A Longitudinal Person-Centered Investigation of the Multidimensional Nature of Employees' Perceptions of Challenge and Hindrance Demands at Work

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Abstract

This research relies on a combination of variable- and person-centered approaches to help improve our understanding of the dimensionality of job demands by jointly considering employees' global levels of job demands exposure and their specific levels of exposure to challenge and hindrance demands. We relied on a sample of 442 workers who completed a questionnaire twice over a three-month period. Our analyses sought to identify the nature of the job demands profiles experienced by these workers, to document the stability of these profiles over time, and to assess their associations with theoretically-relevant outcomes (i.e., work engagement, job boredom, problem-solving pondering, work-related rumination, proactive health behaviors, and sleep quality and quantity). Furthermore, we examined whether these profiles and associations differed as a function of working remotely or onsite. Five profiles were identified and found to be highly stable over time: Globally Exposed, Not Exposed, Not Exposed but Challenged, Exposed but Not Challenged, and Mixed. These profiles shared clear associations with all outcomes, with the most adaptive outcomes associated with the Exposed but Not Challenged profile, whereas the most detrimental ones were observed in the Mixed profile. However, none of these results differed across employees working onsite and those working remotely.

Key words: Job demands; latent transition analyses; work engagement; sleep; recovery; bifactor models

Introduction

The generally harmful impact of job demands (e.g., work interruptions, role ambiguity) has received a lot of scientific attention (e.g., Gonzalez-Mulé et al., 2021; Webster & Adams, 2020). The job demands-resources model (Bakker & Demerouti, 2017) defines demands as job features requiring employees to expand psychological and/or physical efforts in an ongoing manner, and which take a toll on exposed employees. LePine et al. (2005) further noted that not all job demands are harmful and highlighted the need to differentiate hindrances (demands that obstruct personal growth and goal attainment, leading to a health-impairment process) from challenges (demands that provide opportunities for growth, achievement, and learning, leading to a motivational process). However, employees could describe their job demands exposure more holistically, according to a single global dimension (a single score encompassing all types of job demands; Gonzalez-Mulé et al., 2021; Kraimer et al., 2022). This global representation is supported by moderately high correlations between different types of job demands (Gillet et al., 2019; Schilbach et al., 2021), and by the demonstration of stronger associations with outcomes when job demands are defined globally (Bakker et al., 2005; Le Blanc et al., 2001). These observations raise important theoretical questions regarding whether: (a) exposure to challenge and hindrance demands retain specificity beyond the consideration of global levels of job demands; and (b) ratings of exposure to challenge and hindrance demands form one overarching dimension while retaining specificity uniquely associated with each type of job demands, or whether both types of job demands form correlated dimensions without a common core (Morin et al., 2016b, 2017a). Bifactor models can support a more thorough investigation of these theoretical questions (Gillet et al., 2019; Huyghebaert-Zouaghi et al., 2022a).

Moreover, research on job demands has primarily adopted a variable-centered approach, and thus focused on the isolated, additive, or interactive associations between job demands, predictors, and outcomes. Variable-centered approaches also assume that all participants come from the same population for which results can be summarized by a set of "average" parameters. This approach is incompatible with the theoretical recognition that job demands do not occur in a vacuum, that employees typically experience them in combinations, and that these combinations play a determining role on their impact (Crawford et al., 2010). Although traditional variable-centered analyses are able to test for interactions among predictors (e.g., to see if the effect of a challenge differ as a function of a hindrance), these approaches are unable to fully depict the joint effects of variable combinations involving more than two or three interacting predictors (Gillet et al., 2018), as is the focus of the present study (i.e., global job demands, specific challenge demands, and specific hindrance demands). Importantly, interaction analyses are based on the assumption that the effects of one dimension vary linearly as a function of the other one, and testing for potential nonlinearity (Edwards, 2009) greatly complicates interpretations based on more than two interacting predictors (Marsh et al., 2009). Lastly, the variable-centered approach still assumes that interactions equally apply to the whole population, thereby ignoring the possible presence of subpopulations experiencing different associations.

More consistent with these theoretical propositions, person-centered analyses identify subpopulations of workers exposed to qualitatively distinct configurations of job demands and should help us to achieve a clearer theoretical understanding of job demands profiles (Meyer & Morin, 2016). For instance, would high levels of hindrance demands be as problematic for employees on their own or when combined with equally high levels of challenge demands? It remains critical to acknowledge that variable-centered (e.g., regressions, latent interactions) and person-centered (e.g., latent profile analyses; LPA) approaches remain complementary ways to investigate the joint combined effects of global and specific levels of challenge and hindrance demands in the prediction of outcomes. Just like in the analogy of the blind person having to touch different parts of an elephant to identify it as an elephant (rather than as a tree, a cow or a snake), these approaches reveal differentiated, and yet complementary, views of the same underlying phenomenon (Gillet et al., 2018).

In the only previous study focusing solely on job demands, Li et al. (2022) studied employees' appraisals of job demands (i.e., they indicated to what extent they considered their job demands as challenges or hindrances), rather than on their perceptions of exposure to global and specific levels of challenge and hindrance demands (i.e., reporting their exposure to both types of demands) as in the present study. As a result of this relative lack of research, it is still impossible to properly assess the validity of some critical theoretical propositions from the job demands-resources model (Bakker & Demerouti, 2017; Crawford et al., 2010; LePine et al., 2005), which assumes the presence of two complementary, but not fully independent, health-impairment and motivational processes. More specifically, Crawford et al. (2010) showed that challenge and hindrance demands were both associated with high levels of burnout (i.e., a health-impairment process), but that only challenge demands had a positive effect on work engagement (i.e., a motivational process). Nevertheless, at this stage, we do not know what combination of challenge and hindrance demands might better reflect the health-impairment process. Are high scores on both dimensions associated with the most harmful outcomes? Would high levels of exposure to hindrance demands coupled with moderate levels of challenge demands lead to similar effects? Likewise, is the combination of high levels of challenge demands and low levels of hindrance demands be most favorable for employees' work engagement?

This study seeks to achieve five important contributions. First, we rely on a bifactor examination of job demands perceptions to achieve a more accurate separation of the variance attributed to global and specific levels of challenge and hindrance demands, and thus a better understanding of the unique and complementary role of both type of job demands. Second, to better understand how job demands truly combine in the lives of employees, we rely on a person-centered approach to identify a core set of profiles exposed to various levels of global and specific job demands perceptions. Third, we not only document the nature of the job demands profiles observed among a sample of employees, we also consider whether the same set of profiles will be estimated over a three-month period (within-sample similarity) and whether employees' membership into specific profiles will remain unchanged over time (within-person stability; Morin et al., 2016c). In doing so, we expand upon Li et al.'s (2022) longitudinal results while considering a shorter time interval of one trimester (rather than one year). Fourth, we extend Li et al.'s (2022) findings by relying on a Western sample and considering a broader range of outcomes. Fifth, we address the paucity of research examining the unique work experiences of remote workers (Huyghebaert-Zouaghi et al., 2022a) relative to that of onsite workers. More precisely, we examine whether the nature of the profiles, their stability, and their outcomes differ as a function of working remotely or onsite. This is an important concern as work settings have changed rapidly and substantially since the COVID-19 outbreak (Wang et al., 2021), making it vital for organizations to grasp whether and how job demands exposure and influence differ across remote and onsite workers (Charalampous et al., 2019).

This study specifically aims to: (1) achieve a more refined person-centered understanding of the nature and stability of the job demands profiles observed among a sample of employees; (2) document the construct validity of these profiles by examining their associations with theoretically-relevant outcomes; and (3) determine whether the nature, stability and outcomes of the profiles differ as a function of working remotely or onsite. The four research questions guiding this study are: (a) Can distinct job demands profiles with different levels of global and specific challenge and hindrance demands be identified? (b) Will similar profiles be identified over time, and will employees retain a similar profile over time? (c) Will the strength and direction of the associations between job demands profiles and outcomes align with theoretical expectations? (d) To which extent will the results to the three previous questions generalize to employees working remotely or onsite?

From a practical perspective, person-centered results are more naturally aligned with managers and practitioners' tendency to think about employees in terms of categories (person-centered) rather than in terms of complex variable associations (variable-centered; Morin et al., 2011, 2018). Person-centered results allow for the identification of employee profiles associated with more, or less, desirable outcomes, which can then be targeted for intervention. Evidence of within-sample and within-person stability are also key requirements of person-centered interventions, given that rigid or ephemeral profiles are unlikely to be useful from an intervention perspective (Sandrin et al., 2020). As with any longitudinal research designed to guide intervention, one needs to assess the extent to which conclusions obtained using one specific timeframe generalize to other timeframes (Cole & Maxwell, 2003), as evidence of variation is likely to help determine the optimal duration of intervention efforts.

A Person-Centered Perspective on Job Demands

Person-centered research allows for the identification of different profiles of employees exposed to quantitatively and qualitatively distinct job demands configurations (Meyer & Morin, 2016). In this regard, the job demands-resources model (Bakker & Demerouti, 2017) has always assumed that employees could be exposed to unique configurations of job demands (e.g., high levels of hindrances coupled with equally high levels of challenges, low levels of both types of demands, or a profile dominated by a high level of hindrances and a low level of challenges), and that the specific effects of these demands are unlikely to be adequately captured by their isolated consideration.

More specifically, each type of demand is likely to create a context that could modify the experience of other demands. For instance, when employees face high levels of hindrance demands, they may feel that they will never be able to succeed in their professional tasks, as they work in an environment that exhausts and demotivates them (Crawford et al., 2010). They feel that everything they must do is complicated and have a negative judgment on their work characteristics. In such a situation, resignation and disengagement prevail, and employees are unable to identify motivational levers that enable them to bounce back and experience pleasure and satisfaction in their work (LePine et al., 2005). In this context, even when stimulating opportunities captured by challenges demands present themselves, these employees may be unable to benefit from opportunities given the harmful nature of their high levels of exposure to hindrance demands (e.g., Hobfoll, 2002). In contrast, when exposed to low levels of hindrances, the same employees might apprehend the same challenges in a totally different manner. More precisely, despite the difficulties they may encounter on a day-to-day basis, these employees may find that these challenges are particularly stimulating and provide an opportunity for them to develop, while anticipating future gains in their future professional careers (Crawford et al., 2010). Lastly, employees already stimulated by high levels of challenges may also be better able to reframe hindrances as one of many obstacles that they have to overcome to benefit from opportunities, rather than as an all-encompassing impediment to efficient functioning. More generally, by relying on a person-centered approach and identifying profiles presenting different combinations of challenge and hindrance demands, we do not focus on the isolated effects of job demands, but rather on their combined effects, thus providing a better understanding of how these job demands influence employees' functioning (Morin et al., 2017a).

Person-centered research has recently started to look at how challenge and hindrance demands combine. However, most studies have relied on a mixture of job demands and additional constructs (e.g., job resources; Collie et al., 2020, 2021; Moeller et al., 2018) in their profile definition, which makes it impossible to identify the job demands configurations occurring independently from these additional dimensions. Indeed, by considering job demands and resources together, we can identify the different combinations of demands and resources experienced by employees, but the results from this approach will by no means be specific to the different configurations of demands they perceive. For instance, this approach could reveal profiles displaying similar levels of challenges and hindrances and differing from one another solely in terms of resources. As resources are conceptually positioned as moderators of the effects of demands (i.e., they are not positioned at the same level of the theoretically causal chain; Bakker & Demerouti, 2017), this confounding is likely to interfere with our ability to properly understand the combined role of job demands, in and of themselves. To do this, we need to focus solely on job demands, as done in the present study, rather than to jointly focus on other dimensions in the identification of profiles. Similarly, if our objective had been to identify job resources profiles, we would not have had to consider other variables such as job demands.

Li et al. (2022) focused on workers' appraisals of job demands and identified three profiles of employees: (1) low challenge and high hindrance (26% of the sample at Time 1 and 54% at Time 2); (2) high challenge and low hindrance (12% at Time 1 and 11% at Time 2); and (3) low challenge and low hindrance (62% at Time 1 and 36% at Time 2). However, these studies have all ignored the dual global and specific nature of job demands. When applying person-centered analyses to indicators known to present a global and specific structure, Morin et al. (2016b, 2017a) showed that relying on profile indicators that fail to properly differentiate these global and specific components was likely to result in the erroneous estimation of profiles characterized by matching levels across indicators (e.g., such as the *low challenge and low hindrance* profile identified by Li et al., 2022). These profiles then simply reflect the role played by employees' levels of job demands exposure across both types of demands, thus hiding the unique role of challenges and hindrances. Given that any demand can be appraised in both ways (Webster et al., 2011), achieving a clear disaggregation of employees' global (job demands) and specific (challenge vs hindrance) demands is likely to be highly important to our understanding of the role played by both types of demands.

Job demands profiles may differ in terms of quantity (quantitatively: similar scores across all components) or configuration (qualitatively: distinct patterns of high, low, and average scores on the various components). In this study, quantitative differences would reveal distinctions linked to the global level of job demands across dimensions (i.e., globally high, moderate, or low), whereas qualitative differences would reveal distinctions linked to the relative importance of specific types of job demands (i.e., challenges and hindrances) beyond their common core. In either case, a person-centered approach would provide a more holistic picture of employees' job demands exposure.

Theoretical Person-Centered Scenarios

Keeping in mind the importance of disaggregating these global and specific components, a key challenge for research seeking to understand how these components co-occur among distinct types of employees is related to the lack of previous theorization specifically focused at identifying the nature and psychological underpinning of these job demands profiles. In line with Lazarus and Folkman's (1984) transactional model of stress and coping, employees can be expected to appraise job demands as challenging and/or hindering, an assertion that has been previously validated (Kronenwett & Rigotti, 2019; Li et al., 2020). From a purely empirical perspective, it is noteworthy that despite their reliance on a variety of samples, methods, and indicators, the bulk of person-centered evidence also seems to suggest the presence of four profiles characterized by different levels of exposure to both types of demands. More precisely, person-centered results generally reveal a High Challenge and Low Hindrance Demands, a Low Challenge and High Hindrance Demands, a High Demands, and a Moderate Demands configuration (Collie et al., 2020, 2021; Li et al., 2022; Moeller et al., 2018).

