engagement can occur both as a global construct anchored in the variance shared across its dimensions (emotional, physical, and cognitive), themselves retaining some specificity (Gillet et al., 2020). Higher-order results support the idea that both constructs can be represented as global entities (Rich et al., 2010; Sinval et al., 2019). However, a remaining question is whether enough specificity exists in the physical, cognitive, and emotional components once global job engagement is considered, and in the emotional exhaustion and disengagement components once global burnout is considered (Gillet et al., 2020c; Sinval et al., 2019).

Although hierarchical models have often been used to address this question (e.g., Rich et al., 2010; Sinval et al., 2019), these models involve a stringent proportionality constraint in defining how the items relate to the higher-order factor and to the specific part of the first-order factors that is not explained by the higher-order factor (i.e., its disturbance; e.g., Chen et al., 2006). Indeed, in hierarchical models, items define first-order factors, which are used to define a higher-order factor reflecting the variance that is shared among the first-order factors. Yet, the relation between an item and the higher-order factor is indirect (i.e., mediated by the first-order factor). This indirect effect is reflected as the product of (x) the item's first-order factor loading by (y) the loading of this first-order factor on the higher-order factor. This second term (y) is thus a constant for all items associated with a specific first-order factor. Similarly, the relation between an item and the disturbance of the first-order factor to which it is associated is also reflected by the product of this item's loading on the first-order factor (x) and another constant representing the link between the first-order factor and its disturbance (z). These implicit proportionality constraints imply that the ratio of item variance explained by the global (the higher-order factor; e.g., global burnout) and specific (the first-order factors; e.g., emotional exhaustion and disengagement) constructs (xy/xz) is assumed to be identical for each first-order factor (y/z), and unlikely to hold in real life (Morin et al., 2016a).

Bifactor models provide an alternative to hierarchical models (Chen et al., 2006), are not submitted to this unrealistic restriction. Bifactor models thus provide a more flexible way to address the same questions. According to a bifactor operationalization, each item is used to define both a Global (G) factor and one Specific (S) factor. This approach thus provides a way to obtain a direct estimate of the commonalities shared across all items (the G-factor, e.g., global engagement or global burnout), and an equally explicit estimate of the specificity associated with each component (specified as independent from one another) *beyond the variance already explained by the G-factor* (S-factors, e.g., emotional, physical, and cognitive, or emotional exhaustion and disengagement). Apart from this global/specific variance decomposition, it is important to note that the meaning of engagement and burnout dimensions remains the same in bifactor models as in traditional approaches. In the present context, a bifactor representation would result in the estimation of participants' specific levels on each of the job engagement or burnout components to be directly expressed as deviations from their global levels of job engagement or burnout. As such, the S-factors provide a direct representation of the extent to which the levels of each specific component can be considered to be in a state of imbalance relative to participants' global levels of job engagement or burnout. The S-factors representing participants' levels of emotional exhaustion and disengagement would thus reflect the extent to which employees' levels of exhaustion or disengagement are higher, lower, or similar (when = 0) than their levels of burnout across dimensions. More precisely, the burnout S-factor would reflect employees' levels of emotional exhaustion occurring in a manner that is unrelated to burnout (so, possibly, "healthier" levels of exertion or fatigue), and employees' levels of disengagement occurring in a manner that is unrelated to burnout (so, possibly, reflecting simply a drop in motivation and the need for a break). Similarly, emotional, physical, and cognitive job engagement S-factors indicate that employees' levels of emotional, physical, or cognitive job engagement are higher, lower, or similar than their levels of job engagement across dimensions. More precisely, these S-factor would reflect employees' feelings of having to invest a level of emotional, physical, or cognitive resources into their work role in a way that goes beyond their global level of engagement into this role. Numerous studies have demonstrated that a bifactor approach was more suitable than first- and higher-order representations of both burnout (e.g., Barcza-Renner et al., 2016; Isoard-Gautheur et al., 2018; Sinval et al., 2019) and job engagement (e.g., Gillet et al., 2019a, 2020c; Huyghebaert-Zouaghi et al., 2021).

A Person-Centered Perspective on the Complementary Role of Job Engagement and Burnout

Researchers relying on variable-centered analyses assume, often explicitly but sometimes implicitly, that their results would equally apply to all members of the population under study. Although it is possible to verify how the effects of one variable differ as a function of another one, such tests of interaction effects are virtually impossible to decode when more than three predictors interact together, especially in the presence of nonlinear effects. Importantly, adopting a bifactor representation of job engagement and burnout would result in seven interacting predictors, making it impossible to rely on variable-centered analyses to achieve an integrated representation of the combined role played by these two G-factors (burnout and engagement) and five S-factors (emotional exhaustion, disengagement, cognitive engagement, emotional engagement, and physical engagement). Person-centered analyses do not rely on similar assumptions and are specifically designed to identify profiles of employees differing from one another on more or less extensive a set of variables (Meyer & Morin, 2016). Thus, rather than focusing on the additive or interactive effects of each of these variables, the person-centered approach rather focuses on the categorization of employees into discrete profiles differing in their unique experiences of job engagement and burnout dimensions, the outcome implications of these profiles, and the impact of various predictors on employees' likelihood of corresponding to each of these profiles (Meyer & Morin, 2016).

Person-Centered Studies: A Summary. In Appendix 1 of the online supplements, Table S1 provides a summary of the results from previous person-centered research seeking to identify profiles of burnout and or engagement. Despite some variations possibly related to methodological differences (e.g., type of employees, measures), a high level of similarity is apparent across studies (Mäkikangas & Kinnunen, 2016). However, very few of these previous studies have adopted a comprehensive approach simultaneously incorporating multiple facets of engagement and burnout, while relying on a proper disaggregation of global levels of job engagement and burnout from the specificities associated with each job engagement and burnout facet. The estimation of latent profile based on indicators capturing the bifactor structure of job engagement and burnout ratings (i.e., resulting in a proper disaggregation of global and specific levels of job engagement and burnout across facets) would make it possible to identify clearer, and more easily interpretable, profiles differing from one another in relation to both the global (i.e., global job engagement and burnout) and specific components (i.e., the different dimensions of job engagement and burnout dimensions) of these constructs (Morin et al., 2016b, 2017). This approach would thus help us to isolate the unique contribution of each specific dimension associated with both constructs (e.g., Gillet et al., 2019b). Ignoring this dual global/specific structure carries the risk of inaccurately identifying profiles characterized by job engagement and burnout levels solely capturing the global components of these constructs (Morin & Marsh, 2015; Morin et al., 2016b, 2017). When we consider the results from person-centered studies, we can indeed note that many of these studies revealed many profiles mainly characterized by global types of differences. The present investigation, relying on representative sample of Defence employees, adopts an approach developed by Morin et al. (2016b, 2017) to identify profiles of burnout and job engagement while accounting for the global and specific components of these constructs.

Despite our difference in approach, it remains possible for us to expect the identification of profiles dominated by job engagement (i.e., an *Engaged* profile), burnout (i.e., a *Burned-Out/Disengaged* profile), or by low to average levels on both constructs (i.e., a *Normative* profile) (e.g., Gillet et al., 2019a). These expectations are consistent with the conservation of resources theory (Hobfoll, 1989), which sees available material and psychological resources as limited, and stress as emerging from the true or perceived loss of resources. From this perspective, the energizing nature of job engagement stands in stark contrast with the resource depletion nature of burnout. A similar perspective comes from self-determination theory (Ryan & Deci, 2017), which describes job engagement as primarily motivated by autonomous forms of motivation (i.e., driven by pleasure and choice) and burnout as primarily motivated by controlled forms of motivation (i.e., driven by internal or external pressures). Interestingly, recent research has generally supported these assertions in relation to job engagement and burnout (Gillet et al., 2018b, 2020d). From these two theoretical perspectives, it thus seems realistic to anticipate the identification of profiles dominated by either one, or none, of these two constructs.

However, in accordance with the subset of *shape*-differentiated profiles obtained in prior research (e.g., Abós et al., 2019; see Table S1) and with results from previous studies relying on a methodology similar to ours for the study of engagement profiles (Gillet et al., 2019a, 2020c), some employees may also be characterized by profiles presenting differentiated configurations of job engagement and burnout across indicators. For instance, we might identify a *Burned-Out/Involved* profile presenting high global levels of burnout, and moderate to high levels of global, physical, and cognitive job engagement, in accordance with the highly engaged and highly frenetic (Abós et al., 2019) and highly engaged-exhausted (Moeller et al., 2018) profiles identified previously. This expectation makes sense theoretically. As noted earlier, burned-out workers tend to be driven by controlled motivation, whereas engaged workers tend to be driven by autonomous motivation. However, motivation is rarely uniquely autonomous or controlled (Ryan & Deci, 2017), and often involves a combination of both for at least a subset of employees (Gillet et al., 2018a; Howard et al., 2016). These employees would likely form the *Burned-Out/Involved* profile. Moreover, it might be possible for globally high levels of job engagement to be accompanied by specific manifestations of burnout (e.g., exhaustion, thus reflecting the exerting nature of high levels of job engagement) independently of employees' global levels of burnout. Likewise, it might also be possible for globally high levels of burnout to be accompanied by specific manifestations of engagement (e.g., physical engagement, thus reflecting attempts made by burnout employees to maintain an adequate level of performance despite a global lack of psychological energy) independently of employees' global levels of job engagement.

Given the novelty of our approach, it would be possible to speculate regarding the possible identification of a rather large number of qualitatively distinct configurations of job engagement and burnout. However, despite their interest, these possibilities would remain largely speculative. Thus, and in a way that is aligned with the methodologically indicative nature of person-centered analyses, we leave as an open research question the nature of the profiles to be identified.

Research Question 1: Which profiles of job engagement and burnout will be identified among the current sample of Defence employees?

Research Question 2: Will these profiles differ quantitatively (based on employees' global levels of job engagement and burnout), qualitatively (based on their specific configuration of burnout and job engagement components), or both?

Profiles of Burnout and Engagement: Implications for Turnover Intentions

Turnover intentions are the main predictor of voluntary turnover (Heavy et al., 2013), a relation that is particularly marked among military personnel (Lytell & Drasgow, 2009). Turnover itself has always been a ubiquitous outcome for organizations given its costs in terms of performance reduction, recruitment, and training (Heavey et al., 2013). Turnover intentions also present negative relations with job engagement and positive relations with burnout (Alfes et al., 2013; Cheng et al., 2016), indicating that highly involved employees are more likely to want to stay in their job, whereas worn-out ones are more likely to seek alternative employment.

Results from previous person-centered research (see Table S1; e.g., Abós et al., 2019) suggest that profiles characterized by high levels of job engagement and low levels of burnout (e.g., *Engaged*) tend to be associated with lower turnover intentions than profiles characterized by low levels of job engagement and high levels of burnout (e.g., *Burned-Out/Disengaged*). From the perspective of the conservation of resources theory (Hobfoll, 1989), burned-out employees can be seen as lacking the resources required to adequately accomplish their work-related tasks, thus leading to higher levels of dissatisfaction and perceptions of ineffectiveness, which may ultimately result in turnover intentions and voluntary turnover (Cheng et al., 2016). In contrast, engaged employees are seen as more positively disposed toward their work, and as experiencing more positive work-related emotions (Rich et al., 2010), thus increasing their identification with the organization and their willingness to allocate extra time and resources to their organization, which may ultimately reduce their turnover intentions (Gillet et al., 2019a). Moeller et al.'s (2018) observation of low turnover intentions among Apathetic employees (i.e., low burnout and engagement) also suggests that low turnover intentions should be observed in the *Normative* profile. Finally, some additional results (see Table S1; e.g., Moeller et al., 2018) indicate that job engagement may protect employees against the negative effects of burnout, implying that lower turnover intentions should be observed in the *Burned-Out/Involved* profile relative to the *Burned-Out/Disengaged* one. This perspective is also consistent with self-determination theory, which suggests that high levels of controlled motivation could even become beneficial when combined with similarly high levels of autonomous motivation (Gillet et al., 2018a; Howard et al., 2016; Ryan & Deci, 2017). In line with these considerations, we consider the question:

Research Question 3: How do employees' levels of turnover intentions differ as a function of their job engagement and burnout profiles?

A Multilevel Person-Centered Perspective on the Role of Job Demands and Resources

Job Demands. The job demands-resources (JD-R) model (Demerouti et al., 2001) highlights the role of two categories of work conditions, job demands and resources, in the prediction of employees' engagement and burnout. Job characteristics requiring employees to expand psychological and/or physical efforts in an ongoing manner are referred to as job demands and tend to carry a toll for employees feeling exposed to such a work environment (Schaufeli & Bakker, 2004). Moreover, employees tend to perceive job demands as challenging or hindering (Crawford et al., 2010). Challenging job demands have the potential to support mastery, personal growth, or future gains (i.e., demands to be overcome to learn and achieve), whereas hindering job demands have the potential to thwart growth, learning, and goal attainment. We focus on the effects of two types of hindering job demands with a known influence on job engagement and burnout (e.g., Ghorpade et al., 2011; Reinke & Chamorro-Premuzic, 2014): Role ambiguity and work overload. Hindering demands are expected to interfere with employees' functioning by impeding their self-actualization and the satisfaction of their psychological needs for autonomy, competence, and relatedness (Ryan & Deci, 2017). Hindering demands are thus likely to lead to a persistent psychophysiological and cognitive activation (Sonnentag & Fritz, 2015) as a result of being unable to attain personal goals (e.g., Kinnunen et al., 2017). This persistent activation is thus likely to interfere with the work recovery process (e.g., making it harder to psychologically detach; Sonnentag & Bayer, 2005). Not surprisingly, the effects of hindering job demands are well documented in the prediction of a range of outcomes likely to emerge from the quality of the work recovery process, such as higher levels of burnout and lower levels of job engagement (Gillet et al., 2020a, 2021). More specifically, when coping with role ambiguity, employees lack clear and consistent information about work expectations (Kahn et al., 1964). They are thus more likely to report higher levels of job anxiety and strain, subsequently leading to lower job engagement and higher burnout (Bakker & Demerouti, 2017).

Similarly, attempts to cope with work overload may lead employees to exhaust their energetic resources, in turn increasing their likelihood of experiencing lower levels of job engagement and higher levels of burnout (Schaufeli & Bakker, 2004).

Job Resources. Contrasting with job demands, job resources refer to those aspects of a job that contribute to supporting employees in achieving their goals, to reducing the costs associated with job demands, and to stimulating personal development (Demerouti et al., 2001; Xanthopoulou et al., 2009). Job resources are expected to help enhance employees' psychological functioning, both by increasing job engagement and by decreasing burnout (Schaufeli & Bakker, 2004). Nielsen et al. (2017) proposed a multi-level framework focusing on whether job resources originate from the employees, their workgroup, their supervisors, or the organization. They also reported meta-analytic evidence supporting the complementary role of each type of resources for employees' psychological health and behaviors.

Individual Resources. Individual resources are personal characteristics that help employees cope with job demands and achieve satisfactory levels of performance while remaining psychologically healthy (Xanthopoulou et al., 2009). In this study, we focus on psychological empowerment, which encompasses employees' feelings of competence, autonomy, impact, and meaning in relation to their work (Spreitzer, 1995, 2008). Competence refers to feelings of having the abilities required for a successful execution of their work, a cognition close to the concept of self-efficacy. Autonomy refers to feelings of being in control when initiating and regulating work behaviors. Impact refers to feelings of being able to influence operational, strategic, or administrative outcomes at work. Finally, meaning refers to feelings that there is a good fit between work requirements and employees' personal beliefs, standards, and values. Despite their distinct nature, these four cognitions have been systematically shown to converge on a global psychological empowerment construct (Morin et al., 2016c; Seibert et al., 2011). Psychological empowerment is positioned as a core psychological resource allowing employees to play a volitional role at work while feeling in control of their actions, and thus as an important mechanism allowing them to handle the stressfulness of their work (e.g., Spreitzer, 1995, 2008). Meta-analyses support the role of psychological empowerment as a driver of a variety of organizationally-relevant outcomes and psychological health indicators (e.g., Seibert et al., 2011), including lower levels of burnout and higher levels of job engagement (e.g., Calvo & García, 2018; Livne & Rashkovits, 2018). Importantly, psychological empowerment is conceptually distinct from self-determined work motivation (Gagné et al., 1997).

