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Teachers' Profiles of Work Engagement and Burnout Over the Course of a School Year

Sophie Drouin Rousseau[1] †, Alexandre J.S. Morin[2] †, Claude Fernet[3*], Yael Blechman[2], Nicolas Gillet[4]

[1]Département de psychologie, Université du Québec à Trois-Rivières, Canada
[2]Substantive-Methodological Synergy Research Laboratory, Concordia University, Montreal, Québec, Canada
[3]Département de gestion des ressources humaines, Université du Québec à Trois-Rivières, Canada
[4]QualiPsy EE 1901, Université de Tours, Tours, France
Institut Universitaire de France (IUF)

† Since the first two authors (S.D.R. and A.J.S.M.) contributed equally to the preparation of this article, their order was determined at random: both should be considered first authors.

***Corresponding author:**
Claude Fernet, Ph.D.
Département de gestion des ressources humaines
École de gestion, Université du Québec à Trois-Rivières
3351 boul. des Forges, C.P. 500, Trois-Rivières, QC, Canada, G8Z 4M3
Email: Claude.Fernet@uqtr.ca

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Abstract

This research relies on a combination of variable- and person-centered approaches to improve our understanding of the dimensionality of work engagement and burnout. Among 1004 teachers who completed a questionnaire twice over an eight-month period, our results first revealed that work engagement and burnout ratings simultaneously reflected two global overarching constructs co-existing with six specific dimensions (vigor, dedication, and absorption as well as emotional exhaustion, cynicism, and professional efficacy). We then examined the profiles taken by these global and specific dimensions, documented their stability and interrelations over time, and tested their associations with theoretically relevant predictors. Three work engagement (Vigorously Engaged, Disengaged, Engaged) and three burnout (Burned-Out, Adapted, Normative) profiles were identified. Most Disengaged teachers at Time 1 corresponded to the Burned-Out profile at Time 2, and most Burned-Out teachers at Time 1 corresponded to the Disengaged profile at Time 2. Workload perceptions increased teachers' likelihood of membership into the Disengaged profile relative to the Engaged one. In contrast, most job resources perceptions (control, rewards, and values) predicted an increased likelihood of membership into the Engaged profile relative to the Disengaged one.

Key words: Burnout; work engagement; profiles; latent transition analyses; job demands and resources; workload; fairness; bifactor models.

Burnout, which is highly prevalent among teachers (Schaufeli et al., 2009), represents a psychological state of resource depletion encompassing feelings of emotional exhaustion (i.e., depletion of physical energy and fatigue), cynicism (i.e., excessively detached or negative responses to others), and a reduced sense of professional efficacy (i.e., feelings of low productivity and achievement) (Maslach, 2011; Schaufeli et al., 2009). In contrast, work engagement represents “a positive, fulfilling, work-related state of mind” (Schaufeli et al., 2002, p. 74) encompassing vigor (i.e., displaying high levels of energy and persistence at work), dedication (i.e., working hard with a sense of enthusiasm), and absorption (i.e., being fully engrossed with one’s work). Whereas work engagement represents a known precursor of desirable individual (e.g., higher job satisfaction; Goering et al., 2017) and organization (e.g., lower absenteeism, better performance and organizational citizenship behaviors; Neuber et al., 2022) outcomes, burnout is known to hinder individual (e.g., psychological health) and organizational (e.g., absenteeism; Swider & Zimmerman, 2010) functioning in a way interfere with the accomplishment of the school’s educational mission (Chang, 2009).

Although ample research has documented the negative implications of burnout and the benefits of work engagement (e.g., Demerouti et al., 2010; Trógolo et al., 2020), very little is known about the longitudinal dynamic of both constructs (Maricuțoiu et al., 2017). Importantly, although both constructs have often been positioned as the opposite of one another (Maslach & Leiter, 1997; Schaufeli et al., 2002), one important motivational premise of burnout is that in order to burn out, employees must first be fired up (Pines, 1993). Thus, when we turn our attention to the longitudinal dynamics underpinning both psychological states and their interrelations, this motivational premise raises many critically important questions. For instance, will highly engaged teachers necessarily become burned out at some point? Alternatively, are burned out teachers necessarily trapped in a chronic state of resource depletion with little hopes of becoming engaged once again? This issue is important for both research and theory. Indeed, if we acknowledge that work engagement and burnout operate in tandem (Trógolo et al., 2020), it becomes necessary to determine how work engagement and burnout relate to one another longitudinally. From a practical purpose, greater insight into how burnout and work engagement co-develop during a school year would also help teachers and school administrators better understand burnout and work engagement. Although the present study was designed to investigate burnout and work engagement in teachers, it could serve as a springboard to a deeper understanding of how these psychological states relate to individual and organizational outcomes in other at-risk occupational groups, such as health-care workers.

Importantly, our understanding of dynamic interrelations between burnout and work engagement is further complicated by their multidimensional nature. Both burnout (e.g., Sandrin et al., 2022) and work engagement (e.g., Gillet et al., 2019) are known to be experienced holistically as global states (global levels of burnout or of work engagement) defined from a series of components, each retaining some specificity beyond their global components (i.e., specific levels of emotional exhaustion, cynicism, professional efficacy, vigor, dedication, and absorption). Accounting for the global-specific nature of both constructs thus entails a consideration of complex interrelations among a series of global and specific components as they unfold over time. By focusing on subpopulations characterized by distinct configurations, or profiles, on a set of variables, person-centered analyses thus seem naturally suited to study the joint effects of such complex variable combinations (Morin et al., 2018). As an added benefit, the person-centered approach tends to be better aligned with managers’ natural tendency to think in terms of categories rather than complex variable relations (Hofmans et al., 2021). Thus, rather than having to decode complex patterns of interrelations and interactions between variables, person-centered results allow managers to easily identify types of employees and actionable levers of intervention to increase the likelihood of more desirable work engagement and burnout profiles. Emerging person-centered studies have already looked at how work engagement (Gillet et al., 2019; Simbula et al., 2013) and burnout (Berjot et al., 2017; Leiter & Maslach, 2016) components combine within specific profiles of employees. Unfortunately, this emerging research area has generally ignored the dual global-specific nature of work engagement and burnout, as well as how burnout profiles relate to work engagement profiles.

The present study addresses these issues by documenting the nature of teachers’ work engagement and burnout profiles, as well as their longitudinal interrelations. The teaching profession is naturally suited to the present investigation given evidence suggesting that teachers tended to be highly engaged at work (Burić & Macuka, 2018), while also presenting a particularly high risk of burnout (Schaufeli et al., 2009). Moreover, teachers' work-related tasks tend to form a mainly closed cycle covering one school year, thus allowing us to assess how the nature of the profiles and their interrelations changed during a school year (an eight-month period ranging from October to June). To document the construct validity (e.g., Meyer & Morin, 2016) of these profiles, we also consider their relations with job demands (workload) and resources (control, rewards, community, fairness, and values).

Co-Existing Global and Specific Work Engagement and Burnout Components

Burnout (Maslach, 2011) and work engagement (Schaufeli et al., 2002) are explicitly defined as multidimensional constructs encompassing distinct interrelated facets (burnout: Emotional exhaustion, cynicism, and reduced professional efficacy; and work engagement: Vigor, dedication, and absorption) known to share differentiated covariate associations (e.g., Kuijpers et al., 2020; Taylor & Millear, 2016). Despite this acknowledgment of their multidimensional nature, it has also been proposed that employees might experience work engagement and burnout in a more holistic manner (i.e., as global entities) rather than as a collection of specific psychological manifestations (Goering et al., 2017; Moeller et al., 2018). Acknowledging the multidimensionality of these constructs while also accepting the idea that they might be experienced more globally suggest that work engagement and burnout might be better conceptualized as global entities reflecting commonalities among specific dimensions, which themselves may include specificity unexplained by these global entities. Supporting this possibility, research has supported a bifactor representation of these constructs, allowing researchers to estimate global work engagement (Gillet et al., 2019; Huyghebaert-Zouaghi et al., 2021, 2022a) or burnout (Gillet et al., 2022; Sandrin et al., 2022) factors (G-factor) together with specific vigor, dedication, absorption, emotional exhaustion, cynicism, and reduced professional efficacy factors (S-factors) reflecting the unique nature of these facets beyond what they share with one another.

Gillet and colleagues (2019, 2021) noted that, because of this disagregation of global and specific levels of burnout and work engagement, the S-factors provide a direct representation of the degree of balance or imbalance in each specific dimension of burnout and/or work engagement. To illustrate, among all globally engaged employees, some may present a balanced level of engagement across dimensions, whereas others may present higher or lower levels of vigor, dedication or absorption relative to the others and thus relative to their global level of work engagement across all three dimensions. For instance, some globally engaged teachers may struggle more with in terms of absorption relative to their levels of dedication and vigor, thus reflecting a negative imbalance in a specific component of work engagement. Similarly, other teachers with a globally average level of work engagement may still be highly dedicated to their work, despite lower levels of vigor and absorption, thus reflecting a positive imbalance. Alternatively, although not globally characterized by a high level of burnout, some employees may still come to question their ability to properly execute their work, thus reflecting a negative imbalance in a burnout component.

A Person-Centered Perspective on Work Engagement and Burnout

Table S1, reported in the online supplements, summarizes the results from previous person-centered research seeking to identify profiles of burnout or work engagement among diverse samples of employees. Despite some variations, which may reflect methodological differences (e.g., nature of the sample, questionnaire used to assess burnout or engagement), a high level of similarity is apparent in the results obtained across studies. However, very few of the studies described in Table S1 have relied on a proper multidimensional operationalization in which global levels of burnout and work engagement were properly disaggregated from the specificities associated with each component of both constructs. Ignoring the bifactor structure of multidimensional profile indicators tends to erroneously lead to the identification of profiles differing from one another quantitatively (i.e., higher or lower levels across all dimensions, reflecting the role of the global component), rather than qualitatively (i.e., leading to profiles characterized by a truly distinct configuration across components) (Morin et al., 2016c, 2017). As a result, this failure to consider the global-specific nature of both constructs might explain why most previous studies have led to the identification of profiles differing in level (i.e., quantitatively) rather than shape (i.e., qualitatively). The present study addresses this limitation by estimating teachers' burnout and work engagement profiles using indicators reflecting their bifactor nature.

Although the lack of prior research relying on a proper disaggregation of global versus specific ratings makes it hard to formulate a clear set of hypotheses regarding the nature of the burnout and work engagement profiles expected in this study, those previous results still allow us to formulate some expectations. First, and in line with the quantitative differences systematically reported in the previous studies, we can expect to identify at least a *Normative*[1] profile, characterized by average levels of work engagement or burnout across dimensions, for both constructs. We also expect to identify a *High Engagement* (high levels of work engagement across dimensions), a *High Burnout* (high levels of burnout across dimensions), a *Low Engagement* (low levels of work engagement across dimensions), and a *Low Burnout* (high levels of burnout across dimensions) profiles.

However, in accordance with the subset of qualitatively distinct profiles obtained in prior research in which an approach similar to ours was used to operationalize burnout (Sandrin et al., 2022) and work engagement (Gillet et al., 2019), we also expect profiles presenting differentiated configurations of work engagement or burnout across indicators. For instance, we expect a *Vigorously Engaged* profile presenting moderately high global levels of work engagement accompanied by high specific levels of vigor and absorption (Gillet et al., 2019). Moreover, we also expect a *Mentally Distanced* profile dominated by high levels of cynicism (Sandrin et al., 2022). As a result, we suggest that:

Hypothesis 1. *The work engagement profiles identified in the present study will include a High Engagement profile, a Low Engagement profile, a Normative profile, and a Vigorously Engaged profile (i.e., dominated by high global levels of work engagement and high specific levels of vigor).*

Hypothesis 2. *The burnout profiles identified in the present study will include a High Burnout profile (i.e., high scores across dimensions, or a profile dominated by high scores on the global burnout factor and average scores on the specific factors), a Low Burnout profile (i.e., low scores across dimensions, or a profile dominated by low scores on the global burnout factor and average scores on the specific factors), a Normative profile (i.e., average scores across all components), and a Mentally Distanced profile (i.e., dominated by high specific levels of cynicism).*

A Longitudinal Person-Centered Perspective

Within-Sample and Within-Person Stability

Our second objective is to assess the stability of the burnout and work engagement profiles over the course of one school year (i.e., eight months). In addition to being closely connected with the natural cycle of teachers' work, this time interval was selected in alignment with prior research (Grødal et al., 2019; Horwood et al., 2021), because it goes beyond daily fluctuations (e.g., Kim et al., 2021; Klasmeier & Rowold, 2022) while remaining short enough to capture changes that may not be apparent over longer time spans (e.g., Mäkikangas et al., 2017; Tóth-Király et al., 2021a). As noted by Meyer and Morin (2016), it is critical to ascertain the stability of person-centered solutions to support their use as guides for the development of interventions tailored at distinct types, or profiles, of employees. Indeed, the ability to devise such interventions is conditioned on evidence that the profiles themselves reflect neither ephemeral phenomena likely to randomly fluctuate over time, nor highly rigid phenomena unlikely to respond to intervention.

More precisely, we consider two types of longitudinal stability, within-sample and within-person stability (e.g., Huyghebaert-Zouaghi et al., 2022b; Sandrin et al., 2020). Within-sample stability is related to the nature of the profiles themselves (i.e., number, nature, and size), which can change over time. In this regard, drastic changes in the number or nature of the profiles in the absence of any external change likely to explain them would suggest that the profiles have only limited practical utility as they apparently reflect transient phenomena. Alternatively, profile members might become more or less similar to one another over time, and some profiles might become more or less prevalent over time. These two types of changes do not preclude the reliance on person-centered solutions as intervention guides but shows that the profiles possess some malleability. In contrast, within-person stability refers to changes in nurses' membership into specific profiles over time (Huyghebaert-Zouaghi et al., 2022b; Sandrin et al., 2020) and can be observed in the absence of within-sample changes.

Various sources of evidence can help us to better grasp the longitudinal dynamics of work engagement and burnout. For instance, estimates of rank-order stability indicate that ratings of work engagement (r = .61 to .64; Grødal et al., 2019; Heinrichs et al., 2020) and burnout (r = .58 to .72; Frögéli et al., 2019; Kinnunen et al., 2019) tend to be quite stable over periods of one to three years, although similar estimates have also been reported for a shorter period of three months (r = .78; Madigan et al., 2015). Importantly, rank-order stability is not inconsistent with the idea that work engagement and burnout levels might be impacted by work conditions, which are themselves known to be quite

[1] Following a label used previously by Gillet et al. (2019) to describe work engagement profiles, and by Morin et al. (2016a, 2017) to describe one of their profiles in research on psychological health and well-being.

stable over time (Lesener et al., 2019). A recent person-centered study supported the within-sample stability of work engagement profiles over a four-month interval and revealed rates of within-sample stability varying from 92.6% to 100% across profiles over the same interval (Gillet et al., 2019). Interestingly, Mäkikangas et al. (2014, 2017) supported the idea that levels of work engagement and burnout can evolve differentially from one another over time. Likewise, studies examining the longitudinal trajectories of work engagement (e.g., van den Heuvel et al., 2020) and burnout (e.g., May et al., 2020; Wang et al., 2015) have also revealed very stable trajectories. However, some of these studies have also found that work engagement tends to slightly increase as a function of age (James et al., 2011; Kim & Kang, 2017), whereas Zuo et al. (2021) noted that work engagement levels tended to slightly decrease over a period of five days. Yet, average trajectories may mask substantial inter-individual heterogeneity (de Wind et al., 2017; Mäkikangas & Kinnunen, 2016), which can only be uncovered through person-centered analyses. Turning our attention to previous longitudinal person-centered studies of burnout trajectories, accumulating evidence supports both the presence of substantial inter-individual heterogeneity in the shape of these trajectories, as well as the stability of these trajectories over a period of one to two years (Evolahti et al., 2013; Hultell et al., 2013; Mäkikangas & Kinnunen, 2016; Mäkikangas et al., 2012; Rudman & Gustavsson, 2011).

Although informative, it is difficult to reconcile these previous results, due in part to the highly specific nature of their samples (e.g., managers: Mäkikangas et al., 2012; nurses: Rudman & Gustavsson, 2011; entrepreneurs: Zuo et al., 2021; exposed to organizational changes: van den Heuvel et al., 2020; pre-retired older employees: de Wind et al., 2017). This specificity calls into question the generalizability of these previous results, but also makes it impossible to differentiate whether and how conclusions might be related to the nature of the samples. Moreover, other than Gillet et al. (2019), in which a shorter time interval of four months was considered, none of these studies relied on a proper disaggregation of global and specific levels of work engagement or burnout. Thus, although the bulk of prior evidence allows us to formulate some hypotheses regarding within-sample and within-person stability, these hypotheses remain tentative at best. Furthermore, in light of these limitations, it is also impossible to anticipate whether the nature of the dominant within-person transitions in profile membership will be upward (toward a *High Engagement/Low Burnout* profile), downward (toward a *Low Engagement/High Burnout* profile), or lateral (toward profiles presenting similar levels of work engagement and burnout but characterized by a different configuration).

Hypothesis 3. *The profiles will present a high level of within-sample stability over a one-year interval (i.e., the same number of profiles, with the same structure, the same within-profile dispersion, and the same size will be identified).*

Hypothesis 4. *Moderate (60%) to high (75% or more) levels of within-person stability in profile membership will be observed over an eight-month interval.*

Research Question 1. *Will the profiles observed in the present study be characterized by upward, downward, or lateral transitions over time?*

Associations between Burnout and Work Engagement Profile Membership

Our third objective is to investigate the interrelations between teachers' work engagement and burnout profiles. More precisely, we consider how membership into work engagement profiles relates to membership into burnout profiles, and vice versa, at the same time point and over time. Although this study is the first to systematically examine these associations from a person-centered perspective, several studies have previously examined the work engagement-burnout associations over time using different methodological approaches (for meta-analyses, see Cole et al., 2012; Maricuțoiu et al., 2017).

Most modern conceptualizations of work engagement and burnout position them as the opposite of one another, and even as incompatible psychological states (e.g., Maslach & Leiter, 1997; Schaufeli et al., 2002). Indeed, according to the circumplex model of employee well-being (Bakker & Oerlemans, 2012), burnout is characterized by low displeasure and activation, whereas work engagement is characterized by high pleasure and activation. As a result, scholars generally tend to agree that the experience of burnout should be accompanied by lower levels of work engagement (Cole et al., 2012; Crawford et al., 2010). Employees suffering from high levels of burnout report being exposed to more job demands (e.g., workload), making it harder for them to complete their tasks within a reasonable timeframe (Maslach & Leiter, 1997). In turn, job demands require sustained effort on the part of the employees, leading them to experience a drain on their psychological resources (Bakker & Demerouti, 2007), and lower levels of work engagement (Gillet et al., 2015).

However, many classical perspectives have suggested that high levels of work engagement might contribute to the development of burnout (Cherniss, 1980; Freudenberger, 1974). This assertion relies on the motivational premise that only highly engaged employees can present a high risk of burning out (Pines, 1993). More precisely, this view states that, as a result of their high level of investment in their work role, highly engaged employees may come to deplete of their psychological resources over time, leading them to experience a feeling of work-related strain and to withdraw from work in an attempt to protect themselves from further loss of resources (Hobfoll, 1989). Indeed, highly engaged employees tend to spend longer hours at work (Schaufeli et al., 2008), to have less time and energy for off-work activities (Häusser & Mojzisch, 2017), and thus tend to display higher levels of work-family conflict (Halbesleben et al., 2009) and a greater need for recovery (Sonnentag et al., 2008). Supporting this assertion, recent person-centered studies have shown that it was possible for employees to jointly experience burnout and work engagement (Abós et al., 2019; Moeller et al., 2018).