On this basis, we propose a theoretical typology designed to provide a heuristic framework for researchers and practitioners. A first scenario focuses on primarily ***Challenged*** employees, reporting exposure to high levels of challenges and low levels of hindrances. These employees report being exposed to meaningful job demands likely to help them improve their competence and achievement (Crawford et al., 2010). These employees thus report exposure to the type of job demands that is most likely to result in the theoretical motivational process outlined by Crawford et al. (2010) and may thus experience primarily desirable outcomes as a result of their job demands exposure. A second scenario characterizes primarily ***Hindered*** employees, reporting exposure to high levels of hindrances and low levels of challenges. These employees report being exposed to demands that are hard to overcome and that interfere with their growth and development. These employees thus report exposure to a type of job demands that is most likely to result in the theoretical health-impairment process outlined by Crawford et al. (2010), which should lead them to the experience of a resource loss spiral (Bakker & Demerouti, 2017) which could progressively sap their ability to see any new demand as challenges. A third scenario focuses on ***Highly Exposed*** employees, reporting a high exposure to challenges and hindrances. These employees report being exposed to job demands that are simultaneously challenging and hindering, thus providing them with an opportunity for growth coupled with a risk for loss. In this scenario, challenge perceptions should help employees to avoid adopting a pure health-impairment process and falling in a resource loss spiral, at least as long as some of these challenges can eventually be overcome before all of their resources are expanded (Bakker & Demerouti, 2017). Finally, a fourth scenario involves ***Moderately Exposed*** employees, reporting a moderate exposure to both types of job demands. These employees report being exposed to a moderately demanding work context that neither strongly hinders their functioning, nor stimulates their growth. This is consistent with prior person-centered research focusing on other work-related constructs (e.g., Gillet et al., 2019; Morin et al., 2017a), which has shown that for many employees, work do not involve extreme types of experiences, being more aligned with a normative routine.

Investigation of these theoretical scenarios necessitate person-centered analyses, which should result in important empirical insights into the relevance of these scenarios to properly represent the nature of the job demands configurations reported by employees. Based on these theoretical propositions and empirical evidence, we propose that:

Hypothesis 1. At least four profiles will be identified: *Challenged*, *Hindered*, *Highly Exposed*, and *Moderately Exposed* profiles.

A Longitudinal Person-Centered Perspective

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 profiles of employees. Indeed, just like too much stability entails that intervention efforts are likely to be particularly demanding, too much variability means that interventions effects are unlikely to be maintained. In this regard, the present study examines the extent to which the identified job demands profiles remain stable over a period of three months. We selected this specific time lag based on theoretical, methodological, and empirical considerations. Prior studies conducting longitudinal research related to the effects of job demands vary substantially in their chosen time lags (Lesener et al., 2019), from a few days to many years (e.g., Casper & Wehrt, 2022; Tuckey et al., 2015). However, beyond this diversity, other studies have also selected a three-month interval as being particularly relevant to our understanding of the effects of job demands (e.g., Crane & Searle, 2016; Huyghebaert-Zouaghi et al., 2022a). Indeed, this specific time lag is suitable because it goes beyond daily fluctuations, while remaining short enough to capture changes that might be missed over longer time spans (Dormann & Griffin, 2015). It thus facilitates examinations of the dynamism and pace of within-person changes (Kaltiainen et al., 2020). Furthermore, job demands are known to evolve over time, and to be modifiable via relatively short interventions (Hulshof et al., 2020), making it important to study them when considering time intervals relevant to these interventions. Lastly, past investigations have shown that employees' functioning (e.g., work engagement, work-related rumination) can fluctuate over periods as short as three months (e.g., Cheyroux et al., 2023; Gillet et al., 2021b). We thus assumed that a three-month period would be appropriate.

Two distinct forms of longitudinal stability can, and should, be considered (Huyghebaert-Zouaghi et al., 2022a; Sandrin et al., 2020). First, within-sample stability focuses on the nature of the profiles themselves, which can change over time. For example, the number or structure of the profiles could change over time, which would involve that the profiles have a limited utility for intervention as they seem to reflect mainly transient phenomena or that the sample under consideration has recently been exposed to some rather important internal or external changes. Morin et al. (2016c) refer to these two forms of within-sample stability as configural (same number of profiles) and structural (profiles with the same nature) similarity. In contrast, time may alternatively lead to a change in the degree of similarity among profile members (dispersion similarity), or in profile size (distributional similarity). These two forms of within-sample profile stability do not preclude the reliance on person-centered solutions as intervention guides but highlight that the profiles may be reactive to internal or external changes. Second, within-person stability focuses on changes in employees' profile membership over time (Huyghebaert-Zouaghi et al., 2022a; Sandrin et al., 2020) and can be observed in the absence of within-sample changes. These indicators of stability are descriptive, rather than theoretical. Like tests of measurement invariance (Morin et al., 2016c), they concern the generalizability of our solution over time as well as the extent to which we can expect employees to retain the same profile over time.

Empirically, previous research has shown that employees' job demands exposure can change over time as a result of changing work circumstances (Ohly & Fritz, 2010). Despite this acknowledgement, variable-centered longitudinal studies of employees' perceptions of challenge and hindrance demands have generally revealed a high level of stability (reaching 75%) in ratings over periods of two (Tims et al., 2013) to three months (Crane & Searle, 2016). These observations are consistent with the job demands-resources model (Bakker & Demerouti, 2017), which assumes that work circumstances should remain relatively stable over time. Similarly, in their study on workers' appraisals of job demands, Li et al. (2022) reported that membership (i.e., within-person stability) into the *low challenge and high hindrance* (stability of 81%) and *low challenge and low hindrance* (stability of 78%) profiles was highly stable over one year. In contrast, membership in the *high challenge and low hindrance* profile was less stable (stability of 38%), possibly because challenges tend to be resolved over time. Supporting this interpretation, the dominant transitions involved movement toward the *low challenge and low hindrance* profile. Li et al. (2022) also reported evidence supporting the configural, structural, and dispersion within-sample similarity of their profiles, but found that the size of their profiles changed over time. However, this lack of distributional similarity could reflect the high level of attrition of their study (N = 535 at Time 1 and N = 152 at Time 2). Taken together, these empirical and theoretical considerations lead us to expect a high level of within-person stability (≥ 70%; Huyghebaert-Zouaghi et al., 2022b), as well as evidence of configural, structural, and dispersion within-sample similarity. However, given the limited amount of evidence used to support our hypotheses, we leave as open research questions whether the relative size of the profiles (distributional similarity) will change over time, and whether the dominant within-person transitions will also be toward profiles characterized by lower levels of job demands (as in Li et al., 2022) or whether they would also involve profiles characterized by higher levels of job demands or qualitatively distinct profiles presenting similar levels of job demands.

Hypothesis 2. The profiles will display evidence of configural, structural, and dispersion within-sample similarity.

Hypothesis 3. The profiles will display high levels of within-person stability.

A Construct Validation Perspective

Another critical step in the assessment of the construct validity of profiles is to document their theoretical and practical implications via an examination of their associations with theoretically-relevant outcomes (Marsh et al., 2009; Meyer & Morin, 2016). Information on the implications of the profiles in terms of outcomes is critical to the assessment of the true desirability of each profile. It is also a way of identifying the most favorable profiles, so as to implement interventions designed to foster their development. Likewise, identifying the most harmful profiles and capturing their specific nature should also enable to propose tailored interventions to limit the emergence of these profiles. In the present study, we focus on a series of positive and negative indicators of employees' (1) work involvement, including their levels of work engagement (i.e., a positive and fulfilling state of mind encompassing vigor, absorption, and dedication to work; Schaufeli et al., 2019) and job boredom (i.e., an unpleasant state of dissatisfaction and low arousal; Reijseger et al., 2013); (2) work recovery, including problem-solving pondering (i.e., trying to find positive solutions to work-related problems during non-work time; Junker et al., 2021), work-related rumination (i.e., being preoccupied with adverse work-related events during off-job time; Junker et al., 2021), and sleep quality (i.e., the extent to which employees sleep well; Van Laethem et al., 2013) and quantity (i.e., hours of sleep employees get each night; Dietch et al., 2019); and (3) proactive health-related behaviors (i.e., self-initiated preventative measures to improve physical and mental health; Wayne et al., 2020).

These outcomes were selected to achieve a comprehensive understanding of the psychological and physical implications of job demands profiles, as outlined in the job demands-resources model (Bakker & Demerouti, 2017). The undesirable outcomes (i.e., job boredom and work-related rumination) were selected to reflect the health-impairment process proposed by this model, the desirable outcomes (i.e., work engagement, problem-solving pondering, and proactive health-related behaviors) were more aligned with the motivational process, while sleep quality and quantity is likely to be compromised as part of the former process and supported in the latter. These outcomes were also selected given their documented relevance for employees' performance and ability to experience satisfactory career trajectories. Thus, work engagement is recognized as having positive effects on job performance and functioning (e.g., Schaufeli et al., 2019) and is a well-known outcome of job demands (Bakker & Demerouti, 2017). In contrast, job boredom has often been related to reduced performance (Watt & Hargis, 2010) and represents a direct precursor of a wide variety of other undesirable work outcomes (e.g., turnover: Reijseger et al., 2013; absenteeism: Kass et al., 2001). Similarly, poor work recovery tends to be accompanied by various maladaptive outcomes encompassing workers' professional and personal lives (Gillet et al., 2021b; Sonnentag & Fritz, 2015). Moreover, research anchored in the job demands-resources model (Bakker & Demerouti, 2017) has shown that work recovery is important to consider when explaining the effects of job demands on employees' health, attitudes, and behaviors (e.g., Kinnunen et al., 2011). Finally, proactive health behaviors are associated with lower levels of exposure to job demands and more adaptive outcomes at the work-family interface (e.g., work-family enrichment, satisfaction with work-family balance; Wayne et al., 2020), known to contribute to improved well-being and performance at work (Huyghebaert-Zouaghi et al., 2022a).

From a theoretical perspective, the job demands-resources model (Bakker & Demerouti, 2017) proposes that the harmful impact of job demands occurs via a resource depletion mechanism which makes it hard for employees to maintain a satisfactory level of investment at work, to properly recover from work, and to proactively manage their health (e.g., Schaufeli et al., 2019; Sonnentag & Fritz, 2015). More precisely, according to the health-impairment process (Bakker & Demerouti, 2017), employees exposed to high levels of job demands need to devote a lot of time, effort, and cognitive energy to work to properly handle these demands. Yet, the resources available to support this intense investment are limited (Hobfoll, 2002), thus jeopardizing employees' health and ability to maintain a satisfactory investment at work. Moreover, workers exposed to higher levels of job demands also tend to experience feelings of restlessness in their personal life, where they often keep on thinking about work, making it hard for them to properly recover from work (Kinnunen et al., 2017). Supporting these theoretical assertions, research has shown that exposure to higher levels of job demands were associated with multiple detrimental outcomes in (e.g., job boredom) and out (e.g., problem-solving pondering) of work (Crawford et al., 2010; Goering et al., 2017; Howard et al., 2022; Kinnunen et al., 2011, 2017; Van Laethem et al., 2013, 2019; Von Hippel et al., 2019; Yao et al., 2021).

Moreover, whereas challenge demands are expected to help maintain stimulation and involvement, and to help gain resources likely to support more efficient work recovery processes and proactive health behaviors (i.e., the motivational process; Bakker & Demerouti, 2017), hindrance demands are expected to have the opposite effects (Cavanaugh et al., 2000; Crawford et al., 2010; LePine et al., 2005). Indeed, experienced as an opportunity for growth and mastery, challenges should fuel functioning far more than hindrances, which tend to be seen as impeding individual functioning (LePine et al., 2005). Supporting these assertions, meta-analytical reviews (Crawford et al., 2010) and research (Goering et al., 2017; Yao et al., 2021) have demonstrated that challenges tended to be associated with more positive outcomes (e.g., higher work engagement) than hindrances, which generally tend to be associated with more problematic outcomes (e.g., job boredom). Consistent with these findings, Li et al. (2022) demonstrated that the most adaptive outcomes (i.e., higher levels of work engagement and job satisfaction, and lower levels of burnout) were associated with their *high challenge and low hindrance* profile, whereas the other two profiles did not differ from one another.

Based on these considerations, we expect employees characterized by perceptions of being highly exposed to all types of job demands (i.e., the *Highly Exposed* profile) to experience a rather detrimental pattern of outcomes. Yet, this pattern of outcomes should not be as detrimental as that observed for employees perceiving high levels of hindrances without benefiting from some challenges (i.e., the *Hindered* profile; e.g., van Oortmerssen et al., 2020). Finally, we also expect employees primarily exposed to challenging types of demands (i.e., the *Challenged* profile) to experience a generally beneficial pattern of outcomes, although those exposed to lower levels of job demands (*Moderately Exposed*) may display an even more positive pattern of work recovery experiences (Kinnunen et al., 2011; Van Laethem et al., 2013, 2019; Von Hippel et al., 2019). Indeed, *Challenged* workers tend to experience feelings of restlessness in their personal life, where they often keep on thinking about work, making it hard for them to properly recover from work (Kinnunen et al., 2017). They also need to remain in a constant state of activation, forcing them to tap into their personal resources to properly cope with these challenges and making it harder for them to properly recover (Hobfoll, 2002; Sonnentag & Fritz, 2015). We propose that:

Hypothesis 4. The *Challenged* and *Moderately Exposed* profiles should display the most positive outcomes (i.e., higher levels of work involvement, more optimal work recovery processes, and higher levels of proactive health-related behaviors), followed by the *Highly Exposed* profile, and finally by the *Hindered* profile.

Hypothesis 5. The quality of the work recovery experiences should be higher for *Moderately Exposed* employees than for *Challenged* employees.

The Role of Work Type: Remote versus Onsite Work

Previous research has uncovered variations in employees' job demands perceptions as a function of their work setting (Bakker & Demerouti, 2017; Jimmieson et al., 2017). To address this possibility, we examine whether the job demands profiles and their outcome associations generalize to employees working remotely or onsite. Indeed, working remotely could expose employees to new and additional job demands (e.g., Gillet et al., 2022b), which implies that some variations in terms of profiles might be possible. More precisely, working remotely may generate additional role pressures and feelings of personal responsibility likely to entail a rising workload (Gillet et al., 2021a). It also tends to be associated with higher guilt emerging from employees' desire to reciprocate for the flexibility and autonomy afforded by their organization (Sherman, 2020). Remote workers thus often feel the need to be continuously available and to meet organizational expectations, which translates into higher job demands, increased stress, and ongoing difficulties in maintaining a good work-life balance (Huyghebaert-Zouaghi et al., 2022a). Conversely, onsite employees often benefit from more traditional job characteristics, and are thus more likely to have already learned to efficiently cope with these characteristics (Lazarus & Folkman, 1984). They may also benefit from more normative schedules and resourceful work conditions, making it easier for them to find meaning in their job. This reality could lead them to feel exposed to lower levels of job demands than their remote colleagues (Charalampous et al., 2019). Based on these theoretical and empirical considerations, profiles with lower levels of job demands (e.g., *Moderately Exposed*) should thus be less prevalent among remote employees, while profiles with higher levels of job demands (e.g., *Highly Exposed*) should be more prevalent. More precisely, we propose that:

Hypothesis 6: Working remotely should predict a lower likelihood of membership into the

Moderately Exposed profile relative to the other profiles.