Workgroup Resources. Workgroup resources relate to the social and interpersonal context of the workplace; that is, to relationships among group members that foster efficient communications, positive interactions, and trust (Nielsen et al., 2017). In this study, we focus on interpersonal justice, which refers to workgroups in which employees interact respectfully with one another (Colquitt, 2001). Evolving in a workgroup in which employees feel respected across a range of situations is likely to improve the pleasantness of the work, to help employees feel supported when facing adversity, and to protect them against feelings of exhaustion, isolation, and disconnection (Colquitt et al., 2013). The role of interpersonal justice as a driver of positive functioning at work, including higher levels of job engagement and reduced levels of burnout, have been well established in research (Colquitt et al., 2013; Gillet et al., 2013).

Leader Resources. Leader resources refer to vertical interactions between employees and supervisors who may, by virtue of their position and leadership style, provide them with support, guidance, and security (Nielsen et al., 2017). We focus on transformational leadership, which refers to the ability of the supervisor to inspire and motivate employees' loyalty and involvement (Bass & Avolio, 1994). Transformational leaders focus on employees' individual needs, and provide them with a sense of mission and purpose which helps to protect them from adversity while maintaining their positive drive (Hildenbrand et al., 2018). Similar to interpersonal justice, the role of transformational leadership as a mechanism able to support employees' psychological health, including increases in job engagement and protection against burnout, has been supported by extensive research evidence (e.g., Hildenbrand et al., 2018; Montano et al., 2017).

Organizational Resources. Organizational resources refer to the broader work environment context, and the way it is organized and managed to support, motivate, and encourage positive functioning and growth (Nielsen et al. 2017). In this study, we focus on organizational support, which refers to the extent to which the organization values and supports employees' contributions and well-being (Eisenberger et al., 1986). Organizational support contributes to fulfilling employees' basic socioemotional needs at work and is expected to convey the idea that support (material or emotional) will be available to help them maintain adequate levels of performance under stressful conditions (Eisenberger & Stinglhamber, 2011). Not surprisingly, the beneficent role of employees' perceptions of organizational support in relation to a wide range of outcome variables, including job engagement and burnout, has also been well established in research (e.g., Eisenberger & Stinglhamber, 2011; Gillet et al., 2018a).

A Person-Centered Perspective. Despite their importance, no research has examined the effects of these job demands and resources on job engagement and burnout profiles. Indeed, whereas variable-centered predictions simply highlight the role of job demands and resources in the prediction of each burnout or job engagement components considered in isolation, the person-centered perspective makes it possible to consider this role more broadly in the prediction of distinctive multidimensional configurations of job engagement and burnout. In other words, it makes it possible to directly account for the role of these job demands and resources in the prediction of the complete reality of employees' engagement and burnout.

Despite the novelty of our approach, the variable-centered evidence presented thus far suggests that transformational leadership, interpersonal justice, organizational support, and psychological empowerment, as well as lower levels of role ambiguity and work overload, should predict a higher likelihood of membership into the *Engaged* profile followed by the *Normative* profile, and a lower likelihood of membership into the *Burned-Out/Disengaged* profile. However, given that JD-R research considers individual resources as a more proximal driver of employee functioning than work characteristics (Xanthopoulou et al., 2009), we can also assume that psychological empowerment should play a greater role in the prediction of employees' likelihood of membership into these various profiles relative to the other job demands and resources considered in this study, at least at the individual level. Finally, research suggests that work overload tends to be perceived by some employees as a challenging job demand (Crawford et al., 2010). More specifically, when employees feel that their work overload partly falls under their personal control, their work motivation emerging from this work overload is more likely to be driven., at least partially, by autonomous forms of motivation (Ryan & Deci, 2017). In contrast, work overload is also likely to be externally imposed for many employees (e.g., by their supervisor or their colleagues), for whom it would represent a hindering type of job demand (Crawford et al., 2010) and a source of controlled forms of motivation (Ryan & Deci, 2017). As a result, and accounting for the well-established variable-centered positive associations between work overload and burnout (Schaufeli & Bakker, 2004), the potentially challenging nature of work overload may also increase the likelihood of belonging to a *Burned-Out/Involved* profile for some employees, in addition to increasing the likelihood of belonging to a *Burned-Out/Disengaged* profile for other employees.

Building on the JD-R model, we tested these possibilities by considering an individual resource (psychological empowerment) in addition to a series of job demands (work overload and role ambiguity) and workgroup (interpersonal justice), supervisor (transformational leadership), and organizational (organizational support) resources in the prediction of profile membership.

Research Question 4: How will job demands (work overload and role ambiguity) as well as individual (psychological empowerment), workgroup (interpersonal justice), supervisor (transformational leadership), and organizational (organizational support) resources related to employees' likelihood of belonging to the various profiles of job engagement and burnout identified in this study?

A Multilevel Perspective. JD-R research has, for the most part, focused on job demands and resources assessed at the individual level via employees' report, without often considering how the effects of these work-related characteristics may differ at the work unit level. Yet, Bakker and Demerouti (2017) remarked that it would be critical to adopt a more systematic multilevel approach to the study of these multilevel phenomena. Indeed, employees evolve in complex multilayered workplaces in which at least a part of their work experiences are likely to be shared by all members of their workgroups (i.e., reflecting their exposure to more objective work characteristics), thus conflating two sources of influence in a single estimate when relying on single-level analyses (Gonzàlez-Romà & Hernàndez, 2017; Morin et al., 2021). We adopt a multilevel perspective to achieve a clearer understanding of the role played by employees' shared perceptions of the job demands and resources present in their work unit (i.e., a more objective, or at least consensual, picture of their work unit environment) properly disaggregated from their individual exposure to job demands and resources (i.e., inter-individual differences in their perceptions of their work unit).

More precisely, as part of the instructions provided to them in the questionnaires, employees were explicitly asked to report on their individual perceptions of the job demands, as well as the workgroup, supervisor, and organization resources present in their work unit. Using these ratings, our multilevel perspective allowed us to disaggregate their shared perceptions (from the group-level aggregation of their individual perceptions) from their unique individual experiences. In organizational research, this type of rating makes it possible to assess "climate" or "consensus" constructs at the work unit level (Bliese et al., 2007; Quigley et al., 2007; Morin et al., 2021). In fact, many have argued that when the referent of the ratings is the work unit, then it is unreasonable to assume that the unique reality of the individual employee who provided the rating is the only cause of that rating (thus committing the fundamental attribution error of ignoring the work unit reality as an equally important source of influence on the rating; e.g., Ross, 1977). In this case, the proper level at which these predictors should be considered is the work unit (the object of the rating), allowing researchers to separately consider the role played by inter-individual deviations in these ratings. These deviations, however, are more likely to reflect social comparison processes or inter-individual differences in exposure to specific work characteristics than the whole reality of individual levels of exposure to these work characteristics (Marsh et al., 2012; Morin et al., 2014, 2021). This perspective highlights the risk of failing to separate these two layers of influences, especially when focusing on job demands and resources explicitly conceptualized, and measured, as characteristics of the work unit.

In contrast, being explicitly defined as an individual resource, psychological empowerment needs to be studied as such. Although meaningful individual variables can sometimes create a specific work context (such as sex, which is an meaningful individual variable and yet can create a male- or female-dominated work context), previous research has shown that did not happen when psychological empowerment was considered (Morin et al., 2021); that is, that the construct of psychological empowerment (located at the individual level) was qualitatively distinct from the construct of team empowerment (located at the work unit level; Maynard et al., 2013), which is not considered in the present study.

Fortunately, some emerging variable-centered attempts have been made to study the effects of job demands and resources across the individual and group levels. For instance, Demerouti et al. (2001) found similar associations between job demands and resources and employees' burnout and disengagement at the group and individual levels, showing job demands to be associated with higher levels of burnout, and job resources to be associated with lower levels of disengagement. Likewise, Bakker et al. (2008) found supervisor and workgroup resources to be associated with lower levels of cynicism, whereas job demands were positively related to emotional exhaustion at the individual level. Rather than focusing on global constructs reflecting job demands and resources, other studies established the multilevel role of specific work environment characteristics, such as leadership, organizational support, or justice perceptions (e.g., El Akremi et al., 2014; Gagné et al., 2020; Kiersch & Byrne, 2015) in the prediction of various indicators of psychological functioning, including job engagement and burnout. Despite similarities, these studies are inconsistent regarding the relative role of individual perceptions and group aggregates, making it hard to establish clear expectations and to transpose these expectations to the person-centered context.

Research Question 5: How will the associations between job demands and resources and employees' likelihood of profile membership differ across levels of analyses (i.e., inter-individual differences in perceptions of work-related demands and resources and shared perceptions at the work unit level)?

Method

Participants

This study relies on a stratified random sample of Canadian Armed Forces/Department of National Defence (CAF/DND) non-deployed personnel, selected from a sampling frame of 100,018 military and civilian personnel covering a wide range of occupations. Random samples were drawn from 67 organizational strata with proportional allocation for the sector (i.e., Regular Force, Primary Reserve, and civilian personnel), sex, rank (i.e., non-commissioned members and officers) for military personnel, and years of service for civilian personnel. This random sampling scheme yielded a total sample of 41,387 personnel with a small expected margin of error (< 1%). Of those, 13,088 respondents (31.6%), nested within 65 work units (including 46 to 576 employees, M = 201.35; SD = 127.91), took part in the Defence Workplace Well-Being Survey (DWWS) between May and August 2018. This sample size is aligned with the suggestion that such analyses should rely on a sample including at least 50 units including at least 10 to 15 participants each (e.g., Lüdtke et al., 2008, 2011). The DWWS received approval from the CAF/DND Social Science Research Review Board. Participants provided informed consent and were ensured that their responses would remain confidential and that only aggregate data would be reported.

Sampling weights were calculated to ensure that the sample was representative of the target population (i.e., to ensure that the results can be generalized to the whole CAF/DND population from which the sample has been recruited). Taking into account these weights, 55% percent of the population were members of the Regular Force, 20% were members of the Primary Reserve, and 25% were civilian employees. Nineteen percent of the military members were officers, whereas 26% of the civilian employees occupied a managerial or supervisory position. Seventy-five percent of the population was male, 37% percent was younger than 35, 50% was between 35 and 54 years of age, and 13% was older than 54. Thirty-eight percent of the population had served within the CAF/DND for fewer than 11 years, 33% between 11 and 20 years, and 29% served for 20 years or more.

Most respondents (81.7%) completed the English version of the DWWS, whereas the remaining completed the French version. For the few measures (role ambiguity and work overload) not already validated in both official languages of Canada, translators from the Government of Canada's Translation Bureau translated the original English items into French. Bilingual experts from CAF/DND then back-translated these items into English. Discrepancies were resolved by consensus.

Measures

Burnout. Disengagement (four items; α = .81; e.g., *Over time, one can become disconnected from this type of work*) and emotional exhaustion (four items; α = .85; e.g., *During my work, I often feel emotionally drained*) were measured with an eight-item short form of the Oldenburg Burnout Inventory (Demerouti et al., 2003; French version by Chevrier, 2009). All items were rated on a four-point scale ranging from 1-*Strongly Disagree* to 4-*Strongly Agree*.

Job Engagement. Cognitive (six items; α = .93; e.g., *At work, I am absorbed by my job*), physical (six items; α = .93; e.g., *I work with intensity on my job*), and emotional (six items; α = .95; e.g., *I am proud of my job*) engagement were assessed with Rich et al.'s (2010) measure (French version by Gillet et al., 2020c). Items were rated on a five-point scale (1-*Strongly Disagree*; 5-*Strongly Agree*).

Psychological Empowerment (Individual Resource). Feelings of meaning (three items; α = .96; e.g., *The work I do is meaningful to me*) and impact (three items; α = .92; e.g., *I have significant influence over what happens in my department*) were assessed with subscales from Spreitzer's (1995; French version by Boudrias et al., 2010) questionnaire. Feelings of autonomy (six items; α = .81; e.g., *I feel free to do my job the way I think it could best be done*) and competence (four items; α = .90; e.g., *I am good at the things I do in my job*) were assessed with subscales from Van den Broeck et al.'s (2010; French version by Gillet et al., 2020b) questionnaire. Responses were provided using a five-point scale (1-*Totally Disagree*; 5-*Totally Agree*).

Role Ambiguity (Job Demand). Employees' perceptions of role ambiguity were assessed using the relevant six-item scale (α = .92; e.g., *The requirements of my job are not always clear*) from Bowling et al.'s (2017) questionnaire. All items were rated in relation to work conducted within their unit on a seven-point scale (1-*Strongly Disagree*; 7-*Strongly Agree*).

Work Overload (Job Demand). Employees' perceptions of work overload were assessed with the six-item (α = .93) short version (Thiagarajan et al., 2006) of Reilly' (1982) questionnaire. All items (e.g., *I need more hours in the day to do all the things that are expected of me*) were rated in a seven-point frequency scale (1-*Never*; 7-*Always*) in relation to work conducted within their unit.

Transformational Leadership (Supervisor Resource). Perceptions of the supervisors' transformational leadership practices were assessed using the seven-item (α = .96; e.g., *Communicates a clear and positive vision of the future*) Global Transformational Leadership Scale (Carless et al., 2000; French version by Gillet et al., 2016a). Items followed the stem "*Please indicate how often your supervisor …*" on a five-point frequency scale (1-*Rarely or Never*; 5-*Very Frequently, if not Always*) in relation to the behaviors of their work unit's supervisor.

Interpersonal Justice (Work Group Resource). Interpersonal justice perceptions were measured with the four-item subscale (α = .93; e.g., *Treat you with respect*) from Colquitt's (2001) questionnaire (French version by Gillet et al., 2015b). Items followed the stem "*Please indicate the extent to which individuals (coworkers, supervisors, etc.)*" and were rated on a five-point scale ranging from (1-*To a Very Small Extent*; 5-*To a Very Large Extent*) in relation to their work unit more generally.

Organizational Support (Organizational Resource). Respondents described the level of support received from their organization with the French adaptation (Gillet et al., 2015a) of a questionnaire originally developed by Eisenberger et al. (1986). This questionnaire includes eight items (e.g., *The organization really cares about my well-being;* α = .92) and were scored using a seven-point response scale (1-*Strongly Disagree*; 7-*Strongly Agree*) in relation to the reality of their work unit.

Turnover Intentions (Outcome). Turnover intentions were assessed with a measure developed by Colarelli (1984). The four items from this scale (α = .86; e.g., *I frequently think of quitting my job*) were rated on a five-point scale (1-*Strongly Disagree*; 5-*Strongly Agree*).