However, it is important to note that support from either perspective is far from unanimous. For instance, Cole et al.'s (2012) and Crawford et al.'s (2010) meta-analyses revealed negative associations between work engagement and burnout, whereas Mäkikangas et al. (2017) showed that increases in work engagement were not associated with matching increases in burnout. Moreover, focusing on psychological distress rather than burnout, Shimazu et al. (2018) revealed a positive association between work engagement and psychological distress at high levels of work engagement, and a negative relation between these two constructs when work engagement was low. Furthermore, Junker et al. (2021) found that higher initial levels of burnout were associated with increases in work engagement six months later, and that higher initial levels of work engagement tended to be associated with increases in levels of burnout six months later (Junker et al., 2021). This observation led them to suggest that associations may differ when considered cross-sectionally and longitudinally. More precisely, they noted that "engaged employees are less exhausted but face a higher risk of exhaustion over time. At the same time, exhausted employees are less engaged, but they have the potential to become more so over time" (Junker et al., 2021, p. 789). This perspective thus challenges the assumption that work engagement is solely associated with adaptive functioning, suggesting that it may also have a darker side (e.g., Christian et al., 2011; George, 2011).

In sum, additional research is clearly needed to better unpack the cross-sectional and longitudinal associations between employees' work engagement and burnout profiles, which represents a core objective of the present study. However, given the heterogeneity of prior longitudinal evidence, it is difficult to formulate very precise hypotheses regarding the specific profile-to-profile associations likely to be the most frequent in the present study. However, the bulk of previous research evidence allows us to propose distinct generic hypotheses for cross-sectional and longitudinal associations.

Hypothesis 5. *Cross-sectionally, profiles characterized by high global or specific levels of burnout (High Burnout or Mentally Distanced) should be more likely to correspond to profiles characterized by low global or specific levels of work engagement (Low Engagement), and vice versa (i.e., Low Burnout should be related to High Engagement and Vigorously Engaged).*

Hypothesis 6. *Profiles characterized by high global or specific levels of work engagement (High Engagement or Vigorously Engaged) should be more likely to correspond to profiles characterized by high global or specific levels of burnout (High Burnout or Mentally Distanced) at a later time point, and vice versa (i.e., Low Engagement should be related to Low Burnout).*

Hypothesis 7. *Profiles characterized by high global or specific levels of burnout (High Burnout or Mentally Distanced) should be more likely to correspond to profiles characterized by high global or specific levels of work engagement (High Engagement or Vigorously Engaged) at a later time point, and vice versa (i.e., Low Burnout should be related to Low Engagement).*

Predictors of Teacher's Membership into the Burnout and Work Engagement Profiles

Our last objective is to document the role of one job demand (i.e., workload) and various job resources (i.e., control, fairness, community, rewards, and values) as predictors of teachers' membership into the various burnout and work engagement profiles. Job demands require employees to expand psychological and/or physical efforts and tend to carry a toll for exposed employees (Bakker & Demerouti, 2007; Crawford et al., 2010). In this study, we focus on workload, which refers to the amount of work that is required of an employee (Spector & Jex, 1998). In contrast, 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 fostering personal development and well-being (Bakker &

Demerouti, 2007). In the present study, we focus on multiple types of job resources. First, control refers to employees' opportunities to make decisions and exercise control over their work-related tasks (Karasek & Theorell, 1990). Second, fairness refers to employees' perceptions that decisions and resource allocation at work are fair and equitable and that people are treated with consideration and respect (Greenberg & Cropanzano, 2001). Third, community refers to the global quality of social interactions at work (Leiter & Maslach, 2000). Fourth, rewards refer to recognition received from other employees and the organization (including affective, tangible, and monetary rewards; Siegrist, 1996). Finally, values refer to the perception of congruence between an employee's values, goals and expectations, and those of their organization (Maslach & Leiter, 2008).

The role of these specific job demands and resources in relation to the prediction of work engagement and burnout has been clearly established in prior research (Bakker & Demerouti, 2017; Gillet et al., 2018, 2020a; Huyghebaert et al., 2018a; Maslach & Leiter, 2008). More generally, accumulating evidence reveals that job demands and resources play a considerable role in the prediction of work engagement (e.g., Halbesleben, 2010) and burnout (e.g., Alarcon, 2011; Watts & Robertson, 2011). This is consistent with reasonings and empirical evidence from the job demands-resources (JD-R) model (Bakker & Demerouti, 2017), which has shown that job demands drain employees' energy and lead to strain outcomes (e.g., burnout and ill-being), whereas job resources promote employees' motivation and adaptive outcomes (e.g., work engagement and commitment). Inspired by the JD-R model, some studies suggest that, in contrast to job demands, job resources tend to foster adaptive functioning and well-being at work through need satisfaction (e.g., Fernet et al., 2013; Gillet et al., 2012; Huyghebaert et al., 2018b; Trépanier et al., 2015). For instance, overworked employees might be inclined to increase their efforts in the evenings and on weekends to catch up, which would prevent them from recovering from work-related effort (Gillet et al., 2020a). They are thus more likely to report higher levels of job anxiety and strain, subsequently leading to lower levels of work engagement and higher levels of burnout (Gillet et al., 2021). Likewise, individuals who struggle in a work environment that provides insufficient resources might believe that, despite their best efforts, their needs will never be adequately met, thus leading to negative outcomes such as low work engagement and high burnout (Bakker & Demerouti, 2007). Besides being consistent with self-determination theory and research (Deci et al., 2017), this reasoning aligns with several other theoretical perspectives assuming that adaptive functioning and well-being depend on the possibility and capability to actively engage with one's work environment (Hobfoll, 1989; Karasek & Theorell, 1990). We thus propose that:

Hypothesis 8. *Perceptions of high workload will increase the likelihood of membership in profiles characterized by lower global or specific levels of work engagement (i.e., Low Engagement) and higher global or specific levels of burnout (i.e., High Burnout or Mentally Distanced).*

Hypothesis 9. *Positive perceptions of job resources (fairness, control, community, rewards, and values) will increase the likelihood of membership in profiles characterized by higher global or specific levels of work engagement (i.e., High Engagement or Vigorously Engaged) and lower global or specific levels of burnout (i.e., Low Burnout).*

Method

Procedure and participants

Data were collected at two time points, over an eight-month period (October 2008 and June 2009), among a sample of teachers working in the Canadian province of Quebec. The sample was built from a list of 3,000 teachers randomly selected by the Quebec Ministry of Education. Potential participants were contacted via email explaining the purposes of the study and inviting them to complete an online questionnaire twice, eight months apart. It was emphasized that responses would remain anonymous, that participation was voluntary, and that participants were free to stop their participation at any time. Approval for this study was obtained from the Ethic Committee of the third author's institution. All data underlying the findings, Mplus analysis code, and research materials are available upon request to the first two authors. This study was not preregistered.

The sample consisted of 1004 teachers working in primary schools (59.8%), secondary schools (35.5%) or other educational institutions (4.7%) who completed the Time 1 (T1) measures. Participants were mostly women (86.3%), with a mean age of 27.83 years (SD = 4.20) and 3.30 (SD = 1.67) years of experience in teaching. Of those participants, 708 teachers (86.7% women; M_{age} = 27.87, SD = 4.33; $M_{experience}$ = 3.89, SD = 1.66; 59.9% primary schools, 35.0% secondary schools, 5.8% other types of institutions) also completed the Time 2 (T2) measures. A MANOVA was conducted to investigate potential differences between participants who responded at both time points versus those who responded at T1 only in relation to all variables considered in our analyses as well as demographics (age, sex, teaching level, and experience). No statistically significant differences were found between these two groups of participants.

Measures

All measures were administered in French and have been previously validated in this language.

Burnout was measured using the Maslach Burnout Inventory – General Survey (MBI-GS; Schaufeli et al., 1996; French version: Bocéréan et al., 2019). This instrument includes three subscales assessing emotional exhaustion (six items; e.g., "I feel used up at the end of a work day"; $\alpha = 0.921_{T1}$, $\alpha = 0.926_{T2}$), cynicism (five items; e.g., "I doubt the significance of my work"; $\alpha = 0.815_{T1}$, $\alpha = 0.775_{T2}$), and professional efficacy (six items, e.g., "I can effectively solve the problems that arise in my work"; $\alpha = 0.855_{T1}$, $\alpha = 0.861_{T2}$; low scores on this last component are considered to be indicative of burnout). Items were rated on a seven-point scale ranging from 0 (never) to 6 (every day).

Work engagement was measured using the Utrecht Work Engagement Scale – Short Version (UWES-9; Schaufeli et al., 2006; French version: Zecca et al., 2015). This instrument includes three subscales assessing vigor (three items; e.g., "At my work, I feel bursting with energy"; $\alpha = 0.88_{T1}$, $\alpha = 0.857_{T2}$), dedication (three items; e.g., "I am enthusiastic about my work"; $\alpha = 0.855_{T1}$, $\alpha = 0.849_{T2}$), and absorption (three items; e.g., "I am immersed in my work"; $\alpha = 0.\ 587_{T1}$, $\alpha = 0.592_{T2}$). Items were rated on a seven-point scale ranging from 0 (never) to 6 (every day).

Job demands and resources were measured using the Areas of Worklife Scale (AWS; Leiter & Maslach, 2000; French version: Leiter et al., 2009). This instrument includes six subscales assessing workload (six items; e.g., "I do not have time to do the work that must be done"; $\alpha = 0.819_{T1}$, $\alpha = 0.830_{T2}$), control (three items; e.g., "I have control over how I do my work"; $\alpha = 0.570_{T1}$, $\alpha = 0.629_{T2}$), reward (four items; e.g., "I receive recognition from others for my work"; $\alpha = 0.887_{T1}$, $\alpha = 0.890_{T2}$), community (five items; e.g., "I am a member of a supportive work group"; $\alpha = 0.812_{T1}$, $\alpha = 0.790_{T2}$), fairness (six items; e.g., "Resources are allocated fairly here"; $\alpha = 0.775_{T1}$, $\alpha = 0.768_{T2}$), and values (five items; e.g., "My values and the school's values are alike"; $\alpha = 0.790_{T1}$, $\alpha = 0.797_{T2}$). Items were rated on a five-point scale ranging from 1 (totally disagree) to 5 (totally agree).

As **demographic characteristics** have been linked to teachers' burnout and work engagement, a number of demographic variables (sex, teaching level, and experience) potentially related to burnout and engagement were considered. For instance, some studies suggest that women and primary school teachers tend to report higher levels of burnout, not only at the beginning of the school year but also over time (e.g., Fernet et al., 2012). Likewise, teaching experience has been previously shown to account for significant variance in burnout and work engagement (e.g., Antoniou et al., 2022; Fernet et al., 2010; Hakanen et al, 2006).

Analyses

Preliminary Analyses

Preliminary analyses were realized to verify the psychometric properties (i.e., composite reliability, factor structure, and correlations) and longitudinal measurement invariance (Millsap, 2011) of the various measures used in this study. The results from these analyses are reported in Tables S2 to S11 of the online supplements. To account for the construct-relevant multidimensionality (involving the assessment of conceptually-related subscales encompassing a global and specific components) of the burnout and work engagement measures (Morin et al., 2016a, 2016b, 2020b), we retained a bifactor exploratory structural equation modeling (bifactor-ESEM) operationalization of burnout and work engagement, matching recommendations from previous psychometric investigations of these constructs (burnout: e.g., Bianchi, 2020; Doherty et al., 2021; Schonfeld et al., 2019; Tóth-Király et al., 2021b; Verkulien et al., 2021; work engagement: e.g., Gillet et al., 2019, 2020b; Houle et al., 2022). For job demands and resources, we had no reason to account for the presence of a global construct (similar to their global levels of burnout or of work engagement) underlying participants' ratings of job demands and resources, and the results from our preliminary analyses failed to support the need to rely on an ESEM operationalization of these measures. We thus relied on a more parsimonious confirmatory factor analytic (CFA) operationalization of job demands and resources.

Our preliminary analyses also supported the complete invariance of all constructs over time (with the sole exception of the uniqueness from one item from the cynicism subscale which was found to differ slightly over time). Factor scores were saved from the most longitudinally invariant measurement models in standardized units of measurement (with a mean of 0 and a standard deviation of 1) and used in the main analyses. Factor scores provide a partial correction for measurement errors (Skrondal & Laake) and preserve the underlying structure of the measurement models (e.g., bifactor, ESEM, invariance; Morin et al., 2016c, 2016d, 2017). Overall, our preliminary analyses revealed well-defined burnout (ω = .928 at T1 and .922 at T2 due to the non-invariant uniqueness) and work engagement (ω = .927) G-factors, workload (ω = .826), control (ω = .612), reward (ω = .878), community (ω = .826), fairness (ω = .768), and values (ω = .803) factors, as well-defined emotional exhaustion (ω = .856) and professional efficacy (ω = .811) S-factors. In contrast, the remaining S-factors appeared to be weakly defined: Vigor (ω = .439), dedication (ω = .409), absorption (ω = .189), and cynicism (ω = .245 at T1 and .203 at T2 due to the non-invariant uniqueness).

It is important to note that the weak S-factors are to be expected in bifactor solutions because these models rely on two factors to explain the item-level covariance (Morin et al., 2020). When this happens, this simply indicates that the items associated with these S-factors primarily serve to define the G-factor, retaining little specificity on their own (Morin et al., 2020). Furthermore, weak S-factor scores are unlikely to introduce any bias in the estimation of latent profile analyses because these S-factors would simply result in the estimation of profiles in which the levels observed on these S-factors are close to the average and show little variation across profiles. Furthermore, it is also possible for weak S-factors to retain specificity limited to one or two profiles of participants, in which case they may emerge as a defining characteristic of these specific profiles (i.e., since this specificity is limited to a subset of participants, it may not be visible in models estimated on the total sample). A more extensive discussion of this issue is provided in the online supplements. Correlations among all variables included in this study are reported in Table S11 of the online supplements.

Latent Profile Analyses

All analyses relied on the maximum likelihood robust (MLR) estimator implemented in Mplus 8.6 (Muthén & Muthén, 2021), and on full information maximum likelihood procedures to handle missing data (Enders, 2010). The main source of missingness was attrition (from 1004 participants at T1 to 663 at T2). For participants who completed each time of measurement, there were relatively few missing responses at the item level (T1: 0.0% to 4.9%, M = 2.35%; T2: 0.0% to 4.8%, M = 2.38%). Solutions including one to eight profiles, defined using the work engagement (global engagement and specific vigor, dedication, and absorption) or burnout (global burnout, and specific emotional exhaustion, cynicism, and professional efficacy) dimensions, were first estimated at both time points. These solutions were estimated while allowing the mean and variance of the profile indicators to be freely estimated across profiles (Morin et al., 2020a; Peugh & Fan, 2013), and relying on 3,000 random sets of start values, 100 iterations, and 100 final optimizations (e.g., Meyer & Morin, 2016).

The optimal number of profiles present in the data at both time points was determined by examining the statistical adequacy, theoretical conformity, and heuristic value of each solution, and was also guided by the following statistical indicators (Marsh et al., 2009; Muthén, 2003; Morin et al., 2020a): Aikaike information criterion (AIC), Bayesian information criterion (BIC), consistent AIC (CAIC), and sample-adjusted BIC (SABIC). A lower value on these indicators indicates a better level of fit to the data. We also examined the adjusted Lo, Mendell, and Rubin's (2001) likelihood ratio test (aLMR) and the bootstrap likelihood ratio test (BLRT). For these two indicators, statistical significance (p < 0.05) supports a model relative to a model including one less profile. Statistical simulation studies generally support the efficacy of the CAIC, BIC, ABIC, and BLRT in model selection, but not that of the aLMR and AIC (Diallo et al., 2016, 2017; Nylund et al., 2007; Tein et al., 2013; Peugh et al., 2013). Thus, although we report the latter indicators for purposes of full disclosure, we only rely on the former to guide model selection. However, because these indicators are all greatly influenced by sample size, they often fail to converge on a clear solution (e.g., Marsh et al., 2009). It is thus suggested to graphically display them via an elbow plot (Morin et al., 2011; Petras & Masyn, 2010) in which the presence of a flattening in the decrease in the value of the information criteria can be used to suggest an optimal solution. We also report the entropy, an indicator of classification accuracy ranging from 0 (low) to 1 (high), although this indicator should not be used in profile selection (e.g., Lubke & Muthén, 2007).

Longitudinal Tests of Profile Similarity

Once the optimal number of profiles has been selected for work engagement and burnout at both time points, longitudinal tests of profile similarity were conducted to test the equivalence of these solutions over time. These tests were conducted following the sequence recommended by Morin et al.

(2016d) and adapted to longitudinal analyses by Morin and Litalien (2017). For these more complex analyses, we relied on 10,000 random sets of start values, 1,000 iterations, and 500 final optimizations. Starting from a model of configural similarity (same number of profiles), equality constraints were progressively incorporated on the within-profile means of the profile indicators (structural similarity), their within-profile variance (dispersion similarity), and the size of the profiles (distributional similarity). At each step, similarity is supported when two or more of the CAIC, BIC, and ABIC is lower for the more constrained model relative to the previous one in the sequence.

Latent Transition Analyses

The results from the most similar solutions were then converted using the manual three-step approach (Asparouhov & Muthén, 2014) to retain the properties of the most similar solutions in the estimation of latent transition and predictive analyses (i.e., to ensure that the nature and size of the profiles remained unchanged in the subsequent analyses; Morin & Litalien, 2017). Using these stable solutions, we then proceeded to the estimation of a series of latent transition analyses (LTA) seeking to verify the within-person stability of participants' membership in the burnout and work engagement profiles over time (longitudinal same-variables LTA). A similar approach was also used to assess the associations between burnout profiles estimated at T1 and participants' likelihood of membership into the work engagement profiles estimated at T2, as well as the associations between the work engagement profiles estimated at T1 and participants' likelihood of membership into the T2 burnout profiles (longitudinal across-variables LTA). For comparison purposes, we also estimated the cross-sectional associations between the work engagement and burnout profiles at the same time point (cross-sectional across-variables LTA).

Predictors of Profile Membership

Controls (sex: 0 = female, 1 = male; occupational tenure in years; school type: Dummy coded to reflect primary, secondary, or other) and predictors (job demands: Workload; job resources: Control, rewards, community, fairness, and values) were directly included (via a multinomial logistic regression function) to the final LTA solutions. For the demographic predictors, we contrasted a null effects model (all effects constrained to be zero) with a model in which these variables were allowed to influence profile membership, and with a final model in which these variables were allowed to predict profile membership, and specific profile transitions over time (by allowing the predictions of T2 profile membership to vary across T1 profile membership). In addition, for the models used to assess within-person stability in profile membership (i.e., the transitions between membership into the work engagement profiles at T1 and T2, as well as between the burnout profiles at T1 and T2), a last model of predictive similarity (i.e., in which the role of the predictors was expected to be the same over time; Morin et al., 2016d) was also estimated. The same models were then estimated to assess the role of the theoretical predictors. In all models, predictors were allowed to predict the profiles estimated at the same time point, which means that the T2 predictions can be considered to be controlled for the baseline levels of the predictors for the longitudinal analyses. However, for the longitudinal models, one additional specification was tested in which T1 predictors were also allowed to predict the likelihood of profile membership at T2 (consistent with the presence of an effect on changes in profile membership and in which the T2 predictions then come to implicitly reflect the effects of changes in the values of the predictors over time).

Results

Work Engagement Profiles

The results of the LPA solutions estimated at T1 and T2 for work engagement are reported in the top two sections of Table S12 in the online supplements, and graphically represented in the top left (T1) and right (T2) panels of Figure S1 in the same supplements. The lowest CAIC was observed for the four- and five-profile solutions at T1 and for the three-profile solution at T2. The lowest BIC was associated with seven profiles at T1 and four at T2. The ABIC failed to converge on a specific solution at both time points. The BLRT supported the three-profile solution at T2 but failed to converge on a specific solution at T1. The elbow plots associated with these solutions suggested a four-profile solution at T1 and a two-profile solution at T2. For this reason, solutions including two to five profiles were more systematically inspected. This examination revealed that solutions including the same number of profiles were very similar over time, providing early evidence of configural similarity. Furthermore, this examination revealed that additional profiles resulted in a meaningful contribution up to the three-profile solution, whereas adding more profiles only resulted in the arbitrary division of existing profiles into smaller profiles with a similar shape. The three-profile solution was thus retained at both time points for tests of longitudinal profile similarity. The results from these tests are reported in the top section of Table 1 and support the complete similarity of this solution over time (as at least two out of the CAIC, BIC, and ABIC kept on decreasing at each step in the sequence), in accordance with Hypothesis 3. The resulting model of distributional similarity was retained for interpretation and is illustrated in Figure 1 (parameter estimates reported in Table S13 of the online supplements).