In terms of outcomes, research has revealed that working remotely contributed to maximize the effects of both hindrance and challenge demands (Huyghebaert-Zouaghi et al., 2022a). Because working remotely provides employees with more flexibility in the accomplishment of their work activities (Sherman, 2020), this setting should also provide them with more resources to seize growth opportunities and to reap the benefits of challenging job demands. However, in line with recent theoretical developments connected to the job demands-resources model, hindering job demands are more likely to interact with personal/home demands in remote settings, leading to an amplification of their undesirable effects (Demerouti & Bakker, 2022). In contrast, the clearer boundaries between the work and family domains experienced by onsite employees (Wang et al., 2021) should increase their ability to cope with job demands more generally, and hindrances more specifically (e.g., Huyghebaert-Zouaghi et al., 2022a). In sum, these considerations suggest that:

Hypothesis 7. The associations between the profiles and the outcomes should be more pronounced for remote employees than for their colleagues working onsite.

Method

Participants and Procedure

Participants were invited to complete an online questionnaire twice over a period of three months via the Prolific Academic crowdsourcing platform. Participants were informed of the objectives of the research, told that participation was voluntary and confidential, and ensured that they could freely withdraw from the project at any time. Written informed consent (i.e., clicking "agree") was obtained from all individual participants involved in the study. Participants were also asked to provide a unique identifier to allow the research team to match their responses over time while maintaining confidentiality. At both time points, participants were compensated £1.75 for completing the questionnaire (15 minutes). More generally, all procedures implemented in this study follow the ethical standards and principals of the Declaration of Helsinki (World Medical Association, 2013).

Recruitment was limited to participants (1) who spoke English as their main language and (2) who were employed by an organization as their main occupation, rather than self-employed, unemployed, or students. The survey also included two questions assessing attention (e.g., "It is important that you pay attention to our survey, please tick strongly disagree"), and one final question verifying "for scientific reasons", if participants really worked in an organization. Only those who successfully completed all verifications were included, resulting in a final sample of 442 participants (56.6% females) at Time 1 (T1), and 356 (55.6% females) at Time 2 (T2). Of those, 158 reported working mainly onsite, and 284 reported working mainly remotely. Participants lived and worked in the British Isles (81.0%) or the US (19.0%), had a mean age of 39.52 years (SD = 10.38), and had a mean job tenure of 6.89 years (SD = 6.03). Most held a permanent (92.5%) full-time (89.6%) position and held a bachelor degree (94.1%). Participants worked mainly in non-market services (53.2%), market services (33.0%), industry (8.1%), construction (2.3%), agriculture (0.2%), or other sectors (3.2%).

Measures

Job demands. Six items developed by French et al. (2019) were used to assess participants' perceptions of challenge (three items; e.g., "How often does your work demand a high level of skill or expertise?"; α = .66 at both T1 and T2) and hindrance (three items; e.g., "How often do you have a lot of interruptions?"; α = .66 at T1 and α = .64 at T2[1]) demands. More specifically, the challenge items tapped into time pressure, skill discretion, and decision authority (one item each) as numerous studies (e.g., Kinnunen et al., 2017; Kronenwett & Rigotti, 2019) have shown that these dimensions had significant effects on employees' functioning, and more specifically on the outcomes considered in this study (e.g., work engagement, work-related rumination). Similarly, we focused on work overload, interruptions, and poor supervision (one item each) as hindrance demands due to their widely demonstrated effects on our variables of interest (e.g., Puranik et al., 2021; Sousa & Neves, 2020). All

[1] Although acceptable (e.g., $\alpha \geq .60$) these values remain low. However, it is important to keep in mind that alpha is known to be artificially impacted (in a positive manner) by the number of items included in a measure (e.g., Streiner, 2003). It is possible to estimate the impact of length via the Spearman-Brown prophecy formula (Nunnally & Bernstein, 1994), which indicates that the reliability of these measures would have been between .780 and .795 if based on six equivalent items. Yet, this low level of reliability reinforces the importance of relying on an approach providing some control for unreliability in our main analyses (i.e., factor scores).

items were rated on a five-point scale (Never to Always).

Work engagement. Work engagement was assessed using the three-item version of the Utrecht Work Engagement Scale (UWES-3; Schaufeli et al., 2019). All items (e.g., "I am enthusiastic about my job"; α = .88 at T1 and α = .86 at T2) were rated on a seven-point scale (Never to Always).

Job boredom. Job boredom was measured with a three-item version (Rasskazova et al., 2016) of the Dutch Boredom Scale (Reijseger et al., 2013). Items (e.g., "I feel bored when working"; α = .76 at both T1 and T2) were rated on a five-point scale (Never to Always).

Work-related rumination and problem-solving pondering. A short six-item version (Junker et al., 2021) of a longer measure developed by Cropley et al. (2012) was used to assess work-related rumination (three items; e.g., "Do you become tense when you think about work-related issues during your free time?"; α = .93 at both T1 and T2) and problem-solving pondering (three items; e.g., "I find solutions to work-related problems in my free time"; α = .86 at both T1 and T2). All items were rated on a five-point scale (Very seldom or never to Very often or always).

Proactive health behaviors. A four-item scale developed by Wayne et al. (2020) was used to assess proactive health behaviors (e.g., "I ensure I eat a healthy diet"; α = .84 at both T1 and T2). Items were rated on a seven-point scale (Never to Always).

Sleep quantity and quality. We relied on a single-item measure to assess sleep quantity (Dietch et al., 2019). This item asked participants to report the number of hours they generally slept each night in the last month. Participants also completed another item (Dietch et al., 2019) asking about their subjective sleep quality: "My sleep quality each night during the last month was…"). Items were rated on a five-point scale (Very poor to Very good).

Analyses

Preliminary Analyses

The psychometric properties of all multi-item measures were verified in preliminary factor analyses. These analyses (factor structure, invariance over time, across employees working onsite or remotely, and across participants recruited in the British Isles or the US, composite reliability, and factor correlations) are reported in the online supplements (Tables S1 to S5). The main analyses relied on factor scores from these preliminary analyses (Meyer & Morin, 2016; Morin et al., 2016b, 2016c). To ensure comparability over time, factor scores were obtained from models specified as invariant longitudinally (Millsap, 2011), and estimated in standardized units (SD = 1; M = 0). Factor scores provide a partial control for unreliability and preserve the structure of the measurement model (e.g., invariance; Morin et al., 2016b). As noted in the online supplements, we relied on a bifactor representation (Morin et al., 2016a, 2016b, 2020) of job demands, resulting in a global factor representing global level of exposure to job demands, and two specific factors representing exposure to challenge and hindrance demands over and above global job demands. This approach has been shown to help obtained a more accurate picture of qualitative differences between latent profiles when relying on profile indicators reflecting conceptually-overlapping dimensions (Morin et al., 2016b). A MANOVA revealed no differences between participants who completed one versus two time points, except for higher levels of sleep quality (M = 3.25 vs M = 2.95) among employees who participated at both time points [$F(1, 440) = 7.34$, $p < .01$]. A backward logistic regression predicting retention supported this conclusion (b = .574; SE = .163; $p \leq .01$; OR = 1.775) while also showing that these employees had a lower sleep quantity (b = -.344; SE = .146; $p \leq .01$; OR = .709).

Model Estimation

All models were estimated in Mplus 8.7 (Muthén & Muthén, 2021) using the maximum likelihood robust (MLR) estimator. Missing responses were handled using full information maximum likelihood (FIML) procedures, allowing us to estimate longitudinal models using all participants who responded to the first time point (n = 442) rather than relying on a suboptimal listwise deletion strategy including only participants (n = 356) who completed both measurements points. Due to the way the online questionnaire was programmed, there were no missing responses for participants who completed our questionnaires at each measurement occasion. FIML is recognized to be as efficient as multiple imputation, but less computationally demanding (Enders, 2010).

Latent Profile Analyses (LPA)

LPA are designed to summarize the multivariate distribution of scores on a set of profile indicators via the identification of a finite set of latent profiles of participants characterized by distinct configurations on this set of indicators, while allowing for within-profile variability on all indicators

(McLachlan & Peel, 2000). These profiles are similar to prototypes, and called latent to reflect their probabilistic nature (Morin et al., 2018). Each participant is assigned a probability of membership in each of the latent profiles, resulting in a LPA solution controlled for classification errors. In this study, time-specific LPA models were first estimated using the three job demands factors as indicators. At each time point, solutions including one to eight profiles were estimated while allowing the means and variances of the indicators (global job demands, specific challenge demands, and specific hindrance demands) to be freely estimated (Morin & Litalien, 2019). LPA were estimated using 5000 sets of random start values allowed 1000 iterations each, and final stage optimization was conducted on the 200 best solutions (e.g., Hipp & Bauer, 2006). These numbers were changed to 10000, 1000, and 500 for the longitudinal analyses.

Model Comparison and Selection

The decision of how many profiles to retain relies on a consideration of whether the profiles are meaningful, aligned with theory, and statistically adequate (Marsh et al., 2009; Morin, 2016). Statistical indicators (McLachlan & Peel, 2000) can also be consulted. Thus, a lower value on the Akaïke Information Criterion (AIC), Consistent AIC (CAIC), Bayesian Information Criterion (BIC), and sample-size Adjusted BIC (ABIC) indicate better fitting models. Statistically significant p-values on the adjusted Lo, Mendell and Rubin’s (2001) Likelihood Ratio Test (aLMR), and Bootstrap Likelihood Ratio Test (BLRT) indicate better fit relative to a model with one fewer profile.

Statistical research has shown that the BIC, CAIC, ABIC, and BLRT, but not the AIC and aLMR, were efficient to indicate the true number of latent profiles (Diallo et al., 2016, 2017). The AIC and aLMR are thus only reported for purposes of transparency but will not be used for model assessment. These tests all present a strong sample size dependency (Marsh et al., 2009) and often fail to converge on a specific number of profiles. It is thus recommended to rely on a graphical display, referred to as an elbow plot, in which the first plateau in the decrease in the value of these indicators helps to pinpoint the optimal solution (Morin et al., 2011). Finally, the classification accuracy (from 0 to 1) is summarized by the entropy, which should only be considered as a descriptive indicator, not to guide the selection of the optimal number of profiles nor as an indicator of the quality of a solution (Diallo et al., 2016, 2017; Lubke & Muthén, 2007). Diallo et al. (2016) note that entropy values approaching .80 are indicative of a high classification accuracy, whereas values lower than .50 are indicative of a lower accuracy – which is controlled for in person-centered analyses.

Longitudinal Tests of Profile Similarity

Assuming that the same number of profiles are extracted at both time points (Morin & Wang, 2016), the two time-specific LPA solutions will then be combined into a longitudinal LPA for longitudinal tests of within-sample profile similarity (Morin & Litalien, 2017; Morin et al., 2016c). These sequential tests start by assessing whether each measurement occasion results in the same number of profiles. The two time-specific solutions are then combined in a longitudinal model of *configural* similarity. Equality constraints are then imposed on the within-profile means (*structural* similarity), variances (*dispersion* similarity), and size (*distributional* similarity). These tests rely on the CAIC, BIC, and ABIC, so that each type of similarity can be considered supported as long as two indicators decrease following the integration of equality constraints (Morin et al., 2016c).

Latent Transition Analyses (LTA)

The most similar longitudinal LPA solution will then be re-expressed as a latent transition analysis (LTA) to investigate within-person stability and transitions in profile membership (Collins & Lanza, 2010). This LTA, as well as following analyses, were specified using the manual three-step approach outlined by Morin and Litalien (2017). Readers interested in the technical and practical aspects of LPA and LTA estimation should consult Morin and Litalien (2019).

Predictors and Outcomes of Profile Membership

We assessed the extent to which the relations between profiles, predictors (*predictive* similarity), and outcomes (*explanatory* similarity) remained the same over time. For these tests, the predictors and outcomes were directly included into the final LTA solution. However, before proceeding with our main analyses, we empirically verified the possible value of incorporating participants’ demographic characteristics (sex, age, work status, sector, and country) as controlled variables. These variables were considered based on previous research which has shown that they tended to influence employees' job demands perception and exposure. Thus, research has shown that women tended to report higher levels of exposure to job demands than men in Japan, Finland, and the US (Banerjee & Doshi, 2020; Sekine et al., 2011), while opposite differences were reported in the UK (Sekine et al., 2011). Moreover, part-time employment tends to be related to lower levels of exposure to job demands than full-time employment (Bartoll et al., 2014), whereas age positively predicts exposure to job demands (Besen et al., 2015). Lastly, different work settings and sectors tend to be associated with different levels and types of job demands (Bakker & Demerouti, 2017; Jimmieson et al., 2017).

This verification was done via the sequential comparison of four models. First, we estimated a null effects model assuming no relations between the demographic variables and the profiles. Second, the effects of these variables were freely estimated and allowed to vary over time and as a function of T1 profile membership (to assess the effects on specific profile transitions). Third, predictions were allowed to differ over time only. Finally, a model of *predictive* similarity was estimated by constraining these associations to be equal over time. Relations between work type and profile membership were then assessed using the same sequence.

Time-specific outcome measures (work engagement, job boredom, problem-solving pondering, work-related rumination, proactive health behaviors, and sleep quality and quantity) were included and allowed to vary as a function of profile membership at the same time point. T2 outcome measures can be considered to be controlled for what they share with their T1 counterparts (i.e., stability) due to their joint inclusion. *Explanatory* similarity was assessed by constraining these associations to be equal over time. The multivariate delta method was used to test the statistical significance of between-profile differences in outcome levels (Raykov & Marcoulides, 2004).