Analyses

Mplus 8.3 (Muthén & Muthén, 2019) was used to conduct analyses via Maximum Likelihood-Robust (MLR) estimation, which is robust to multilevel nesting and non-normality. Missing data was handled with Full information Maximum Likelihood (Enders, 2010). Preliminary measurement models estimated for the individual-level measures of job engagement, burnout, empowerment, and turnover intentions, as well as unconditional LPA based on the indicators of job engagement and burnout were estimated at the individual level. For these models, we relied on Mplus design-based correction procedures (Asparouhov, 2005) to obtain standard errors and tests of model fit that accounted for participants' nesting within work units. Preliminary measurement models for the multilevel constructs of job demands and workgroup, supervisor, and organization resources were specified as multilevel with employees (L1) nested under work units (L2). These latent variable models make it possible to assess constructs corrected for measurement errors at both levels of analyses (via the estimation of latent factors), together with L2 ratings reflecting aggregated individual perceptions corrected for inter-rater reliability, and L1 ratings reflecting inter-individual differences in perceptions of the L2 reality (Marsh et al., 2012; Morin et al., 2014, 2021). Conditional multilevel LPA were then used to allow L1 predictors to influence the likelihood of profile membership at the individual level (L1) and L2 predictors allowed to influence the frequency of occurrence of each profile at the work unit level (L2) (Finch & French, 2014; Mäkikangas et al., 2018). All models were estimated while incorporating stratified sampling weights using Mplus complex survey design functionalities (Asparouhov, 2005).

Preliminary Analyses

Preliminary analyses were conducted to verify the psychometric properties of all measures. These analyses were also used to obtain factor scores (estimated in standardized units with $M = 0$ and $SD = 1$), which were included as profile indicators, predictors, and outcomes in the main analyses. The decision to rely on factor scores made it possible to achieve a partial control for measurement errors (Skrondal & Laake, 2001) and to maintain the psychometric properties of the measurement models while maximizing the simplicity of the estimated models (e.g., Morin et al., 2016b, 2017).

A first measurement model was estimated for the profile indicators. In this model, participants' ratings of burnout and job engagement were represented together by bifactor confirmatory factor analytic (bifactor-CFA) models including one global factor per construct (G-factor: Global burnout and Global engagement) and a series of orthogonal specific factors (S-factors; for burnout: Disengagement and emotional exhaustion; for job engagement: Cognitive, physical, and emotional engagement; Morin et al., 2016b, 2017). Bifactor models make it possible to explicitly isolate one global component underlying participants' responses to all burnout or engagement items from specific components associated with responses to items forming each subscale left unexplained by the global components and reflecting imbalanced levels of burnout or engagement across dimensions. This approach is consistent with the high correlations typically observed among burnout (e.g., Demerouti et al., 2003) and job engagement (Rich et al., 2010) components, and with research supporting a similar operationalization of burnout (Barcza-Renner et al., 2016; Isoard-Gautheur et al., 2018; Sinval et al., 2019) and engagement (Gillet et al., 2019a, 2020c). Importantly, this approach has been recommended to identify clearer profiles in situations where a global construct is assumed to co-exist with specificities assessed from the same indicators (Morin et al., 2016b, 2017). Bifactor factor scores result in cleaner differentiations between the profiles as the indicators are uncorrelated (their "overlap" is rather explicitly represented by the global factor). Then, the indicators are free to vary independently of one another to provide a clearer representation of the distinct configurations (or profiles) observed in the sample. This has been extensively discussed in statistical (Morin et al., 2016b) and statistically-oriented (Morin et al., 2017) publications.

A second model was estimated for the individual covariates. In this model, one higher-order factor was used to define participants' global levels of psychological empowerment from four first-order factors reflecting autonomy, meaning, impact, and competence matching the well-established higher-order structure of this construct (Morin et al., 2016c; Seibert et al., 2011). One additional factor was included to reflect turnover intentions. Three a priori correlated uniquenesses were incorporated to this model to reflect the negative wording of three items from the autonomy subscale (Marsh et al., 2010).

A third model was estimated for the multilevel constructs. In this model, participants' ratings of role ambiguity, work overload, transformational leadership, interpersonal justice, and organizational support were used to estimate five a priori CFA factors at the individual (L1) and work unit (L2) levels. These multilevel CFA models were estimated using doubly latent procedures to estimate latent constructs corrected for measurement errors at both levels, while also relying on a latent aggregation procedure to correct for agreement among work unit members in the assessment of the L2 constructs (Marsh et al., 2012; Morin et al., 2014, 2021). These models included six a priori correlated uniquenesses at the individual level (L1) to control for the negative wording of three items from the role ambiguity subscale and three items from the organizational support subscale (Marsh et al., 2010). Doubly latent models rely on an automatic group-mean centering procedure, so that L1 ratings can be directly interpreted as inter-individual deviations from the average rating of the L2 group reality, which has been shown to be the appropriate centering procedure for the type of constructs considered in the present study (Morin et al., 2014, 2021). This multilevel model was also used to assess the measurement *isomorphism* (or equivalence) of the constructs across levels (Bliese et al., 2007). Isomorphism makes it possible to compare constructs across levels (Metha & Neale, 2005) and helps stabilize the model estimation process (Lüdtke et al., 2011).

Once the optimal models were identified, we combined all three solutions into a global single level (L1) measurement model to assess the measurement invariance (Millsap, 2011) of participants' responses as a function of their language (English vs. French), sex (males vs. females), and status (military vs. civilian). Goodness-of-fit was estimated using the Root Mean Square Error of Approximation (RMSEA), the Tucker-Lewis Index (TLI), the Comparative Fit Index (CFI), and a visual examination of parameter estimates. The robust χ^2 will also be reported. According to common guidelines, RMSEA values under .06 and .08, and TLI/CFI values above .95 and .90 respectively support excellent and acceptable fit (Hu & Bentler, 1999; Marsh et al., 2005). The results from these analyses are reported in Appendix B (Tables S2 to S6) of the online supplements and support the adequacy of all measurement models, their isomorphism, and their measurement invariance.

We relied on these measurement models to estimate factor correlations, intra-class correlations, and composite reliability for all constructs. The omega coefficient of composite reliability (ω; McDonald, 1970) relies on the standardized parameter estimates from a measurement model to assess inter-item reliability for single-level (ω) and multilevel (ω_{L1}, ω_{L2}) models (Geldhof et al., 2014) and has been shown to be equally relevant to first-order, higher-order, and bifactor models (Morin et al., 2020). The first intra-class correlation coefficient (ICC1) indicates the proportion of the total variance in rating occurring at L2, whereas the second one (ICC2) provides an estimate of the reliability of the group (L2) aggregate (i.e., inter-rater reliability). The various omegas and the ICC2 and can be interpreted as any other reliability estimates (e.g., α). These coefficients supported the adequacy of our measures and are reported, together with correlations among all variables used in the present study, in Table 1.

More precisely, although the first-order model was able to achieve an acceptable level of fit to the data, the bifactor model with two G-factors (burnout and engagement) and five S-factors (emotional exhaustion, disengagement, cognitive engagement, emotional engagement, and physical engagement) was able to achieve a better level of fit across all indicators. This bifactor solution revealed two G-factors that were both well-defined by strong positive loadings from all items (λ = .538 to .797 for burnout and λ = .587 to .791 for job engagement). Over and above this G-factor, four S-factors retained a satisfactory level of specificity: Physical engagement (λ = .279 to .519), emotional engagement (λ = .481 to .695), cognitive engagement (λ = .209 to .505), and exhaustion (λ = .265 to .482). In contrast, the S-disengagement factor ($|\lambda|$ = .041 to .455) appeared to be weakly defined, suggesting that disengagement ratings mainly served to define G-levels of burnout, and only retained a limited amount of specificity when these G-levels were taken into account. The fact that this S-factor retained less specificity does not mean that it has no meaning, especially when modelled using an approach that explicitly controls for both measurement errors and associations with the G-burnout construct, such as the approach taken in the present study. It should also be noted that, despite this low level of specificity, the factor scores used as input to our main analyses remain corrected for measurement errors (e.g., Skrondal & Laake, 2001; Morin et al., 2020).

Latent Profile Analyses (LPA)

The procedures used to select the optimal number of latent profiles present in our data is fully disclosed in Appendix C of the online supplements and led to the selection of a five-profile solution in which the means of the profile indicators were allowed to differ across profiles. Multilevel relations (Finch & French, 2014; Mäkikangas et al., 2018) between the L1 predictors and participants' likelihood of membership in the various profiles, as well as between L2 predictors and the relative frequency of each profile occurring at the work unit level were assessed with a multilevel multinomial logistic regression link function based on the direct inclusion of the predictors into the final LPA solution (Diallo et al., 2017). The profiles were also contrasted in relation to participants' turnover intentions, which were directly included to the final solution, using the multivariate delta method (Raykov & Marcoulides, 2004). Annotated Mplus inputs, used to estimate our main analytic models, are reported in Appendix D of the online supplements.

Results

Latent Profiles

The results from the five-profile solution are illustrated in Figure 1 (see Appendix C of the online supplements for details). The first profile was characterized by high global levels of burnout (1.25 SD above the sample mean) and low global levels of job engagement (2 SD under the average), coupled with close to average to moderately low specific levels of job engagement across dimensions (between .2 and .6 SD under the average), moderately low specific levels emotional exhaustion (.5 SD under the average), and high specific levels of disengagement (.6 SD above the average). This means that employees' levels of emotional, physical, and cognitive job engagement are moderately lower than their global levels of job engagement across dimensions, suggesting that these employees do not feel the need to invest any specific resource beyond their already low levels of job engagement. Similarly, employees' levels of emotional exhaustion are moderately lower than their global levels of burnout across dimensions, indicating that these employees do not feel exertion going beyond their levels of burnout. In contrast, employees' levels of disengagement were higher than their levels of global burnout across dimensions, suggesting feelings of disengagement or demoralization going beyond their global levels of burnout. This *Burned-Out/Disengaged* profile was the smallest, corresponding to 7.13% of the employees, and shared similarities with the disengaged-underchallenged and worn-out profile identified in previous research (e.g., Abós et al., 2019; Mäkikangas & Kinnunen, 2016).

The second profile was also characterized by high global levels of burnout (+1.4 SD), but only by close to average levels (-.2 SD) of job engagement. In addition, employees' corresponding to this profile presented moderately high to high specific levels of physical (+.7 SD) and cognitive (+.4 SD) engagement, coupled with specific levels of emotional exhaustion corresponding to the sample average, moderately low specific levels of disengagement (-.5 SD), and low specific levels of emotional engagement (-1.5 SD). This *Burned-Out/Involved* profile was slightly larger, corresponding to 12.13% of the employees, and was similar to the highly engaged and highly frenetic (Abós et al., 2019) and highly engaged and exhausted (Moeller et al., 2018) profile identified in previous research. The third profile presented a diametrically opposite configuration, with high global levels of job engagement (+1 SD) and low global levels of burnout (-1.2 SD), moderately high specific levels of emotional engagement (+.5 SD) and slightly below average specific levels on the remaining dimensions (0 to -.3 SD). This *Engaged* profile corresponded to 18.14% of the sample, and matched similar profiles identified in previous research (Moeller et al., 2018; Salmela-Aro et al., 2019).

The fourth profile was characterized by slightly above average global levels of burnout (+.2 SD) and job engagement (+.5 SD), coupled with low specific levels of disengagement (-.3 SD), and moderately high (+.2 SD) to high (+1 SD) specific levels of physical engagement, emotional engagement, cognitive engagement, and emotional exhaustion. This *Engaged/Exhausted* profile corresponded to 15.50% of the employees, and shared similarities with the highly engaged and moderately frenetic profile previously identified by Abós et al. (2019). The fifth profile was the largest (47.10%) and was characterized by close to average levels (-.3 SD to +.2 SD) across all dimensions, being neither engaged nor disengaged, and neither burned-out nor energized. This *Normative* profile thus characterizde close to half of the employees for whom work is neither an occasion for high levels of involvement, nor a context that drags them down. A similar *Normative* profile was previously identified in work engagement research (Gillet et al., 2019a), as well as in research focusing on related constructs (need satisfaction: Gillet et al., 2019b; health and well-being: Morin et al., 2016b, 2017).

Turnover Intentions

Turnover differed in a statistically significant ($p \leq .05$) manner across all profiles. These levels were highest in the *Burned-Out/Disengaged* profile (1.192; 95% confidence interval [CI] = 1.141 to 1.243), closely followed by the *Burned-Out/Involved* profile (1.082; CI = 1.030 to 1.134), then by the *Engaged/Exhausted* profile (.083; CI = .033 to .133), followed by the *Normative* profile (-.104; CI = -.143 to -.065), with the lowest levels observed in the *Engaged* profile (-1.031; CI = -1.082 to -.980).

Job Demands and Resources

The results from the multilevel predictive analyses are reported in Table 2. At the individual level, levels of psychological empowerment were systematically related to the likelihood of membership into all of the profiles. More precisely, higher levels of psychological empowerment increased employees' likelihood of membership into the *Engaged* (3) profile relative to all other profiles, followed by the *Engaged/Exhausted* (4) profile, then by the *Normative* (5) profile, followed by the *Burned-Out/Involved* (2) profile, and finally by the *Burned-Out/Disengaged* (1) profile.

In terms of job demands, inter-individual deviations in the perception of the work overload occurring at the individual unit level was systematically associated with the likelihood of membership into all of the profiles in a manner that was the direct opposite of psychological empowerment. More precisely, higher work overload perceptions were linked to an increased likelihood into the *Burned-Out/Disengaged* (1) profile relative to all other profiles, followed by the *Burned-Out/Involved* (2) profile, then by the *Normative* (5) profile, followed by the *Engaged/Exhausted* (4) profile, and finally by the *Engaged* (3) profile. Inter-individual deviations in the perception of the role ambiguity displayed a similar, yet not as widespread, pattern of associations with the likelihood of profile membership. More precisely, higher role ambiguity perceptions were associated an increased likelihood of membership into the *Burned-Out/Disengaged* (1) profile relative to all other profiles, as well as into the *Normative* (5) profile relative to the *Engaged* (3) and *Engaged/Exhausted* (4) profiles.

For job resources, inter-individual deviations in perceptions of the interpersonal justice occurring at the individual unit level were linked to an increased likelihood of membership into the *Engaged* (3) profile relative to all other profiles, whereas deviations in perceptions of transformational leadership occurring at the individual unit level were associated with an increased likelihood of membership into the *Engaged* (3) and *Engaged/Exhausted* (4) profiles relative to the *Normative* (5) profile. The effects of inter-individual deviations in the perception of the organizational support occurring at the individual unit level were, however, more widespread. More precisely, these perceptions were related to an increased likelihood of membership into the *Engaged* (3) profile relative to all other profiles, followed by the *Normative* (5) profile, and then equally by the *Engaged/Exhausted* (4) and *Burned-Out/Disengaged* (1) profiles, and finally by the *Burned-Out/Involved* (2) profile.

Results were not as numerous at the work unit level. In terms of job demands, work unit levels of work overload were associated a higher frequency of occurrence of the *Burned-Out/Involved* (2) profile relative to the *Engaged* (3), *Normative* (5), and *Burned-Out/Disengaged* (1) profiles, as well as into *Engaged/Exhausted* (4) profile relative to the *Normative* (5) and *Burned-Out/Disengaged* (1) profiles. Work overload was also related to a higher frequency of occurrence of the *Engaged* (3) profile relative to the *Engaged/Exhausted* (4) profile. In contrast, work unit levels of role ambiguity did not predict the relative frequency of occurrence of any profile. In terms of job resources, work unit levels of interpersonal justice were linked to a higher frequency of occurrence of the *Engaged/Exhausted* (4) profile relative to the *Normative* (5) profile, whereas work unit levels of transformational leadership did not predict the relative frequency of occurrence of any profile. Finally, work unit levels of organizational support were related to a higher frequency of occurrence of the *Engaged* (3) profile relative to the *Burned-Out/Disengaged* (1) and *Engaged/Exhausted* (4) profiles.