Profile 1 (*Vigorously Engaged*) corresponded to a relatively small proportion of the sample (2.26%) characterized by high global levels of work engagement (i.e., as the profile indicators are in standardized units, this level is .5 SD above the sample mean) accompanied by similarly high specific levels of vigor, moderately high specific levels of absorption, and average specific levels of dedication. Profile 2 (*Disengaged*) corresponded to 39.71% of the sample characterized by low global levels of work engagement accompanied by average levels on all specific factors. Finally, Profile 3 (*Engaged*) corresponded to the majority of the sample (58.03%) presenting high global levels of work engagement accompanied by average levels on all specific factors. This pattern of results is consistent with the relatively low levels of specificity associated with the S-factors, revealing that levels on these S-factors remain close to the sample average for most of the sample while displaying a level higher (at least for the vigor and absorption S-factors) than what could be expected from participants' global levels of work engagement in Profile 1. These results thus partially support Hypothesis 1. A key test of the true meaningfulness of this distinctive, albeit small, profile would come from the demonstration of our ability to differentially (or not) predict membership into this profile relative to the other ones.

Burnout Profiles

The results of the LPA solutions estimated at T1 and T2 for burnout are reported in the bottom two sections of Table S12 in the online supplements, and graphically represented in the bottom left (T1) and right (T2) panels of Figure S1 in the same supplements. The lowest CAIC and BIC were associated with the five-profile solution at T1 and with the seven-profile solution at T2. The ABIC and BLRT supported the seven-profile solution at T1 and failed to converge on a specific solution at T2. The elbow plots suggested the presence of two to four profiles at both time points. For this reason, solutions including two to five profiles were more systematically inspected. This examination first revealed that the solutions including the same number of profiles were highly similar across time points, providing early evidence of configural similarity. This examination also showed that adding profiles resulted in a meaningful contribution to the three-profile solution, whereas adding more profiles only resulted in the arbitrary division of existing profiles into smaller profiles with a similar shape. The three-profile solution was thus retained for tests of profile similarity.

The results from the longitudinal tests of profile similarity are reported in the second section of Table 1. These results failed to support the structural and dispersion similarity of this solution over time. However, the parameter estimates from the configural model indicated that the lack of structural similarity was limited to the professional efficacy S-factor, which was slightly lower in Profile 3 at T1 than at T2. Likewise, the lack of dispersion similarity seemed limited to the three S-factors, which had slightly higher levels of within-profile variability in Profile 3 at T1 than at T2, which is consistent with the lower sample available for our analyses at T2 relative to T1. Relaxing equality constraints on these indicators in Profile 3 resulted in models of partial structural and dispersion similarity which were supported by the data. Likewise, the last model of distributional similarity was also supported by the data, thus providing partial support to Hypothesis 3. The final model of distributional similarity (with partial structural and dispersion similarity) was retained for interpretation and is graphically illustrated in Figure 2 (detailed parameter estimates are reported in Table S14 of the online supplements).

Profile 1 (*Burned-Out*) corresponded to 49.74% of the sample and presented high global levels of burnout, accompanied by close to average specific levels of emotional exhaustion, cynicism, and professional efficacy. Profile 2 (*Adapted*) corresponded to 8.27% of the sample and presented very low global levels of burnout, low specific levels of emotional exhaustion, average specific levels of cynicism, and high specific levels of professional efficacy. Profile 3 (*Normative*) corresponded to 42.26% of the sample and presented low global levels of burnout, accompanied by close to average specific levels of emotional exhaustion, cynicism, and professional efficacy. Despite the slightly lower specific level of professional efficacy observed in this profile at T2, the shape of the profiles was highly consistent over time. These results partially support Hypothesis 2.

Latent Transition Analyses (LTA)

The transition probabilities associated with the various LTA are reported in Table 3, and partially support Hypothesis 5. Starting first with the cross-sectional solutions (reported in the top two sections of Table 3), the results showed that the majority of employees corresponding to the *Vigorously Engaged* profile at one specific point in time corresponded to the *Normative* burnout profile at the same time point (89.4% at T1 and 77.5% at T2), although a small proportion of them also corresponded to the *Burned-Out* profile at the matching time point (10.2% at T1 and 22.5% at T2). In contrast, almost all *Disengaged* employees corresponded to the *Burned-Out* profile at the matching time point (94.0% at T1 and 97.7% at T2). Finally, although a majority of *Engaged* employees corresponded to the *Normative* burnout profile at the matching time point (69.3% at T1 and 64.7% at T2), some of them also corresponded to the *Burned-Out* (12.4% at T1 and 24.4% at T2) and to the *Adapted* (18.3% at T1 and 10.8% at T2) profiles at the same time point.

Over time, the longitudinal analyses revealed a similar pattern of associations (see the middle two sections of Table 3). Looking first at the T1 work engagement profiles, most *Vigorously Engaged* employees at T1 corresponded to the *Normative* burnout profile at T2, although a small number of them corresponded to the *Burned-Out* profile at T2 (9.8%). Although most *Disengaged* employees at T1 corresponded to the *Burned-Out* profile at T2 (79.8%), thus matching the cross-sectional results, it was encouraging to note than roughly a fifth of them corresponded to the *Normative* profile at T2. Lastly, roughly half (56.6%) of the *Engaged* employees at T1 corresponded to the *Normative* burnout profile at T2, whereas a significant proportion of them also corresponded to the *Burned-Out* (31.0%) and *Adapted* (12.4%) profiles at T2. Taken together, these results partially support Hypothesis 6. Turning our attention to the opposite pattern of transitions, the results suggested very similar patterns of longitudinal associations. Thus, most *Burned-Out* employees at T1 corresponded to the *Disengaged* profile at T2 (70.2%), although a third of them also corresponded to the *Engaged* profile at T2 (29.8%). Almost all *Adapted* employees at T1 corresponded to the *Engaged* profile at T2 (98.9%). Finally, most employees corresponding to the *Normative* burnout profile at T1 corresponded to the *Engaged* profile at T2 (88.5%). These results provide partial support to Hypothesis 7.

In terms of within-person stability (see the last two sections of Table 3), it is interesting to note that, for work engagement, membership into the *Disengaged* (89.7%; although 10.3% of them also transitioned toward an *Engaged* profile over time) and *Engaged* (97.3%) profiles was highly stable over time, whereas membership into the *Vigorously Engaged* profile was harder to maintain over time (11.7%), involving frequent transitions toward the *Engaged* profile at T2 (88.3%). For the burnout profiles, membership into the *Burned-Out* (95.1%) and *Normative* (87.2%; although 12.4% of them also transitioned toward a *Burned-Out* profile over time) profiles was highly stable over time. Although membership into the *Adapted* profile was also very stable over time (67.5%), this profile also involved frequent transitions toward the *Normative* profile over time (24.6%), and rarer transitions toward the *Burned-Out* profile (7.8%). These results support Hypothesis 4 for burnout, but only partially support this Hypothesis for work engagement. In relation to Research Question 1, our results revealed a combination of upward (toward "better" profiles) and lateral transitions for work engagement, and a majority of downward transitions for burnout (toward "worst" profiles).

Demographic Predictors

The results from the first set of analyses designed to verify the predictive role of demographic predictors in relation to employees' likelihood of membership into the various profiles, to verify the relevance of incorporating these variables as controls in further analyses, are reported in Table S15 of the online supplements. Across all types of analyses, these results consistently support the null effects model (systematically associated with the lowest values on the CAIC, BIC, and ABIC). These results indicate a lack of effects of these variables on employees' likelihood of membership into the work engagement or burnout profiles, as well as their likelihood of experiencing specific profile transitions.

Job Demands and Resources

The results from the predictive analyses designed to verify the role of our theoretical predictors are reported in the middle and bottom sections of Table 1. These results are consistent with an effect of the predictors on employees' likelihood of membership that generalizes over time (i.e., predictive similarity), but not with the presence of an effect of the predictors on specific profile transitions, or of longitudinal effects of T1 predictors on the likelihood of profile membership at T2. Indeed, the results systematically support the results from the model including free effects of the predictors on profile membership (without added longitudinal paths or effects on specific transitions), and the model of predictive similarity for analyses of within-person stability (these models systematically resulted in the lowest values on two out of the CAIC, BIC, and ABIC).

The results from these predictions are reported in Table 3[2], and first indicate that workload perceptions increased employees' likelihood of membership into the *Disengaged* profile relative to the *Engaged* one, as well as into the *Engaged* profile relative to the *Vigorously Engaged* one. Workload perceptions also increased employees' likelihood of membership into the *Burned-Out* profile relative to the *Normative* and *Adapted* ones, as well as into the *Normative* profile relative to the *Adapted* one. These results thus support Hypothesis 8.

Employees' perceptions of rewards and values both predicted an increased likelihood of membership into the *Engaged* profile relative to the *Disengaged* one, into the *Normative* and *Adapted* profiles relative to the *Burned-Out* one, and into the *Adapted* profile relative to the *Normative* one. Employees' perceptions of control predicted an increased likelihood of membership into the *Engaged* profile relative to the *Disengaged* one. In contrast, their perceptions of fairness predicted the opposite association, increasing their likelihood of membership into the *Disengaged* profile relative to the *Engaged* one. Lastly, employees' perceptions of community predicted an increased likelihood of membership into the *Vigorously Engaged* profile relative to the *Engaged* one. Taken together, these results partially support Hypothesis 9. In a final set of exploratory analyses, we also tested for possible interactions between job demands (i.e., workload perceptions) and resources (i.e., control, rewards, community, fairness, and values) and found no evidence supporting the presence of any form of interactions between these variables.

Discussion

In the present study, we adopted a combined variable- and person-centered approach to investigate the value of jointly considering global and specific dimensions of work engagement (Gillet et al., 2019; Huyghebaert-Zouaghi et al., 2021, 2022a) and burnout (Gillet et al., 2022; Sandrin et al., 2022). In doing so, we were able to achieve an improved representation of the measurement structure of both constructs, as well as of the nature of the work engagement and burnout profiles commonly observed among our sample of teachers. Through the adoption of a longitudinal design, we were also able to test the within-person and within-sample stability of these profiles (Huyghebaert-Zouaghi et al., 2022b; Sandrin et al., 2020). This approach also allowed us to consider how membership into work engagement profiles was related to membership into burnout profiles, and vice versa, both within each time point and over time across an eight-month period. Finally, the criterion-related validity of both sets of profiles was investigated by examining their associations with theoretically relevant predictors including job demands (workload) and resources (control, rewards, community, fairness, and values).

Work Engagement and Burnout as Multidimensional Constructs

Research has recently documented the need to account for the dual nature of work engagement (Gillet et al., 2019; Huyghebaert-Zouaghi et al., 2021, 2022a) and burnout (Gillet et al., 2022; Sandrin et al., 2022) as global entities (the work engagement and burnout G-factors) measured from distinct dimensions retaining some degree of specificity of their own (the S-factors). In this regard, our results confirmed our expectations and replicated previous conclusions supporting the superiority of a bifactor representation of work engagement and burnout. These two solutions revealed co-existing G-factors representing teachers' global levels of work engagement and burnout, as well as S-factors reflecting their specific levels of vigor, dedication, absorption, emotional exhaustion, cynicism, and professional efficacy left unexplained by these global levels. In both solutions, the S-factors were more weakly defined that the G-factor, although they still retained some degree of specificity consistent with the idea that all of these subscales strongly contributed to the assessment of teachers' global levels of work engagement and burnout, while also retaining something unique. This research thereby extends our knowledge about the dimensionality of both constructs and capitalizes on this improved representation to achieve a clearer picture of teachers' profiles of burnout and work engagement.

Work Engagement and Burnout Profiles

Our results revealed that three profiles best summarized the work engagement configurations observed among the current sample of teachers: (1) *Vigorously Engaged*, (2) *Disengaged*, and (3)

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[2] The results were virtually identical across the different types of LTA estimated. We report the results from the models of predictive similarity given their greater parsimony (i.e., in these models, the two time points are used to estimate a single set of predictive paths set to be equivalent over time).

Engaged. Likewise, three distinct profiles best represented the teachers' burnout configurations observed among this sample: (1) *Burned-Out*, (2) *Adapted*, and (3) *Normative*. Although these results only partially supported our hypotheses (i.e., no *Normative* profile was identified for work engagement, and no *Mentally Distanced* profile was identified for burnout), all of these profiles were expected based on their identification in prior person-centered studies of work engagement (e.g., Gillet et al., 2019; Simbula et al., 2013) and burnout (e.g., Leiter & Maslach, 2016; Sandrin et al., 2022), as summarized in Table S1 of the online supplements. It is interesting to note that despite methodological differences the percentage of teachers in most profiles is similar to that reported in previous person-centered studies. For instance, in a study of teachers, Gillet et al. (2022) reported 60.1% (of the sample) in moderate to high burnout profiles. More importantly, in addition to providing evidence of replicability for these prior results to the current sample of teachers, despite a few minor differences related to the *Normative* burnout profile, our results also supported the generalizability of these across two time points, taken over the course of a school year. These observations indicate that these profiles seem to reflect core psychological mechanisms involved in the experience of work engagement and burnout among employees, rather than sample-specific or ephemeral phenomena reflecting random sampling variations. More precisely, this evidence of replicability across studies, types of employees, and time supports the value and likely generalizability of devising interventions strategies targeting specific profiles of work engagement and burnout (e.g., Meyer & Morin, 2016).

Adding to the evidence obtained as part of our measurement analyses, these person-centered results also further reinforced the value of relying on a proper disaggregation of the global and specific components of work engagement (Gillet et al., 2019) and burnout (Sandrin et al., 2022) in person-centered investigations. Indeed, none of the profiles identified in this study was characterized by matching levels across all work engagement (i.e., global work engagement and specific vigor, dedication, and absorption) and burnout (i.e., global burnout and specific emotional exhaustion, cynicism, and professional efficacy) indicators. Consequently, although the components of each of those constructs are complementary and known to be highly intercorrelated (Leiter & Maslach, 2000; Schaufeli et al., 2002), our findings demonstrate the value of capturing this overlap via the estimation of a global factor underpinning all components associated with each construct to obtain a clearer picture of the role uniquely played by each component beyond this global construct. Indeed, 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 work engagement and burnout. In the present study, and consistent with the central role played by the G-factors as capturing the core of work engagement and burnout across dimensions, we found that a majority of the profiles were primarily defined by their global levels of work engagement (*Disengaged* and *Engaged*) and burnout (*Burned-Out* and *Normative*). However, and clearly supporting the value of also considering the S-factors, two of our profiles were found to be substantially defined by at least one of these specific components (*Vigorously Engaged* and *Adapted*). Yet, it would be particularly important for future investigations to more systematically understand whether and how these profiles would differ across different occupational groups (e.g., nurses, managers) or cultures (e.g., North America, Europe, Asia), as well as whether intervention strategies can be devised to nurture more desirable profiles.

In terms of within-person stability, our results revealed that membership into the three burnout profiles (67.5% to 95.1%), as well as into the *Disengaged* (89.7%) and *Engaged* (97.3%) profiles was highly stable over time, whereas membership into the *Vigorously Engaged* profile was not as stable (11.7%). These results suggest that membership into five of the six profiles identified in this study is unlikely to change on its own in the absence of a systematic exposure to external changes or interventions. Indeed, although exposure to changes or interventions was not directly measured in the present study, such changes are unlikely to have affected all teachers in a systematic manner, suggesting that most teachers probably underwent a normative work experience over the course of the study. Importantly, the rates of stability observed in this study are aligned with previous results showing that employees' levels of work engagement (Grødal et al., 2019; Heinrichs et al., 2020) and burnout (Frögéli et al., 2019; Kinnunen et al., 2019) tend to be moderately to highly stable over time. As far as teachers are concerned, the very nature of teaching involving multiple relationships, challenges, and demands requires them to expend constant energy to engage daily in these activities, which may explain the stability of these psychological states. Membership into the *Vigorously Engaged* profile appeared to be highly unstable over time (11.7%). This observation suggests that it might be easier for interventions to support change among employees corresponding to this profile, although they more realistically suggest that interventions might be needed to help support these employees in maintaining their high levels of work engagement over time. These results suggest that it might be harder to maintain a profile characterized by a more imbalanced configuration over time and, maybe more importantly, by the lowest levels of dedication. This last observation could be linked to the constant chase of efficiency that characterizes modern societies, leading to a work intensification phenomenon (Huyghebaert et al., 2018a) known to be particularly present in socially-valued specialized occupations such as teaching (Lawrence et al., 2019). This result suggests that maintaining high levels of work engagement, vigor, and absorption may be particularly hard for teachers lacking matching levels of dedication, even in a rather short period of time (i.e., during a school year), in a society that values hard work (Gillet et al., 2018).

Associations between Burnout and Work Engagement Profile Membership

Cross-sectionally, many teachers corresponding to the *Vigorously Engaged* profile corresponded to the *Normative* burnout profile, whereas almost all *Disengaged* teachers corresponded to the *Burned-Out* profile. Although a majority of *Engaged* teachers corresponded to the *Normative* burnout profile, some of them also corresponded to the *Burned-Out* and *Adapted* profiles. Over a period of eight months, our longitudinal analyses revealed a similar pattern of associations over time between these two sets of profiles (T1 work engagement profiles to T2 burnout profiles). Furthermore, many teachers corresponding to the *Burned-Out* profile at T1 corresponded to the *Disengaged* profile at T2, whereas almost all *Adapted* teachers at T1 corresponded to the *Engaged* profile at T2. Finally, many teachers corresponding to the *Normative* burnout profile at T1 corresponded to the *Engaged* profile at T2.

In sum, these results indicate strong associations between the *Engaged* profile and the *Adapted* profile, as well as between the *Disengaged* profile and the *Burned-Out* profile, consistent with the idea that, for many employees, these two constructs represent incompatible psychological states (e.g., Bakker & Demerouti, 2007; Cole et al., 2012; Crawford et al., 2010). However, strong associations were also observed between the two highly engaged profiles and the *Normative* burnout profile. This second set of result suggests that the aforementioned incompatibility might have a threshold preventing most highly engaged employees to display high levels of burnout, without necessarily being sufficient to protect them against the experience of more normative levels of burnout.

However, our results also revealed that some *Vigorously Engaged* and *Engaged* teachers also presented a *Burned-Out* profile. This result indicates that, as hypothesized, some teachers may jointly experience burnout and work engagement (Abós et al., 2019; Moeller et al., 2018), thus reinforcing the idea that although both states might be incompatible for many employees, this incompatibility is far from absolute. Indeed, highly engaged employees spend longer hours at work and display a greater need for recovery, which can both be involved in the emergence of burnout (Schaufeli et al., 2008; Sonnentag et al., 2008). In this regard, *Engaged* teachers are also more likely to transition to the *Burned-Out* profile (31.0%) than their *Vigorously Engaged* colleagues (9.8%), just like roughly a third of the *Burned-Out* teachers (29.8%) transitioned to the *Engaged* profile over time (none transitioned to the *Vigorously Engaged* profile). These results clearly suggest that *Engaged* teachers may be less protected against burnout than *Vigorously Engaged* ones. On the one hand, this result reinforces the importance of the high specific levels of vigor and absorption displayed by the *Vigorously Engaged* teachers (e.g., Gillet et al., 2019). On the other hand, part of this result could also reflect the lower level of dedication observed in the *Vigorously Engaged* profile. Indeed, research suggests that when employees are excessively enthusiastic and challenged at work, they eventually lack the opportunity to recover and restore their resources (Sonnentag, 2011). Thus, this result suggests that in the absence of high levels of dedication, highly engaged teachers are unlikely to be able to maintain the investment of enough energy and resources in their work to generate burnout.