Results

Latent Profile Analyses (LPA)

The statistical indicators associated with the time-specific LPA solutions are reported in Table S6 and illustrated in Figures S1 and S2 of the online supplements. These indicators failed to pinpoint a clearly dominant solution at both time points. The CAIC supported a five-profile solution at T1 and T2, the BIC supported a five-profile solution at T1 and a six-profile solution at T2, while the ABIC and BLRT both supported a seven-profile solution at T1 and an eight-profile solution at T2. The elbow plots revealed that the optimal solution was located between three and six profiles at both time points. Solutions including three to six profiles were thus carefully examined.

This examination revealed that these solutions were already highly similar across time points, and that adding profiles had a meaningful contribution to the model up to five profiles (in alignment with the CAIC and BIC results). More specifically, the second, fourth, and fifth profiles included in our final solution illustrated in Figure 1 were already present in the three-profile solution. Adding a fourth profile resulted in the addition of the first profile illustrated in Figure 1, which corresponded to our *Highly Exposed* theoretical scenario (i.e., high global levels of job demands). Then, adding a fifth profile resulted in the addition of the third profile illustrated in Figure 1, which formed the conceptual counterpart to the fourth profile already present in the solution. However, adding a sixth profile resulted in the splitting of one already identified profile into smaller ones with a similar configuration (i.e., a very small profile, similar in shape to Profile 5, and including fewer than 2% of the sample). On this basis, we retained the five-profile solution at both time points for further analyses to answer our research questions. These results support Hypothesis 1 regarding the number of profiles identified.

The statistical indicators associated with all longitudinal models are reported in Table 1. Starting with a model of *configural* similarity including five profiles per time point, equality constraints were progressively integrated. From this model, the second, third, and fourth models of *structural*, *dispersion*, and *distributional* similarity all resulted in lower BIC, CAIC, and ABIC values, and were thus supported by the data. The final model of *distributional* similarity was thud retained for interpretation and is graphically represented in Figure 1. These results support Hypothesis 2. The detailed parameter estimates from this model are reported in Tables S7 and S8 of the online supplements. As shown in Table S8, this solution is associated with a high level of classification accuracy, ranging from 73.7% to 81.5% across T1 profiles, from 69.9% to 83.1% at T2, and summarized in a moderately high entropy of .689.

Profile 1 displays high global levels of job demands, average specific levels of hindrance demands, and moderately low specific levels of challenge demands. This *Globally Exposed* profile characterizes 12.66% of the participants. Profile 2 corresponds to participants reporting low global levels of job demands, moderately low specific levels of hindrance demands, and average specific levels of challenge demands. This *Not Exposed* profile characterizes 10.19% of the participants. Profile 3 corresponds to participants reporting low global levels of job demands, average specific levels of hindrance demands, and high specific levels of challenge demands. This *Not Exposed but Challenged* profile characterizes 9.27% of the participants. Profile 4 corresponds to participants reporting high global levels of job demands coupled with moderately low specific levels of hindrance demands and low levels of challenge demands. This *Exposed but Not Challenged* profile characterizes 41.70% of the participants. Finally, Profile 5 corresponds to participants reporting low global levels of job demands coupled with high specific levels of hindrance and challenge demands. This *Mixed* profile characterizes 26.17% of the participants. These results partially support Hypothesis 1 with regard to the characteristics of the profiles identified.

Latent Transitions Analyses (LTA)

The profile transition probabilities are reported in Table 2 and support Hypothesis 3. Membership into Profiles 1 (*Globally Exposed*: Stability of 100.0%), 2 (*Not Exposed*: Stability of 95.7%), 3 (*Not Exposed but Challenged*: Stability of 100.0%), 4 (*Exposed but Not Challenged*: Stability of 100.0%), and 5 (*Mixed*: Stability of 100.0%) was highly stable over time. For members of the *Not Exposed* profile at T1, the main transitions involved the *Not Exposed but Challenged* profile at T2 (4.3%).

Predictors of Profile Membership

For the demographic controls, the results reported in Table 1 indicate that the lowest values on all information criteria were associated with the null effects model, consistent with a lack of association between profile membership and these variables. This interpretation was supported by the parameter estimates of these models, which also revealed a lack of associations between the demographic variables and the profiles. The next set of results indicated that the associations between work type and participants' likelihood of profile membership generalized over time (i.e., supporting the model of *predictive* similarity). These analyses indicated that working remotely predicted a higher likelihood of membership into the *Not Exposed but Challenged* (3) profile relative to the *Exposed but Not Challenged* (4) profile (b = 1.087, SE = .422, p < .05, OR = 2.964), failing to support Hypothesis 6.

Outcomes of Profile Membership

For the outcomes, as shown in Table 1, the model of *explanatory similarity* resulted in the lowest values on all information criteria, and was thus supported by the data. The mean outcome levels in each profile are reported in Table 3. The results revealed clear differentiations across all profiles.

Profiles 1 (*Globally Exposed*) and 4 (*Exposed but Not Challenged*) were equally associated with the highest levels of work engagement, followed by Profile 3 (*Not Exposed but Challenged*), which did not differ from Profile 1 (*Globally Exposed*), then by Profile 2 (*Not Exposed*), and finally by Profile 5 (*Mixed*). Profile 5 (*Mixed*) was associated with higher levels of job boredom than all other profiles, which rarely differed from one another. The only exception was that Profile 2 (*Not Exposed*) was also associated with higher levels of job boredom than Profile 4 (*Exposed but Not Challenged*).

Profile 1 (*Globally Exposed*) displayed higher levels of problem-solving pondering than all other profiles. Likewise, Profiles 1 (*Globally Exposed*) and 5 (*Mixed*) displayed similarly higher levels of work-related rumination than all other profiles. The highest levels of proactive health behaviors were associated with Profile 4 (*Exposed but Not Challenged*) which, however, only differed significantly from Profiles 2 (*Not Exposed*) and 5 (*Mixed*) on this outcome. Similarly, levels of sleep quantity were equally higher in Profiles 2 (*Not Exposed*) and 4 (*Exposed but Not Challenged*), although these profiles only differed significantly from Profile 1 (*Globally Exposed*) on this outcome. Finally, levels of sleep quality were equally higher in Profiles 2 (*Not Exposed*), 3 (*Not Exposed but Challenged*), and 4 (*Exposed but Not Challenged*) than in Profiles 1 (*Globally Exposed*) and 5 (*Mixed*), although these levels did not differ significantly between Profiles 1 (*Globally Exposed*) and 3 (*Not Exposed but Challenged*). More generally, these results partially support Hypotheses 4 and 5.

To investigate whether and how these associations differed as a function of working remotely or onsite (a work type that could change for individual employees over time), we estimated multi-group LPA solutions separately at each time point (with work type as the grouping variable). The results from these additional analyses are reported in Tables S9 and S10 of the online supplements (the elbow plots are reported in Figure S3 of the online supplements). These results confirmed the superiority of the five-profile solution across groups and time points, as well as the *configural*, *structural*, *dispersion*, and *distributional* similarity of this solution across groups at T1 and T2. Outcomes were thus integrated separately to the two multi-group solutions of *distributional* similarity. The T1 and T2 results supported the *explanatory* similarity of this solution across samples of employees working remotely or onsite, consistent with the presence of outcome associations corresponding to those previously reported which did not differ across groups. These results do not support Hypothesis 7.

Discussion

This longitudinal person-centered study sought to increase our understanding of employees' job demands exposure through the identification of the various profiles taken by these job demands. We also examined the generalizability of these profiles (within-sample stability) and the stability of employees' profile membership (within-person stability) over a three-month period. Finally, we documented the criterion-related validity of these profiles in relation to theoretically-relevant outcomes (i.e., work engagement, job boredom, problem-solving pondering, work-related rumination, proactive health behaviors, and sleep quality and quantity), while considering whether and how these associations changed as a function of working remotely or onsite.

Toward a Typology of Job Demands Profiles

Our main contribution arguably lies in the partial validation of the theoretical scenarios outlined in the introduction as a guide for future multidimensional research on job demands. Indeed, our results revealed five distinct job demands profiles, corresponding in part to the scenarios outlined in the introduction, while providing a finer-grained perspective on the distinct role played by global and specific components of job demands perceptions. Taken together, these profiles provide a novel theoretically-driven heuristic framework to help guide researchers in achieving a comprehensive understanding of the role played by job demands. Supporting their generalizability, these profiles were similar to profiles identified in prior research focusing on workers' job demands appraisals (e.g., Li et al., 2022) and replicated over time and across samples of employees working remotely or onsite. These profiles thus seem to capture core mechanisms involved in employees' job demands perceptions expected to help identify distinct categories of employees.

Two profiles matched our *Highly Exposed* scenario, albeit in a very different manner. The first of those is the *Globally Exposed* profile, which primarily displayed a high undifferentiated global level of job demands. The second is the *Mixed* profile, which displayed high specific levels of challenge and hindrance demands, but low global levels of undifferentiated job demands. This difference is subtle, but important, and intimately related to our bifactor representation of job demands perceptions. Indeed, high scores on the global factor reflect a perception of exposure to a high undifferentiated level of job demands, meaning that *Globally Exposed* employees saw their employment as demanding, without distinguishing whether these demands are challenging or hindering. In contrast, the *Mixed* employees more clearly differentiated between both types of job demands and reported being exposed to both of them at work. This interpretation is consistent with the highlights of the critical importance of perceptions in the assessment of the specific nature (challenging or hindering) of job demands (Webster et al., 2011). Such results also underline the importance of jointly considering global levels of job demands exposure, as proposed by the job demands-resources model (Bakker & Demerouti, 2017), while also seeking to identify employees' specific levels of exposure to uniquely challenging or hindering job demands (Crawford et al., 2010). Simply asking employees to report on both types of job demands is unlikely to be sufficient, given the large level of overlap between these two types of reports (Gillet et al., 2019; Schilbach et al., 2021). The bifactor approach advocated in the present study is uniquely suited to disaggregating the variance shared across these two types of job demands (i.e., an undifferentiated global level of job demands) from that unique to each type of demands (challenges and hindrances). Only by relying on this type of model does it become possible to clearly assess the uniquely differential role played by challenge and hindrance demands in a way that matches the theoretical propositions of the job demands-resources model (e.g., Bakker & Demerouti, 2017; Crawford et al., 2010). In this regard, among employees matching our *Highly Exposed* scenario, some fail to discriminate among both types of job demands (*Globally Exposed*), whereas other more clearly differentiate both types of job demands (*Mixed*).

Matching our theoretical *Challenged* scenario, we also identified a *Not Exposed but Challenged* profile. Employees corresponding to this profile primarily reported exposure to specific challenges at work. This profile was particularly interesting in relation to our *Exposed but Not Challenged* profile, which was rather characterized by high undifferentiated global levels of job demands accompanied by particularly low specific levels of challenges. As no profile directly matched our *Hindered* theoretical scenario, it would seem that few employees specifically assess their workplace as primarily hindering. Our results rather indicate that employees who see their workplace as providing them with relatively few challenges may come to see it as simply "demanding", rather than hindering. In this regard, it is interesting to note that specific levels of challenges were also relatively low in the *Globally Exposed* profile. Challenging, rather than hindering, demands might thus be a particularly important driver of employees' job demands profiles. More precisely, challenged employees seem to describe their workplace as uniquely challenging (*Not Exposed but Challenged*) or as both challenging and hindering (*Mixed*). In contrast, employees reporting low to very low levels of challenges rather simply seem to describe their workplace as globally demanding (*Globally Exposed* or *Exposed but Not Challenged*), or not (*Not Exposed*). These observations support the theoretical extension of the job demands-resources model highlighting the importance of considering challenges as a qualitatively distinct type of job demands (Cavanaugh et al., 2000; Crawford et al., 2010; LePine et al., 2005). As noted above, this unique contribution of the present research is linked to our bifactor operationalization of job demands, which provided an empirical way of disaggregating global job demands perceptions from specific challenges and hindrances. Doing so allows us to enrich the job demands-resources literature (Demerouti & Bakker, 2022) by showing that employees may truly only differentiate "demands" from "challenges", considering that "hindrances" simply fall under the large umbrella of job demands.

Finally, albeit the job demands levels observed in the *Not Exposed* profile were slightly lower than anticipated, this profile still matched our *Moderately Exposed* scenario, in addition to highlighting that not all employees are necessarily exposed to a work environment seen as truly demanding. However, it should be kept in mind that this profile remained relatively small (10.19%). Whereas we noted that specific challenge perceptions seemed to influence employees' ability to differentiate among distinct types of job demands, employees who feel exposed to high (*Globally Exposed*) or low (*Not Exposed*) undifferentiated levels of job demands at work also do not seem to differentiate among challenges and hindrances. Providing some support to LePine et al.'s (2005) representation of job demands as encompassing challenges and hindrances, this distinction may be more valuable for those exposed to moderate levels of job demands.

Within-Person Stability in Profile Membership

Profile membership remained highly stable (95.7% to 100.0%) over a three-month period. These high rates of stability are aligned with previous results showing that employees' levels of (perceived) exposure to job demands tend to be highly stable over two (Tims et al., 2013) to three months (Crane & Searle, 2016). These rates are also consistent with the idea that employees' perceptions of their work environment tend to be influenced by rather stable individual and environmental characteristics, which rarely change on their own in the absence of internal or external transformations (Lazarus & Folkman, 1984). Work typically involves exposure to multiple persistent challenges and hindrances requiring employees to continuously expend energy (Bakker & Demerouti, 2017). Homeostatic mechanisms are also known to generate some stability in employees' experiences (Bowling et al., 2005; Morin et al., 2013, 2017b). Importantly, these results indicate that the profiles identified in this study reflect relatively stable phenomena upon which differential intervention strategies could be anchored, while highlighting that profile membership is unlikely to rapidly change on its own in the absence of intervention (Meyer & Morin, 2016). Lastly, it was noteworthy that membership into the *Not Exposed* profile was the least stable (95.7%). This slightly lower rate of stability could be related to the constant chase of efficiency and speed resulting from the work intensification phenomenon to which modern societies are exposed (Huyghebaert-Zouaghi et al., 2022a).

Outcomes of Profile Membership

Supporting their criterion-related validity, the profiles identified in this study shared clear associations with all outcomes. Interestingly, there were benefits to profiles characterized by high, relative to low, global levels of undifferentiated job demands (e.g., more engagement, less boredom), in addition to a greater tendency to rely on problem-solving pondering as part of one's work recovery processes. Prior research has similarly shown that job demands may sometimes be associated with positive outcomes. For instance, Crawford et al. (2010) have shown that challenge demands predicted higher levels of work engagement. LePine et al. (2005) also found that challenge demands had a positive effect on work performance. Nevertheless, these benefits were limited to challenge demands. By relying on a more precise differentiation between global (undifferentiated) levels of job demands and specific levels of challenges and hindrances, our results revealed a slightly different picture. More precisely, our results showed that the dual exposure to distinct, and well-differentiated, sets of challenge and hindrance demands (i.e., the *Mixed* profile) seemed particularly problematic in terms of functioning, whereas exposure to a high undifferentiated global level of job demands that is not seen as too challenging seemed to help employees function efficiently in spite of these demands.