Discussion

The dual global and specific multidimensional nature of job engagement and burnout is well established in research. Job engagement can be seen as a global construct, which also encompasses physical, cognitive, and emotional facets (Rich et al., 2010), just like burnout can be viewed as a global construct minimally encompassing emotional exhaustion and disengagement (Demerouti et al., 2010). However, despite the widely acknowledged recognition of the complementary role these two multidimensional constructs play in shaping employees' psychological functioning (Salmela-Aro et al., 2019), the most typical configurations taken by the combination of the global and specific facets of job engagement and burnout among distinct subpopulations, or profiles, of employees remain essentially unknown. The present study sought to address this limitation while building on recent person-centered research conducted on burnout (Berjot et al., 2017; Guidetti et al., 2018; Laverdière et al., 2018; Leiter & Maslach, 2016; Portoghese et al., 2018), job engagement (Gillet et al., 2019a, 2020c; Simbula et al., 2013), and both constructs (see Table S1 in the online supplements) without relying on a comprehensive operationalization of their multidimensionality (Abós et al., 2019; Mäkikangas et al., 2012, 2014, 2017; Moeller et al., 2018; Salmela-Aro et al., 2019). To document the practical relevance and construct validity of these profiles, we also considered their implications for turnover intentions and adopted a multilevel perspective to investigate the role of job demands and resources in the prediction of profile membership.

Employees' Profiles of Job Engagement and Burnout (Research Questions 1 and 2)

Our results revealed that five distinct profiles best represented the job engagement and burnout configurations observed among a nationally representative sample of Canadian Defence employees: (1) *Burned-Out/Disengaged*; (2) *Burned-Out/Involved*; (3) *Engaged*; (4) *Engaged/Exhausted*; and (5) *Normative*. These profiles generally matched our expectations, anchored in the results obtained as part of prior person-centered studies summarized in Table S1. Despite this similarity, the nature of these profiles also emphasizes the importance of adopting a finer-grained representation of job engagement and burnout by simultaneously considering both their global levels and the specific nature of their different components. When considering our results, it is important to keep in mind that the specific facets of both constructs no longer reflect the whole variance shared among the items from these subscales. Rather, while they retain a similar meaning, these specific facets now represent the degree of discrepancy (or imbalance) between employees' raw scores on each subscale and their global levels of engagement and burnout. In this regard, our results showed that four out of five of the profiles identified in this study were characterized by a configuration in which employees' specific levels on various job engagement and burnout components deviated from their global levels of job engagement and burnout, and from the sample average. This result suggests that job engagement and burnout levels tend to deviate across dimensions beyond their ability to depict a common core. These deviations may explain why no profile was identified in which employees experienced high (or low) and matching levels of job engagement and burnout across dimensions.

More specifically, our results also showed that a more imbalanced configuration of specific-facet scores seemed to be associated with profiles displaying high global levels of burnout (*Burned-Out/Disengaged* and *Burned-Out/Involved*), whereas a more balanced configuration seemed to accompany the *Normative* profile in which global levels of burnout and job engagement were closer to the sample average. Between these two extremes, the two profiles characterized by higher global levels of job engagement (*Engaged* and *Engaged/Exhausted*), while showing some variation across specific facets, still displayed a far more aligned configuration than the *Burned-Out/Disengaged* and *Burned-Out/Involved* profiles. Taken together, these results thus suggest that global levels of burnout played a greater role in creating imbalanced levels of psychological health across dimensions relative to global levels of job engagement. Yet, a comparison between the *Engaged* and *Engaged/Exhausted* profiles globally shows that engaged employees who go beyond the call of duty in terms of physical engagement without backing up this physical engagement with matching levels of emotional and cognitive engagement appear to be at higher risk of experiencing emotional exhaustion than employees experiencing more balanced levels of engagement.

A key take home message from the present study is that the similarity between the current results and those obtained in the context of previous studies (see Table S1) relying on different measures and methodological approaches reinforces the robustness of our findings, and the idea that the current profiles might be generalizable enough to support developing interventions seeking to maximize employees' likelihood of experiencing more desirable profiles. Beyond similarity, however, the differences and specificities between our results and previous ones supports the need to rely on a precise operationalization of the multidimensional nature of job engagement and burnout. By providing the first direct source of evidence of job engagement and burnout profiles defined according to their recently recommended bifactor operationalization (e.g., Gillet et al., 2020c; Isoard-Gautheur et al., 2018), the present study represents an important step forward in job engagement and burnout research. Indeed, the reliance on a more traditional approach (ignoring the dual global and specific nature of job engagement and burnout) would have simply resulted in the estimation of profiles suggesting that there was little value in considering the unique nature of each dimension over and above these global levels. In contrast, our results show that both components seem to play a key role in the definition of job engagement and burnout profiles, and thus bring valuable information to our understanding of job engagement and burnout.

The Implications of the Profiles for Turnover Intentions (Research Question 3)

Supporting the meaningfulness of these profiles, our results revealed that they shared well-differentiated associations with turnover intentions in a way that matched our expectations and previous results see Table S1). Indeed, employees presenting the lowest levels of global job engagement coupled with high levels of global burnout (*Burned-Out/Disengaged*) displayed the highest turnover intentions, whereas *Engaged* employees presented the lowest turnover intentions. More generally, employees characterized by high global levels of burnout (*Burned-Out/Disengaged* and *Burned-Out/Involved*) were subjected to higher levels of turnover intentions than those characterized by low to moderate global levels of burnout (*Engaged*, *Engaged/Exhausted*, and *Normative*). It is noteworthy that the turnover intentions observed in the *Normative* profile were lower than in the *Engaged/Exhausted* profile, suggesting that globally high levels of engagement are not enough to limit the risks of turnover intentions, at least when accompanied by above average levels of burnout. Indeed, experiencing a globally average job engagement and burnout configuration seems to limit turnover intentions to a greater extent than presenting a highly engaged, but exhausted, configuration. This result suggests that a highly engaged configuration, in and of itself, might contribute to increase employees' risks of emotional exhaustion (e.g., Bakker & Demerouti, 2017).

On the one hand, these results reinforce the idea that more aligned levels of job engagement and burnout yield higher benefits in terms of turnover intentions. The idea that alignment among these components could be, in some situations, more important than overall levels of psychological functioning as been previously documented in self-determination theory (e.g., Gillet et al., 2019b) and job engagement (e.g., Gillet et al., 2019a, 2020c) research. Our results demonstrate that these observations extend to a more comprehensive consideration of psychological functioning, encompassing burnout and job engagement. This observation suggests that this form of balance could stem from a more adequate allocation of ones' psychological resources at work, which is known to help reduce stress and recovery. On the other hand, the *Normative* profile was also found to present more pronounced turnover intentions than the *Engaged* profile. This second observation suggests that, despite the aforementioned benefits of alignment in terms of psychological functioning, some degree of imbalance reflecting a more engaged work orientation might still be beneficial for alternative outcomes, such as reducing turnover intentions. These observations clearly reinforce the need for future research to consider a much broader range of desirable (e.g., in-role and extra-role behaviors) and undesirable (e.g., absenteeism, sabotage, or work-family conflicts) outcomes.

A Multilevel Perspective on the Impact of Job Demands and Resources (Research Questions 4 and 5)

Individual-level predictions. Our results supported the role of interpersonal justice, transformational leadership, organizational support, and psychological empowerment as key drivers of psychological functioning at work (e.g., Colquitt et al., 2013; Eisenberger & Stinglhamber, 2011; Montano et al., 2017; Seibert et al., 2011). More specifically, individual levels of psychological empowerment, perceptions of interpersonal justice, and perceptions of organizational support were associated with membership into the *Engaged* profile, consistent with variable-centered evidence supporting the role of these resources in the prediction of job engagement and burnout (Calvo & García, 2019; Gillet et al., 2013, 2018a). Likewise, employees' perceptions of transformational leadership were associated with the *Engaged/Exhausted* and *Engaged* profiles, relative to the *Normative* one, supporting the benefits of transformational leadership on job engagement (Montano et al., 2017). More generally, and as expected (e.g., Xanthopoulou et al., 2009), psychological empowerment, as an individual resource, had stronger, and more widespread, effects on job engagement and burnout than the remaining job demands and resources considered in the present study.

In contrast, and unexpectedly, perceptions of organizational support were associated with an increased likelihood of membership into the *Burned-Out/Disengaged* profile relative to the *Burned-Out/Involved* profile. Our results thus show that inter-individual differences in the perception of organizational support may be detrimental to their global engagement, especially among burned-out employees. This result is interesting given that prior variable-centered research has unanimously positioned perceived organizational support as a positive driver of psychological health in a "the more, the better" perspective (e.g., Caesens et al., 2014). In fact, this assumption is so strong that possible ceiling effects to the benefits of organizational support in terms of psychological health have yet to be empirically verified (Morin et al., 2013).

Nevertheless, Caesens et al.'s (2020) recent findings suggest that high levels of social support perceptions might be detrimental in some situations. This "too much of a good thing" interpretation is aligned with prior variable-centered results revealing curvilinear relations between employees' perceptions of organizational support and their levels of affective organizational commitment, trust, in-role performance, taking charge behaviors, extra-role performance, and deviance (Burnett et al., 2015; Harris & Kacmar, 2018). Just like here, these studies reveal that higher levels of perceived organizational support are not always associated with more desirable outcomes. In line with this, Gillet et al. (2019b) also found that perceived organizational support was negatively related to specific levels of imbalance in the satisfaction of employees' need for competence. They interpreted this result by suggesting that higher levels of perceived organizational support could lead employees to believe that their organization has doubts regarding their competence, ultimately leading to negative consequences (e.g., lower global levels of job engagement). What the present results suggest is that these undesirable effects of organizational support perceptions might be particularly marked among burned-out employees. Clearly, additional studies are needed to replicate the present results and to identify the mechanisms underlying these unexpected relations.

In terms of job demands, inter-individual differences in perceptions of work overload and role ambiguity were related to membership into the arguably least desirable *Burned-Out/Disengaged* profile, in accordance with variable-centered evidence showing that job demands are positively related to burnout and negatively related to job engagement (Bakker & Demerouti, 2017; Schaufeli & Bakker, 2004). Work overload and role ambiguity were also associated with membership into the *Normative* profile relative to the *Engaged* and *Engaged/Exhausted* profiles, thus supporting the detrimental effects of job demands on job engagement demonstrated in past studies (e.g., Reinke & Chamorro-Premuzic, 2014).

Work Unit-Level Predictions. To answer repeated calls for increases in multilevel research focusing on the effects of job demands and resources (e.g., Bakker & Demerouti, 2007), we examined the role of work overload, role ambiguity, interpersonal justice, transformational leadership, and organizational support at the work unit level in the prediction of the relative frequency of occurrence of the profiles at the work unit level. Supporting the documented role of work overload in the emergence of burnout (e.g., Reinke & Chamorro-Premuzic, 2014), our results showed that work overload was associated with membership into the *Burned-Out/Involved* and *Engaged/Exhausted* profiles. This observation is consistent with the idea that the efforts required to cope with job demands can deplete employees' psychological resources, thus increasing their risk of psychological difficulties (Crawford et al., 2010). In addition, *Engaged/Exhausted* employees displayed above-average scores on the specific cognitive and physical (but not emotional) job engagement factors. As both specific factors might reflect exertion and fatigue resulting from the expenditure of extra efforts going beyond employees' global levels of job engagement, it is not surprising that work overload predicted a higher likelihood of membership in this profile.

Surprisingly, work overload was also related to an increased likelihood of membership into the *Burned-Out/Involved* profile relative to the *Burned-Out/Disengaged* profile, into the *Engaged/Exhausted* profile relative to the *Burned-Out/Disengaged* profile, and into the *Engaged* profile relative to the *Engaged/Exhausted* one. Contrary to the unilaterally undesirable effects of individual perceptions of work overload, these results suggest that work unit levels of work overload might also have positive effects on global levels of job engagement among specific subtypes of employees. Although job demands have long been considered to have only negative effects on employees' engagement, there is growing evidence that job demands can sometimes trigger motivational gains (LePine et al., 2004). Work overload, for instance, has been found to be positively related to job engagement, showing its motivating (i.e., challenging) potential (Crawford et al., 2010). Indeed, challenge demands have the potential to support growth and to foster the achievement of personal goals (LePine et al., 2005), thus nurturing job engagement. Because challenge demands enhance opportunities for future gains, investing resources (e.g., energy) may be beneficial (Crawford et al., 2010). Beyond these considerations, what the present result suggest is that the motivational effects of work overload might be limited to shared perceptions of work overload occurring at the work unit level, suggesting that equity could be critical to these benefits (Colquitt et al., 2013). In contrast, feelings of having a larger workload than one's colleagues seem to lead to more unilaterally undesirable effects. Indeed, equity in workload might provide a more fertile ground for employees' perception of this job demand in challenging terms, whereas inequity might lead them to perceive their unique work overload as hindering their performance in relation to that of other team members. As mentioned above, it would also be interesting for upcoming studies to consider how employees' levels of autonomous and controlled work motivation may contribute to explain the differential effects of work overload at the individual and work unit level (e.g., Gillet et al., 2016b). More generally, future research is needed to examine the multilevel role of other challenge (e.g., information processing, problem solving) and hindrance (e.g., interruptions, harassment) demands in predicting job engagement and burnout profiles.

In contrast, role ambiguity and transformational leadership were unrelated to the frequency of profile occurrence at the work unit level. This result differs from that of previous variable-centered research (e.g., De Clercq, 2019; Montano et al., 2017), which could be explained by our adoption of a multivariate perspective in which various job demands and resources are simultaneously considered. Adopting a multivariate perspective means that all of the variance that is shared among the various predictors is controlled for (once the moderate correlations among them, as shown in Table 2, are accounted for), allowing for a more precise identification of the unique contribution of the most potent predictors. More precisely, what the present results suggest is that these specific job demands and resources do not seem to further contribute to the prediction of the relative frequency of occurrence of the various profiles at the work unit level once the effects of other, arguably more potent, types of job demands and resources are considered. These findings thus encourage researchers to look at how various job demands and resources uniquely contribute to employees' job engagement and burnout profiles.

Finally, work unit levels of interpersonal justice were related to an increased likelihood of membership into the *Engaged/Exhausted* profile relative to the *Normative* profile, while organizational support was associated with an increased likelihood of membership into the *Engaged* profile relative to the *Burned-Out/Disengaged* and *Engaged/Exhausted* ones. As in prior studies (Gillet et al., 2013, 2018a), these findings confirm that interpersonal justice and organizational support have positive effects on global levels of job engagement. These results also suggest that the previously identified limits to the benefits of organizational support perceptions might be limited to the individual level and fail to generalize to perceptions of organizational support shared among work unit members. More unexpected was the observation that interactional justice perceptions, at the work unit level, increased the likelihood of membership into an engagement profile that was also exhausted (rather than simply into an engaged profile). This observation suggests that work units characterized by more positive interpersonal justice climates might contribute to push engaged employees to invest more of their personal resource than they should. This possibility suggests, beyond the benefits of interpersonal justice in terms of job engagement, organizations should be aware that in this context some of their most engaged employees might need support to avoid exhaustion. However, clearly, future research is needed to better understand the mechanisms underpinning this unexpected effect and to empirically verify whether and how these conclusions generalize to other job resources (e.g., psychological safety, contingent reward, interpersonal respect culture). More generally, conclusions generally converge in showing that both levels of analyses (i.e., inter-individual differences in perceptions and shared perceptions at the work unit level) played a complementary and non-redundant role in the prediction of job engagement and burnout profiles, but also that the role of individual perceptions seemed to be slightly greater than that of work unit aggregates.