Finally, contrary to their *Engaged* colleagues (12.4%), *Vigorously Engaged* teachers never transitioned to the *Adapted* profile. Likewise, *Adapted* teachers almost never transitioned to the *Vigorously Engaged* profile (0.3%), although most of them transitioned to the *Engaged* profile (98.9%). These results suggest that the more imbalanced configuration displayed by *Vigorously Engaged* teachers may not be not compatible with an *Adapted* burnout configuration. Indeed, these teachers seem to be simultaneously driven by autonomous (pleasure, interest, or personal values) and controlled (internal or external pressures) regulations, resulting in an incompletely integrated internalization process (Trépanier et al., 2015). The use of accommodation mechanisms, such as compensatory motives (e.g., overinvestment in a job where one feels competent or appreciated), would allow for some collateral satisfaction with a work life that generates a more imbalanced work engagement configuration (Gillet et al., 2019). Furthermore, their global levels of work engagement would certainly offer these individuals the psychological nutrients they need to be highly functional at work (Huyghebaert-Zouaghi et al., 2022a), although a negative imbalance between these work engagement components may still make it harder for them to truly experience a complete lack of negative manifestations of burnout. These findings thus capitalize on the growing person-centered research stream in organizational studies (Hofmans et al., 2021) to provide a more nuanced perspective on the motivational premise of burnout. However, as many of our explanations remain tentative, we hope that they will help to generate further research into the psychological mechanisms underpinning these person-centered associations between burnout and work engagement.

Job Demands and Resources as Predictors of Profile Membership

By considering the role played by job demands (workload) and resources (control, rewards, community, fairness, and values) in the prediction of profile membership, our results provided practical guidance regarding some of the likely drivers of the distinct work engagement and burnout configurations among teachers. More specifically, workload was associated with a higher likelihood of membership into the *Disengaged* profile relative to the *Engaged* one, into the *Burned-Out* profile relative to the *Normative* and *Adapted* ones, and into the *Normative* profile relative to the *Adapted* one. These results add further evidence supporting the undesirable impact of job demands in relation to work engagement and burnout (Crawford et al., 2010; Lesener et al., 2019), in a way that matched the assumptions of the job demands-resources model (Bakker & Demerouti, 2007). These results are consistent with the idea that exposure to higher levels of job demands decrease the satisfaction of employees' basic psychological needs at work (Fernet et al., 2013; Trépanier et al., 2015) and their ability to properly recover from work (Gillet et al., 2020a), both of which are known to be associated with lower levels of work engagement and higher levels of burnout (Gillet et al., 2021). Nonetheless, our findings invite future research to consider specific types of job demands (e.g., role ambiguity, conflict) and source of stress (e.g., students, colleagues, principal) among teachers to enrich our understanding of the predictors involved in shaping each profile.

Teachers' perceptions of rewards and values were associated with an increased likelihood of membership into the *Engaged* profile relative to the *Disengaged* one, into the *Normative* and *Adapted* profiles relative to the *Burned-Out* one, and into the *Adapted* burnout profile relative to the *Normative* one. Moreover, their perceptions of control were also associated with their likelihood of membership into the *Engaged* profile relative to the *Disengaged* one. These results confirm the role of rewards, values, and control as key drivers of psychological functioning at work, expending upon prior variable-centered research supporting the role of these variables in the prediction of work engagement and burnout (Crawford et al., 2010; Goering et al., 2017). These results are consistent with the idea that teachers exposed to a work environment in which sufficient resources are available to properly satisfy their psychological needs should be more likely to experience positive motivational states (e.g., autonomous motivation, self-efficacy; Fernet et al., 2012) and optimal functioning at work (Bakker & Demerouti, 2007; Fernet et al., 2016; Gillet et al., 2012).

It was, however, interesting to note that teachers' perceptions of workload were also associated with their likelihood of membership into the *Engaged* profile relative to the *Vigorously Engaged* one, whereas the opposite was true for their perceptions of community. In addition to reinforcing the distinction between these two profiles, these results also support the previous observation of associations between these two facets of the work environment and teachers' specific levels of vigor and absorption (negative for workload: Reis et al., 2017; Sonnentag & Niessen, 2008; and positive for community: Gillet et al., 2015; Maslach & Leiter, 2008). For workload, this association has been explained by the fact that job demands require energy and effort, thus taking a toll of one's personal resources (Bakker & Demerouti, 2007). Furthermore, teachers exposed to higher workloads may come to display higher levels of activation and to exhibit withdrawal behaviors that are incompatible with their ability to feel vigorous and absorbed at work (Meurs & Perrewé, 2011). In contrast, job resources, such as community, have been previously shown to promote creativity and proactive behaviors, to yield opportunities for development, to result in opportunities to contribute to new stimulating projects or strategies, and to contribute to psychological need satisfaction, autonomous motivation, and flow (Bakker & Demerouti, 2007; Gillet et al., 2012), all of which share conceptual connections with vigor and absorption at work.

Lastly, teachers' perceptions of fairness were unexpectedly associated with their membership into the *Disengaged* profile relative to the *Engaged* one. These results thus show that inter-individual differences in fairness perceptions may be detrimental to teacher's global levels of work engagement. This result is interesting given that prior variable-centered research has consistently positioned fairness as a positive driver of psychological health in a "the more, the better" perspective (e.g., Fouquereau et al., 2020; Greenberg & Cropanzano, 2001). Nevertheless, recent findings rather suggest a "too much of a good thing" interpretation according to which high levels of fairness perceptions might be detrimental in some situations (Brockner et al., 2009; Rodwell & Fernando, 2015; Tremblay et al., 2018). Indeed, higher levels of fairness could be stressful, especially for busy teachers, who might consider the need to act in a fair and equitable manner toward their colleagues and students as a job demands, rather than as a pure type of job resources when considered solely from the perspective of their own treatment at work. Clearly, additional studies are needed to replicate the present results and to identify the mechanisms underlying these unexpected relations.

Limitations and Future Directions

The present research has some limitations, which nevertheless open the way to promising new research avenues. First, the fact that this study relied solely on self-report measures increases the risk of social desirability and self-report biases. To alleviate these concerns, it would be useful for future studies to consider incorporating objective measures (e.g., organizational data on absenteeism) and informant ratings of employees' functioning (e.g., colleagues, school administrators). Second, the present study was conducted among a sample of Canadian teachers. Further research is thus needed to generalize the current results in different work settings, countries, languages, and cultures. Third, the current research assessed the stability of work engagement and burnout profiles over an eight-month period (i.e., a typical school year), which was not characterized by any specific or systematic change or transition for most participants. Clearly, estimates of stability reported in the current investigation could be reduced if longer time intervals were considered, or if continuity and change were assessed across more meaningful transitions or interventions (e.g., professional training). Future studies should thus examine the extent to which our findings would generalize to longer periods of time, transitions, interventions, and changes. Finally, workload, control, rewards, community, fairness, and values were the only predictors of interest in our research. Yet, it would be interesting to examine how other personal characteristics (e.g., psychological capital, self-efficacy) as well as hindrance (e.g., role conflict, overload, and ambiguity) and challenge (e.g., role responsibility and complexity) demands relate to employees' work engagement and burnout. Likewise, positive (e.g., organizational citizenship behaviors, creativity) and negative (e.g., absenteeism, counterproductive behaviors) outcomes could be included to better understand the implications of the work engagement and burnout profiles. Of particular interest in educational settings, future studies should consider how teachers' engagement and burnout profiles relate to student achievement and motivational outcomes during a school year.

Practical Implications

From an intervention perspective, our findings suggest that school administrators should be particularly attentive to teachers exposed to high workload and low rewards, values, and control. Indeed, our results showed that these employees were less likely to belong to the *Engaged* and *Adapted* profiles and more likely to belong to the *Disengaged* and *Burned-Out* profiles. Therefore, changes designed to increase teachers' rewards, values, and control, and to reduce their workload should contribute to better functioning. For instance, workload could be limited at the organizational level by stating clear segmentation norms and encouraging balanced and healthier lifestyles (Kreiner et al., 2006). Workload could also be reduced at the individual level through coaching or counseling (e.g., developing new habits and replacing one's old malfunctioning behaviors; Van Gordon et al., 2017). Likewise, interventions seeking to create well-being-oriented work environments, and by offering enabling versus enclosing work-life policies might be considered (Bourdeau et al., 2019). More generally, it might be useful to encourage more efficient work recovery processes to protect teachers' professional well-being and to facilitate positive spillover between their work and personal roles (Demsky et al., 2014). Efficient work recovery can be developed and trained, and approaches to successfully train work recovery have been previously shown to be efficient. For instance, participants involved in a recovery training program (e.g., time management, self-reflection) displayed better recovery (e.g., relaxation) and sleep quality after the training, in comparison to those not involved in this training (Hahn et al., 2011). Mindfulness-based interventions are also useful to increase recovery during off-job time (Hülsheger et al., 2015).

Similarly, interventions seeking to increase rewards, values, and control seem particularly interesting for teachers as a way to reduce their likelihood of membership into profiles characterized by high global levels of burnout and low global levels of work engagement. For instance, moving towards high-involvement managerial systems (e.g., opportunity-enhancing practices including flexible job design, work teams, and information sharing) may help to improve teachers' psychological empowerment (Rehman et al., 2019), leading to higher work engagement and reducing the risk of burnout (Boudrias et al., 2012). Organizations should also allocate resources to enactive mastery experiences, to promote self-directed decision-making, and to create opportunities for personal growth. More generally, school administrators might promote a supportive culture by providing teachers with the resources they need to perform their job effectively, and by providing useful training and developmental programs (Eisenberger & Stinglhamber, 2011). Finally, programs designed to sensitize school administrators to the benefits of adopting a more autonomy-supportive approach, and to provide them with tools on how to implement such an approach, might prove beneficial (Gillet et al, 2012).

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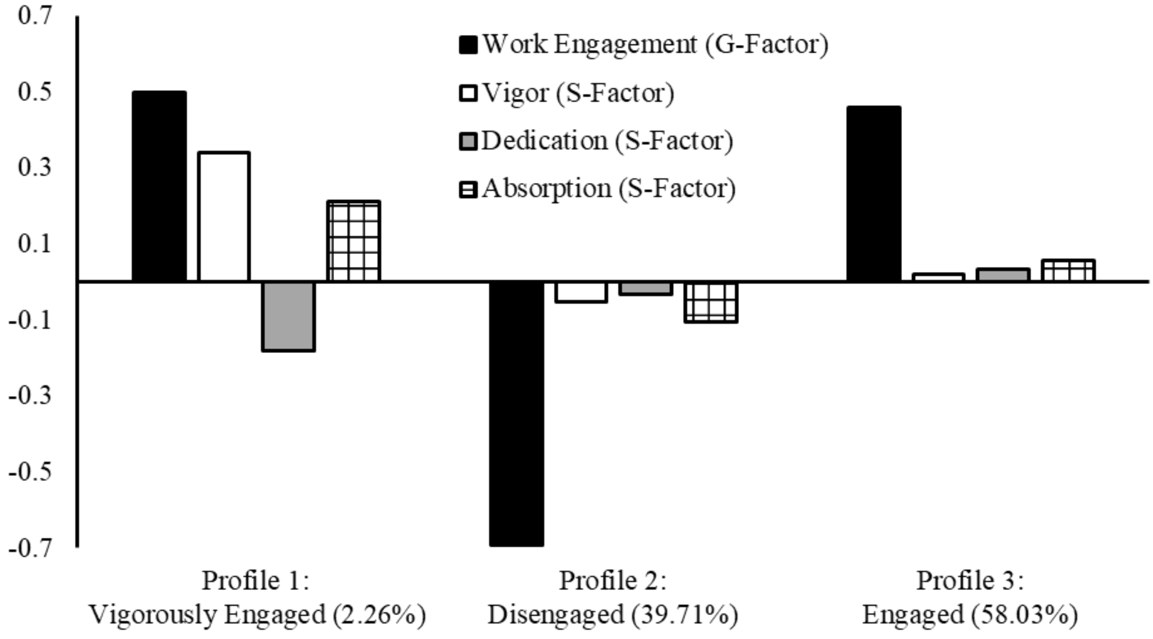

Figure 1. *Final 3-Profile Solution for Work Engagement (Distributional Similarity)*
Note. The profile indicators are factor scores estimated in standardized units (*M* = 0; *SD* = 1).

Figure 2. *Final 3-Profile Solution for Burnout (Partial Structural Similarity, Partial Dispersion Similarity, and Distributional Similarity).*
Note. The profile indicators are factor scores estimated in standardized units (*M* = 0; *SD* = 1).

Table 1

Results from the Longitudinal Latent Profile Analyses and Latent Transition Analyses with Predictors

Description	LL	#fp	Scaling	AIC	CAIC	BIC	ABIC
Longitudinal Tests of Profile Similarity: Work Engagement							
Configural Similarity	-7551.767	56	1.114	15215.534	15546.312	15490.312	15312.453
Structural Similarity	-7549.999	44	1.201	15187.998	15447.895	15403.895	15264.148
Dispersion Similarity	-7583.617	32	1.443	15231.233	15440.249	15388.249	15286.616
Distributional Similarity	-7584.155	28	1.532	15224.309	15389.698	15361.698	15272.769
Longitudinal Tests of Profile Similarity: Burnout							
Configural Similarity	-8535.401	52	1.392	17174.801	17482.212	17430.212	17265.057
Structural Similarity	-8579.708	40	1.293	17239.416	17475.886	17435.886	17308.844
Partial Structural Similarity	-8575.488	41	1.274	17232.977	17475.359	17434.359	17304.140
Dispersion Similarity	-8649.242	29	1.457	17356.483	17527.924	17498.924	17406.818
Partial Dispersion Similarity	-8595.967	32	1.428	17255.934	17445.110	17413.110	17311.476
Distributional Similarity	-8599.339	30	1.469	17258.677	17436.030	17406.030	17310.748
LTA with Predictors: Work Engagement T1 - Burnout T1							
Null Effects Model	-8398.419	35	1.081	16866.838	17074.881	17039.881	16928.717
Free Effects on Profile Membership and Transitions	-8146.091	59	1.035	16410.182	16760.884	16701.884	16514.492
Free Effects on Profile Membership	-8121.818	95	.684	16433.635	16998.324	16903.324	16601.592
LTA with Predictors: Work Engagement T2 - Burnout T2							
Null Effects Model	-7238.979	35	1.174	14547.958	14756.001	14721.001	14609.836
Free Effects on Profile Membership	-7034.028	59	1.179	14186.057	14536.758	14477.758	14290.367
Free Effects on Profile Membership and Transitions	-7018.591	95	.757	14227.183	14791.871	14696.871	14395.139
LTA with Predictors: Work Engagement T1 - Work Engagement T2							
Null Effects Model	-10883.847	98	1.323	21963.694	22546.214	22448.214	22136.954
Free Effects on Profile Membership	-10765.049	122	1.280	21774.097	22499.276	22377.276	21989.789
Free Effects on Profile Membership and Transitions	-10753.298	158	1.079	21822.597	22761.763	22603.763	22101.935
Free Effects on Profile Membership and Longitudinal Predictions	-10738.152	134	1.125	21744.304	22540.812	22406.812	21981.211
Predictive Similarity (equality over time)	-10771.794	110	1.286	21763.588	22417.437	22307.437	21958.063
LTA with Predictors: Burnout T1 - Burnout T2							
Null Effects Model	-11203.906	98	1.341	22603.811	23186.332	23088.332	22777.071
Free Effects on Profile Membership	-10930.563	122	1.306	22105.125	22830.304	22708.304	22320.816
Free Effects on Profile Membership and Transitions	-10897.260	158	1.074	22110.520	23049.685	22891.685	22389.857
Free Effects on Profile Membership and Longitudinal Predictions	-10872.220	134	1.040	22012.440	22808.948	22674.948	22249.347
Predictive Similarity (equality over time)	-10947.441	110	1.326	22114.882	22768.732	22658.732	22309.358
LTA with Predictors: Work Engagement T1 - Burnout T2							
Null Effects Model	-11166.594	98	1.333	22529.187	23111.708	23013.708	22702.447
Free Effects on Profile Membership	-10940.401	122	1.268	22124.802	22849.981	22727.981	22340.494
Free Effects on Profile Membership and Transitions	-10924.929	158	1.001	22165.859	23105.025	22947.025	22445.197
Free Effects on Profile Membership and Longitudinal Predictions	-10934.616	134	1.330	22137.232	22933.740	22799.740	22374.139
LTA with Predictors: Burnout T1 - Work Engagement T2							
Null Effects Model	-11147.971	98	1.340	22491.942	23074.463	22976.463	22665.202
Free Effects on Profile Membership	-10886.932	122	1.284	22017.863	22743.042	22621.042	22233.554
Free Effects on Profile Membership and Transitions	-10875.993	158	1.037	22067.985	23007.151	22849.151	22347.323
Free Effects on Profile Membership and Longitudinal Predictions	-10879.852	134	1.266	22027.705	22824.212	22690.212	22264.611

Note. LTA = Latent transition analysis; LL = Loglikelihood; #fp = Free parameters; Scaling = Scaling correction factor; AIC = Akaïke information criterion; CAIC = Consistent AIC; BIC = Bayesian information criterion; ABIC = Sample size adjusted BIC.

Table 2

Transitions Probabilities from the Cross-Sectional Across-Variables and Longitudinal Within-Variables and Across-Variable Latent Transition Analyses

	Transition Toward (Burnout Time 1)		
Initial Profile (Work Engagement Time 1)	Profile 1 (Burned-Out)	Profile 2 (Adapted)	Profile 3 (Normative)
Profile 1 (Vigorously Engaged)	.102	.004	.894
Profile 2 (Disengaged)	.940	.000	.060
Profile 3 (Engaged)	.124	.183	.693
	Transition Toward (Burnout Time 2)		
Initial Profile (Work Engagement Time 2)	Profile 1 (Burned-Out)	Profile 2 (Adapted)	Profile 3 (Normative)
Profile 1 (Vigorously Engaged)	.225	.000	.775
Profile 2 (Disengaged)	.977	.000	.023
Profile 3 (Engaged)	.244	.108	.647
	Transition Toward (Burnout Time 2)		
Initial Profile (Work Engagement Time 1)	Profile 1 (Burned-Out)	Profile 2 (Adapted)	Profile 3 (Normative)
Profile 1 (Vigorously Engaged)	.098	.000	.902
Profile 2 (Disengaged)	.798	.000	.202
Profile 3 (Engaged)	.310	.124	.566
	Transition Toward (Work Engagement Time 2)		
Initial Profile (Burnout Time 1)	Profile 1 (Vigorously Engaged)	Profile 2 (Disengaged)	Profile 3 (Engaged)
Profile 1 (Burned-Out)	.000	.702	.298
Profile 2 (Adapted)	.003	.008	.989
Profile 3 (Normative)	.042	.073	.885
	Transition Toward (Work Engagement Time 2)		
Initial Profile (Work Engagement Time 1)	Profile 1 (Vigorously Engaged)	Profile 2 (Disengaged)	Profile 3 (Engaged)
Profile 1 (Vigorously Engaged)	.117	.000	.883
Profile 2 (Disengaged)	.000	.897	.103
Profile 3 (Engaged)	.027	.000	.973
	Transition Toward (Burnout Time 2)		
Initial Profile (Burnout Time 1)	Profile 1 (Burned-Out)	Profile 2 (Adapted)	Profile 3 (Normative)
Profile 1 (Burned-Out)	.951	.000	.049
Profile 2 (Adapted)	.078	.675	.246
Profile 3 (Normative)	.124	.004	.872

Table 3

Results from the Predictive Analyses (Predictive Similarity Over Time)

	Work Engagement Profiles						**Burnout Profiles**					
	Vigorously Engaged vs. Engaged		Disengaged vs. Engaged		Vigorously Engaged vs. Engaged		Burned-out vs. Normative		Adapted vs. Normative		Burned-out vs. Adapted	
	Coef. (SE)	OR	Coef. (SE)	OR	Coef. (SE)	OR	Coef. (SE)	OR	Coef. (SE)	OR	Coef. (SE)	OR
Workload	-.122 (.197)	.885	.359 (.116)**	1.432	-.481 (.209)*	.618	1.183 (.148)**	3.263	-.927 (.200)*	.396	2.110 (.241)**	8.249
Control	-.347 (.335)	.707	-.539 (.202)**	.584	.192 (.360)	1.211	.072 (.215)	1.075	.486 (.343)	1.625	-.414 (.393)	.661
Rewards	-.143 (.236)	.867	-.511 (.130)**	.600	.368 (.242)	1.445	-.611 (.152)**	.543	1.145 (.313)**	3.144	-1.756 (.339)**	.173
Community	.391 (.185)*	1.478	.161 (.109)	1.175	.230 (.215)	1.258	.176 (.122)	1.192	-.310 (.217)	.734	.486 (.258)	1.625
Fairness	.225 (.277)	1.253	.509 (.159)**	1.663	-.284 (.299)	.753	.069 (.163)	1.071	-.389 (.264)	.678	.457 (.296)	1.580
Values	-.360 (.281)	.698	-.892 (.158)**	.410	.533 (.264)	1.703	-.658 (.170)**	.518	1.133 (.344)**	3.104	-1.791 (.381)**	.167

Note. * $p < .05$; ** $p < .01$; SE = Standard error of the coefficient; OR = Odds ratio; the Coef. (coefficients) and OR refer to the effects of the predictors on the likelihood of membership into the first listed profile relative to the second one; predictors are factor scores estimated in standardized units ($M = 0$; $SD = 1$).