These intriguing results raise interesting questions about the true benefits of challenges (LePine et al., 2005), especially when they occur in combination with high levels of hindrances (i.e., *Mixed* profile), or of undifferentiated job demands (i.e., *Exposed but Not Challenged* profile). In these contexts, these challenges may become the drop that makes the glass overflow. The *Mixed* profile seemed to be particularly harmful for employees, possibly as a result of the toll taken by having to face hindrances likely to interfere with their ability to meet challenges, as well as because the specific level of hindrances was higher in this profile relative to the others. Supporting these interpretations, the accumulation of job demands (Jimmieson et al., 2017), and of hindrances more specifically, have been previously found to be associated with particularly negative outcomes (Bakker & Demerouti, 2017; Gonzalez-Mulé et al., 2021; van Oortmerssen et al., 2020). Previous research has already shown that hindrances interfere with autonomous motivation because employees are likely to believe that no reasonable level of effort will be adequate to meet these demands, and that any effort expended on these demands will sap resources (Hobfoll, 2002) that could otherwise be used to handle more stimulating challenges (LePine et al., 2005).

Furthermore, although global levels of job demands might be a core driver of functioning, it does not appear sufficient to consider these global levels without also considering the specific facets. For instance, although the *Exposed but Not Challenged* profile was associated with lower levels of work-related rumination and problem-solving pondering, as well as with higher levels sleep quantity and quality, relative to the *Globally Exposed* profile, these two profiles did not differ in terms of work engagement, job boredom, and proactive health behaviors. Furthermore, these two profiles were both associated with higher levels of work engagement than the *Mixed* profile. High levels of exposure to global undifferentiated levels of demands may thus sometimes be associated with positive outcomes (e.g., work engagement), particularly when employees do not also face high levels of challenges beyond this global level. Indeed, that global undifferentiated job demands could be associated with motivation, as employees are likely to anticipate a positive association between their efforts at coping with these demands and their likelihood of meeting them, as well as between their success at meeting these demands and valued outcomes (LePine et al., 2005).

Moreover, the high global level of job demands present in the *Globally Exposed* profile seem to be accompanied with detrimental outcomes in terms of work-related rumination, problem-solving pondering, and sleep difficulties. The negative impact of this profile on sleep quality might be explained, at least in part, by its associations with work-related rumination and problem-solving pondering, two known drivers of sleep difficulties (Gillet et., 2021b; Sonnentag & Fritz, 2015; Van Laethem et al., 2019). The *Mixed* and *Not Exposed but Challenged* profiles also present similar levels of undifferentiated global demands and of specific challenges, but different levels of specific hindrances. Yet, employees' levels of work engagement were higher, and their levels of job boredom and work-related rumination lower, in the *Not Exposed but Challenged* profile relative to the *Mixed* one, thus supporting the detrimental effects of hindrances (Crawford et al., 2010) and highlighting the potential benefits of challenges (Crane & Searle, 2016), while suggesting that these benefits may only occur when challenges are not matched by hindrances.

Interestingly, the *Not Exposed* profile was associated with lower levels of work engagement than the *Not Exposed but Challenged*, *Globally Exposed*, and *Exposed but Not Challenged* profiles, and with higher levels of job boredom and lower levels of proactive health behaviors than the *Exposed but Not Challenged* profile. Consequently, there might be limits to the benefits of low levels of exposure to job demands. Although these results seem to contradict the positive relations reported between challenge demands and well-being in previous studies (Crawford et al., 2010; LePine et al., 2005), it is important to acknowledge that these previous variable-centered results focus on the average relations observed within a sample, and thus are not directly comparable to the present person-centered results focusing on distinctive configurations of global and specific job demands. These unexpected findings could be explained by the fact that employees perceiving moderate to low levels of global and specific demands might also display low levels of well-being and proactive health behaviors due to their sub-optimal level of arousal (Sousa & Neves, 2020). Our person-centered approach thus sheds a new light on the challenge-hindrance distinction anchored in the job demands-resources model (Bakker & Demerouti, 2017), by providing a nuanced examination of the implications of challenges and hindrances.

However, beyond these negative outcomes associated with the *Not Exposed* profile, it remains important to keep in mind that this profile still presented higher levels of work engagement and sleep quality, and lower levels of job boredom and work-related rumination than the *Mixed* profile, as well as higher levels of sleep quantity and quality, and lower levels of work-related rumination and problem-solving pondering than the *Globally Exposed* profile. These results support the idea that employees facing high levels of job demands do spend an excessive amount of time and effort at work at the expense of their personal life, thus decreasing their work-life balance and the quality of their work recovery experiences (Huyghebaert-Zouaghi et al., 2022a; Sonnentag & Fritz, 2015).

Generalizability to Onsite or Remote Work Contexts

Beyond supporting the replicability of our profiles and of their outcomes over time, and contrary to our expectations, our results were also replicated across samples of employees working remotely or onsite. These results stand in contrast to previous studies demonstrating that working remotely may buffer the undesirable effects of job demands on employees' professional and personal functioning (e.g., Bakker & Demerouti, 2017; Collie et al., 2020). On the contrary, job demands profiles and their effects may be more immune to the effects of the work context than the isolated variable-centered effects of job demands. Likewise, our results do not support the expectation that working remotely might carry additional burden for employees due to the need to handle the complex requirements of combining their work and personal environments (Wang et al., 2021). Our results rather revealed that remote and onsite work do not seem to play a significant role in employees' job demands perceptions or with their ability to cope with these demands (Lazarus & Folkman, 1984).

As such, our results further add to an arguably inconsistent body of research focusing on the differences between remote and onsite work, thus reinforcing the need for additional research in this area. For instance, Gillet et al. (2022b) showed that working remotely blurred employees' traditional points of reference, decreased their feelings of connection with their work role, and increased interference between the family and work domains, resulting in lower levels of functioning. In contrast, other studies have shown that working remotely could provide employees with greater flexibility, which can be used to better face job demands, in turn reducing the likelihood of maladaptive outcomes (Huyghebaert-Zouaghi et al., 2022a). Likewise, Gillet et al. (2022a) found that employees working remotely experienced higher levels of psychological detachment than those working onsite. Although working remotely seemed to act as a double-edged sword (Huyghebaert-Zouaghi et al., 2022a), as far as job demands profiles and their outcomes are considered, work setting seems to be rather unimportant.

However, working remotely was not completely inactive, and still predicted membership in the *Not Exposed but Challenged* profile relative to the *Exposed but Not Challenged* profile. Working remotely may thus provide an opportunity for growth and development (Lazarus & Folkman, 1984). Yet, given that the *Exposed but Not Challenged* profile was associated with higher levels of work engagement than the *Not Exposed but Challenged* profile, remote work may be associated with a higher likelihood of exposure to a job demands profile that might be slightly more detrimental for employees' work engagement and well-being, possibly because this work setting tends to exacerbate work-life conflict and to decrease the availability of social support (Charalampous et al., 2019).

Limitations and Future Research Directions

The present research has some limitations, which nevertheless open the way to 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 (Podsakoff et al., 2012). To alleviate these concerns, it would be useful for future studies to consider incorporating objective measures (e.g., observational measures or official reports of job demands, organizational data on work performance and absenteeism) and informant ratings of employees' functioning (e.g., colleagues, supervisors, spouse). Second, the reliability of the specific challenge and hindrance factors used in our analyses were at the lower limit of acceptability. Although this low reliability is unlikely to have interfered with the profile estimation process (due to the way profiles are estimated, but also our reliance on factor scores incorporating a control for unreliability), it would be important for future research to rely on instruments with more established evidence of reliability, while also considering other types of challenge (e.g., job complexity) and hindrance (e.g., role conflict and ambiguity) demands (Cavanaugh et al., 2000; LePine et al., 2016; Rodell & Judge, 2009). Third, the present study was conducted among a mixed sample of employees working in the British Isles or the US. Further research is thus needed to generalize the current results in different work settings, occupational groups, countries, languages, and cultures (Cendales & Gómez

Ortiz, 2019).

Fourth, we assessed the stability of job demands profiles over a three-month period, which was not characterized by any specific or systematic change or transition. As a result, stability estimates could potentially 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, job redesign). Moreover, despite our reliance on state-of-the-art missing data procedures, it remains true that the transitions themselves (within-person stability) could only be inferred based on information obtained from the subsample (n = 356) who responded both time points (relative to the total sample of n = 442). Future studies should thus examine the extent to which our findings would generalize to longer periods of time, transitions, interventions, and changes (Huyghebaert-Zouaghi et al., 2022a). Fifth, we did not assess the reasons for which employees ended up working remotely (e.g., whether it was a choice, something that was imposed by the organization, or a consequence of the COVID-19 pandemic). We also did not consider the context in which this remote work occurred (e.g., access to childcare or to a proper home office, whether employees were trained, supported and provided resources to support their work). It would be important for future research to consider how these characteristics might influence the impact of remote work on job demands perceptions and their outcomes (Huyghebaert-Zouaghi et al., 2022a). Finally, we only considered the predictive role of demographics (sex, age, work status, sector, and country) and work setting (remote *versus* onsite). It would be interesting to examine how other personal characteristics (e.g., job crafting, change readiness, cognitive appraisal) relate to these profiles (e.g., Tims et al., 2013). Likewise, positive (e.g., organizational citizenship behaviors, creativity) and negative (e.g., absenteeism, counterproductive behaviors) outcomes as well as psychological mechanisms (e.g., need satisfaction) could be included to better understand the implications of the job demands profiles (e.g., Gillet et al., 2019).

Practical Implications

From a practical perspective, the high stability of our job demands profiles supports the importance of devising profile-based interventions, as these profiles do not seem to capture ephemeral phenomena that will disappear on their own (Meyer & Morin, 2016). Moreover, these rates of stability also entail that interventions would need to be quite intensive to override that stability. For instance, employees may need to take part to two one-hour training sessions each week during at least a four-week period as illustrated in some job crating interventions (Mukherjee & Dhar, 2023). Given the high level of stability that characterizes all profiles, such intensive interventions may apply to all profiles identified. Nevertheless, even more intensive interventions could be proposed to ensure that employees transition as quickly as possible from a profile associated with many negative outcomes (e.g., *Mixed* profile) to one that is significantly more adaptive (e.g., *Exposed but Not Challenged* profile). More generally, by providing evidence of generalizability over time and across samples of employees working remotely or onsite, our results represent a major step forward in job demands research by supporting the value of devising generic interventions without having to adapt these interventions to specific work settings.

Given the desirability of the *Not Exposed* profile, particularly in terms of sleep quantity and quality, it would seem important for organizations to consider implementing actions to help employees who do not feel exposed to high levels of job demands maintain this desirable profile over time. This could possibly be accomplished by helping these employees craft their job. More specifically, Petrou et al. (2012), who anchored job crafting within the job demands-resources model (Bakker & Demerouti, 2017), defined job crafting as a proactive employee behavior targeted at seeking job resources and challenges, and reducing job demands, to achieve a better fit between their job and their personal preferences and abilities (Tims et al., 2013). Taking a closer look at the seeking resources strategies, it stems from the idea that employees are motivated to accumulate resources that they can use to protect other valued resources (Hobfoll, 2002). This accumulation of resources is associated with optimal functioning (e.g., high levels of well-being and performance) and also helps limit the detrimental effects of job demands (Bakker & Demerouti, 2017). Such interventions may subsequently be expanded to help all employees optimize their work experiences while bearing in mind that, if priority is to be given, it must first and foremost be given to actions aimed at facilitating transitions from the most detrimental profiles in terms of functioning to the most favorable ones.

From an intervention perspective, changes designed to reduce specific hindrance demands could be associated with better recovery experiences and functioning. For instance, high levels of hindrance demands could be reduced by stating clear segmentation norms and encouraging balanced and healthier lifestyles (Kreiner, 2006), by creating well-being-oriented work environments, and by offering enabling versus enclosing work-life policies (Bourdeau et al., 2019). They could also be decreased at the individual level through coaching or counseling (Van Gordon et al., 2017). Moreover, because self-regulatory resource depletion is an important reason for the negative effects of work interruptions (Puranik et al., 2021), interventions that are targeted specifically at managing work interruptions or which are focused more generally on reducing self-regulatory demands in the work environment (e.g., redesigning workplaces to reduce distracting background noises, implementing less stringent norms of emotional labor in the workplace), could help reduce the negative effects of specific hindrance demands (Parker et al., 2017). Knight et al. (2021) showed that employees exposed to a higher generic workload tended to benefit more, possibly as a result of a higher motivation to decrease this workload (Hobfoll, 2002), from job crafting interventions seeking to decrease hindrance demands. Research has also demonstrated that short-term interventions targeted at helping individuals see stressors as challenging rather than hindering, were helpful in changing how stressors, such as job demands, were perceived (Crum et al., 2017).