Limitations and Directions for Future Research

Even though this study represents the first systematic attempt to investigate the nature, predictors, and outcomes of employees' job engagement and burnout profiles while relying on a methodological approach allowing us to properly disaggregate the global and specific components of these multidimensional constructs, limitations remain. First, the present study relied entirely on self-reports, raising possible concerns regarding the possible impact of various forms of self-report biases and social desirability. It would thus seem desirable for researchers to incorporate more objective, or multi-informant, measures to future investigations of similar issues. Second, although we have no reason to expect that our results would differ among other samples of employee (which is supported by the similarity between the nature of the profiles observed in this study relative to previous studies relying on different measures and methods), this study was conducted within a Canadian military organization which serves to limit the generalizability of our findings. As a result, it would be important for future research to me systematically verify the replicability of our results among more diversified samples of workers from different types of organizations (e.g., less hierarchical or authoritarian, or without the same level of job security and benefits) and cultures. The ability to demonstrate generalizability is important to support the value of interventions inspired by person-centered solutions. Third, we relied on a cross-sectional research design which made it impossible to verify the directionality of the observed associations, or even the possibility of changes. Although predictors or outcomes were selected based on their theoretical relevance (Bakker & Demerouti, 2017), it remains important for future research to extend our results longitudinally. Fourth, the novelty of our inductive approach made it impossible to rely on an a priori selection of predictors or outcomes that would allow us to precisely tease apart the observed qualitatively differences observed between out profiles. Based on our results, we thus suggest that future research might benefit from a consideration of a wider set of outcomes (e.g., job performance, work-family conflicts) and from predictors likely to explain the specificity of the identified profiles (e.g., factors likely to explain involvement among otherwise burned-out employees or exertion among otherwise engaged employees). Finally, we considered the role of work characteristics at the individual and work unit levels in the prediction of employees' likelihood of membership into the various profiles identified here. Alternative, and complementary, approaches would include the investigation of work unit profiles characterized by different frequencies of occurrence of individual profiles, as well as investigating work unit profiles characterized by distinctive sets of job demands and resources (e.g., Collie et al., 2020; Mäkikangas et al., 2018).

Practical Implications for Assessment, Research, and Intervention

In terms of research, the present investigation highlights the importance of accounting for the dual global and specific nature of employees' multidimensional ratings of burnout and job engagement. Ignoring this dual nature might lead to the erroneous conclusion that each specific component of these two constructs are relatively independent from one another and result in similar effects caused in fact by employees' global levels of burnout and job engagement. More concerning is the fact that these apparently comparable effects would in fact mask the likely unique role played by each specific component beyond this global level. For applied researchers, this observation is particularly worrisome, given that biased results may serve as guides for the development of incomplete, or improper, interventions tailored at distinct profiles of employees defined by considering their global levels of burnout and job engagement but completely ignoring the specificities related to their unique manifestations of burnout and engagement.

In terms of measurement, our results pinpoint the value of adopting a bifactor operationalization of burnout and job engagement. Indeed, the failure to do so is likely to increase the risk of multicollinearity by the estimation of construct scores reflecting a confusing combination of global and specific components. Importantly, although bifactor models can separate the variance of both constructs shared across dimensions from the unique role of each specific dimension, it is important to note that the meaning of these global and specific dimensions remains the same as in more traditional approaches. Although it is reasonably simple to adopt this recommendation in research, practical applications of a bifactor operationalization for scoring purposes are not as straightforward. Indeed, the ability to score employees' ratings of burnout and job engagement will require the development of online calculators, developed based on results from more representative *normative* samples. Although Perreira et al. (2018) rightly note that the Mplus statistical package can be used to generate factor scores (using the results from this, or any other, bifactor investigation of burnout or job engagement), this approach still requires samples of participants and will not work using ratings obtained from individual employees. In the meantime, this means that the practical implications will have to remain focused on a more "holistic" assessment of employees' profiles and on practitioners' ability to grasp the general principles identified in this study.

In terms of intervention and practice, this study reinforces the value of managerial practices seeking to reduce burnout and nurture engagement. Managers need to pay attention to employees feeling exposed to particularly high workloads, or who lack the ability or opportunity to adopt a volitional approach at work (i.e., low psychological empowerment). These individuals seem to be at risk of experiencing low global levels of job engagement coupled with high global levels of burnout, leading them to develop higher turnover intentions. Care should be taken to ensure that any unforeseen increase in workload be shared, in a reasonably equitable manner, among colleagues. Changes in the work organization designed to increase psychological empowerment levels might sustainably increase job engagement and decrease burnout levels in the long run. For instance, moving towards or enhancing high-involvement managerial systems (e.g., performance-related remuneration schemes) may help to improve employees' psychological empowerment (Rehman et al., 2019). Organizations should also allocate resources to enactive mastery experiences, promote self-directed decision-making, and create opportunities for personal growth. Efforts to promote justice perceptions in terms of workload allocations also seem promising (Emery et al., 2019).

Moreover, our findings suggest that initiatives seeking to increase employees' perceptions of organizational support at work are likely to have widespread benefits when care is taken to ensure that this increase is perceived equivalently by all work unit members. Among possible ways to achieve this objective, top management might promote a supportive culture within their organization, for instance, by providing employees with the resources or materials they need to perform their job effectively, by providing useful training and developmental programs, by providing assurance of security during stressful times, and by promoting justice and fairness in the way policies are implemented and rewards distributed (Eisenberger & Stinglhamber, 2011). Importantly, care should be taken to maximally limit perceptions of inequity in the availability of these improved support mechanisms. Finally, programs designed to sensitize managers to the benefits of adopting a more transformational approach, and to provide them with tools on how to implement such an approach, might prove beneficial.

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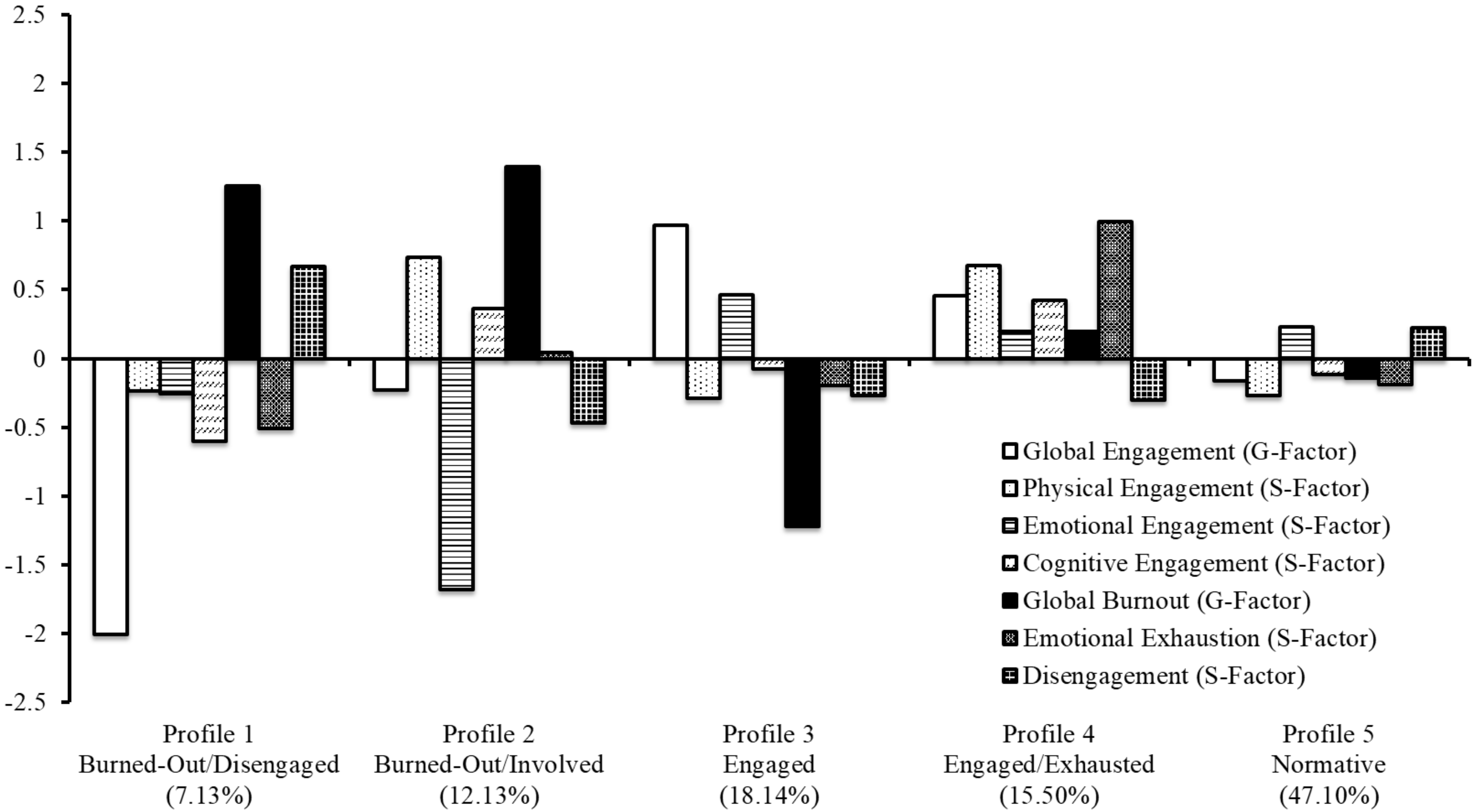

Figure 1. Final Five-Profile Solution.

Note. Profile indicators are factor scores with a mean of 0 and a standard deviation of 1.

Table 1

Weighted Correlations and Reliability for all Variables Used in the Present Study

		1	2	3	4	5	6	7	8	9	10	11	12	13	14
1	Global Job Engagement														
2	Specific Physical Engagement	0[§]													
3	Specific Emotional Engagement	0	0												
4	Specific Cognitive Engagement	0	0	0											
5	Global Burnout	-.532**	.326**	-.540**	.083**										
6	Specific Exhaustion	.157**	.306**	.128**	.244**	0									
7	Specific Disengagement	-.231**	-.122**	.183**	-.150**	0	0								
8	Turnover Intentions	-.408**	.158**	-.414**	.042**	.612**	-.015	.019**							
9	Psychological Empowerment	.504**	-.125**	.474**	-.024*	-.665**	.068**	-.035**	-.646**						
10	Work Overload	-.080**	.339**	-.256**	.187**	.452**	.284**	-.116**	.328**	-.296**					
11	Role Ambiguity	-.347**	.139**	-.285**	.019	.483**	.010	.014	.409**	-.503**	.327**				
12	Interpersonal Justice	.350**	-.124**	.295**	-.035*	-.509**	-.010	-.039**	-.398**	.524**	-.235**	-.454**			
13	Transformational Leadership	.306**	-.129**	.306**	-.024	-.488**	.007	-.024*	-.395**	.494**	-.268**	-.490**	.620**		
14	Organizational Support	.368**	-.220**	.408**	-.064**	-.643**	-.049**	.007	-.526**	.607**	-.400**	-.532**	.633**	.618**	
Reliability															
	ω or ω_{L1}	.969	.720	.892	.792	.905	.566	.226	.740	.868	.928	.896	.938	.962	.917
	ω_{L2}	NA	NA	NA	NA	NA	NA	NA	NA	NA	.999	.999	.999	.999	.998
	ICC1	NA	NA	NA	NA	NA	NA	NA	NA	NA	.030	.017	.037	.017	.028
	ICC2	NA	NA	NA	NA	NA	NA	NA	NA	NA	.861	.777	.885	.782	.852

Note. * $p < .05$; ** $p < .01$; [§] correlations taken from bifactor models are equal to 0 due to the orthogonality of bifactor measurement; ω: Omega coefficient of composite reliability (McDonald, 1970); ω_{L1}: Omega coefficient of composite reliability obtained at the individual level); ω_{L2}: Omega coefficient of composite reliability obtained at the work unit level; ICC1: Intra-class correlation coefficient (reflecting the proportion of the total variance in rating occurring at the work unit level for multilevel constructs); ICC2: Reliability of the work unit aggregates (i.e., inter-rater reliability); NA: Not applicable (these are not multilevel constructs).

Table 2

Results from the Predictive Analyses

	Profile 1 vs 5		Profile 2 vs 5		Profile 3 vs 5		Profile 4 vs 5		Profile 1 vs 4	
Predictors	Coef. (SE)	OR	Coef. (SE)	OR	Coef. (SE)	OR	Coef. (SE)	OR	Coef. (SE)	OR
Individual Level (L1)										
Psychological Empowerment	-3.065 (.097)**	.047	-2.487 (.090)**	.083	2.938 (.111)**	18.873	.680 (.080)**	1.973	-3.745 (.108)**	.024
Work overload	.266 (.090)**	1.305	1.268 (.076)**	3.553	-.343 (.073)**	.709	1.902 (.056)**	6.701	-1.636 (.092)**	.195
Role Ambiguity	.289 (.066)**	1.334	-.060 (.059)	.942	-.287 (.086)**	.750	-.110 (.051)*	.896	.398 (.077)**	1.489
Interpersonal Justice	.111 (.090)	1.117	.132 (.074)	1.141	.639 (.104)**	1.895	-.015 (.062)	.985	.126 (.104)	1.135
Transformational Leadership	.146 (.079)	1.157	.109 (.057)	1.115	.216 (.103)*	1.242	.111 (.052)*	1.117	.035 (.077)	1.036
Organizational Support	-.409 (.083)**	.664	-.743 (.066)**	.476	.402 (.091)**	1.495	-.371 (.052)**	.690	-.038 (.092)	.963
Work Unit Level (L2)										
Work overload	.092 (.420)	1.096	1.408 (.420)**	4.088	.047 (.444)	1.048	2.223 (.454)**	9.235	-2.131 (.639)**	.119
Role Ambiguity	-.378 (.570)	.685	-1.052 (.564)	.349	.495 (.455)	1.640	-1.094 (.573)	.335	.716 (.927)	2.047
Interpersonal Justice	-.847 (1.064)	.429	-.354 (.797)	.702	1.084 (.927)	2.956	1.171 (.589)*	3.225	-2.018 (1.123)	.133
Transformational Leadership	2.462 (1.339)	11.728	.048 (.961)	1.049	-.742 (.958)	.476	-.849 (1.018)	.428	3.311 (1.844)	27.412
Organizational Support	-2.027 (1.124)	.132	-.676 (1.098)	.509	1.768 (.993)	5.859	-.760 (.893)	.468	-1.267 (1.326)	.282

	Profile 2 vs 4		Profile 3 vs 4		Profile 1 vs 3		Profile 2 vs 3		Profile 1 vs 2	
Predictors	Coef. (SE)	OR	Coef. (SE)	OR	Coef. (SE)	OR	Coef. (SE)	OR	Coef. (SE)	OR
Individual Level (L1)										
Psychological Empowerment	-3.167 (.101)**	.042	2.258 (.135)**	9.564	-6.003 (.144)**	.002	-5.425 (.150)**	.004	-.578 (.102)**	.561
Work overload	-.635 (.066)**	.530	-2.245 (.067)**	.106	.610 (.104)**	1.840	1.611 (.086)**	5.007	-1.001 (.091)**	.367
Role Ambiguity	.049 (.069)	1.051	-.177 (.097)	.837	.576 (.110)**	1.778	.227 (.117)	1.255	.349 (.066)**	1.417
Interpersonal Justice	.148 (.086)	1.159	.655 (.109)**	1.924	-.528 (.134)**	.590	-.507 (.111)**	.602	-.021 (.073)	.979
Transformational Leadership	-.001 (.072)	.999	.106 (.104)	1.112	-.071 (.117)	.932	-.107 (.117)	.898	.037 (.059)	1.037
Organizational Support	-.372 (.085)**	.689	.773 (.103)**	2.166	-.811 (.109)**	.444	-1.145 (.107)**	.318	.334 (.095)**	1.396
Work Unit Level (L2)										
Work overload	-.815 (.521)	.443	-2.176 (.520)**	.113	.046 (.751)	1.047	1.362 (.618)*	3.904	-1.316 (.494)**	.268
Role Ambiguity	.042 (.692)	1.043	1.589 (.840)	4.900	-.873 (.821)	.418	-1.547 (.815)	.213	.674 (.633)	1.963
Interpersonal Justice	-1.525 (.989)	.218	-.087 (1.011)	.917	-1.932 (1.434)	.145	-1.438 (1.346)	.237	-.493 (1.042)	.611
Transformational Leadership	.896 (1.016)	2.450	.107 (1.334)	1.113	3.204 (1.727)	24.636	.789 (1.398)	2.202	2.415 (1.333)	11.188
Organizational Support	.084 (1.214)	1.088	2.527 (1.290)*	12.522	-3.795 (1.742)*	.022	-2.443 (1.601)	.087	-1.351 (1.074)	.259

Note. * $p < .05$; ** $p < .01$; 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 estimated from factor scores with a standard deviation of 1 and a mean of 0; Profile 1 = *Burned-Out/Disengaged*; Profile 2 = *Burned-Out/Involved*; Profile 3 = *Engaged*; Profile 4 = *Engaged/Exhausted*; and Profile 5 = *Normative*.