Online Supplemental Material for:

Teachers' Profiles of Work Engagement and Burnout Over the Course of a School Year

Table S1

Number and Characteristics of Profiles Identified in Previous Studies

Study	Sample	Analysis	Indicators	Profiles	Covariates
Timms et al. (2012)	953 members of the Queensland Independent Education Union	Mixture-likelihood based approach to clustering	Dedication; Vigor; Absorption Exhaustion; Disengagement	Profile 1: Empowered (low exhaustion and disengagement, and high vigor, dedication, and absorption) Profile 2: Under-pressure (above mean score for engagement and above mean score for burnout) Profile 3: Unengaged (low exhaustion and disengagement, and vigor, dedication, and absorption) Profile 4: Burnout (high exhaustion and disengagement, and low vigor, dedication, and absorption) Profile 5: Severe burnout (very high exhaustion and disengagement, and high vigor, dedication, and absorption)	Job control:1 > 2, 3, 4, 5 Workload: 2 > 1, 3 > 4, 5 Reward: 1 > 2, 3 > 4, 5 Community: 1 > 2, 3, 4, 5 Fairness: 1 > 2, 3 > 4, 5 Values: 1 > 2, 3, 4, 5 Work hours: 2 > 1, 3, 4, 5
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
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)	

Study	**Sample**	**Analysis**	**Indicators**	**Profiles**	**Covariates**
Gillet et al. (2019)	730 employees (non self-employed recruited from 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	Energy; Dedication; Absorption Exhaustion; Cynicism; Inadequacy	Profile 1: Engaged-Burnout (high engagement and burnout symptoms) Profile 2: Highly Engaged (high engagement and low burnout symptoms)	High workload: 1 > 2 Increase in class size: 1 > 2 Job control: 2 > 1 High resilience: 2 > 1
Rice & Liu (2020)	760 Taiwan research and development employees	Latent Profile Analysis	Emotional Exhaustion; Cynicism; Reduced Prof. Efficacy	Profile 1: Burnout (high exhaustion & cynicism; moderately high inefficacy) Profile 2: Overextended (moderately high exhaustion & cynicism; average inefficacy) Profile 3: Disengaged (average levels across dimensions) Profile 4: Ineffective (moderately low exhaustion & cynicism; average inefficacy) Profile 5: Engagement (low high exhaustion & cynicism; moderately low inefficacy)	
Upadyaya & Salmela-Aro (2020)	766 Finnish employees	Latent Profile Analysis	Exhaustion; Cynicism; Sense of inadequacy; Energy; Dedication; Absorption (2 times: 1 year apart)	Profile 1: High Engagement (average exhaustion, cynicism, and inadequacy – high energy, dedication, and absorption) Profile 2: Increasing Burnout (relatively high exhaustion, cynicism, and inadequacy – average energy, dedication, and absorption)	Work related social resources: 1 > 2 Personal resources: 1 > 2 Work related demands: 2 > 1 Personal social demands: 2 > 1
Mäkikangas et al. (2021)	169 Finnish employees with a managerial or leadership position	Latent Profile Analysis	Emotional Exhaustion; Cynicism; Reduced Prof. Efficacy (5 times: 8-year period)	Profile 1: Stable, low burnout Profile 2: Exhaustion instigated, increasing burnout (increasing high exhaustion; low cynicism & inefficacy) Profile 3: Cynicism and reduced professional efficacy dominated, inverted U-shaped burnout	Job demands: 2 > 1, 3 Job control: 1 > 3 Supportive organizational climate: 1 > 2, 3

Study	Sample	Analysis	Indicators	Profiles	Covariates
Pyhältö et al. (2021)	2310 Finnish teachers	Latent Profile Analysis	Exhaustion, Inadequacy; Cynicism	Profile 1: No burnout risk (low levels across dimensions) Profile 2: Minor burnout risk (moderate levels across dimensions) Profile 3: Increased exhaustion (high exhaustion; moderate inadequacy & cynicism) Profile 4: Increased exhaustion and cynicism (high exhaustion; moderate cynicism; low inadequacy) Profile 5: High burnout risk (high exhaustion & inadequacy; moderate cynicism)	Self-regulation: 4, 5 > 3 > 2 > 1 Co-regulation: 5 > 2, 3 > 1
Sandrin et al. (2022)	654 French firefighters	Latent Profile Analysis	Emotional Exhaustion; Cynicism; Reduced Prof. Efficacy	Profile 1: Very Low Burnout Risk (very low global burnout; moderately low cynicism; low emotional exhaustion & inefficacy) Profile 2: Mentally Distanced (average global burnout; high cynicism; moderately low emotional exhaustion; low inefficacy) Profile 3: Low Burnout Risk (low global burnout & inefficacy; moderately low cynicism; average emotional exhaustion) Profile 4: High Burnout Risk (high global burnout; average emotional exhaustion, cynicism, & inefficacy) Profile 5: Moderately High Burnout Risk (moderately high global burnout; high inefficacy; average emotional exhaustion; low cynicism)	Colleagues recognition: 1 > 2, 3, 4 > 5 Supervisor recognition: 3 > 2, 4, 5 Job satisfaction: 1, 2, 3 > 4 > 5

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Preliminary Measurement Models

Analyses

The Bifactor-ESEM Framework

To account for the construct-relevant multidimensionality (involving the assessment of conceptually related subscales encompassing a global and specific components) of the burnout and work engagement measures (Morin et al., 2016a, 2016b, 2020), previous studies have supported a bifactor exploratory structural equation modeling (bifactor-ESEM) operationalization of burnout (e.g., Bianchi, 2020; Doherty et al., 2021; Schonfeld et al., 2019; Tóth-Király et al., 2021; Verkulien et al., 2021) and work engagement (e.g., Gillet et al., 2019, 2020; Houle et al., 2022). The ESEM component makes it possible to account for the conceptually related nature of the subscales forming these measures via the incorporation of cross-loadings, which have been demonstrated to result in more accurate factor definitions (Asparouhov et al., 2015; Mai et al., 2018). The bifactor component makes it possible to disaggregate employees' ratings into one global component (G-factor) reflecting the variance shared among all items forming a specific measure (i.e., global levels of burnout and global levels of work engagement), and into a series of orthogonal (i.e., non-redundant) specific factors (S-factors) reflecting the variance uniquely shared among the items forming each subscale beyond that explained by the G-factor (i.e., specific levels of emotional exhaustion, cynicism, professional efficacy, vigor, dedication, and absorption).

When relying on the bifactor-ESEM analytic framework, alternative confirmatory factor analytic (CFA), ESEM, bifactor-CFA, and bifactor-ESEM solutions need to be compared (Morin et al., 2016a, 2016b, 2020). Although model fit information plays a role in this comparison, an examination of the parameter estimates is also required. Morin et al. (2016a, 2016b, 2020) indicate that this examination should start by comparing the CFA and ESEM solutions. Observing factors that are defined similarly well (by strong main factor loadings) across solutions, together with reduced factors correlations in ESEM relative to CFA, supports the value of the ESEM solution. Cross-loadings remaining small or easy to explain further support the ESEM solution, although large and unexplainable cross-loadings suggest that the measure itself should be re-examined. Observing multiple moderate-to-large cross-loadings also suggests the need to consider a bifactor solution. The model retained in this first comparison should then be contrasted with its bifactor counterpart. In this second comparison, in addition to model fit, a well-defined G-factor, accompanied by at least a subset of well-defined S-factors, supports the value of the bifactor solution.

No formal guidelines exist regarding the exact values beyond which one can interpret factors to be well-defined and S-factors to retain enough specificity. However, prior research on work engagement and burnout suggest that G-factors defined by loadings equal or higher than .400 and composite reliability coefficients (McDonald's, 1970, omega ω) $\geq$ .600 can be considered well-defined (e.g., Gillet et al., 2019, 2022). Bifactor solutions often result in weaker S-factors because these models rely on two factors to explain the item-level covariance (Morin et al., 2020). For this reason, slightly lower factor loadings and composite reliability coefficients approaching .500 remain acceptable to suggest that the S-factors retain enough specificity to be meaningful (e.g., Morin et al., 2020; Perreira et al., 2018). Moreover, Morin (2022; also see Morin et al., 2020) notes that the identification of weak (i.e., with low factor loadings, and composite reliability even lower than .500) S-factors is something that should be expected in bifactor estimation, and simply indicates that the items associated with these S-factor primarily serve to define the G-factor, retaining little specificity on their own.

In addition, the present study relies on factor scores, which provide a partial control for unreliability. Furthermore, in bifactor models (and factor scores extracted from them), the G- and S-factors are completely independent from one another (uncorrelated, orthogonal; see Morin et al., 2020). As a result, including a S-factor score characterized by low levels of specificity (and yet corrected for measurement errors) is not likely to introduce any bias in the estimation of the profiles. One the one hand, an "empty" S-factor would simply result in the estimation of profiles in which the levels observed on this S-factor are close to the average and show little variation. On the other hand, it is also possible for this S-factor to retain specificity limited to one or two profiles of participants, in which case it will emerge as a defining characteristic of this specific profile (i.e., since this specificity is limited to a subset of participants, it may not be visible in models estimated on the total sample). To understand this, we need to consider that profiles are not estimated based on the covariance among factor scores, but rather from their multivariate normal distribution, to locate discrete multivariate normal subpopulations which combine to represent the observed multivariate distribution. As such, the extent to which variables are correlated or not with one another is not as relevant, in and of itself, as it is in other types of latent variable models. In addition, the unreliability main effect is to reduce correlations between construct, which is a non-issue for orthogonal factor scores. In relation to the multivariate normal distribution, the incorporation of unreliable indicators would simply, as noted above, result in this indicator not contributing to the differentiation between the profiles.

Model Specification

For all constructs, time-specific CFA solutions were estimated by allowing each factor to be defined solely by their a priori indicators, without cross-loading, and allowing all factors to be correlated. The time-specific ESEM solutions allowed each factor to be primarily defined by their a priori indicators while allowing all cross-loadings to be freely estimated but targeted to take a value as close to zero as possible through the reliance on a confirmatory oblique target rotation approach (Browne, 2001). Factor correlations were also freely estimated. The bifactor-CFA and bifactor-ESEM solutions relied on a specification of the S-factors that was similar to that of the CFA and ESEM solutions, although a G-factor was also estimated from all items. This was accomplished through a confirmatory orthogonal bifactor target rotation approach (Reise et al., 2011). All factors were specified to be orthogonal, based on typical bifactor specifications (Morin et al., 2016a, 2016b, 2020). For the job demands and resources variables, we had no reason to account for the presence of a global construct underlying participants' ratings of job demands and resources. However, given the conceptually related nature of these measures, we still contrasted a CFA and an ESEM representation of job demands and resources. These two models included a series of *a priori* correlated uniquenesses to control the methodological artefact due to the negative wording of eight of the 28 items included in this questionnaire (Marsh et al., 2010, 2013).

Measurement Invariance

Once the best measurement model has been selected for all variables (work engagement, burnout, and job demands-resources), the longitudinal measurement invariance of the retained solution was investigated in sequence (Millsap, 2011): (a) configural invariance; (b) weak invariance (invariance of the factor loadings); (c) strong invariance (invariance of loadings and intercepts); (d) strict invariance (invariance of loadings, intercepts, and uniquenesses); (e) invariance of the latent variances-covariances (invariance of loadings, intercepts, uniquenesses, and latent variances-covariances); and (f) latent means invariance (invariance of loadings, intercepts, uniquenesses, latent variances-covariances, and latent means). For the job demands-resources solution, one additional step was included between (d) and (e) to test the invariance of the correlated uniquenesses used to control for the negative wording of a subset of items. In all longitudinal models used for these tests, correlations among the uniquenesses of the matching indicators used to assess the constructs over time were included *a priori* to avoid converging on inflated estimates of stability (Marsh, 2007).

Model Fit Assessment

All analyses relied on the Maximum Likelihood robust (MLR) estimator implemented in Mplus 8.6 (Muthén & Muthén, 2021), and on full information maximum likelihood procedures to handle missing data (Enders, 2010). For all preliminary analyses, model fit was assessed using the Comparative Fit Index (CFI), the Tucker-Lewis Index (TLI), and the Root Mean Square Error of Approximation (RMSEA) with its 90% confidence interval. CFI and TLI values $\geq .90$ and $\geq .95$ respectively indicate an adequate and an excellent level of fit to the data, whereas RMSEA values $\leq .08$ and $\leq .06$ respectively indicate an adequate and an excellent level of fit to the data (Hu & Bentler, 1999; Marsh et al., 2005). For tests of invariance, a decrease in CFI or TLI $\leq .01$ and an increase in RMSEA $\leq .015$ support the superiority of a model relative to the previous model in the sequence (Chen, 2007; Cheung & Rensvold, 2002; Marsh et al., 2005). Although we also report the chi square test of exact fit and scaled chi square difference tests to ensure full disclosure, these tests are not interpreted due to their oversensitivity to sample size and to minor model misspecifications (Marsh et al., 2005).

Results

Work Engagement

The goodness-of-fit results associated with the alternative time specific measurement models of work engagement are reported in the top section of Table S2, and the parameter estimates from these models are reported in Tables S3 (Time 1) and S4 (Time 2). These results first show that all four models had an acceptable level of fit to the data, although the fit of the bifactor-ESEM model was clearly superior to that of the alternatives at both time points. Considering first the comparison between the CFA and ESEM solutions, the results show that both solutions resulted in factors that were well-defined by their main target loadings at both time points (CFA λ = .254 to .862, M_λ = .751; ESEM λ = .208 to .993, M_λ = .593), although the loading of item Vigor 1 was clearly lower in the ESEM solution (Time 1 λ = .225; Time 2 λ: 208) relative to the CFA solution (Time 1 λ = .826; Time 2 λ = .800), due to a strong cross-loading between this item and the dedication factor (Time 1 λ = .602; Time 2 λ = .559). Likewise, item Absorption 2 presented a slightly weaker loading in the CFA solution (Time 1 λ = .269; Time 2 λ = .254) than in the ESEM solution (Time 1 λ = .357; Time 2 λ = .421). Providing strong support for the ESEM solution, relative to the CFA solution, the factor correlations were substantially smaller in ESEM (r = .421 to .785) relative to CFA (r = .771 to .962). In fact, the CFA correlations were high enough to call into question the discriminant validity of the factors. However, across models, the factor correlations were high enough to suggest the presence of an unmodelled G-factor. Lastly, with the exception of the cross-loading between Vigor 1 and the dedication factor, out of 34 remaining cross-loadings across time points, no other cross-loading was problematically high: Seven were higher than |.200| and eight were between |.100| and |.200|.

The ESEM solution was thus retained for a comparison with its bifactor-ESEM counterpart. In addition to resulting in an improved level of fit to the data, the bifactor-ESEM model also resulted in the estimation of a more limited number of cross-loadings higher than |.200| (one across time points) or between |.100| and |.200| (11 across time points) generally smaller in magnitude ($M_{|\lambda|}$ = .140 in ESEM and .075 in bifactor-ESEM). Importantly, the issue related to item Vigor 1 also seemed to be resolved in this new solution, where it is fairly clear that this item mainly serves to defined the work-engagement G-factor across time points (λ = .847 at Time 1 and .824 at Time 2) rather than any S-factor ($|\lambda|$ = .008 to .167 across S-factors at Times 1 and 2), which explained the presence of the problematically high cross-loading associated with this item in the ESEM solution. In this bifactor-ESEM solution, the G-factor was well-defined at Time 1 ($|\lambda|$ = .244 to .898; $M_{|\lambda|}$ = .718; ω = .929) and Time 2 ($|\lambda|$ = .160 to .848; $M_{|\lambda|}$ = .697; ω = .925), with the weakest loading remaining associated with item Absorption 2, which was similarly weak in all other models. However, the S-factors were more weakly defined that the G-factor, although they still appeared to retain some degree of specificity: (a) vigor at Time 1 ($|\lambda|$ = .008 to .452; $M_{|\lambda|}$ = .271; ω =.504) and Time 2 ($|\lambda|$ = .167 to .303; $M_{|\lambda|}$ = .229; ω = .378); (b) dedication at Time 1 ($|\lambda|$ = .095 to .250; $M_{|\lambda|}$ = .147; ω = .189) and Time 2 ($|\lambda|$ = .245 to .278; $M_{|\lambda|}$ = .306; ω = .486); and (c) absorption at Time 1 ($|\lambda|$ = .197 to .390; $M_{|\lambda|}$ = .324; ω = .357) and Time 2 ($|\lambda|$ = .314 to .428; $M_{|\lambda|}$ = .378; ω = .458). It is important to note that the superiority of this solution is further supported by the observation of similarly weak S-factors in the bifactor-CFA solution, as well as by the fact that a one-factor solution failed to achieve an acceptable level of fit to the data.

The bifactor-ESEM solution was retained for longitudinal tests of measurement invariance. The results from these tests are reported in the top section of Table S9 and support the complete invariance of this solution. The parameter estimates from the most invariant solution (i.e., latent means invariance) are reported in the top section of Table S10, and replicate the time-specific conclusions, revealing a strongly defined work engagement G-factor (λ = .212 to .849; M_λ = .713; ω = .927) accompanied by weakly defined vigor ($|\lambda|$ = .144 to .328; $M_{|\lambda|}$ = .244; ω = .439), dedication ($|\lambda|$ = .223 to .330; $M_{|\lambda|}$ = .264; ω = .409), and absorption ($|\lambda|$ = .242 to .337; $M_{|\lambda|}$ = .370; ω = .189) S-factors.

Burnout

The goodness-of-fit results associated with the alternative time specific measurement models of burnout are reported in the middle section of Table S2, and the parameter estimates from these models are reported in Tables S5 (Time 1) and 6 (Time 2). These results first show that all four models had an acceptable level of fit to the data, although the fit of the bifactor-CFA, ESEM, and bifactor-ESEM solutions was roughly comparable to one another and superior to that of the CFA. Considering first the comparison between the CFA and ESEM solutions, the results show that both solutions resulted in factors that were well-defined by their main target loadings at both time points (CFA λ = .475 to .908, M_λ = .739; ESEM λ = .380 to .995, M_λ = .715). Supporting the ESEM, relative to CFA, the factor correlations were also smaller in ESEM ($|r|$ = .373 to .669) relative to CFA ($|r|$ = .391 to .734). The ESEM solution revealed no problematically high cross-loading across time points and, out of a total of 64 cross-loadings, resulted in two cross-loadings higher than |.200| and 11 between |.100| and |.200|, supporting the need for this methodological control (Asparouhov et al., 2015).