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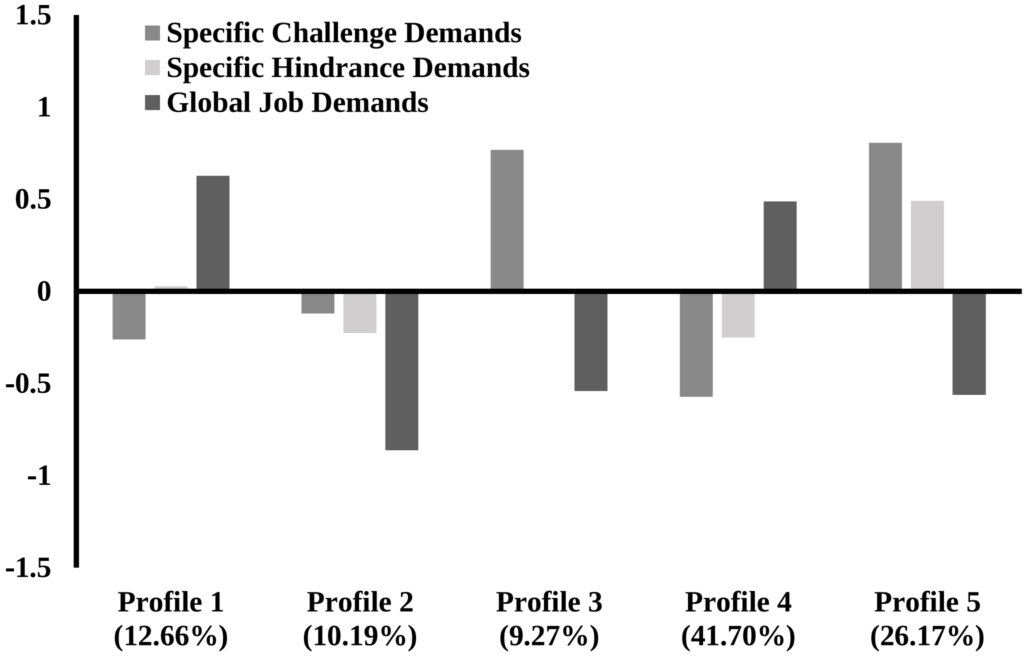
Figure 1
Final Five-Profile Solution



Note. Profile indicators are factors scores estimated in standardized units (*M* = 0; *SD* = 1). Profile 1: *Globally Exposed*; Profile 2: *Not Exposed*; Profile 3: *Not Exposed but Challenged*; Profile 4: *Exposed but Not Challenged*; and Profile 5: *Mixed*.

Table 1

Results from the Time-Specific and Longitudinal Models

Model	LL	#fp	Scaling	AIC	CAIC	BIC	ABIC	Entropy
Final Latent Profile Analyses								
Time 1	-1656.377	34	1.110	3380.755	3553.859	3519.859	3411.959	.727
Time 2	-1656.198	34	1.027	3380.395	3553.500	3519.500	3411.599	.682
Longitudinal Latent Profile Analyses								
Configural Similarity	-3312.575	68	1.068	6761.150	7107.359	7039.359	6823.558	.704
Structural Similarity	-3315.486	53	1.251	6736.972	7006.812	6953.812	6785.614	.702
Dispersion Similarity	-3321.835	38	1.696	6719.669	6913.139	6875.139	6754.544	.689
Distributional Similarity	-3322.280	34	1.877	6712.560	6885.665	6851.665	6743.764	.689
Predictive Similarity: Demographics								
Null Effects Model	-2504.270	44	.585	5096.540	5320.558	5276.558	5136.922	.917
Profile-Specific Free Relations with Predictors	-2458.194	184	.378	5284.387	6221.188	6037.188	5453.257	.915
Free Relations with Predictors	-2465.295	84	.578	5098.590	5526.260	5442.260	5175.683	.923
Equal Relations with Predictors	-2484.837	64	.717	5097.673	5423.517	5359.517	5156.410	.919
Predictive Similarity: Predictor								
Profile-Specific Free Relations with Predictor	-1317.755	57	.329	2749.510	3039.714	2982.714	2801.823	.917
Free Relations with Predictor	-1317.757	37	.508	2709.513	2897.891	2860.891	2743.471	.918
Equal Relations with Predictor	-1318.371	33	.488	2702.742	2870.755	2837.755	2733.028	.918
Explanatory Similarity								
Free Relations with Outcomes	-8823.809	108	1.003	17863.618	18413.480	18305.480	17962.738	.943
Equal Relations with Outcomes	-8828.071	73	1.373	17802.143	18173.808	18100.808	17869.140	.943

Note. LL: Model loglikelihood; #fp: Number of free parameters; Scaling: Scaling correction factor associated with robust maximum likelihood estimates; AIC: Akaïke information criteria; CAIC: Constant AIC; BIC: Bayesian information criteria; ABIC: Sample size adjusted BIC.

Table 2

Transitions Probabilities

	Profile 1	Profile 2	Profile 3	Profile 4	Profile 5
Profile 1	1.000	.000	.000	.000	.000
Profile 2	.000	.957	.043	.000	.000
Profile 3	.000	.000	1.000	.000	.000
Profile 4	.000	.000	.000	1.000	.000
Profile 5	.000	.000	.000	.000	1.000

Note. Profile 1: *Globally Exposed*; Profile 2: *Not Exposed*; Profile 3: *Not Exposed but Challenged*; Profile 4: *Exposed but Not Challenged*; and Profile 5: *Mixed*.

Table 3

Associations between Profile Membership and the Outcomes Taken from the Model of Explanatory Similarity (Equal across Time Points)

	Profile 1 M [CI]	Profile 2 M [CI]	Profile 3 M [CI]	Profile 4 M [CI]	Profile 5 M [CI]	Summary of Statistically Significant Differences
Engagement	.413 [.128; .698]	-.197 [-.473; .079]	.181 [-.005; .367]	.569 [.393; .744]	-.969 [-1.302; -.636]	4 > 3 > 2 > 5; 1 = 4; 1 = 3 > 2 > 5
Boredom	-.265 [-.552; .021]	.088 [-.157; .333]	-.250 [-.592; .092]	-.603 [-.800; -.406]	.999 [.728; 1.271]	5 > 1 = 2 = 3; 1 = 4; 5 > 3 = 4; 2 > 4
Problem-solving	.889 [.664; 1.115]	-.350 [-.613; -.087]	-.002 [-.344; .340]	-.297 [-.588; -.006]	-.106 [-.362; .149]	1 > 2 = 3 = 4 = 5
Rumination	.577 [.364; .789]	-.353 [-.613; -.093]	-.322 [-.692; .048]	-.538 [-.801; -275]	.512 [.303; .721]	1 = 5 > 2 = 3 = 4
Proactive behaviors	-.151 [-.500; .198]	-.121 [-.422; .180]	.119 [-.204; .443]	.288 [.060; .515]	-.245 [-.449; -.041]	4 > 2 = 5; 1 = 2 = 3 = 5; 1 = 3 = 4
Sleep quantity	6.369 [6.061; 6.678]	6.848 [6.604; 7.093]	6.818 [6.389; 7.247]	6.959 [6.753; 7.165]	6.623 [6.362; 6.884]	2 = 4 > 1; 2 = 3 = 4 = 5; 1 = 3 = 5
Sleep quality	2.726 [2.461; 2.990]	3.375 [3.152; 3.598]	3.316 [3.006; 3.627]	3.582 [3.387; 3.778]	2.944 [2.726; 3.162]	2 = 3 = 4 > 1; 3 = 5; 2 = 4 > 1 = 5

Note. M: Mean; CI: 95% confidence interval; indicators of work engagement, job boredom, problem-solving pondering, work-related rumination, and proactive health behaviors are estimated from factor scores with a mean of 0 and a standard deviation of 1; Profile 1: *Globally Exposed*; Profile 2: *Not Exposed*; Profile 3: *Not Exposed but Challenged*; Profile 4: *Exposed but Not Challenged*; and Profile 5: *Mixed*.

Online Supplements for:

A Longitudinal Person-Centered Investigation of the Multidimensional Nature of Employees' Perceptions of Challenge and Hindrance Demands at Work

Authors' note

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

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

Preliminary Measurement Models

Longitudinal measurement models were estimated in Mplus 8.7 (Muthén & Muthén, 2021) using the maximum likelihood robust (MLR) estimator, which provides parameter estimates, standard errors, and goodness-of-fit that are robust to the non-normality of the response scales used in the present study. These models were estimated in conjunction with full information maximum likelihood (FIML; Enders, 2010) to handle missing data. Due to the complexity of the longitudinal models underlying all constructs assessed in the present study, preliminary analyses were conducted separately for the job demands variables and for the multi-item outcome measures (work engagement, job boredom, problem-solving pondering, work-related rumination, and proactive health behaviors).

A bifactor-confirmatory factor analytic (CFA; Morin et al. 2016, 2020) model including one global job demands factor (G-factor) and two orthogonal specific factors (S-factors) reflecting levels of exposure to challenge and hindrance demands left unexplained by the G-factor was estimated at both Time 1 (T1) and Time 2 (T2). To ascertain the value of this solution (Morin et al., 2016, 2020), it was contrasted with a simpler CFA solution in which items were only allowed to load on their a priori dimension and allowing all factors to correlate. When interpreting bifactor-CFA results, it is important to keep in mind that, because bifactor models rely on two factors to explain the item-level covariance for each specific item, factor loadings on G- and S-factors are typically lower than their first-order counterparts (e.g., Morin et al., 2016, 2020; Perreira et al., 2018). As such, the critical question when interpreting a bifactor solution is whether the G-factor really taps into a meaningful amount of covariance shared among all items, and whether there remains sufficient specificity at the subscale level unexplained by the G-factor to result in the estimation of meaningful S-factors. A CFA model was also estimated for the multi-item outcome variables at both T1 and T2 and included a total of five factors (work engagement, job boredom, problem-solving pondering, work-related rumination, and proactive health behaviors) at each time point. All factors were freely allowed to correlate.

Each retained solution was submitted to sequential tests of measurement invariance (Millsap, 2011): (1) configural invariance; (2) weak invariance (loadings); (3) strong invariance (loadings and intercepts); (4) strict invariance (loadings, intercepts, and uniquenesses); (5) invariance of the latent variance-covariance matrix (loadings, intercepts, uniquenesses, correlated uniquenesses, and latent variances-covariances); and (6) latent means invariance (loadings, intercepts, uniquenesses, correlated uniquenesses, latent variances-covariances, and latent means). These tests were first conducted across groups of employees working remotely or onsite at T1, and then at T2, before being conducted for the total sample across measurement occasions (longitudinal invariance). Similar tests were then conducted across groups of employees working in the US or UK at T1, and then at T2.

Given the known oversensitivity of the chi-square test of exact fit (χ^2) to sample size and minor model misspecifications (e.g., Marsh et al., 2005), we relied on sample-size independent goodness-of-fit indices to describe the fit of the alternative models (Hu & Bentler, 1999): The comparative fit index (CFI), the Tucker-Lewis index (TLI), as well as the root mean square error of approximation (RMSEA) and its 90% confidence interval. Values greater than .90 for the CFI and TLI indicate adequate model fit, although values greater than .95 are preferable. Values smaller than .08 or .06 for the RMSEA respectively support acceptable and excellent model fit. Invariance was assessed by considering changes in CFI and RMSEA (Chen, 2007; Cheung & Rensvold, 2002). A ΔCFI/TLI of .010 or less and a ΔRMSEA of .015 or less between a more restricted model and the previous one support the invariance hypothesis. The composite reliability of each a priori factor was calculated using the standardized parameters with McDonald (1970) omega (ω) coefficient:

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

where $|\lambda_i|$ are the standardized factor loadings associated with a factor in absolute values, and δi, the item uniquenesses. Based on the aforementioned interpretation caveat for bifactor models, it has been previously indicated that omega values approaching .500 remain acceptable for bifactor S-factors, whereas traditional interpretation guidelines for reliability estimates continue to apply for CFA factors and bifactor G-factors (Morin et al., 2020; Perreira et al. 2018).

The goodness-of-fit results from all job demands models are reported in Table S1. These results support the adequacy of the a priori bifactor-CFA model underlying the job demands measure (with all CFI and TLI ≥ .95, and all RMSEA ≤ .05) and its superiority relative to the CFA model (ΔCFI = .040

to .053; ΔTLI = .076 to .080; ΔRMSEA = .076 to .079). These results also support the configural, weak, strong, strict, latent variance-covariance, and latent means invariance of this solution across time points. At T1, the results also support the configural, weak, strong, and strict invariance of this solution across groups of employees working remotely or onsite, whereas at T2, they support the configural, weak, strong, strict, and latent variance-covariance invariance of the solution across groups. At T1, the results also support the configural, weak, strong, strict, latent variance-covariance, and latent means invariance of this solution across groups of employees working in the US or UK. In contrast, possibly due to the small sample size in the US, it proved impossible to test the invariance of the job demands measure across countries at T2. Indeed, all attempted models failed to converge, or to converge on proper solutions, despite multiple attempts (e.g., increasing iterations, decreasing convergence, using constrained estimation procedures).

These results thus show that, despite the presence of some meaningful (i.e., unbiased) group differences in relation to the latent means (revealing mainly non-statistically significant mean differences at T1, and slightly higher scores on the global demands factor at T2 among remote employees) and latent variances (revealing a slightly lower level of variability on all three factors among remote employees at T1), this bifactor-CFA solution resulted in a fully equivalent (unbiased) measurement of participants' job demands ratings over time and groups. Factor scores were extracted from the final longitudinal model of latent means invariance. Parameter estimates from this final longitudinal model of latent means invariance are reported in Table S2, and reveal a well-defined G-factor (ω = .802) with strong positive loadings from the challenge (λ = .519 to .907) and hindrance (λ = .224 to .663) items. Although the S-factors obtained in this solution appear weaker than the G-factor ($|\lambda|$ = .288 to .398, ω = .460 for challenge; and λ = .412 to .479, ω = .512 for hindrance), it is important to reinforce that both S-factors do retain some meaningful specificity anchored in a subset of items presenting construct-relevant variance left unexplained by the G-factor.

Importantly, such observations are frequent with bifactor modeling, leading Morin et al. (2016) to reinforce that, whereas the observation of a well-defined G-factor is critical to support the adequacy of a bifactor solution, it is not necessary for the S-factors to be equally well-defined. Morin et al. (2020) add that this observation simply suggests that the items associated with these S-factors only retain a limited amount of specificity once the variance explained by the G-factor is taken into account, which should not be taken to suggest that this minimal specificity is not relevant to consider – especially if unreliability can be controlled as part of the analyses – which is the case in this study. They also reinforce the fact that typical interpretation guidelines for reliability cannot be directly applied to S-factors given that a bifactor model involves the division of the reliable variance present at the item level into two distinct factors. In this regard, Perreira et al. (2018) suggest that acceptability guidelines should be closer to .500 for S-factors, which is consistent with the values obtained for the challenge (ω = .460) and hindrance (ω =.512) S-factors. In any case, these observations reinforce the need to rely on analytical methods providing some degree of control for unreliability.

The goodness-of-fit results associated with the outcomes measurement models are reported in Table S3. These results support the adequacy of the a priori model (with all CFI/TLI ≥ .90 and all RMSEA ≤ .08), as well as its configural, weak, strong, strict, latent variances-covariances, and latent means invariance across groups and time points (ΔCFI ≤ .010; ΔTLI ≤ .010; and ΔRMSEA ≤ .015). The parameter estimates and composite reliability scores obtained from the most invariant longitudinal measurement models (latent means invariance) are reported in Table S4. These results show that all factors are well-defined by satisfactory factor loadings (λ = .392 to .999), resulting in satisfactory composite reliability coefficients, ranging from ω = .785 to .929. Factor scores were saved from this most invariant measurement model and used as outcome indicators in the main research. The correlations between all variables are reported in Table S5.