Online Supplemental Materials for:

A Multilevel Person-Centered Perspective on the Role of Job Demands and Resources for Employees' Job Engagement and Burnout Profiles

Appendix A

Table S1

Number and Characteristics of Profiles Identified in Previous Studies

Study	Sample	Analysis	Indicators	Profiles	Covariates
Simbula et al. (2013)	488 Italian teachers	Cluster Analysis	Vigor; Dedication; Absorption	Profile 1: Highly engaged (high levels across dimensions) Profile 2: Average engaged (moderate levels across dimensions)	Personal development: 1 > 2 Work-family balance: 1 > 2 Self-efficacy: 1 > 2 Job satisfaction: 1 > 2 Altruism: 1 > 2 Civic virtue: 1 > 2 Social dysfunction: 2 > 1 General dysphoria: 2 > 1
Mäkikangas et al. (2014)	256 Finnish health and social care employees	Growth Mixture Modeling	Vigor; Exhaustion (5 consecutive workdays)	Profile 1: Constantly vigorous (high levels of vigor and low levels of exhaustion that both remained stable) Profile 2: Concurrently vigorous and exhausted (moderate and stable levels of vigor, and moderate and slightly decreasing levels of exhaustion) Profile 3: Constantly exhausted (high levels of exhaustion and low levels of vigor that both remained stable)	Recovery: 1 > 2, 3
Leiter & Maslach (2016)	Study 1 (S1): 1766 Canadian health care employees Study 2 (S2): 1166 Canadian health care employees	Latent Profile Analysis	Emotional Exhaustion; Cynicism; Reduced Prof. Efficacy	Profile 1: Burnout (high levels across dimensions) Profile 2: Disengaged (high levels of cynicism, and moderate to high levels of exhaustion and inefficacy) Profile 3: Overextended (high levels of exhaustion, and moderate levels of cynicism and inefficacy) Profile 4: Ineffective (high levels of inefficacy, and moderate levels of cynicism and exhaustion) Profile 5: Engagement (low levels across dimensions)	Workload S1: 1, 3 > 4 > 2 > 5 Workload S2: 1, 2, 3 > 4 > 5 Resources S1: 5 > 4 > 2, 3 > 1 Resources S2: 5 > 3 > 4 > 2 > 1 Social context S1: 5 > 3, 4 > 2 > 1 Social context S2: 5 > 3 > 4 > 2 > 1 Satisfaction S1: 5 > 4 > 3 > 2 > 1 Satisfaction S2: 5 > 3, 4 > 2 > 1
Berjot et al. (2017)	664 French psychologists	Cluster Analysis	Emotional Exhaustion; Cynicism; Reduced Prof. Efficacy	Profile 1: High risk of burnout (high across dimensions) Profile 2: Risk of burnout through low personal accomplishment (low exhaustion & cynicism; high inefficacy) Profile 3: Risk of burnout through emotional exhaustion (moderate to high exhaustion; moderate cynicism & inefficacy) Profile 4: No risk of burnout (low across dimensions)	
Mäkikangas et al. (2014)	168 Finnish white-collar professionals	Latent Profile Analysis	Exhaustion; Vigor (5 times: 2006, 2008, 2010, 2012, 2014)	Profile 1: Low stable exhaustion-high stable vigor Profile 2: Fluctuating exhaustion and vigor (low unstable exhaustion; average-unstable vigor) Profile 3: Stable average exhaustion-decreasing vigor	Goal progress: 1 > 2, 3

Study	Sample	Analysis	Indicators	Profiles	Covariates
Mäkikangas et al. (2014)	168 Finnish white-collar professionals	Latent Profile Analysis	Cynicism; Dedication (5 times: 2006, 2008, 2010, 2012, 2014)	Profile 1: Low stable cynicism-high stable dedication Profile 2: Increasing cynicism-decreasing dedication Profile 3: Decreasing cynicism-increasing dedication	Goal progress: 1 > 2, 3
Guidetti et al. (2018)	689 Italian teachers	Cluster Analysis	Enthusiasm; Emotional Exhaustion; Indolence; Guilt	Profile 1: Enthusiastic (high enthusiasm; low exhaustion, indolence, & guilt) Profile 2: Exhausted (low enthusiasm, indolence, & guilt; high exhaustion) Profile 3: Exhausted-indifferent (low enthusiasm & guilt; high exhaustion & indolence) Profile 4: Exhausted-guilty (low enthusiasm; high exhaustion, indolence, & guilt)	Commitment: 1 > 2 > 3, 4 Stress: 3, 4 > 2 > 1
Laverdière et al. (2018)	240 Canadian psychotherapists	Latent Profile Analysis	Emotional Exhaustion; Cynicism; Reduced Prof. Efficacy; Satisfaction with Life; Distress	Profile 1: At-risk (moderately high burnout & distress; moderately low life satisfaction) Profile 2: High functioning (low burnout & distress; high life satisfaction) Profile 3: Well-adapted (moderately burnout & distress; moderately high life satisfaction) Profile 4: Highly symptomatic (very high burnout & distress; very low life satisfaction)	Workload: 4 > 2, 3
Moeller et al. (2018)	1085 US employees from various sectors	Latent Profile Analysis	Burnout; Engagement	Profile 1: Engaged (high engagement; low burnout) Profile 2: Moderately engaged-exhausted (moderate engagement & burnout) Profile 3: Highly engaged-exhausted (high engagement & burnout) Profile 4: Apathetic (very low engagement & burnout) Profile 5: Burned-out (low engagement; high burnout)	Positive emotions: 1 > 4 > 2, 5; 1 > 3, 5; 3 > 4 > 2. Negative emotions: 3, 4, 5 > 2 > 1 Skill acquisition: 1 > 3 > 2, 4; 2 > 5; 1 > 3 > 4, 5 Turnover intentions: 3 > 1, 5; 2 > 1 > 4; 3 > 5 > 2; 5 > 4
Portoghese et al. (2018)	7757 Italian university students	Latent Profile Analysis	Emotional Exhaustion; Cynicism; Reduced Prof. Efficacy	Profile 1: Burned-out (high across dimensions) Profile 2: Overextended (moderately high exhaustion; moderate cynicism & inefficacy) Profile 3: Engaged (low cynicism & inefficacy; moderate exhaustion)	

Study	Sample	Analysis	Indicators	Profiles	Covariates
Abós et al. (2019)	584 Spanish teachers	Cluster Analysis	Frenetic, Underchallenged, & Wornout Burnout; Engagement	Profile 1: Disengaged-underchallenged/wornout (very low engagement; low frenetic; moderately high underchallenged & wornout). Profile 2: Lowly engaged-underchallenged/wornout (moderately low engagement; average frenetic; high underchallenged & wornout) Profile 3: Highly engaged-high frenetic (very high frenetic; high engagement; average wornout; moderately low underchallenged) Profile 4: Highly engaged-moderate frenetic (high engagement; moderately high frenetic; low underchallenged; very low wornout) Profile 5: Moderately engaged-low burnout (moderately high engagement; moderately low frenetic, underchallenged, & wornout)	Anxiety: 3 > 1; 1, 2 > 4, 5; 3 > 4, 5 Depression: 1, 2, 3 > 4, 5 Sleep quality: 4, 5 > 1, 2, 3 Intention to quit: 2 > 1 > 3 > 5 > 4
Gillet et al. (2019a)	730 employees (Prolific)	Latent Profile Analysis	Vigor; Dedication; Absorption (2 times: 4 months apart)	Profile 1: Engaged yet distanced (moderately high global engagement, vigor, & dedication; very low absorption) Profile 2: Normative (average across indicators) Profile 3: Vigorously absorbed (moderately low global engagement; average dedication; very high vigor & absorption) Profile 4: Disengaged-vigorous (moderately low global engagement & absorption; low dedication; very high vigor). Profile 5: Totally disengaged (low to very low global engagement, vigor, dedication, & absorption)	Stress: 4 > 5 > 2 > 1; 3 > 1 Intentions to quit: 4 > 5 > 2 > 1; 3 > 1 Job satisfaction: 1 > 2 > 3 > 5 > 4 Health: 1 > 2 > 3, 5 > 4
Salmela-Aro et al. (2019)	149 Finnish teachers	Latent Profile Analysis	Engagement; Emotional Exhaustion; Cynicism; Reduced Prof. Efficacy	Profile 1: Engaged-burnout (high engagement & burnout) Profile 2: Highly engaged (very high levels engagement; low burnout)	Workload: 1 > 2 Control: 2 > 1 Resilience: 2 > 1
Gillet et al. (2020c)	264 French employees from various sectors	Latent Profile Analysis	Physical, Cognitive, & Emotional Job Engagement	Profile 1: Globally disengaged (moderately low emotional & cognitive engagement; moderately high physical engagement) Profile 2: Globally engaged (average physical engagement; moderately high emotional & cognitive engagement) Profile 3: Globally but not emotionally engaged (average physical & cognitive engagement; moderately low emotional engagement) Profile 4: Moderately engaged (average across dimensions)	Task variety: 2 > 4 > 1; 2 > 3 Feedback: 2, 3, 4 > 1 Affective commitment: 2 > 3, 4 > 1 Normative commitment: 2, 4 > 3 > 1 Emotional exhaustion: 1, 3 > 2, 4 Ill-being: 1, 3, 4 > 2

Appendix B

Results from the Preliminary Measurement Models

Table S2

Goodness-of-Fit Statistics of the Preliminary Measurement Models

Description	χ^2 (*df*)	CFI	TLI	RMSEA	RMSEA CI
Measurement Models for the Profile Indicators (Burnout and Job Engagement)					
First-order model	6168.326 (289)*	.944	.936	.039	.039; .040
Bifactor with a single G-factor	8873.956(273)*	.917	.902	.049	.048; .050
Bifactor with two G-factors (burnout, job engagement)	5307.170 (261)*	.952	.940	.038	.038; 039
Measurement Model for Individual Covariates (Psychological Empowerment and Turnover Intentions)					
First-order model	1960.906 (157)*	.967	.960	.030	.028; .031
Second-order model for psychological empowerment	2161.494 (162)*	.963	.957	.031	.030; .032
Measurement Model for the Multilevel Predictors					
Multilevel measurement	13048.085 (842)*	.965	.962	.033	NA
Multilevel measurement with isomorphism	13577.578 (873)*	.964	.962	.033	NA
Total Model (single Level, for Tests of Measurement Invariance)					
Total model	19770.781 (2687)*	.949	.945	.022	.022; .022

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; CI: 90% confidence interval (not available with multilevel models); NA: not applicable.

Table S3

Standardized Factor Loadings (λ) and Uniquenesses (δ) for the Burnout and Job Engagement Bifactor Measurement Models

Items	S-λ	G- λ	δ
Physical Engagement			
Item 1	.311	.742	.354
Item 2	.319	.791	.273
Item 3	.494	.733	.218
Item 4	.285	.740	.372
Item 5	.519	.648	.311
Item 6	.279	.747	.364
Emotional Engagement			
Item 1	.530	.687	.246
Item 2	.481	.657	.337
Item 3	.580	.616	.284
Item 4	.569	.604	.312
Item 5	.695	.587	.172
Item 6	.677	.615	.163
Cognitive Engagement			
Item 1	.209	.711	.451
Item 2	.428	.772	.221
Item 3	.492	.772	.162
Item 4	.388	.626	.457
Item 5	.491	.745	.204
Item 6	.505	.761	.166
Exhaustion			
Item 1	.265	.538	.640
Item 2	.384	.720	.334
Item 3	.294	.777	.309
Item 4	.482	.700	.277
Disengagement			
Item 1	*-.041*	.797	.363
Item 2	.455	.678	.333
Item 3	.165	.691	.495
Item 4	.047	.690	.522

Note. G: Global factor from a bifactor measurement model; S: Specific factor from a bifactor measurement model; λ: factor loading; δ: item uniqueness; parameter estimates that are non-statistically significant ($p > .05$) are marked in italics.

Table S4

Standardized Factor Loadings (λ) and Uniquenesses (δ) for the Psychological Empowerment and Turnover Intentions Measurement Models

Items	λ	δ
Meaning		
Item 1	.898	.194
Item 2	.944	.109
Item 3	.961	.076
Self-Determination		
Item 1	.667	.555
Item 2	.352	.876
Item 3	.560	.687
Item 4	.731	.466
Item 5	.711	.495
Item 6	.575	.669
Impact		
Item 1	.768	.410
Item 2	.940	.116
Item 3	.950	.098
Competence		
Item 1	.786	.383
Item 2	.896	.197
Item 3	.885	.216
Item 4	.761	.420
Higher-Order Factor		
Meaning	.660	.564
Self-Determination	.960	.079
Impact	.549	.699
Competence	.348	.879
Turnover Intentions		
Item 1	.664	.560
Item 2	.836	.301
Item 3	.812	.341
Item 4	.836	.301

Note. λ: factor loading; δ: item uniqueness; all parameter estimates are significant ($p \leq .01$).

Table S5

Standardized Factor Loadings (λ) and Uniquenesses (δ) for the Multilevel Job Demands and Resources Isomorphic Measurement Model

Items	Level 1 λ	Level 1 δ	Level 2 λ	Level 2 δ
Work Overload				
Item 1	.815	.336	.998	.004
Item 2	.907	.177	.998	.005
Item 3	.916	.161	.997	.007
Item 4	.865	.251	.999	*.001*
Item 5	.732	.465	.997	.006
Item 6	.706	.502	.995	.010
Role Ambiguity				
Item 1	.837	.300	.998	.003
Item 2	.848	.281	.999	*.001*
Item 3	.902	.186	.999	*.002*
Item 4	.665	.558	.999	*.002*
Item 5	.673	.548	.998	.004
Item 6	.661	.563	.998	*.003*
Interpersonal Justice				
Item 1	.919	.156	.999	.003
Item 2	.975	.050	.999	*.001*
Item 3	.953	.091	.999	.001
Item 4	.686	.529	.993	.014
Transformational Leadership				
Item 1	.825	.319	.998	*.004*
Item 2	.897	.195	.999	*.001*
Item 3	.892	.205	.999	.001
Item 4	.929	.137	.999	.001
Item 5	.860	.260	.999	.002
Item 6	.876	.232	.999	*.001*
Item 7	.907	.177	.999	*.001*
Organizational Support				
Item 1	.680	.537	.991	.017
Item 2	.670	.551	.992	.017
Item 3	.800	.361	.990	.020
Item 4	.882	.223	.999	*.001*
Item 5	.634	.598	.996	.008
Item 6	.728	.470	.987	.026
Item 7	.850	.278	.997	.006
Item 8	.821	.326	.999	*.001*

Note. λ: factor loading; δ: item uniqueness; parameter estimates that are non-statistically significant ($p > .05$) are marked in italics.