The ESEM solution was thus retained for a comparison with its bifactor-ESEM counterpart. This solution also resulted in the estimation of a more limited number of cross-loadings higher than |.200|

(one across time points) or between |.100| and |.200| (eight across time points) generally smaller in magnitude ($M_{|\lambda|}$ = .068 in ESEM and .051 in bifactor-ESEM). In this solution, the G-factor was well-defined at Time 1 (|λ| = .199 to .862; $M_{|\lambda|}$ = .565; ω = .930) and Time 2 (|λ| = .376 to .703; $M_{|\lambda|}$ = .556; ω = .922). These G-factors were accompanied by similarly well-defined emotional exhaustion (Time 1: |λ| = .456 to .735; $M_{|\lambda|}$ = .587; ω = .857; Time 2: |λ| = .491 to .689; $M_{|\lambda|}$ = .601; ω = .884) and professional efficacy (Time 1: |λ| = .479 to .660; $M_{|\lambda|}$ = .567; ω = .805; Time 2: |λ| = .371 to .678; $M_{|\lambda|}$ = .543; ω = .798) S-factors, as well as by a weaker cynicism (Time 1: |λ| = .055 to .679; $M_{|\lambda|}$ = .225; ω = .393; Time 2: |λ| = .151 to .329; $M_{|\lambda|}$ = .221; ω = .305) S-factor.

The bifactor-ESEM solution was retained for tests of longitudinal measurement invariance. The results from these tests are reported in the middle section of Table S9 and support the configural, weak, strong, latent variance covariance, and latent means invariance of this solution, but not its strict invariance. A detailed examination of the parameter estimates from the solution of strong invariance, as well as of the modification indices from failed model of strict invariance indicated that this lack of invariance was limited to a single item (Cynicism 2), which had a slightly higher uniqueness at Time 2 (.558) relative to Time 1 (.248). Once the equality constraints on this uniqueness were removed, the results supported the model of partial strict invariance. The parameter estimates from the most invariant solution (i.e., latent means invariance with partial strict invariance) are reported in the middle section of Table S10, and replicate the time-specific conclusions. More precisely, these results reveal a strongly defined burnout G-factor (|λ| = .244 to .834; $M_{|\lambda|}$ = .575; ω = .928 at Time 1 and .922 at Time 2), emotional exhaustion S-factor (|λ| = .407 to .731; $M_{|\lambda|}$ = .568; ω = .856), and professional efficacy S-factor (|λ| = .463 to .626; $M_{|\lambda|}$ = .559; ω = .811), accompanied by a weaker cynicism S-factor (|λ| = .104 to .235; $M_{|\lambda|}$ = .181; ω = .245 at Time 1 and .203 at Time 2) S-factors.

Job Demands and Resources

The goodness-of-fit results associated with the alternative time specific measurement models of job demands and resources are reported in the bottom section of Table S2, and the parameter estimates from these models are reported in Tables S7 (Time 1) and S8 (Time 2). These results first show that, although both models had an acceptable level of fit to the data, the fit of the ESEM solution was higher than that of the CFA solution. However, and examination of the results from both solutions revealed that, although all factors seemed to be well-defined at both time points in the CFA solution, the ESEM solution resulted in a very weakly-defined control factor and in various problematically high cross-loadings at Time 1, arguing against the suitability of this solution. Moreover, the factor correlations generally remained reasonably low-to-moderate in the CFA solution (|*r*| = .207 to .646; $M_{|r|}$ = .438), and not reduced substantially in ESEM (|*r*| = .373 to .669; $M_{|r|}$ = 318). For all of these reasons, the more parsimonious CFA solution was retained for tests of measurement invariance. The results from these tests are reported in the bottom section of Table S9 and support the complete invariance of this solution. The parameter estimates from the most invariant solution (i.e., latent means invariance) are reported in the bottom section of Table S10, and reveal well-defined factors: (a) workload (λ = .476 to .862; M_{λ} = .657; ω = .826); (b) control (λ = .515 to .623; M_{λ} = .586; ω = .612); (c) reward (λ = .733 to .879; M_{λ} = .800; ω = .878); (d) community (λ = .363 to .924; M_{λ} = .680; ω = .826); (e) fairness (λ = .470 to .823; M_{λ} = .626; ω = .768); and (f) values (λ = .433 to .796; M_{λ} = .663; ω = .803).

References used in this supplement

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Table S2

Goodness-of-Fit Statistics of the Alternative Time-Specific Measurement Models

Model	χ^2	df	CFI	TLI	RMSEA	90% CI RMSEA
Work Engagement: Time 1						
CFA	179.957*	24	.956	.933	.082	[.071; .093]
Bifactor-CFA	100.288*	18	.977	.953	.069	[.056; .082]
ESEM	18.521	12	.998	.994	.024	[.000; .044]
Bifactor-ESEM	2.609	6	1.000	1.006	.000	[.000; .023]
Work Engagement: Time 2						
CFA	116.144*	24	.959	.938	.077	[.064; .092]
Bifactor-CFA	63.174*	18	.980	.960	.063	[.046; .080]
ESEM	40.686*	12	.987	.962	.061	[.041; .082]
Bifactor-ESEM	3.317	6	1.000	1.007	.064	[.000; .035]
Burnout: Time 1						
CFA	495.463*	101	.939	.927	.063	[.058; .069]
Bifactor-CFA	300.904*	88	.967	.955	.050	[.044; .056]
ESEM	304.013*	75	.964	.943	.056	[.050; .063]
Bifactor-ESEM	231.919*	62	.974	.949	.053	[.046; .060]
Burnout: Time 2						
CFA	327.608*	101	.946	.935	.059	[.052; .066]
Bifactor-CFA	243.146*	88	.963	.949	.052	[.045; .060]
ESEM	242.045*	75	.960	.936	.059	[.051; .067]
Bifactor-ESEM	197.197*	62	.968	.937	.058	[.049; .068]
Job Demands-Resources: Time 1						
CFA	1023.698*	307	.928	.912	.043	[.045; .051]
ESEM	459.560*	197	.974	.950	.036	[.032; .041]
Job Demands-Resources: Time 2						
CFA	831.895*	307	.923	.905	.051	[.047; .055]
ESEM	476.070*	197	.959	.921	.046	[.041; .051]

Note. * $p < .01$; CFA = Confirmatory factor analysis; ESEM = Exploratory structural equation modeling; df = Degrees of freedom; χ^2 = Robust chi-square test of exact fit; CFI = Comparative fit index; TLI = Tucker-Lewis index; RMSEA = Root mean square error of approximation; CI = Confidence interval.

Table S3

Standardized Factor Loadings (λ), Item Uniquenesses (δ), and Factor Correlations for the Alternative Work Engagement Measurement Models at Time 1

	Confirmatory Factor Analysis				Exploratory Structural Equation Modeling			
Items	Vigor λ	Dedication λ	Absorption λ	δ	Vigor λ	Dedication λ	Absorption λ	δ
Vigor 1	**.826****			.318**	**.225****	.602**	.094*	.272**
Vigor 2	**.850****			.277**	**.665***	.037	.201**	.268**
Vigor 3	**.861****			.258**	**.993****	.004	-.079**	.104
Dedication 1		**.831****		.309**	.203**	**.395****	.304**	.334**
Dedication 2		**.856****		.267**	.096*	**.770****	.084*	.185**
Dedication 3		**.762****		.419**	.290**	**.506****	.015	.430**
Absorption 1			**.741****	.452**	.050	.009	**.699****	.446**
Absorption 2			**.269****	.928**	-.198**	.126*	**.357****	.908**
Absorption 3			**.806****	.350**	.117	-.015	**.716****	.357**
Correlations								
Vigor	-				-			
Dedication	.947**	-			.724**	-		
Absorption	.873**	.840**	-		.785**	.675**	-	

	Bifactor-Confirmatory Factor Analysis					Bifactor-Exploratory Structural Equation Modeling				
Items	S-Vigor λ	S-Dedication λ	S-Absorption λ	G-Engagement λ	δ	S-Vigor λ	S-Dedication λ	S-Absorption λ	G-Engagement λ	δ
Vigor 1	**.103**			**.863****	.245**	**.008**	-.044	-.052	**.847****	.278**
Vigor 2	**-.320****			**.813****	.237**	**.452****	-.075	.099*	**.788****	.159*
Vigor 3	**-.358****			**.828****	.186*	**.354****	.117*	.031	**.803****	.215**
Dedication 1		**.135**		**.806****	.332**	.022	**.096**	.115*	**.809****	.323**
Dedication 2		**.183***		**.840****	.262**	-.118*	**-.095**	-.105*	**.898****	.160*
Dedication 3		**.328***		**.727****	.364**	-.024	**.250**	-.075	**.760****	.354**
Absorption 1			**.381****	**.643****	.442**	.085*	-.006	**.384****	**.632****	.446**
Absorption 2			**.171****	**.229****	.919**	-.126*	.018	**.197****	**.244****	.886**
Absorption 3			**.385****	**.697****	.367**	.121*	.003	**.390****	**.683****	.367**

Note. * $p < .05$; ** $p < .01$; G/S: Global and specific factors from a bifactor model; target factor loadings (λ) are in bold; δ = Standardized item uniqueness.

Table S4

Standardized Factor Loadings (λ), Item Uniquenesses (δ), and Factor Correlations for the Alternative Work Engagement Measurement Models at Time 2

	Confirmatory Factor Analysis				Exploratory Structural Equation Modeling			
Items	Vigor λ	Dedication λ	Absorption λ	δ	Vigor λ	Dedication λ	Absorption λ	δ
Vigor 1	**.800****			.360**	**.208**	.559**	.118	.337**
Vigor 2	**.811****			.342**	**.594****	.045	.245	.306**
Vigor 3	**.839****			.296**	**.893****	.073	-.057	.182
Dedication 1		**.816****		.334**	.387**	**.333****	.158*	.364**
Dedication 2		**.862****		.257**	.107	**.829****	.014	.155**
Dedication 3		**.758****		.426**	.082	**.603****	.126	.427**
Absorption 1			**.747****	.442**	-.008	.004	**.776****	.404**
Absorption 2			**.254****	.936**	-.228*	.078	**.421****	.896**
Absorption 3			**.825****	.319**	.175	-.047	**.686***	.365**
Correlations								
Vigor	-				-			
Dedication	.962**	-			.732**	-		
Absorption	.864**	.771**	-		.421**	.686**	-	

	Bifactor-Confirmatory Factor Analysis					Bifactor-Exploratory Structural Equation Modeling				
Items	S-Vigor λ	S-Dedication λ	S-Absorption λ	G-Engagement λ	δ	S-Vigor λ	S-Dedication λ	S-Absorption λ	G-Engagement λ	δ
Vigor 1	**.854****			**.858****	-.446	**-.167**	.085	-.069	**.824****	.281**
Vigor 2	**-.134**			**.836****	.283**	**.216***	.000	.120*	**.795****	.307**
Vigor 3	**-.101**			**.861****	.249**	**.303***	.007	-.053	**.848****	.186*
Dedication 1		**.199***		**.768****	.371**	.148*	**.245****	.079	**.763****	.330**
Dedication 2		**.268****		**.809****	.274**	-.138*	**.278****	-.096	**.840****	.189*
Dedication 3		**.540****		**.672****	.256*	-.026	**.394****	.040	**.686****	.371**
Absorption 1			**.555****	**.611****	.318*	.055	.045	**.392****	**.623****	.453**
Absorption 2			**.234****	**.177****	.914**	.036	.235*	**.314****	**.160****	.820**
Absorption 3			**.348****	**.686****	.409**	-.026	-.194*	**.428****	**.730****	.246

Note. * $p < .05$; ** $p < .01$; G/S: Global and specific factors from a bifactor model; target factor loadings (λ) are in bold; δ = Standardized item uniqueness.

Table S5

Standardized Factor Loadings (λ), Item Uniquenesses (δ), and Factor Correlations for the Alternative Burnout Measurement Models at Time 1

	Confirmatory Factor Analysis				Exploratory Structural Equation Modeling			
Items	Exhaust. λ	Cynicism λ	Prof. Efficacy λ	δ	Exhaust. λ	Cynicism λ	Prof. Efficacy λ	δ
Emo. Exh. 1	**.833****			.306**	**.798****	.056	.007	.304**
Emo. Exh. 2	**.855****			.270**	**.995****	-.175**	.005	.217**
Emo. Exh. 3	**.826****			.318**	**.841****	-.041	-.036	.313**
Emo. Exh. 4	**.808****			.347**	**.648****	.210**	-.002	.352**
Emo. Exh. 5	**.863****			.255**	**.784****	.122	.030	.263**
Cynicism 1		**.829****		.312**	.051	**.808****	.003	.292**
Cynicism 2		**.870****		.243**	.086*	**.802****	-.010	.247**
Cynicism 3		**.475****		.774**	.022	**.479****	.020	.767**
Cynicism 4		**.568****		.677**	.085	**.380****	-.176**	.684**
Cynicism 5		**.660****		.565**	.051	**.545****	-.125*	.563**
Prof. Efficacy 1			**.480****	.770**	-.030	.183**	**.597****	.729**
Prof. Efficacy 2			**.719****	.484**	-.004	-.137**	**.619****	.496**
Prof. Efficacy 3			**.697****	.514**	-.055	.191**	**.819****	.451**
Prof. Efficacy 4			**.800****	.360**	.091*	-.161**	**.739****	.354**
Prof. Efficacy 5			**.790****	.376**	.089*	-.090*	**.770****	.375**
Prof. Efficacy 6			**.779****	.394**	-.096*	-.037	**.711****	.396**
Correlations								
Emo. Exh.	-				-			
Cynicism	.734**	-			.669**	-		
Prof. Efficacy	-.643**	-.415**	-		-.390**	-.580**	-	

	Bifactor-Confirmatory Factor Analysis					Bifactor-Exploratory Structural Equation Modeling				
Items	S-Exhaust. λ	S-Cynic. λ	S- Prof. Eff. λ	G-Burnout λ	δ	S-Exhaust. λ	S-Cynic. λ	S-Prof. Eff. λ	G-Burnout λ	δ
Emo. Exh. 1	**.563****			**.614****	.305**	**.574****	.011	.021	**.604****	.305**
Emo. Exh. 2	**.727****			**.525****	.196**	**.735****	.011	.017	**.514****	.194**
Emo. Exh. 3	**.595****			**.572****	.318**	**.607****	-.070*	-.019	**.563****	.310**
Emo. Exh. 4	**.447****			**.667****	.355**	**.456****	.005	.015	**.660****	.356**
Emo. Exh. 5	**.556****			**.653****	.265**	**.562****	-.006	.038*	**.645****	.266**
Cynicism 1		**.230***		**.829****	.260**	.008	**-.141****	.022	**.846****	.263**
Cynicism 2		**.177***		**.860****	.230**	.043	**-.122***	.005	**.862****	.240**
Cynicism 3		**-.101**		**.487****	.752**	.008	**.055**	.025	**.475****	.771**
Cynicism 4		**-.239***		**.588****	.598**	.051	**.127***	-.127**	**.542****	.671**
Cynicism 5		**-.306***		**.704****	.410**	-.044*	**.679****	-.016	**.729****	.006**
Prof. Efficacy 1			**.476**	**-.205****	.731**	-.014	-.031	**.479****	**-.199****	.730**
Prof. Efficacy 2			**.487**	**-.517****	.496**	.008	-.044	**.492****	**-.510****	.496**
Prof. Efficacy 3			**.644**	**-.350****	.463**	-.030	.017	**.660****	**-.339****	.448**
Prof. Efficacy 4			**.596**	**-.534****	.360**	.083**	-.022	**.587****	**-.541****	.354**
Prof. Efficacy 5			**.630**	**-.480****	.372**	.078**	.017	**.617****	**-.489****	.374**
Prof. Efficacy 6			**.549**	**-.543****	.403**	-.058*	-.002	**.567****	**-.529****	.396**

Note. * $p < .05$; ** $p < .01$; G/S: Global and specific factors from a bifactor model; target factor loadings (λ) are in bold; δ = Standardized item uniqueness.

Table S6

Standardized Factor Loadings (λ), Item Uniquenesses (δ), and Factor Correlations for the Alternative Burnout Measurement Models at Time 2

	Confirmatory Factor Analysis				Exploratory Structural Equation Modeling			
Items	Exhaust. λ	Cynicism λ	Prof. Efficacy λ	δ	Exhaust. λ	Cynicism λ	Prof. Efficacy λ	δ
Emo. Exh. 1	**.820****			**.328****	**.793****	.053	.019	.322**
Emo. Exh. 2	**.883****			**.220****	**.992****	-.153**	.010	.204**
Emo. Exh. 3	**.838****			**.298****	**.817****	.030	.008	.303**
Emo. Exh. 4	**.782****			**.389****	**.640****	.183*	-.028	.378**
Emo. Exh. 5	**.908****			**.175****	**.905****	-.007	-.018	.178**
Cynicism 1		**.720****		**.482****	.070	**.636****	-.046	.490**
Cynicism 2		**.565****		**.681****	.031	**.622****	.091*	.650**
Cynicism 3		**.485****		**.765****	-.059	**.615****	.084	.721**
Cynicism 4		**.706****		**.501****	.016	**.551****	-.204**	.501**
Cynicism 5		**.752****		**.434****	.043	**.698****	-.025	.447**
Prof. Efficacy 1			**.537****	**.711****	.039	-.049	**.515****	.717**
Prof. Efficacy 2			**.726****	**.472****	.052	-.125	**.659****	.480**
Prof. Efficacy 3			**.722****	**.479****	.042	.040	**.773****	.459**
Prof. Efficacy 4			**.790****	**.376****	-.063	.070	**.818****	.360**
Prof. Efficacy 5			**.784****	**.386****	.020	.034	**.821****	.369**
Prof. Efficacy 6			**.776****	**.398****	-.094	-.060	**.690****	.404**
Correlations								
Emo. Exh.	-				-			
Cynicism	.698**	-			.667**	-		
Prof. Efficacy	-.667**	-.391**	-		-.373**	-.614**	-	

	Bifactor-Confirmatory Factor Analysis					Bifactor-Exploratory Structural Equation Modeling				
Items	S-Exhaust. λ	S-Cynic. λ	S- Prof. Eff. λ	G-Burnout λ	δ	S-Exhaust. λ	S-Cynic. λ	S- Prof. Eff. λ	G-Burnout λ	δ
Emo. Exh. 1	**.583****			**.582****	.320**	**.491****	-.163*	.121*	**.673****	.265**
Emo. Exh. 2	**.751****			**.516****	.170**	**.689****	-.169	.090*	**.584****	.148**
Emo. Exh. 3	**.600****			**.578****	.306**	**.620****	.100*	.019	**.561****	.290**
Emo. Exh. 4	**.466****			**.630****	.386**	**.549****	.280*	-.057	**.562****	.301*
Emo. Exh. 5	**.658****			**.618****	.186**	**.657****	.042	.015	**.619****	.184**
Cynicism 1		**.680****		**.731****	.004**	.054	**.170**	-.035	**.689****	.492**
Cynicism 2		**.164****		**.541****	.680**	.066	**.244***	.042	**.531****	.652**
Cynicism 3		**-.076**		**.502****	.742**	.034	**.329****	.010	**.437****	.700**
Cynicism 4		**-.120***		**.738****	.441**	-.001	**.151**	-.149**	**.679****	.493**
Cynicism 5		**-.015**		**.749****	.439**	.052	**.213**	-.033	**.703****	.457**
Prof. Efficacy 1			**.408****	**-.344****	.716**	.085	.033	**.371****	**-.376****	.712**
Prof. Efficacy 2			**.505****	**-.509****	.485**	.106	.037	**.478****	**-.540****	.467**
Prof. Efficacy 3			**.584****	**-.435****	.470**	.086	.029	**.578****	**-.440****	.464**
Prof. Efficacy 4			**.626****	**-.501****	.357**	-.057	-.092	**.678****	**-.449****	.327**
Prof. Efficacy 5			**.635****	**-.480****	.366**	.006	-.081	**.675****	**-.436****	.348**
Prof. Efficacy 6			**.510****	**-.576****	.407**	.030	.100	**.479****	**-.623****	.371**

Note. * $p < .05$; ** $p < .01$; G/S: Global and specific factors from a bifactor model; target factor loadings (λ) are in bold; δ = Standardized item uniqueness.