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Table S1

Goodness-of-Fit Statistics for the Estimated Models (Job Demands)

Description	χ^2 (*df*)	CFI	TLI	RMSEA	90% CI	CM	$\Delta\chi^2$ (*df*)	ΔCFI	ΔTLI	ΔRMSEA
Job Demands										
Time 1 CFA	31.829 (8)*	.960	.924	.082	[.053; .113]	-	-	-	-	-
Time 1 B-CFA	3.056 (3)	1.000	1.000	.006	[.000; .081]	-	-	-	-	-
Time 2 CFA	25.910 (8)*	.957	.920	.079	[.046; .114]	-	-	-	-	-
Time 2 B-CFA	2.721 (3)	1.000	1.000	.000	[.000; .086]	-	-	-	-	-
Job Demands: Longitudinal Invariance										
M1. Configural invariance	46.649 (27)*	.989	.974	.041	[.019; .060]	-	-	-	-	-
M2. Weak invariance	39.738 (36)	.998	.996	.015	[.000; .038]	M1	1.148 (9)	+.009	+.022	-.026
M3. Strong invariance	47.179 (39)	.996	.992	.022	[.000; .041]	M2	5.408 (3)	-.002	-.004	+.007
M4. Strict invariance	40.365 (45)	1.000	1.000	.000	[.000; .026]	M3	1.709 (6)	+.004	+.008	-.022
M5. Variance-covariance invariance	42.792 (48)	1.000	1.000	.000	[.000; .025]	M4	2.483 (3)	.000	.000	.000
M6. Latent means invariance	45.524 (51)	1.000	1.000	.000	[.000; .025]	M5	2.740 (3)	.000	.000	.000
Job Demands: Multi-Group (Remote vs. Onsite) Invariance Time 1										
M7. Configural invariance	1.348 (6)	1.000	1.000	.000	[.000; .000]	-	-	-	-	-
M8. Weak invariance	10.928 (15)	1.000	1.000	.000	[.000; .045]	M7	11.552 (9)	.000	.000	.000
M9. Strong invariance	11.996 (18)	1.000	1.000	.000	[.000; .034]	M8	.877 (3)	.000	.000	.000
M10. Strict invariance	19.025 (24)	1.000	1.000	.000	[.000; .040]	M9	7.628 (6)	.000	.000	.000
M11. Variance-covariance invariance	48.161 (27)*	.963	.959	.060	[.031; .086]	M10	45.685 (3)*	-.037	-.041	+.060
M12. Latent means invariance	80.383 (30)*	.913	.913	.087	[.064; .110]	M11	14.898 (3)*	-.050	-.046	+.027
Job Demands: Multi-Group (Remote vs. Onsite) Invariance Time 2										
M13. Configural invariance	14.108 (6)*	.981	.906	.087	[.026; .147]	-	-	-	-	-
M14. Weak invariance	19.600 (15)	.989	.979	.042	[.000; .087]	M13	4.921 (9)	+.008	+.073	-.045
M15. Strong invariance	23.613 (18)	.987	.978	.042	[.000; .084]	M14	4.296 (3)	-.002	-.001	.000
M16. Strict invariance	30.107 (24)	.986	.982	.038	[.000; .075]	M15	6.674 (6)	-.001	+.004	-.004
M17. Variance-covariance invariance	33.182 (27)	.986	.984	.036	[.000; .072]	M16	3.014 (3)	.000	+.002	-.002
M18. Latent means invariance	49.970 (30)*	.954	.954	.061	[.029; .090]	M17	12.921 (3)*	-.032	-.030	+.025
Job Demands: Multi-Group (US vs UK) Invariance Time 1										
M19. Configural invariance	28.541 (6)*	.964	.818	.131	[.085; .181]	-	-	-	-	-
M20. Weak invariance	21.401 (15)	.990	.979	.044	[.000; .083]	M19	5.826 (9)	+.026	+.161	-.087
M21. Strong invariance	28.741 (18)	.983	.971	.052	[.000; .086]	M20	38.961 (3)*	-.007	-.008	+.008
M22. Strict invariance	36.662 (24)*	.980	.974	.049	[.006; .079]	M21	8.591 (6)	-.003	+.003	-.003
M23. Variance-covariance invariance	39.548 (27)	.980	.977	.046	[.000; .075]	M22	2.126 (3)	.000	+.003	-.003
M24. Latent means invariance	47.798 (30)*	.971	.971	.052	[.021; .079]	M23	7.283 (3)	-.009	-.006	+.006

Note. * $p < .05$; CFA: Confirmatory factor analyses; B: Bifactor; 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; 90% CI: 90% confidence interval; CM: Comparison model; and Δ: Change in fit relative to the CM.

Table S2

Standardized Factor Loadings (λ) and Uniquenesses (δ) for the M6 Solution (Longitudinal Latent Means Invariance Job Demands)

Items	G-factor λ	S-Challenge λ	S-Hindrance λ	δ
Challenge				
Time pressure	.907	.398		.019
Skill discretion	.617	.318		.519
Decision authority	.519	.288		.647
Hindrance				
Work overload	.663		.479	.331
Interruptions	.480		.412	.600
Poor supervision	.224		.440	.756
ω	.802	.460	.512	

Note. λ: Factor loading; δ: Item uniqueness; ω: Omega coefficient of composite reliability; all parameters are significant ($p < .05$).

Table S3

Goodness-of-Fit Statistics for the Estimated Models (Outcomes)

Description	χ^2 (*df*)	CFI	TLI	RMSEA	90% CI	CM	$\Delta\chi^2$ (*df*)	ΔCFI	ΔTLI	ΔRMSEA
Outcomes										
Time 1 CFA	345.227 (94)*	.938	.920	.078	[.069; .087]	-	-	-	-	-
Time 2 CFA	305.983 (94)*	.932	.913	.080	[.070; .090]	-	-	-	-	-
Outcomes: Longitudinal Invariance										
M1. Configural invariance	824.617 (403)*	.955	.944	.049	[.044; .053]	-	-	-	-	-
M2. Weak invariance	844.589 (414)*	.954	.945	.049	[.044; .053]	M1	19.595 (11)	-.001	+.001	.000
M3. Strong invariance	865.444 (425)*	.953	.945	.048	[.044; .053]	M2	20.742 (11)*	-.001	.000	-.001
M4. Strict invariance	882.712 (441)*	.953	.947	.048	[.043; .052]	M3	20.037 (16)	.000	+.002	.000
M5. Variance-covariance invariance	892.099 (456)*	.953	.949	.047	[.042; .051]	M4	9.102 (15)	.000	+.002	-.001
M6. Latent means invariance	903.883 (461)*	.953	.949	.047	[.042; .051]	M5	11.956 (5)*	.000	.000	.000
Outcomes: Multi-Group Invariance Time 1										
M7. Configural invariance	474.432 (188)*	.931	.911	.083	[.074; .092]	-	-	-	-	-
M8. Weak invariance	480.623 (199)*	.932	.918	.080	[.071; .089]	M7	7.531 (11)	+.001	+.007	-.003
M9. Strong invariance	495.369 (210)*	.931	.921	.078	[.070; .087]	M8	14.294 (11)	-.001	+.003	-.002
M10. Strict invariance	500.271 (226)*	.934	.929	.074	[.065; .083]	M9	13.470 (16)	+.003	+.008	-.004
M11. Variance-covariance invariance	520.658 (241)*	.932	.933	.074	[.064; .081]	M10	20.090 (15)	-.002	+.004	.000
M12. Latent means invariance	533.756 (246)*	.930	.932	.073	[.064; .081]	M11	13.204 (5)*	-.002	-.001	-.001
Outcomes: Multi-Group Invariance Time 2										
M13. Configural invariance	425.531 (188)*	.926	.906	.084	[.074; .095]	-	-	-	-	-
M14. Weak invariance	451.511 (199)*	.921	.905	.084	[.074; .095]	M13	26.051 (11)*	-.005	-.001	.000
M15. Strong invariance	467.091 (210)*	.920	.909	.083	[.073; .093]	M14	15.042 (11)	-.001	+.004	-.001
M16. Strict invariance	471.426 (226)*	.924	.919	.078	[.068; .088]	M15	12.750 (16)	+.004	+.010	-.005
M17. Variance-covariance invariance	489.688 (241)*	.923	.923	.076	[.066; .086]	M16	18.157 (15)	-.001	+.004	-.002
M18. Latent means invariance	500.028 (246)*	.921	.923	.076	[.067; .086]	M17	10.349 (5)	-.002	.000	.000

Note. * $p < .05$; CFA: Confirmatory factor analyses; 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; 90% CI: 90% confidence interval; CM: Comparison model; and Δ: Change in fit relative to the CM.

Table S4

Standardized Factor Loadings (λ) and Uniquenesses (δ) for the M6 Solution (Longitudinal Latent Means Invariance Outcomes)

Items	Engagement λ	Boredom λ	Problem-solving λ	Rumination λ	Proactive behaviors λ	δ
Engagement						
Item 1	.804					.354
Item 2	.901					.189
Item 3	.794					.370
Boredom						
Item 1		.802				.358
Item 2		.920				.154
Item 3		.460				.789
Problem-solving						
Item 1			.813			.339
Item 2			.934			.127
Item 3			.738			.455
Rumination						
Item 1				.895		.200
Item 2				.914		.164
Item 3				.898		.194
Proactive behaviors						
Item 1					.916	.162
Item 2					.392	.846
Item 3					.559	.688
Item 4					.999	*.001*
ω	.872	.785	.870	.929	.829	

Note. λ: Factor loading; δ: Item uniqueness; ω: Omega coefficient of composite reliability; the non-significant ($p > .05$) parameter is marked in italics.

Table S5

Correlations Between Variables

	1	2	3	4	5	6	7	8	9	10	11	12	13	14
1. Sex	-													
2. Age	.039	-												
3. Status	-.134**	.008	-											
4. Sector	-.238**	.106*	.025	-										
5. Country	.146**	-.040	-.071	-.098*	-									
6. G-Job demands (T1)†	-.183**	.072	-.146**	.022	-.112*	-								
7. S-Challenge demands (T1)†	.114*	-.051	-.006	.048	.021	-.341**	-							
8. S-Hindrance demands (T1)†	-.006	-.021	-.008	.063	-.088	-.065	.327**	-						
9. Engagement (T1)†	-.114*	.151**	-.080	.022	-.014	.300**	.058	-.241**	-					
10. Boredom (T1)†	.072	-.315**	.060	-.040	.019	-.211**	-.015	.271**	-.754**	-				
11. Problem-solving (T1)†	-.113*	-.039	-.085	.002	-.125**	.361**	.040	.280**	.231**	-.068	-			
12. Rumination (T1)†	-.072	-.184**	-.034	-.025	-.077	.294**	-.041	.379**	-.285**	.419**	.496**	-		
13. Proactive behaviors (T1)†	.029	-.004	-.074	.096*	-.028	.025	.085	-.084	.176**	-.143**	.076	-.079	-	
14. Sleep quality (T1)	.058	.020	.010	.054	.051	-.159**	.096*	-.238**	.222**	-.209**	-.206**	-.332**	.294**	-
15. Sleep quantity (T1)	.106*	-.064	.041	.045	-.008	-.143**	.063	-.139**	.022	-.017	-.158**	-.142**	.298**	.524**
16. Work type (T1)	.092	-.086	-.055	-.034	.000	-.028	.139**	-.068	-.125**	.153**	-.020	.037	.050	-.015
17. G-Job demands (T2)†	-.198**	.050	-.131**	.043	-.115*	.970**	-.319**	-.045	.288**	-.202**	.365**	.301**	.018	-.180**
18. S-Challenge demands (T2)†	.092	-.053	-.019	.063	-.008	-.365**	.920**	.315**	.050	-.004	.029	-.038	.074	.098*
19. S-Hindrance demands (T2)†	-.023	-.028	-.003	.073	-.099*	-.097*	.240**	.978**	-.264**	.287**	.261**	.376**	-.098*	-.246**
20. Engagement (T2)†	-.100*	.161**	-.068	.011	-.053	.305**	-.012	-.292**	.889**	-.744**	.210**	-.280**	.165**	.181**
21. Boredom (T2)†	.065	-.316**	.015	-.039	.027	-.171**	.019	.315**	-.687**	.929**	.031	.459**	-.147**	-.227**
22. Problem-solving (T2)†	-.153**	-.050	-.080	-.013	-.096*	.366**	.011	.260**	.216**	-.066	.883**	.465**	.065	-.220**
23. Rumination (T2)†	-.119*	-.179**	.079	-.006	-.085	.313**	-.044	.419**	-.253**	.368**	.496**	.800**	-.060	-.315**
24. Proactive behaviors (T1)†	.077	-.013	-.101*	.070	-.047	.042	.081	-.065	.157**	-.112*	.087	-.083	.855**	.244**
25. Sleep quality (T2)	.105*	.000	.032	.084	.082	-.197**	.090	-.248**	.139**	-.165**	-.210**	-.287**	.291**	.724**
26. Sleep quantity (T2)	.084	-.050	.039	.088	.039	-.141**	.096	-.139**	-.007	-.005	-.098	-.115*	.244**	.420**
27. Work type (T2)	.090	-.047	-.114*	.014	.061	-.123*	.184**	-.056	-.072	.054	-.053	-.090	.105*	.014

Note. * $p < .05$; ** $p < .01$; † variables estimated from factor scores with mean of 0 and a standard deviation of 1; sex was coded 0 for women and 1 for men; status was coded 0 for employed full-time and 1 for employed part-time; sector was coded 0 for private sector and 1 for public sector; country was coded 0 for UK and 1 for USA; and work type was coded 0 for onsite workers and 1 for remote workers.