Table S6

Goodness-of-Fit Statistics of the Measurement Invariance Models

Description	χ^2 (*df*)	CFI	TLI	RMSEA	RMSEA CI	CM	$\Delta\chi^2$ (*df*)	ΔCFI	ΔTLI	ΔRMSEA
English versus French Version										
English respondents only	17269.365 (2687)*	.948	.943	.023	.022; .023	--	--	--	--	--
French respondents only	7284.541 (2687)*	.942	.937	.024	.026; .027	--	--	--	--	--
F1. Configural invariance (First-Order)	25898.114 (5374)*	.947	.942	.024	.024; .024	--	--	--	--	--
F2. Weak invariance (First-Order)	26492.020 (5460)*	.945	.941	.024	.024; .025	F1	553.005 (86)*	-.002	-.001	.000
F3. Strong invariance (First-Order)	28556.161 (5520)*	.940	.936	.025	.024; .026	F2	2768.615 (60)*	-.005	-.005	+.001
F4. Strict invariance(First-Order)	29398.114 (5597)*	.938	.935	.025	.025; .026	F3	609.551 (77)*	-.002	-.001	.000
F5. Correlated Uniq. (First-Order)	29407.574 (5606)*	.938	.935	.025	.025; .026	F4	23.268 (9)*	.000	.000	.000
F6. Latent Var.-Covar. (First-Order)	30689.465 (5750)*	.935	.934	.026	.025; .026	F5	1367.188 (144)*	-.003	-.001	+.001
F7. Latent Means (First-Order)	31681.365 (5767)*	.932	.931	.026	.026; .026	F6	1971.518 (17)*	-.003	-.003	.000
English respondents only	19552.071 (2728)*	.940	.935	.024	.024; .024	--	--	--	--	--
French respondents only	8004.670 (2728)*	.933	.928	.028	.028; .029	--	--	--	--	--
S1. Configural invariance (Second-Order)	34229.353 (5783)*	.926	.925	.027	.027; .028	--	--	--	--	--
S2. Weak invariance (Second-Order)	34266.808 (5786)*	.926	.925	.027	.027; .028	S1	53.602 (3)*	.000	.000	.000
S3. Strong invariance (Second-Order)	34530.934 (5789)*	.925	.924	.028	.027; .028	S2	486.801 (3)*	-.001	-.001	+.001
S4. Strict invariance(Second-Order)	34587.316 (5793)*	.925	.924	.028	.027; .028	S3	42.988 (4)*	.000	.000	.000
S5. Latent Var.-Covar. (Second-Order)	34609.864 (5807)*	.925	.924	.028	.027; .028	S4	14.861 (14)	.000	.000	.000
S6. Latent Means (Second-Order)	34616.891 (5808)*	.925	.924	.028	.027; .028	S5	6.704 (1)*	.000	.000	.000
Male versus Females Respondents										
Male respondents only	15190.549 (2687)*	.949	.944	.022	.022; .023	--	--	--	--	--
Female respondents only	8602.797 (2687)*	.946	.941	.024	.023; .024	--	--	--	--	--
F1. Configural invariance (First-Order)	24063.310 (5374)*	.948	.943	.023	.023; .023	--	--	--	--	--
F2. Weak invariance (First-Order)	24424.660 (5460)*	.947	.943	.023	.023; .023	M1	364.397 (86)*	-.001	.000	.000
F3. Strong invariance (First-Order)	24736.869 (5520)*	.946	.943	.023	.023; .023	M2	309.519 (60)*	-.001	.000	.000
F4. Strict invariance(First-Order)	24844.564 (5597)*	.946	.944	.023	.023; .023	M3	230.854 (77)*	.000	+.001	.000
F5. Correlated Uniq. (First-Order)	24845.817 (5606)*	.946	.944	.023	.023; .023	M4	16.322 (9)	.000	.000	.000
F6. Latent Var.-Covar. (First-Order)	25211.612 (5750)*	.946	.945	.023	.022; .023	M5	382.689 (144)*	.000	+.001	.000
F7. Latent Means (First-Order)	25630.141 (5767)*	.945	.944	.023	.023; .023	M6	484.263 (17)*	-.001	-.001	.000
Male respondents only	17101.566 (2728)*	.941	.937	.024	.024; .024	--	--	--	--	--
Female respondents only	9669.266 (2728)*	.937	.932	.026	.025; .026	--	--	--	--	--
S1. Configural invariance (Second-Order)	28274.654 (5783)*	.937	.937	.024	.024; .025	--	--	--	--	--
S2. Weak invariance (Second-Order)	28313.179 (5786)*	.937	.936	.024	.024; .025	S1	30.601 (3)*	.000	-.001	.000

Description	χ^2 (*df*)	CFI	TLI	RMSEA	RMSEA CI	CM	$\Delta\chi^2$ (*df*)	ΔCFI	ΔTLI	ΔRMSEA
S3. Strong invariance (Second-Order)	28490.147 (5789)*	.937	.936	.024	.024; .025	S2	185.977 (3)*	.000	.000	.000
S4. Strict invariance(Second-Order)	28503.478 (5793)*	.937	.936	.024	.024; .025	S3	13.067 (4)	.000	.000	.000
S5. Latent Var.-Covar. (Second-Order)	28539.241 (5807)*	.937	.936	.024	.024; .025	S4	33.601 (14)*	.000	.000	.000
S6. Latent Means (Second-Order)	28543.204 (5808)*	.937	.936	.024	.024; .024	S5	3.112 (1)	.000	.000	.000
Military versus Civilian Respondents										
Military respondents only	14076.865 (2687)*	.949	.945	.022	.022; .023	--	--	--	--	--
Civilian respondents only	12475.008 (2687)*	.950	.945	.028	.027; .028	--	--	--	--	--
F1. Configural invariance (First-Order)	26903.142 (5374)*	.949	.945	.025	.024; .025	--	--	--	--	--
F2. Weak invariance (First-Order)	27232.389 (5460)*	.949	.945	.025	.024; .025	M1	340.369 (86)*	.000	.000	.000
F3. Strong invariance (First-Order)	28514.923 (5520)*	.946	.943	.025	.025; .026	M2	1303.317 (60)*	-.003	-.002	.000
F4. Strict invariance(First-Order)	29271.286 (5597)*	.944	.942	.025	.025; .026	M3	579.963 (77)*	-.002	-.001	.000
F5. Correlated Uniq. (First-Order)	29261.935 (5606)*	.944	.942	*.025*	.025; .026	M4	7.957 (9)	.000	.000	.000
F6. Latent Var.-Covar. (First-Order)	29849.765 (5750)*	.943	.942	.025	.025; .026	M5	583.427 (144)*	-.001	.000	.000
F7. Latent Means (First-Order)	30754.855 (5767)*	.941	.940	.026	.025; .026	M6	760.063 (17)*	-.002	-.002	+.001
Military respondents only	15951.544 (2728)*	.941	.937	.024	.024; .024	--	--	--	--	--
Civilian respondents only	13964.268 (2728)*	.942	.938	.030	.029; .030	--	--	--	--	--
S1. Configural invariance (Second-Order)	33194.348 (5783)*	.935	.935	.027	.027; .027	--	--	--	--	--
S2. Weak invariance (Second-Order)	33230.196 (5786)*	.935	.935	.027	.027; .027	S1	30.643 (3)*	.000	.000	.000
S3. Strong invariance (Second-Order)	33857.084 (5789)*	.934	.933	.027	.027; .028	S2	1218.567 (3)*	-.001	-.002	.000
S4. Strict invariance(Second-Order)	33881.859 (5793)*	.934	.933	.027	.027; .028	S3	86.519 (4)*	.000	.000	.000
S5. Latent Var.-Covar. (Second-Order)	33944.446 (5807)*	.934	.933	.027	.027; .027	S4	61.454 (14)*	.000	.000	.000
S6. Latent Means (Second-Order)	33970.246 (5808)*	.934	.933	.027	.027; .028	S5	16.876 (1)*	.000	.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; CM: comparison model; Δ: change in fit relative to the CM.

Appendix C.
Selection of the Optimal Number of Profiles

Analyses

Latent Profile Analyses (LPA) including one to ten profiles were estimated at the individual level, allowing the means of the profile indicators to vary across profiles. Despite the advantages of models also allowing indicators' variances to be freely estimated across profiles (Peugh & Fan, 2013), these alternative models resulted in important convergence difficulties (e.g., nonconvergence, impossible parameter estimates). These difficulties suggest the inadequacy of these alternative models (overparameterization), and the superiority of the parsimonious specification used here (Chen et al., 2001). To avoid converging on local solutions, LPA were estimated using 10,000 randomly generated sets of starting values and 1000 iterations; final optimization was conducted on the 500 best solutions (Hipp & Bauer, 2006).

The optimal number of profiles was determined by considering the theoretical nature and meaning of the profiles, as well as by consulting statistical indicators to guide model selection (Marsh et al., 2009; Muthén, 2003). We relied on the following indicators to guide model selection (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 Integrated Classification Likelihood BIC (ICL-BIC); and (vi) the adjusted Lo, Mendell and Rubin's (2001) Likelihood Ratio Test (aLMR)[1]. Lower values on the AIC, CAIC, BIC, ABIC, and ICL-BIC suggest a better fitting model, whereas a statistically significant aLMR value supports the target solution when compared to a solution including one less profile.

Statistical simulation studies have supported the efficacy of some of those indicators (i.e., BIC, CAIC, ABIC, and ICL-BIC), but not of the others (i.e., aLMR and AIC) (e.g., Diallo et al., 2016, 2017; Peugh & Fan, 2013). As such, the latter indicators will be reported to ensure full disclosure, but not used to guide model selection. The sample size dependency of these indicators can lead them to keep on supporting additional of profiles beyond the optimal solution (Marsh et al., 2009). In this situation, a graphical representation (i.e., elbow plot) should be inspected to better locate the inflection point in the reduction of the value of the CAIC, BIC, ABIC, and ICL-BIC (Morin et al., 2011).

Results

The results associated with the alternative LPA solutions are reported in Table S7 of these online supplements. All indicators kept on decreasing without ever reaching a minimum. The elbow plot, reported in Figure S1 of these online supplements, suggests that this rate of decrease is steady until the four-profile solution, after which it becomes slightly less pronounced, before decreasing again around seven profiles. Looking closely at the solutions including four to seven profiles revealed that adding a fifth profile to the solution resulted in a meaningful addition to the model, whereas adding profiles beyond five resulted in the arbitrary division of existing profiles into smaller similarly shaped profiles. For these reasons, the five-profile solution was retained. The detailed results from this solution are reported in Tables S8 and S9 of these online supplements. The classification accuracy of the solution (synthesizes by an entropy of .803) was quite high, revealing that participants had a likelihood of 83.9% to 91.1% of being classified in their most likely profile.

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Table S7

Results from the Latent Profiles Analyses

	LL	#fp	Scaling	AIC	CAIC	BIC	ABIC	ICL-BIC	Entropy	aLMR
1 Profile	-112170.058	14	6.9978	224368.115	224486.828	224472.828	224428.337	Na	Na	Na
2 Profiles	-107229.722	22	7.5497	214503.445	214689.993	214667.993	214598.079	212291.153	.869	.110
3 Profiles	-104328.146	30	5.4369	208716.291	208970.675	208940.675	208845.338	204943.414	.861	.003
4 Profiles	-102277.392	38	5.2627	204630.783	204953.003	204915.003	204794.242	197294.598	.790	.093
5 Profiles	-100550.777	46	5.3686	201193.553	201583.608	201537.608	201391.424	193238.265	.803	.449
6 Profiles	-99325.789	54	5.0257	198759.578	199217.469	199163.469	198991.862	190861.975	.823	.474
7 Profiles	-98336.205	62	5.0365	196796.410	197322.136	197260.136	197063.106	188448.183	.827	.595
8 Profiles	-97472.541	70	4.8057	195085.083	195678.644	195608.644	195386.191	186409.727	.831	.540
9 Profiles	-96726.964	78	5.0662	193609.928	194271.326	194193.326	193945.449	184933.483	.839	.545
10 Profiles	-96062.191	86	4.2444	192296.382	193025.614	192939.614	192666.315	183416.564	.842	.232

Note. The solution labelled as "Final" (last line) has been re-estimated with the Mplus design based correction for nesting to maximise accuracy; LL = model loglikelihood; #fp = number of free parameters; AIC = Akaïke information criterion; CAIC = consistent AIC; BIC = Bayesian information criterion; ABIC = sample-size adjusted BIC; ICL-BIC = integrated classification likelihood BIC; aLMR = Lo-Mendel and Rubin's likelihood ratio test; BLRT = bootstrap likelihood ratio test; Na = not applicable.

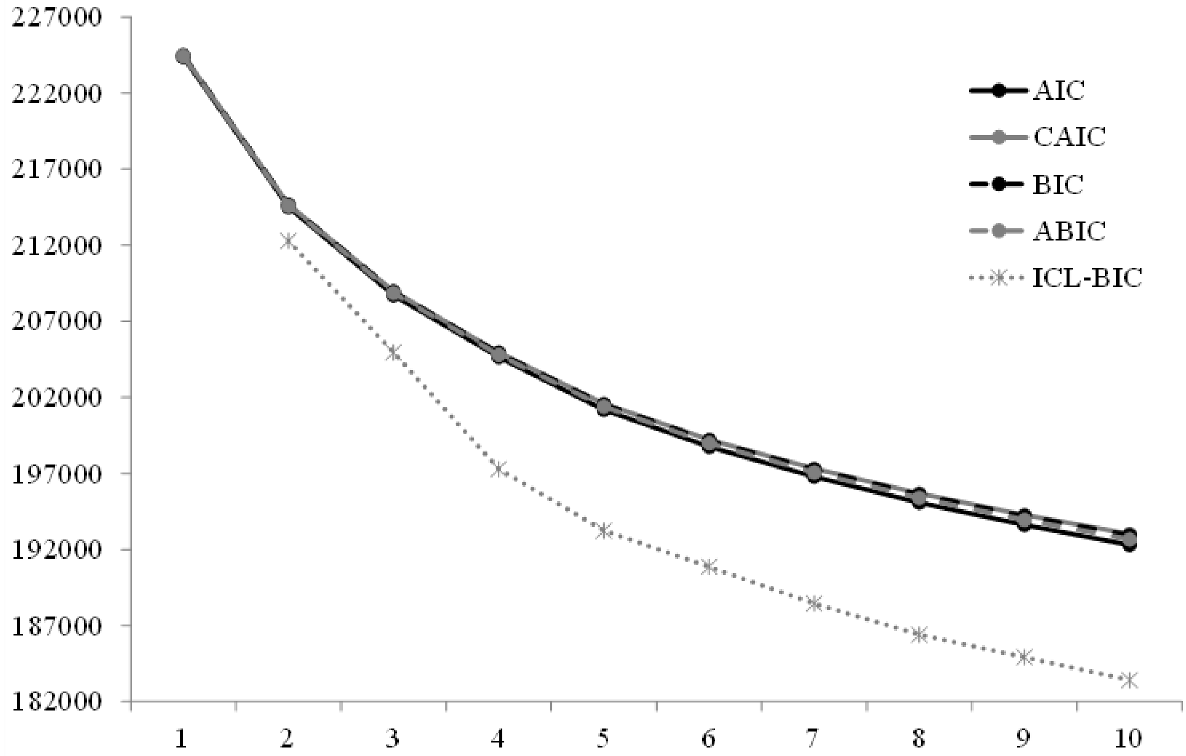

Figure S1. Elbow plot of the information criteria for the latent profile analyses.