Table S7

Standardized Factor Loadings (λ), Item Uniquenesses (δ), and Factor Correlations for the Job Demands-Resources Measurement Models at Time 1

	Confirmatory Factor Analysis							Exploratory Structural Equation Modeling						
Items	Workload λ	Control λ	Reward λ	Community λ	Fairness λ	Values λ	δ	Workload λ	Control λ	Reward λ	Community λ	Fairness λ	Values λ	δ
Workload 1	**.466****						**.793****	**.510****	-.120**	.137**	-.045	-.051	.148**	.732**
Workload 2	**.638****						**.593****	**.819****	.585**	-.047*	.005	.009	-.013	.008**
Workload 3	**.847****						**.283****	**.784****	-.217**	-.055*	.007	.050	-.068*	.294**
Workload 4	**.853****						**.272****	**.821****	-.303**	.017	-.037	.042	-.029	.217**
Workload 5	**.631****						**.602****	**.636****	.148**	-.037	.012	-.012	-.060	.539**
Workload 6	**.487****						**.763****	**.437****	-.226**	-.003	.001	-.099*	.108**	.730**
Control 1		**.494****					**.756****	-.424**	**.025**	.027	-.005	.069	.085	.752**
Control 2		**.610****					**.628****	-.049	**.108****	.233**	-.037	.281**	.057	.753**
Control 3		**.586****					**.656****	-.160**	**.027**	.207**	-.032	.121*	.071	.838**
Reward 1			**.871****				**.241****	.042*	.009	**.865****	.060*	-.034	.015	.241**
Reward 2			**.815****				**.335****	.030	.003	**.865****	-.012	.001	-.045	.303**
Reward 3			**.758****				**.425****	-.071**	.012	**.667****	.049*	.065*	.028	.418**
Reward 4			**.746****				**.443****	-.027	.022	**.687****	.037	.022	.053	.439**
Community 1				**.378****			**.857****	-.036	.000	-.137**	**.289****	.182**	.129**	.807**
Community 2				**.789****			**.378****	.046*	.009	.084**	**.749****	-.012	.027	.378**
Community 3				**.933****			**.130****	-.003	-.007	-.044*	**.970****	-.015	-.004	.109**
Community 4				**.877****			**.231****	-.010	-.040*	.003	**.891****	-.004	-.042	.235**
Community 5				**.458****			**.790****	-.028	.038	.162**	**.380****	-.009	.012	.765**
Fairness 1					**.651****		**.577****	-.029	.004	.012	.166**	**.431****	.153**	.581**
Fairness 2					**.479****		**.771****	-.011	.053	.013	-.044	**.320****	.239**	.759**
Fairness 3					**.838****		**.297****	.076**	-.036	.011	-.020	**.897****	.012	.233**
Fairness 4					**.695****		**.517****	-.001	-.021	.007	.024	**.763****	-.093*	.471**
Fairness 5					**.467****		**.782****	-.045	.071**	.009	.038	**.465****	-.035	.754**
Values 1						**.791****	**.374****	-.003	.009	-.023	.035	.009	**.779****	.373**
Values 2						**.392****	**.846****	.097**	.019	.009	-.056	-.075	**.519****	.796**
Values 3						**.756****	**.429****	.017	-.019	.028	.019	-.011	**.767****	.395**
Values 4						**.729****	**.468****	.032	.011	.037	.051	.103**	**.620****	.484**
Values 5						**.623****	**.612****	-.125**	.015	-.012	.056	.079	**.510****	.605**
Correlations														
Workload	-							-						
Control	-.359**	-						-.048	-					
Reward	-.283**	.545**	-					-.278**	-.005	-				
Community	-.207**	.324**	.460**	-				-.188**	.031	.432**	-			
Fairness	-.318**	.595**	.530**	.472**	-			-.332**	.079**	.492**	.438**	-		
Values	-.294**	.481**	.467**	.481**	.646**	-		-.260**	-.015	.419**	.444**	.562**	-	

Note. * $p < .05$; ** $p < .01$; target factor loadings (λ) are in bold; δ = Standardized item uniqueness.

Table S8

Standardized Factor Loadings (λ), Item Uniquenesses (δ), and Factor Correlations for the Job Demands-Resources Measurement Models at Time 2

	Confirmatory Factor Analysis							Exploratory Structural Equation Modeling						
Items	Workload λ	Control λ	Reward λ	Community λ	Fairness λ	Values λ	δ	Workload λ	Control λ	Reward λ	Community λ	Fairness λ	Values λ	δ
Workload 1	**.491****						.759**	**.568****	.106	.020	.034	-.101*	.129*	.708**
Workload 2	**.647****						.582**	**.604****	-.040	-.083	.068	.003	-.075	.572**
Workload 3	**.824****						.321**	**.793****	-.041	-.018	-.003	.025	-.036	.331**
Workload 4	**.882****						.222**	**.886****	-.032	.053	-.048	.003	.023	.207**
Workload 5	**.666****						.556**	**.606****	-.020	-.034	-.012	.064	-.159**	.556**
Workload 6	**.520****						.730**	**.492****	-.090	.000	-.067	-.015	.126*	.723**
Control 1		**.562****					.684**	-.249**	**.511****	-.039	.009	-.020	.009	.610**
Control 2		**.636****					.595**	.005	**.395****	.142*	.001	.183**	.031	.638**
Control 3		**.656****					.570**	.082*	**.792****	.047	-.017	-.026	.002	.401*
Reward 1			**.892****				.204**	.069*	.066	**.840****	.078*	-.024	.020	.212**
Reward 2			**.844****				.288**	.077*	.109*	**.796****	.053	-.029	.022	.278**
Reward 3			**.769****				.409**	-.125**	-.021	**.710****	.031	.087*	-.010	.363**
Reward 4			**.697****				.514**	-.080*	-.040	**.702****	-.062	.074*	.024	.464**
Community 1				**.359****			.871**	.032	.052	-.117*	**.271****	.126**	.139*	.830**
Community 2				**.815****			.335**	.035	.022	.096*	**.754****	.030	-.010	.345**
Community 3				**.901****			.189**	.012	.045	-.047	**.974****	-.045	-.037	.129**
Community 4				**.826****			.318**	-.022	-.038	-.007	**.806****	.054	-.014	.335**
Community 5				**.454****			.794**	-.064	-.137*	.199**	**.375****	-.071	.085	.765**
Fairness 1					**.677****		.542**	-.023	.063	-.062	**.204****	.470**	.129*	.552**
Fairness 2					**.526****		.723**	-.012	.044	-.031	.030	**.399****	.130*	.747**
Fairness 3					**.800****		.360**	.034	.019	.004	-.080*	**.934****	-.029	.204*
Fairness 4					**.642****		.588**	.019	-.002	.064	.027	**.641****	-.051	.569**
Fairness 5					**.419****		.825**	-.071	-.033	.167**	-.035	**.314****	.043	.807**
Values 1						**.802****	.356**	.015	-.052	-.006	.062*	.056	**.778****	.347**
Values 2						**.518****	.731**	.115*	.045	-.010	-.049	-.050	**.607****	.680**
Values 3						**.798****	.364**	-.022	.022	.026	-.032	-.019	**.810****	.338**
Values 4						**.700****	.510**	-.034	.060	.012	.057	.110*	**.553****	.524**
Values 5						**.557****	.690**	-.129*	.006	.054	.024	0.45	**.448****	.685**
Correlations														
Workload	-							-						
Control	-.461**	-						-.353**	-					
Reward	-.256**	.605	-					-.247**	.431**	-				
Community	-.237**	.359**	.499**	-				-.214**	.284**	.433**	-			
Fairness	-.245**	.580**	.564**	.466**	-			-.224**	.411**	.495**	.411**	-		
Values	-.283**	.550**	.493**	.452**	.619**	-		-.233**	.436**	.412**	.419**	.516**	-	

Note. * $p < .05$; ** $p < .01$; target factor loadings (λ) are in bold; δ = Standardized item uniqueness.

Table S9

Goodness-of-Fit Statistics of the Longitudinal Tests of Measurement Invariance

Description	χ^2	df	CFI	TLI	RMSEA	90% CI RMSEA	$\Delta\chi^2$	Δdf	ΔCFI	ΔTLI	ΔRMSEA
Work Engagement											
Configural invariance	57.985	68	1.000	1.003	.000	[.000; .012]	-		-	-	-
Weak invariance	101.285	88	.998	.997	.012	[.000; .022]	39.108*	20	-.002	-.006	+.012
Strong invariance	104.329	93	.998	.997	.011	[.000; .021]	3.332	5	.000	.000	-.001
Strict invariance	121.545	102	.997	.996	.014	[.000; .022]	18.549	9	-.001	-.001	+.003
Latent variance-covariance invariance	128.794	112	.998	.997	.012	[.000; .021]	7.348	10	+.001	+.001	-.002
Latent means invariance	140.038	116	.997	.996	.014	[.000; .022]	9.537	4	-.001	-.001	+.002
Burnout											
Configural invariance	674.852*	348	.974	.963	.031	[.027; .034]	-		-	-	-
Weak invariance	741.185*	396	.972	.966	.029	[.026; .033]	72.304	48	-.002	+.003	-.002
Strong invariance	778.850*	408	.970	.964	.030	[.027; .033]	30.840*	12	-.002	-.002	+.001
Strict invariance	993.145*	424	.955	.947	.037	[.034; .040]	460.816*	16	-.015	-.017	+.007
Partial Strict invariance	824.253*	423	.968	.962	.031	[.028; .034]	56.163*	15	-.002	-.002	+.001
Latent variance-covariance invariance	849.015*	433	.967	.962	.031	[.028; .034]	20.857	10	-.001	.000	.000
Latent means invariance	870.986*	437	.965	.961	.031	[.028; .034]	5.125	4	-.002	-.001	.000
Job Demands-Resources											
Configural invariance	2742.117*	1334	.928	.917	.032	[.030; .034]	-		-	-	-
Weak invariance	2766.482*	1356	.928	.918	.032	[.030; .033]	24.563	22	.000	+.001	.000
Strong invariance	2842.596*	1378	.925	.916	.032	[.030; .034]	59.838*	22	-.003	-.002	.000
Strict invariance	2933.941*	1406	.922	.914	.032	[.031; .034]	99.534*	28	-.003	-.002	.000
Correlated uniquenesses invariance	2965.757*	1434	.921	.916	.032	[.030; .034]	35.020	28	-.001	+.002	.000
Latent variance-covariance invariance	3022.297*	1455	.920	.915	.032	[.031; .034]	52.041	49	-.002	+.001	.000
Latent means invariance	3057.417*	1461	.918	.914	.032	[.031; .034]	20.817*	6	-.002	-.001	.000

Note. * $p < .01$; χ^2 = Scaled 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 = Confidence interval; $\Delta\chi^2$ = Scaled chi-square difference tests; Δ = Change in fit relative to the previous model.

Table S10

Longitudinally Invariant Factor Loadings (λ) and Item Uniquenesses (δ) for all Measures

	S-Vigor λ	S-Dedic. λ	S-Absor. λ	G-Engage. λ			δ
Work Engagement							
Vigor 1	**-.144**	.077	-.081**	**.846****			.250*
Vigor 2	**.260****	.066	.065	**.823****			.247**
Vigor 3	**.328***	.048	-.033	**.837****			.189*
Dedication 1	.060	**.239****	.112**	**.780****			.319**
Dedication 2	-.145**	**.223***	-.079	**.849****			.202**
Dedication 3	-.005	**.330***	.003	**.710****			.387**
Absorption 1	.040	-.018	**.406****	**.648****			.414**
Absorption 2	-.057	.147*	**.242****	**.212****			.872**
Absorption 3	.064	-.098	**.337****	**.712****			.365**
	S-Exhaust. λ	S-Cynic. λ	S-Prof. Eff. λ	G-Burnout λ			δ
Burnout							
Emot. Exhaustion 1	**.578****	.119	-.006	**.598****			.295**
Emot. Exhaustion 2	**.731****	.011	.009	**.535****			.179**
Emot. Exhaustion 3	**.560****	-.040	.019	**.613****			.309**
Emot. Exhaustion 4	**.407****	-.064	.053	**.698****			.340**
Emot. Exhaustion 5	**.562****	-.014	.045**	**.671****			.232**
Cynicism 1	.008	**.209**	-.001	**.783****			.343**
Cynicism 2	.028/.021[§]	**.235/.180**[§]	.024/.018[§]	**.834**/.639****[§]			.248**/.558**[§]
Cynicism 3	-.006	**.104****	.028	**.464****			.773**
Cynicism 4	.050	**.186**	-.169**	**.561****			.620**
Cynicism 5	.030	**.171**	-.077*	**.655****			.535**
Prof. Efficacy 1	.010	-.023	**.463****	**-.244****			.726**
Prof. Efficacy 2	.012	-.141**	**.556****	**-.465****			.455**
Prof. Efficacy 3	.031	.069	**.606****	**-.391****			.474**
Prof. Efficacy 4	.137**	.210	**.532****	**-.593****			.302**
Prof. Efficacy 5	.133**	.174**	**.571****	**-.534****			.340**
Prof. Efficacy 6	-.075**	-.170*	**.626****	**-.501****			.323**
Items	Workload λ	Control λ	Reward λ	Community λ	Fairness λ	Values λ	δ
Job Demands-Resources							
Workload 1	**.476****						.774**
Workload 2	**.646****						.583**
Workload 3	**.839****						.297**
Workload 4	**.862****						.256**
Workload 5	**.640****						.590**
Workload 6	**.480****						.769**
Control 1		**.515****					.735**
Control 2		**.623****					.612**
Control 3		**.620****					.616**
Reward 1			**.879****				.228**
Reward 2			**.821****				.326**
Reward 3			**.768****				.411**
Reward 4			**.733****				.462**
Community 1				**.363****			.869**
Community 2				**.798****			.363**
Community 3				**.924****			.147**
Community 4				**.863****			.256**
Community 5				**.451****			.796**
Fairness 1					**.656****		.569**
Fairness 2					**.494****		.756**
Fairness 3					**.823****		.323**
Fairness 4					**.686****		.529**
Fairness 5					**.470****		.779**
Values 1						**.796****	.366**
Values 2						**.433****	.812**
Values 3						**.774****	.401**
Values 4						**.717****	.485**
Values 5						**.597****	.643**

Note. * $p < .05$; ** $p < .01$; G/S: Global and specific factors from a bifactor model; target factor loadings (λ) are in bold; δ = Standardized item uniqueness; [§] : The uniqueness of item “Cynicism 2” was not invariant, we thus report the results for Time 1 first, followed by Time 2.

Table S11

Correlations and Composite Reliability (ω) for all Variables

Variables	ω	1	2	3	4	5	6	7	8	9	10	11
1. Sex (0: Female, 1: Male)	-	-										
2. Experience (years)	-	-.004	-									
3. School Dummy 1 (1: Primary; 0: Other)	-	-.218**	-.032	-								
4. School Dummy 2 (1: Secondary; 0: Other)	-	.236**	.019	-.904**	-							
5. Workload (T1)	.826	-.087**	.034	.026	**-.003**	-						
6. Control (T1)	.612	.043	.015	.064*	-.083	-.620**	-					
7. Rewards (T1)	.878	.004	-.026	.111*	-.114*	-.317**	.662**	-				
8. Community (T1)	.826	-.012	-.035	.025	-.042	-.232**	.403**	.509**	-			
9. Fairness (T1)	.768	-.066*	-.031	.231**	-.232**	-.354**	.713**	.607**	.533**	-		
10. Values (T1)	.803	-.060	-.052	.198**	-.205**	-.330**	.602**	.525**	.534**	.728**	-	
11. Workload (T2)	.826	-.105**	.025	.035	-.026	.849**	-.536**	-.243**	-.183**	-.275**	-.228**	-
12. Control (T2)	.612	.051	.007	.051	-.058	-.592**	.842**	.534**	.273**	.565**	.437**	-.619**
13. Rewards (T2)	.878	-.018	-.022	.120*	-.112*	-.356**	.563**	.757**	.429**	.581**	.457**	-.337**
14. Community (T2)	.826	-.038	-.062*	.069*	-.081*	-.287**	.394**	.340**	.627**	.504**	.479**	-.280**
15. Fairness (T2)	.768	-.031	-.056	.225**	-.226**	-.364**	.642**	.516**	.411**	.831**	.565**	-.341**
16. Values (T2)	.803	-.070*	-.095**	.195**	-.195**	-.384**	.472**	.386**	.377**	.611**	.733**	-.356**
17. Work Engagement G-factor (T1)	.927	.049	.045	.055	-.060	.498**	-.531**	-.476**	-.329**	-.430**	-.512**	.392**
18. Vigor S-factor (T1)	.439	-.102**	-.024	-.074*	.087**	.539**	-.237**	-.030	.014	-.062*	.002	.511**
19. Dedication S-factor (T1)	.409	-.034	-.047	-.014	-.006	.074*	-.171**	-.152**	-.114**	-.158**	-.133**	.108**
20. Absorption S-factor (T1)	.189	-.003	.017	.078*	-.062	-.048	.266**	.291**	.133**	.171**	.192**	-.055
21. Burnout G-factor (T1)	.928	.010	.036	-.071*	.080*	.506**	-.481**	-.401**	-.260**	-.364**	-.401**	.524**
22. Emotional Exhaustion S-factor (T1)	.856	-.097**	-.033	.116*	-.097**	.435**	-.204**	-.032	.012	-.059	.039	.556**
23. Cynicism S-factor (T1)	.245	-.030	-.081*	-.051	.039	-.127**	.048	.029	.021	.027	.015	-.042
24. Professional Efficacy S-factor (T1)	.811	-.050	-.020	.013	-.019	-.029	.223**	.265**	.110**	.178**	.180**	-.012
25. Work Engagement G-factor (T2)	.927	-.030	-.067*	.059	-.072*	-.390**	.488**	.453**	.289**	.357**	.444**	-.315**
26. Vigor S-factor (T2)	.439	.051	.055	-.078*	.076	-.146**	.128**	.087**	.015	.050	.003	-.184**
27. Dedication S-factor (T2)	.409	-.068*	-.046	-.004	-.017	.067*	.058	.150**	.110**	.077*	.161**	.110**
28. Absorption S-factor (T2)	.189	-.049	.022	.082**	-.086**	.163**	-.053	-.024	-.058	-.011	-.006	.166**
29. Burnout G-factor (T2)	.922	-.034	-.089**	-.050	.066*	-.371**	.421**	.380**	.210**	.322**	.340**	-.369**
30. Emotional Exhaustion S-factor (T2)	.856	.050	.044	.074*	-.078*	-.108**	.056	.033	-.007	-.013	-.066*	-.157**
31. Cynicism S-factor (T2)	.203	-.058	-.070*	-.010	-.027	.018	.081*	.170**	.105**	.101**	.176**	.050
32. Professional Efficacy S-factor (T2)	.811	-.082**	-.004	.044	-.059	.156**	-.017	.013	.003	.000	.025	.188**

Note. *p < .05; **p < .01; variables 5 to 32 are factor scores saved from preliminary measurement models in standardized units (M = 0; SD = 1); § factors taken from a bifactor model are orthogonal (uncorrelated).