Table S8

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	Profile 5
Profile 1	.882	.033	.000	.004	.080
Profile 2	.022	.911	.001	.032	.034
Profile 3	.000	.001	.874	.026	.100
Profile 4	.001	.027	.035	.839	.098
Profile 5	.014	.010	.054	.048	.874

Note. The profile indicators are estimated from factor scores with a mean of 0 and a standard deviation of 1; Profile 1 = *Burned-Out/Disengaged*; Profile 2 = *Burned-Out/Involved*; Profile 3 = *Engaged*; Profile 4 = *Engaged/Exhausted*; Profile 5 = *Normative*.

Table S9

Detailed Results from the Final Latent Profile Analytic Solution

	Profile 1 Mean [CI]	Profile 2 Mean [CI]	Profile 3 Mean [CI]	Profile 4 Mean [CI]	Profile 5 Mean [CI]	Variance [CI]
Physical Engagement (S-Factor)	-.233 [-.596; .130]	.736 [.641; .832]	-.288 [-.361; -.215]	.678 [.617; .738]	-.266 [-.333; -.200]	.436 [.407; .466]
Emotional Engagement (S-Factor)	-.256 [-.427; -.086]	-1.677 [-1.825; -1.530]	.464 [.426; .502]	.196 [.132; .260]	.227 [.169; .286]	.396 [.367; .425]
Cognitive Engagement (S-Factor)	-.599 [-.783; -.415]	.364 [.206; .521]	-.074 [-.124; -.025]	.425 [.351; .499]	-.114 [-.159; -.069]	.589 [.551; .627]
Emotional Exhaustion (S-Factor)	-.506 [-.700; -.312]	.041 [-.021; .102]	-.197 [-.273; -.120]	.998 [.893; 1.104]	-.187 [-.240; -.133]	.369 [.345; .393]
Disengagement (S-Factor)	.668 [.558; .778]	-.468 [-.578; -.358]	-.266 [-.325; -.207]	-.305 [-.409; -.200]	.222 [.190; .254]	.307 [.291; .324]
Global Engagement (G-Factor)	-2.005 [-2.413; -1.598]	-.231 [-.344; -.118]	.971 [.896; 1.046]	.455 [.286; .624]	-.161 [-.238; -.084]	.386 [.352; .420]
Global Burnout (G-Factor)	1.257 [.953; 1.560]	1.397 [1.316; 1.478]	-1.218 [-1.297; -1.138]	.196 [.075; .317]	-.145 [-.235; -.055]	.287 [.272; .303]

Note. CI = 95% confidence interval; the profile indicators are estimated from factor scores with a mean of 0 and a standard deviation of 1. Profile 1 = *Burned-Out/Disengaged*; Profile 2 = *Burned-Out/Involved*; Profile 3 = *Engaged*; Profile 4 = *Engaged/Exhausted*; Profile 5 = *Normative*.

Appendix D

Annotated Mplus Input Files for our Main Analytic Models

Readers interested in learning about the estimation of multilevel measurement models (including bifactor and higher-order models) should consult:

Morin, A.J.S., Blais, A.-R., & Chénard-Poirier, L.-A. (2021, in press). Doubly latent multilevel procedures for organizational assessment and prediction. *Journal of Business & Psychology* Advance online publication. doi 10.1007/s10869-021-09736-5

Readers interested in learning about the estimation of latent profile analyses with predictors and outcomes should consult:

Morin, A.J.S., & Litalien, D. (2019). Mixture modelling for lifespan developmental research. In *Oxford Research Encyclopedia of Psychology*. Oxford University Press. doi: 10.1093/acrefore/9780190236557.013.364

Readers interested in learning about the estimation of multilevel latent profile analyses with predictors and outcomes should consult:

Collie, R.J., Martin, A.J., Morin, A.J.S., Malmberg, L-E., & Sammons, P. (2021). A multilevel person-centered examination of teachers' workplace experiences: Replication and extension with links to instructional support and achievement. *Frontiers in Psychology, 12*, 711173

Collie, R.J., Malmberg, L.-E., Martin, A.J., Sammons, P., & Morin, A.J.S. (2020). A multilevel person-centered examination of teachers' workplace demands and resources: Links with work-related well-being. *Frontiers in Psychology, 11*, 626.

All of these resources incorporate extensive set of annotated input files as part of their online supplements.

```
TITLE: Unconditional 5 Profile Model;
DATA:
FILE IS indicators.dat;
! Annotations are preceded by ! and indicated ion greyscale.
! Each command should end with a ;
! The TITLE section is optional, and used to give a name to a specific input file.
! The DATA section is used to indicate the name of your data set (ideally in the same folder)
! NAMES ARE: indicate all variables appearing in your data file, in order of appearance.
! USEVARIABLE ARE: indicate the variables used in your analyses.
VARIABLE:
NAMES ARE
ENG_PH ENG_EM ENG_CO BO_EX BO_DIS WBG BOG
TI PEH OVER2 AMB2 JUST2 LEAD2 POS2
OVER_B2 AMB_B2 JUST_B2 LEAD_B2 POS_B2
WEIGHTS ID LINK;

USEVARIABLES ARE
ENG_PH ENG_EM ENG_CO BO_EX BO_DIS WBG BOG;

IDVAR IS ID; ! Indicate the unique identifier of the participants.
CLUSTER IS LINK; ! Indicate the identifier for the level 2 units (work unit).
WEIGHT IS WEIGHTS; ! Indicate the variables used to identify the sampling weights.
MISSING =  *; !Indicate the missing data code.

CLASSES = c (5);
! Indicate the number of profiles, and the name of the variables used to identify the profiles (here: C)

ANALYSIS:
ESTIMATOR IS MLR; ! to request MLR estimation
TYPE IS MIXTURE COMPLEX;
! to request a latent profile model and a correction for the multilevel nesting structure and the weights
STARTS = 10000 500;
STITERATIONS = 1000;
! As noted, LPA were estimated using 10,000 random sets of starting values and 1000 iterations;
! Final optimization was conducted on the 500 best solutions

MODEL:
! To request the free estimation of the indicators means [] in each profile.
! For models including less or more profiles, change the number appearing above (CLASSES =) and
! add or remove profiles (e.g., %c#6%).
%OVERALL%
[ENG_PH ENG_EM ENG_CO BO_EX BO_DIS WBG BOG ];
%c#1%
[ENG_PH ENG_EM ENG_CO BO_EX BO_DIS WBG BOG ];
%c#2%
[ENG_PH ENG_EM ENG_CO BO_EX BO_DIS WBG BOG ];
%c#3%
[ENG_PH ENG_EM ENG_CO BO_EX BO_DIS WBG BOG ];
%c#4%
[ENG_PH ENG_EM ENG_CO BO_EX BO_DIS WBG BOG ];
%c#5%
[ENG_PH ENG_EM ENG_CO BO_EX BO_DIS WBG BOG ];
! standard set of output sections
OUTPUT:
SAMPSTAT STANDARDIZED RESIDUAL CINTERVAL MODINDICES (3.0);
 TECH1 TECH2 TECH3 TECH4 TECH7 TECH11 TECH13 TECH14 SVALUES;
```

```
TITLE: Final 5-Profile Solution with the outcome;
! To replicate the final solution, while ensuring no change in the nature of the model, use the results
! from the final solution using @, and deactivate the random starts.
! The outcome mean ([TI]) and variance (TI)is then requested to be freely estimated in each profile
! outcome mean is accompanied by a unique label in parenthesis
[…]
USEVARIABLES ARE
ENG_PH ENG_EM ENG_CO BO_EX BO_DIS WBG BOG TI;
ANALYSIS:
ESTIMATOR IS MLR;
TYPE IS MIXTURE COMPLEX;
STARTS = 0;
MODEL:
%OVERALL%
   %C#1%
    [ eng_ph@-0.23286 ];
    [ eng_em@-0.25628 ];
    [ eng_co@-0.59894 ];
    [ bo_ex@-0.50628 ];
    [ bo_dis@0.66758 ];
    [ wbg@-2.00544 ];
    [ bog@1.25658 ];
    eng_ph@0.43610 (8);
    eng_em@0.39618 (9);
    eng_co@0.58884 (10);
    bo_ex@0.36938 (11);
    bo_dis@0.30746 (12);
    wbg@0.38618 (13);
    bog@0.28743 (14);
[ti] (p1);
ti;
    %C#2%
    [ eng_ph@0.73648 ];
    [ eng_em@-1.67745 ];
    [ eng_co@0.36352 ];
    [ bo_ex@0.04061 ];
    [ bo_dis@-0.46799 ];
    [ wbg@-0.23097 ];
    [ bog@1.39704 ];
    eng_ph@0.43610 (8);
    eng_em@0.39618 (9);
    eng_co@0.58884 (10);
    bo_ex@0.36938 (11);
    bo_dis@0.30746 (12);
    wbg@0.38618 (13);
    bog@0.28743 (14);
[ti] (p2);
ti;
    %C#3%
    [ eng_ph@-0.28790 ];
    [ eng_em@0.46419 ];
    [ eng_co@-0.07445 ];
    [ bo_ex@-0.19678 ];
    [ bo_dis@-0.26599 ];
    [ wbg@0.97122 ];
```

```
    [ bog@-1.21781 ];
    eng_ph@0.43610 (8);
    eng_em@0.39618 (9);
    eng_co@0.58884 (10);
    bo_ex@0.36938 (11);
    bo_dis@0.30746 (12);
    wbg@0.38618 (13);
    bog@0.28743 (14);
[ti] (p3);
ti;
    %C#4%
    [ eng_ph@0.67751 ];
    [ eng_em@0.19561 ];
    [ eng_co@0.42485 ];
    [ bo_ex@0.99832 ];
    [ bo_dis@-0.30469 ];
    [ wbg@0.45519 ];
    [ bog@0.19579 ];
    eng_ph@0.43610 (8);
    eng_em@0.39618 (9);
    eng_co@0.58884 (10);
    bo_ex@0.36938 (11);
    bo_dis@0.30746 (12);
    wbg@0.38618 (13);
    bog@0.28743 (14);
[ti] (p4);
ti;
    %C#5%
    [ eng_ph@-0.26639 ];
    [ eng_em@0.22749 ];
    [ eng_co@-0.11402 ];
    [ bo_ex@-0.18652 ];
    [ bo_dis@0.22211 ];
    [ wbg@-0.16078 ];
    [ bog@-0.14526 ];
    eng_ph@0.43610 (8);
    eng_em@0.39618 (9);
    eng_co@0.58884 (10);
    bo_ex@0.36938 (11);
    bo_dis@0.30746 (12);
    wbg@0.38618 (13);
    bog@0.28743 (14);
[ti] (p5);
ti;
! Using the labels associated with the outcome means, the following section is used to request the
! estimation of tests of statistical differences in outcome levels across profiles, with new variables
! (p1p2) referring to these differences.
MODEL CONSTRAINT:
new (p1p2 p1p3 p1p4 p1p5 p2p3 p2p4 p2p5 p3p4 p3p5 p4p5);
p1p2 = p1 - p2; p1p3 = p1 - p3;
p1p4 = p1 - p4; p1p5 = p1 - p5;
p2p3 = p2 - p3; p2p4 = p2 - p4;
p2p5 = p2 - p5; p3p4 = p3 - p4;
p3p5 = p4 - p5; p4p5 = p4 - p5;
```

```
TITLE: Final 5-Profile Solution with multilevel predictors;
[…]
USEVARIABLES ARE
ENG_PH ENG_EM ENG_CO BO_EX BO_DIS WBG BOG
PEH OVER2 AMB2 JUST2 LEAD2 POS2
OVER_B2 AMB_B2 JUST_B2 LEAD_B2 POS_B2;
IDVAR IS ID;
CLUSTER IS LINK;
WEIGHT IS WEIGHTS;
MISSING =  *;
CLASSES = c (5);
! To indicate variables only used at the individual level.
WITHIN = ENG_PH ENG_EM ENG_CO BO_EX BO_DIS WBG BOG PEH
OVER2 AMB2 JUST2 LEAD2 POS2;
! To indicate variables only used at the work unit level.
BETWEEN= OVER_B2 AMB_B2 JUST_B2 LEAD_B2 POS_B2;
ANALYSIS:
ESTIMATOR IS MLR;
TYPE IS MIXTURE TWOLEVEL;
! to request a multilevel latent profile model (also accounting for the weights)
STARTS = 0;
MODEL:
! The WITHIN section of the model is used to define the profiles,
! and the individual level predictions (C ON…) are specified in the %OVERALL% section
%WITHIN%
%OVERALL%
C on PEH OVER2 AMB2 JUST2 LEAD2 POS2;
   %C#1%
    [ eng_ph@-0.23286 ];
    [ eng_em@-0.25628 ];
    [ eng_co@-0.59894 ];
    [ bo_ex@-0.50628 ];
    [ bo_dis@0.66758 ];
    [ wbg@-2.00544 ];
    [ bog@1.25658 ];
    eng_ph@0.43610 (8);
    eng_em@0.39618 (9);
    eng_co@0.58884 (10);
    bo_ex@0.36938 (11);
    bo_dis@0.30746 (12);
    wbg@0.38618 (13);
    bog@0.28743 (14);
    %C#2%
    [ eng_ph@0.73648 ];
    [ eng_em@-1.67745 ];
    [ eng_co@0.36352 ];
    [ bo_ex@0.04061 ];
    [ bo_dis@-0.46799 ];
    [ wbg@-0.23097 ];
    [ bog@1.39704 ];
    eng_ph@0.43610 (8);
    eng_em@0.39618 (9);
    eng_co@0.58884 (10);
    bo_ex@0.36938 (11);
    bo_dis@0.30746 (12);
```

```
    wbg@0.38618 (13);
    bog@0.28743 (14);
    %C#3%
    [ eng_ph@-0.28790 ];
    [ eng_em@0.46419 ];
    [ eng_co@-0.07445 ];
    [ bo_ex@-0.19678 ];
    [ bo_dis@-0.26599 ];
    [ wbg@0.97122 ];
    [ bog@-1.21781 ];
    eng_ph@0.43610 (8);
    eng_em@0.39618 (9);
    eng_co@0.58884 (10);
    bo_ex@0.36938 (11);
    bo_dis@0.30746 (12);
    wbg@0.38618 (13);
    bog@0.28743 (14);
    %C#4%
    [ eng_ph@0.67751 ];
    [ eng_em@0.19561 ];
    [ eng_co@0.42485 ];
    [ bo_ex@0.99832 ];
    [ bo_dis@-0.30469 ];
    [ wbg@0.45519 ];
    [ bog@0.19579 ];
    eng_ph@0.43610 (8);
    eng_em@0.39618 (9);
    eng_co@0.58884 (10);
    bo_ex@0.36938 (11);
    bo_dis@0.30746 (12);
    wbg@0.38618 (13);
    bog@0.28743 (14);
    %C#5%
    [ eng_ph@-0.26639 ];
    [ eng_em@0.22749 ];
    [ eng_co@-0.11402 ];
    [ bo_ex@-0.18652 ];
    [ bo_dis@0.22211 ];
    [ wbg@-0.16078 ];
    [ bog@-0.14526 ];
    eng_ph@0.43610 (8);
    eng_em@0.39618 (9);
    eng_co@0.58884 (10);
    bo_ex@0.36938 (11);
    bo_dis@0.30746 (12);
    wbg@0.38618 (13);
    bog@0.28743 (14);
! The BETWEEN section of the model is used to request the predictions estimated at the level of
! the work units (C ON…) in the %OVERALL% section
%BETWEEN%
%OVERALL%
C ON OVER_B2 AMB_B2 JUST_B2 LEAD_B2 POS_B2;
OUTPUT:
SAMPSTAT STANDARDIZED RESIDUAL CINTERVAL MODINDICES (3.0);
 TECH1 TECH2 TECH3 TECH4 SVALUES;
```