Table S11 (Continued 1)

Correlations and Composite Reliability (ω) for all Variables

	12	13	14	15	16	17	18	19	20	21	22
12. Control (T2)	-										
13. Rewards (T2)	.695**	-									
14. Community (T2)	.435**	.541**	-								
15. Fairness (T2)	.716**	.662**	.560**	-							
16. Values (T2)	.619**	.569**	.562**	.731**	-						
17. Work Engagement G-factor (T1)	-.449**	-.428**	-.319**	-.373**	-.427**	-					
18. Vigor S-factor (T1)	-.281**	-.093**	-.061	-.119**	-.108**	0§	-				
19. Dedication S-factor (T1)	-.161**	-.165**	-.103**	-.134**	-.111**	0§	0§	-			
20. Absorption S-factor (T1)	.245**	.251**	.114**	.171**	.158**	0§	0§	0§	-		
21. Burnout G-factor (T1)	-.549**	-.482**	-.363**	-.425**	-.506**	.769**	.270**	.151**	-.147**	-	
22. Emotional Exhaustion S-factor (T1)	-.287**	-.090**	-.024	-.118**	-.078*	.048	.704**	-.019	.018	0§	-
23. Cynicism S-factor (T1)	-.054	-.063*	-.033	-.052	-.084**	-.201**	-.101**	.300**	-.029	0§	0§
24. Professional Efficacy S-factor (T1)	.244**	.312**	.178**	.227**	.202**	-.154**	.198**	-.160**	.722**	0§	0§
25. Work Engagement G-factor (T2)	.418**	.411**	.281**	.318**	.360**	-.770**	-.036	-.009	.487**	-.641**	-.022
26. Vigor S-factor (T2)	.153**	.106**	.015	.081*	.005	-.041	-.113**	.042	.198**	-.054	-.160**
27. Dedication S-factor (T2)	.017	.105**	.079*	.031	.098**	-.175**	.262**	-.025	.298**	-.084**	.250**
28. Absorption S-factor (T2)	-.079*	-.075*	-.070*	-.039	-.027	.046	.110**	.104**	.152**	.088**	.110**
29. Burnout G-factor (T2)	.480**	.461**	.330**	.396**	.431**	-.611**	-.099**	-.083**	.398**	-.739**	-.087**
30. Emotional Exhaustion S-factor (T2)	.091**	.069*	-.009	.039	-.036	.060	-.113**	-.002	.061	-.006	-.151**
31. Cynicism S-factor (T2)	.085**	.174**	.123**	.090**	.162**	-.205**	.221**	-.079*	.268**	-.198**	.242**
32. Professional Efficacy S-factor (T2)	-.071*	-.059	-.017	-.032	.003	-.005	.153**	.075*	.140**	.051	.158**

Note. *p < .05; **p < .01; variables 5 to 32 are factor scores saved from preliminary measurement models in standardized units (M = 0; SD = 1); § factors taken from a bifactor model are orthogonal (uncorrelated).

Table S11 (Continued 2)

Correlations and Composite Reliability (ω) for all Variables

	23	24	25	26	27	28	29	30	31	32
23. Cynicism S-factor (T1)	-									
24. Professional Efficacy S-factor (T1)	0§	-								
25. Work Engagement G-factor (T2)	.167**	.408**	-							
26. Vigor S-factor (T2)	.014	.126**	0§	-						
27. Dedication S-factor (T2)	-.033	.253**	0§	0§	-					
28. Absorption S-factor (T2)	.011	.086**	0§	0§	0§	-				
29. Burnout G-factor (T2)	.072*	.518**	.797**	.113**	-.008	.021	-			
30. Emotional Exhaustion S-factor (T2)	.058	.127**	-.039	.681**	-.208**	-.263**	.049	-		
31. Cynicism S-factor (T2)	-.072*	.302**	.172**	-.302**	.935**	-.237**	.126**	-.252**	-	
32. Professional Efficacy S-factor (T2)	.090**	.183**	.105**	-.288**	.129**	.590**	.066*	-.076*	-.069*	-

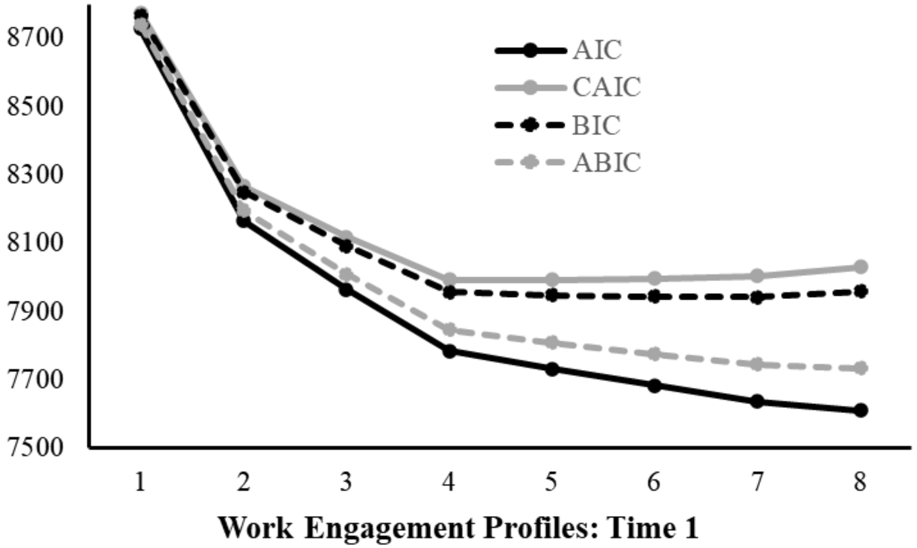
Note. *p < .05; **p < .01; variables 5 to 32 are factor scores saved from preliminary measurement models in standardized units (M = 0; SD = 1); § factors taken from a bifactor model are orthogonal (uncorrelated).

Table S12

Results from the Work Engagement Latent Profile Analysis Models Estimated Separately at Each Time Point

Model	LL	#fp	Scaling	AIC	CAIC	BIC	ABIC	Entropy	aLMR	BLRT
Work Engagement: Time 1										
1 Profile	-4356.085	8	1.4127	8728.170	8775.424	8767.424	8742.015	Na	Na	Na
2 Profiles	-4066.053	17	1.1089	8166.106	8266.521	8249.521	8195.528	.614	< .001	< .001
3 Profiles	-3956.575	26	1.2082	7965.150	8118.726	8092.726	8010.148	.736	< .001	< .001
4 Profiles	-3857.764	35	1.2781	7785.528	7992.264	7957.264	7846.102	.793	.012	< .001
5 Profiles	-3822.164	44	1.2933	7732.328	7992.225	7948.225	7808.479	.741	.079	< .001
6 Profiles	-3789.029	53	1.2515	7684.058	7997.116	7944.116	7775.786	.683	.062	< .001
7 Profiles	-3756.715	62	1.1619	7637.429	8003.648	7941.648	7744.733	.705	.255	< .001
8 Profiles	-3734.242	71	1.2734	7610.484	8029.864	7958.864	7733.364	.714	.346	< .001
Work Engagement: Time 2										
1 Profile	-3929.218	8	1.3989	7874.435	7921.689	7913.689	7888.281	Na	Na	Na
2 Profiles	-3630.909	17	1.1031	7295.818	7396.233	7379.233	7325.240	.595	< .001	< .001
3 Profiles	-3580.104	26	1.1707	7212.208	7365.783	7339.783	7257.206	.688	.048	< .001
4 Profiles	-3546.418	35	1.1533	7162.835	7369.572	7334.572	7223.410	.753	.794	.666
5 Profiles	-3520.391	44	1.3283	7128.783	7388.680	7344.680	7204.934	.641	.922	1.000
6 Profiles	-3496.859	53	1.2276	7099.718	7412.776	7359.776	7191.445	.606	.669	1.000
7 Profiles	-3448.145	62	1.1183	7020.291	7386.510	7324.510	7127.594	.662	.330	< .001
8 Profiles	-3425.670	71	1.1031	6993.339	7412.719	7341.719	7116.219	.637	.457	.140
Burnout: Time 1										
1 Profile	-4897.578	8	1.1549	9811.155	9858.449	9850.449	9825.041	Na	Na	Na
2 Profiles	-4643.809	17	1.0688	9321.617	9422.117	9405.117	9351.124	.604	< .001	< .001
3 Profiles	-4544.640	26	1.1797	9141.281	9294.986	9268.986	9186.409	.717	.004	< .001
4 Profiles	-4509.339	35	1.1775	9088.679	9295.590	9260.590	9149.428	.729	.069	< .001
5 Profiles	-4472.238	44	1.1665	9032.476	9292.593	9248.593	9108.846	.710	.031	< .001
6 Profiles	-4446.168	53	1.0890	8998.336	9311.659	9258.659	9090.327	.722	.040	< .001
7 Profiles	-4420.118	62	1.0727	8964.236	9330.764	9268.764	9071.848	.746	.050	< .001
8 Profiles	-4407.357	71	1.0316	8956.714	9376.448	9305.448	9079.948	.760	.244	.077
Burnout: Time 2										
1 Profile	-4372.278	8	1.3679	8760.556	8807.850	8799.850	8774.441	Na	Na	Na
2 Profiles	-4055.210	17	1.1926	8144.420	8244.920	8227.920	8173.927	.614	< .001	< .001
3 Profiles	-3990.760	26	1.6043	8033.521	8187.226	8161.226	8078.648	.643	.390	< .001
4 Profiles	-3950.060	35	1.4066	7970.120	8177.031	8142.031	8030.869	.627	.158	< .001
5 Profiles	-3905.587	44	1.2113	7899.173	8159.290	8115.290	7975.543	.650	.068	< .001
6 Profiles	-3865.576	53	1.3838	7837.152	8150.475	8097.475	7929.144	.668	.449	< .001
7 Profiles	-3827.757	62	1.4008	7779.515	8146.043	8084.043	7887.127	.646	.788	< .001
8 Profiles	-3802.795	71	1.1874	7747.590	8167.324	8096.324	7870.823	.675	.133	< .001

Note. LL = Loglikelihood; #fp = Free parameters; Scaling = Scaling correction factor; AIC = Akaïke information criterion; CAIC = Consistent AIC; BIC = Bayesian information criterion; ABIC = Sample size adjusted BIC; aLMR = Adjusted Lo-Mendel-Rubin likelihood ratio test; BLRT = Bootstrap likelihood ratio test; NA = not applicable.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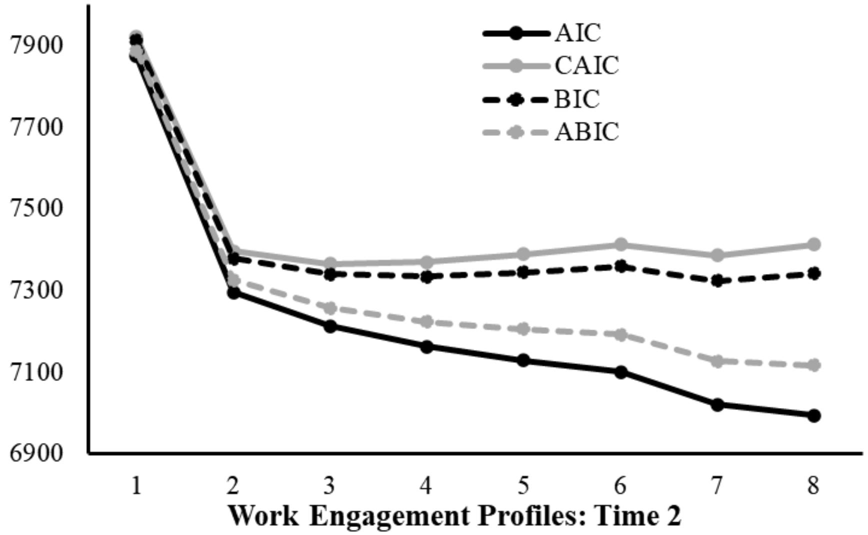
Work Engagement Profiles: Time 1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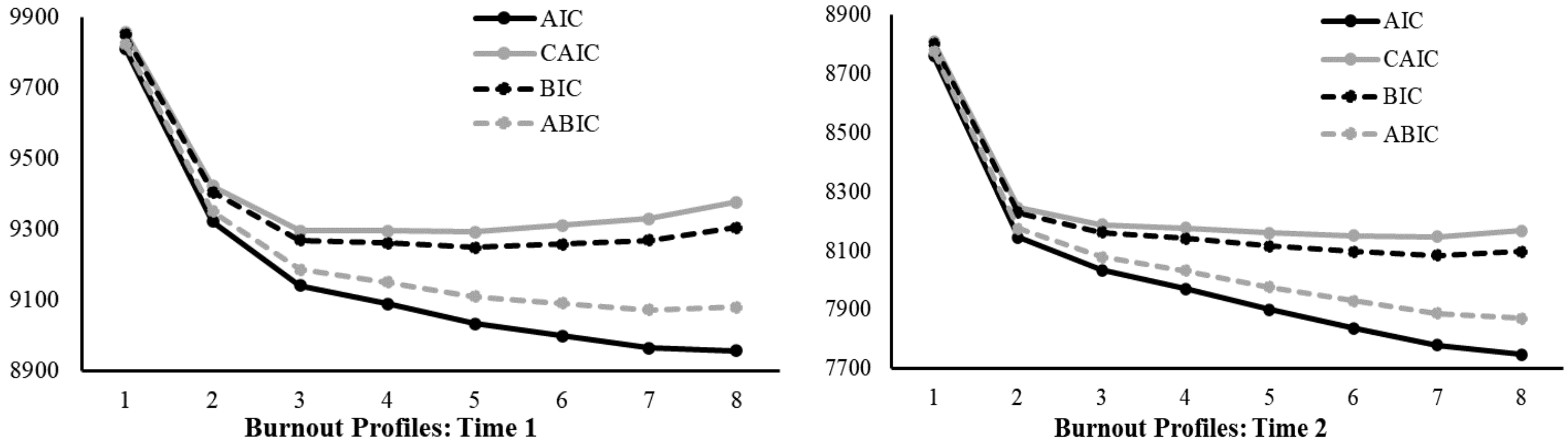

Figure S1. *Elbow Plot of Associated with the Alternative Time-Specific Latent Profile Solutions*

Table S13

Final Longitudinal Latent Profile Solution for Work Engagement (Distributional Similarity)

	Profile 1 Mean [CI]	Profile 2 Mean [CI]	Profile 3 Mean [CI]
Work Engagement G-Factor	.500 [.492; .508]	-.691 [-.819; -.562]	.460 [.379; .542]
Vigor S-Factor	.339 [.325; .354]	-.053 [-.137; .032]	.022 [-.019; .062]
Dedication S-Factor	-.182 [-.234; -.130]	-.032 [-.114; .051]	.035 [-.002; .073]
Absorption S-Factor	.212 [.177; .248]	-.105 [-.181; -.030]	.058 [.020; .096]
	Variance [CI]	Variance [CI]	Variance [CI]
Work Engagement G-Factor	.000 [.000; .001]	.851 [.733; .969]	.317 [.265; .370]
Vigor S-Factor	.002 [.001; .003]	.776 [.646; .885]	.187 [.157; .216]
Dedication S-Factor	.012 [.000; .024]	.630 [.504; .756]	.162 [.138; .187]
Absorption S-Factor	.007 [.003; .012]	.720 [.616; .824]	.176 [.146; .205]

Note. The profile indicators are factor scores estimated in standardized units (M = 0; SD = 1); CI = 95% confidence interval; Profile 1 = Vigorously Engaged; Profile 2 = Disengaged; Profile 3 = Engaged.

Table S14

Final Longitudinal Latent Profile Solution for Burnout (Partial Structural Similarity, Partial Dispersion Similarity, and Distributional Similarity)

	Profile 1 Mean [CI]	Profile 2 Mean [CI]	Profile 3 Time 1 Mean [CI]	Profile 3 Time 2 Mean [CI]
Burnout G-Factor	.512 [.413; .610]	-1.057 [-1.116; -.998]	-.392 [-.474; -.310]	-.392 [-.474; -.310]
Emotional Exhaustion S-Factor	.250 [.162; .337]	-.458 [-.587; -.328]	-.166 [-.246; -.086]	-.166 [-.246; -.086]
Cynicism S-Factor	.033 [-.022; .089]	.032 [-.043; .107]	-.001 [-.033; .030]	-.001 [-.033; .030]
Professional Efficacy S-Factor	-.093 [-.177; -.009]	.796 [.668; .923]	***-.090 [-.193; .013]***	***.002 [-.075; .079]***
	Variance [CI]	Variance [CI]	Variance [CI]	Variance [CI]
Burnout G-Factor	.852 [.753; .952]	.023 [.011; .034]	169 [.130; .207]	.169 [.130; .207]
Emotional Exhaustion S-Factor	.973 [.864; 1.081]	.169 [.079; .259]	***.379 [.262; .495]***	***.231 [.159; .303]***
Cynicism S-Factor	.574 [.500; .647]	.069 [.034; .104]	***.253 [.196; .309]***	***.049 [.029; .070]***
Professional Efficacy S-Factor	.925 [.818; 1.032]	.087 [.033; .141]	***.390 [.298; .482]***	***.271 [.212; .330]***

Note. The profile indicators are factor scores estimated in standardized units (M = 0; SD = 1); CI = 95% confidence interval; Profile 1 = Burned-out; Profile 2 = Adapted; Profile 3 = Normative; parameters freely estimated over time are in bold italic.

Table S15

Results from the Latent Transition Analyses with the Demographics

Description	LL	#fp	Scaling	AIC	CAIC	BIC	ABIC
LTA with Demographics: Work Engagement T1 - Burnout T1							
Null Effects Model	-4131.440	22	1.3957	8306.879	8439.733	8417.733	8347.854
Free Effects on Profile Membership and Transitions	-4115.289	38	1.2593	8306.578	8536.052	8498.052	8377.353
Free Effects on Profile Membership	-4110.256	62	.8504	8344.512	8718.916	8656.916	8459.985
LTA with Demographics: Work Engagement T2 - Burnout T2							
Null Effects Model	-4023.280	22	1.3508	8090.560	8223.413	8201.413	8131.535
Free Effects on Profile Membership	-4011.572	38	1.2245	8099.144	8328.617	8290.617	8169.918
Free Effects on Profile Membership and Transitions	-4000.232	62	.8134	8124.464	8498.868	8436.868	8239.938
LTA with Demographics: Work Engagement T1 - Work Engagement T2							
Null Effects Model	-3843.482	22	1.3105	7730.965	7863.818	7841.818	7771.939
Free Effects on Profile Membership	-3830.527	38	1.1513	7737.054	7966.528	7928.528	7807.829
Free Effects on Profile Membership and Transitions	-3826.949	62	.7908	7777.899	8152.303	8090.303	7893.372
Predictive Similarity (equality over time)	-3837.543	30	1.2419	7735.087	7916.250	7886.250	7790.961
LTA with Demographics: Burnout T1 – Burnout T2							
Null Effects Model	-4163.541	22	1.3915	8371.082	8503.935	8481.935	8412.057
Free Effects on Profile Membership	-4154.857	38	1.2811	8385.713	8615.187	8577.187	8456.487
Free Effects on Profile Membership and Transitions	-4149.710	62	.9297	8423.419	8797.824	8735.824	8538.893
Predictive Similarity (equality over time)	-4158.953	30	1.2901	8377.905	8559.069	8529.069	8433.780
LTA with Demographics: Work Engagement T1 – Burnout T2							
Null Effects Model	-4126.230	22	1.3565	8296.460	8429.313	8407.313	8337.434
Free Effects on Profile Membership	-4111.481	38	1.2567	8298.962	8528.436	8490.436	8369.737
Free Effects on Profile Membership and Transitions	-4104.359	62	.8722	8332.718	8707.123	8645.123	8448.192
LTA with Demographics: Burnout T1 - Work Engagement T2							
Null Effects Model	-4107.607	22	1.3883	8259.214	8392.068	8370.068	8300.189
Free Effects on Profile Membership	-4098.315	38	1.3440	8272.631	8502.105	8464.105	8343.405
Free Effects on Profile Membership and Transitions	-4091.033	62	.8670	8306.066	8680.470	8618.470	8421.540

Note. LTA = Latent transition analysis; LL = Loglikelihood; #fp = Free parameters; Scaling = Scaling correction factor; AIC = Akaïke information criterion; CAIC = Consistent AIC; BIC = Bayesian information criterion; ABIC = Sample size adjusted BIC.