Table S5 (Continued)

Correlations Between Variables

	15	16	17	18	19	20	21	22	23	24	25	26	27
15. Sleep quantity (T1)	-												
16. Work type (T1)	.097*	-											
17. G-Job demands (T2)†	-.158**	-.028	-										
18. S-Challenge demands (T2)†	.078	.128**	-.352**	-									
19. S-Hindrance demands (T2)†	-.138**	-.080	-.059	.299**	-								
20. Engagement (T2)†	.026	-.071	.306**	-.021	-.305**	-							
21. Boredom (T2)†	-.038	.124**	-.168**	.016	.319**	-.766**	-						
22. Problem-solving (T2)†	-.148**	.009	.394**	.030	.265**	.230**	-.016	-					
23. Rumination (T2)†	-.126**	.062	.338**	-.018	.430**	-.254**	.430**	.551**	-				
24. Proactive behaviors (T1)†	.292**	.075	.044	.050	-.084	.173**	-.133**	.056	-.046	-			
25. Sleep quality (T2)	.501**	.030	-.208**	.069	-.263**	.177**	-.217**	-.214**	-.317**	.315**	-		
26. Sleep quantity (T2)	.641**	.120*	-.150**	.110*	-.141**	.027	-.054	-.091	-.142**	.227**	.548**	-	
27. Work type (T2)	.144**	.794**	-.126*	.195**	-.064	-.035	.041	-.022	-.024	.137**	.029	.102	-

Note. * $p < .05$; ** $p < .01$; † variables estimated from factor scores with mean of 0 and a standard deviation of 1; sex was coded 0 for women and 1 for men; status was coded 0 for employed full-time and 1 for employed part-time; sector was coded 0 for private sector and 1 for public sector; country was coded 0 for UK and 1 for USA; and work type was coded 0 for onsite workers and 1 for remote workers.

Table S6

Results from the Latent Profile Analysis Models at Times 1 and 2

Model	LL	#fp	Scaling	AIC	CAIC	BIC	ABIC	Entropy	aLMR	BLRT
Time 1										
1 Profile	-1788.345	6	1.222	3588.689	3619.237	3613.237	3594.196	Na	Na	Na
2 Profiles	-1754.758	13	1.273	3535.516	3601.703	3588.703	3547.447	.801	.056	< .001
3 Profiles	-1711.306	20	1.261	3462.612	3564.438	3544.438	3480.967	.646	.033	< .001
4 Profiles	-1682.669	27	1.224	3419.338	3556.803	3529.803	3444.117	.668	.036	< .001
5 Profiles	-1656.377	34	1.110	3380.755	3553.859	3519.859	3411.959	.727	.051	< .001
6 Profiles	-1639.749	41	1.023	3361.497	3570.241	3529.241	3399.126	.758	.361	< .001
7 Profiles	-1617.734	48	1.079	3331.468	3575.851	3527.851	3375.521	.719	.611	.032
8 Profiles	-1615.677	55	1.005	3341.355	3621.377	3566.377	3391.832	.773	.240	.235
Time 2										
1 Profile	-1784.577	6	1.191	3581.154	3611.702	3605.702	3586.661	Na	Na	Na
2 Profiles	-1747.229	13	1.211	3520.458	3586.645	3573.645	3532.389	.492	.005	< .001
3 Profiles	-1713.495	20	1.116	3466.990	3568.817	3548.817	3485.346	.658	.022	< .001
4 Profiles	-1682.661	27	1.106	3419.322	3556.788	3529.788	3444.102	.601	.021	< .001
5 Profiles	-1656.198	34	1.027	3380.395	3553.500	3519.500	3411.599	.682	.222	< .001
6 Profiles	-1633.754	41	.983	3349.507	3558.251	3517.251	3387.136	.715	.068	.033
7 Profiles	-1618.666	48	.943	3333.332	3577.714	3529.714	3377.385	.737	.085	< .001
8 Profiles	-1603.171	55	.935	3316.342	3596.364	3541.364	3366.820	.766	.355	< .001

Note. LL: Model loglikelihood; #fp: Number of free parameters; scaling: Scaling correction factor associated with robust maximum likelihood estimates; AIC: Akaïke information criteria; CAIC: Constant AIC; BIC: Bayesian information criteria; ABIC: Sample size adjusted BIC; aLMR: Adjusted Lo-Mendel-Rubin likelihood ratio test; and BLRT: Bootstrap likelihood ratio test.

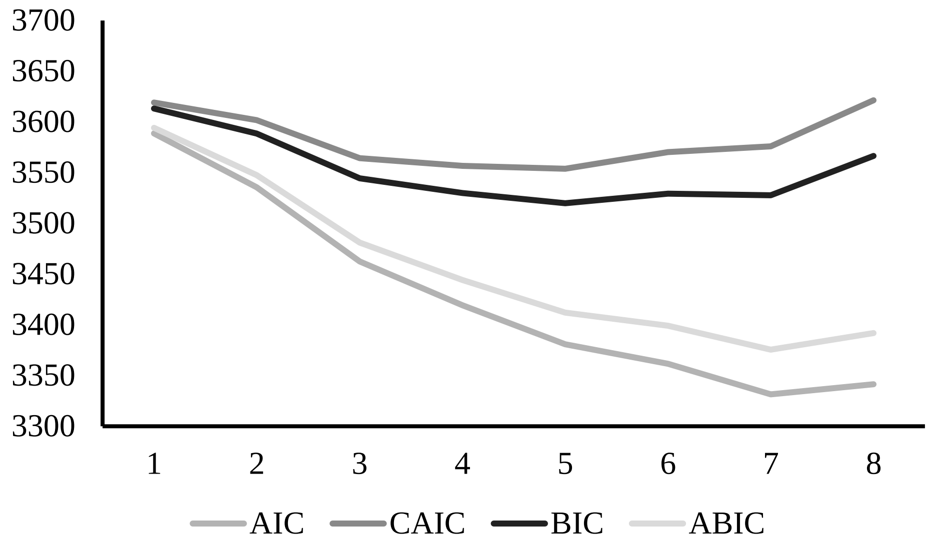

Figure S1

Elbow Plot of the Value of the Information Criteria for Solutions Including Different Numbers of Latent Profiles at Time 1

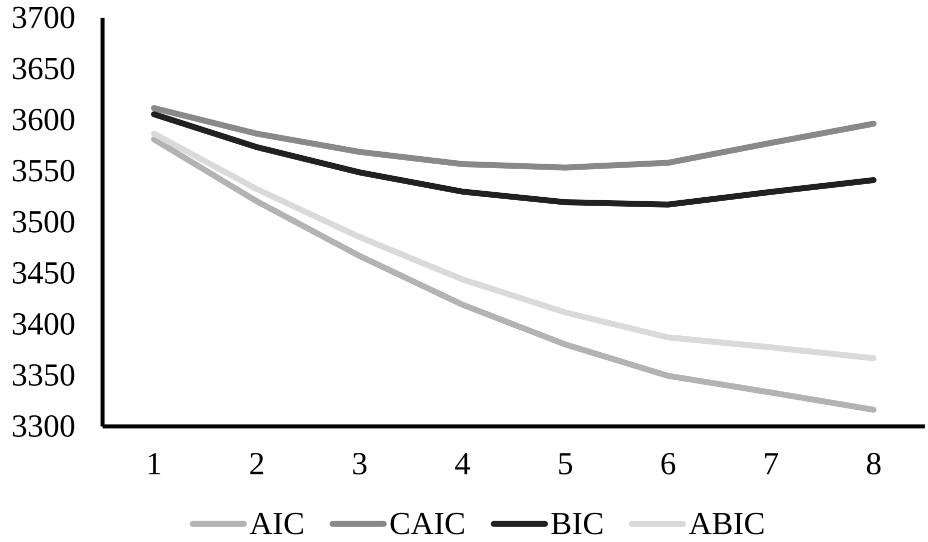

Figure S2

Elbow Plot of the Value of the Information Criteria for Solutions Including Different Numbers of Latent Profiles at Time 2

Table S7

Detailed Parameter Estimates from the Final LPA Solution (Distributional Similarity)

	Profile 1	Profile 2	Profile 3	Profile 4	Profile 5
	Mean [CI]	Mean [CI]	Mean [CI]	Mean [CI]	Mean [CI]
Specific Challenge Demands	-.261 [-.672; .149]	-.121 [-.271; .030]	.768 [.629; .908]	-.573 [-.849; -.297]	.806 [.518; 1.094]
Specific Hindrance Demands	.028 [-.463; .518]	-.226 [-.431; -.020]	-.013 [-.245; .219]	-.251 [-.445; -.057]	.492 [.296; .687]
Global Job Demands	.627 [.546; .709]	-.863 [-.909; -.817]	-.542 [-.604; -.481]	.488 [.314; .663]	-.562 [-.943; -.181]
	Profile 1	Profile 2	Profile 3	Profile 4	Profile 5
	Variance [CI]	Variance [CI]	Variance [CI]	Variance [CI]	Variance [CI]
Specific Challenge Demands	.121 [-.048; .289]	.097 [.035; .158]	.081 [.036; .126]	.898 [.569; 1.227]	.771 [.473; 1.070]
Specific Hindrance Demands	.505 [.277; .732]	.317 [.188; .447]	.313 [.191; .435]	.709 [.546; .872]	.557 [.393; .721]
Global Job Demands	.016 [-.003; .036]	.014 [.009; .019]	.018 [.008; .028]	.664 [.464; .865]	1.479 [1.004; 1.954]

Note. CI = 95% confidence interval; Profile indicators are factors scores estimated in standardized units (M = 0; SD = 1); Profile 1: *Globally Exposed*; Profile 2: *Not Exposed*; Profile 3: *Not Exposed but Challenged*; Profile 4: *Exposed but Not Challenged*; and Profile 5: *Mixed*.

Table S8

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

	Profile 1	Profile 2	Profile 3	Profile 4	Profile 5
Time 1					
Profile 1	.737	.000	.000	.221	.042
Profile 2	.000	.807	.026	.081	.087
Profile 3	.000	.023	.774	.060	.143
Profile 4	.052	.006	.003	.815	.124
Profile 5	.007	.008	.024	.155	.806
Time 2					
Profile 1	.699	.000	.000	.249	.052
Profile 2	.000	.787	.032	.093	.088
Profile 3	.000	.017	.761	.070	.152
Profile 4	.052	.004	.002	.831	.111
Profile 5	.002	.010	.014	.163	.810

Note. Profile 1: *Globally Exposed*; Profile 2: *Not Exposed*; Profile 3: *Not Exposed but Challenged*; Profile 4: *Exposed but Not Challenged*; and Profile 5: *Mixed*.

Table S9

Results from the Latent Profile Analysis Models Estimated Separately Across Groups and Time Points

Model	LL	#fp	Scaling	AIC	CAIC	BIC	ABIC	Entropy	aLMR	BLRT
Onsite Workers: Time 1										
1 Profile	-656.549	6	1.179	1325.098	1349.474	1343.474	1324.481	Na	Na	Na
2 Profiles	-639.277	13	1.020	1304.554	1357.368	1344.368	1303.217	.639	.023	< .001
3 Profiles	-620.481	20	1.012	1280.962	1362.214	1342.214	1278.905	.768	.116	.238
4 Profiles	-604.601	27	1.115	1263.201	1372.891	1345.891	1260.423	.799	.277	.040
5 Profiles	-593.066	34	1.064	1254.133	1392.261	1358.261	1250.635	.829	.468	.600
6 Profiles	-580.956	41	1.240	1243.913	1410.479	1369.479	1239.695	.847	.809	.333
7 Profiles	-571.984	48	.961	1239.968	1434.973	1386.973	1235.030	.869	.427	.286
8 Profiles	-556.323	55	.974	1222.646	1446.089	1391.089	1216.988	.876	.101	< .001
Onsite Workers Time 2										
1 Profile	-532.623	6	1.213	1077.245	1100.623	1094.263	1075.289	Na	Na	Na
2 Profiles	-515.433	13	.769	1056.867	1106.738	1093.738	1052.628	1.000	.051	< .001
3 Profiles	-501.641	20	.822	1043.281	1120.007	1100.007	1036.761	.757	.014	.027
4 Profiles	-492.481	27	.897	1038.962	1142.542	1115.542	1030.160	.773	.306	.077
5 Profiles	-478.861	34	.866	1025.722	1156.156	1122.156	1014.637	.800	.330	.125
6 Profiles	-471.926	41	.765	1025.851	1183.139	1142.139	1012.484	.836	.207	< .001
7 Profiles	-464.270	48	.762	1024.541	1208.682	1160.682	1008.892	.834	.023	< .001
8 Profiles	-455.032	55	.800	1020.064	1231.060	1176.060	1002.133	.835	.940	.091
Remote Workers: Time 1										
1 Profile	-1121.910	6	1.238	2255.820	2283.714	2277.714	2258.688	Na	Na	Na
2 Profiles	-1097.000	13	1.423	2220.000	2280.436	2267.436	2226.213	.568	.218	< .001
3 Profiles	-1057.974	20	1.228	2155.948	2248.927	2228.927	2165.506	.656	.127	< .001
4 Profiles	-1036.654	27	1.162	2127.308	2252.831	2225.831	2140.213	.771	.165	.013
5 Profiles	-1016.594	34	1.258	2101.188	2259.253	2225.253	2117.438	.729	.539	< .001
6 Profiles	-998.909	41	1.133	2079.818	2270.426	2229.426	2099.413	.768	.470	< .001
7 Profiles	-984.352	48	1.020	2064.705	2287.856	2239.856	2087.646	.791	.529	< .001
8 Profiles	-974.749	55	1.087	2059.499	2315.192	2260.192	2085.785	.782	.762	.182
Remote Workers Time 2										
1 Profile	-903.024	6	1.152	1818.048	1844.676	1838.676	1819.660	Na	Na	Na
2 Profiles	-881.094	13	1.312	1788.189	1845.884	1832.884	1791.682	.483	.185	< .001
3 Profiles	-860.694	20	.967	1761.388	1850.150	1830.150	1766.762	.854	.063	< .001
4 Profiles	-845.923	27	.899	1745.845	1865.673	1838.673	1753.100	.882	.042	.028
5 Profiles	-833.403	34	.946	1734.805	1885.700	1851.700	1743.941	.679	.230	.100
6 Profiles	-820.773	41	.855	1723.546	1905.507	1864.507	1734.562	.768	.733	.154
7 Profiles	-809.652	48	.960	1715.305	1928.333	1880.333	1728.202	.719	.481	< .001
8 Profiles	-802.297	55	.841	1714.593	1958.688	1903.688	1729.371	.772	.031	.120

Note. LL: Model loglikelihood; #fp: Number of free parameters; scaling: Scaling correction factor associated with robust maximum likelihood estimates; AIC: Akaïke information criteria; CAIC: Constant AIC; BIC: Bayesian information criteria; ABIC: Sample size adjusted BIC; aLMR: Adjusted Lo-Mendel-Rubin likelihood ratio test; and BLRT: Bootstrap likelihood ratio test.

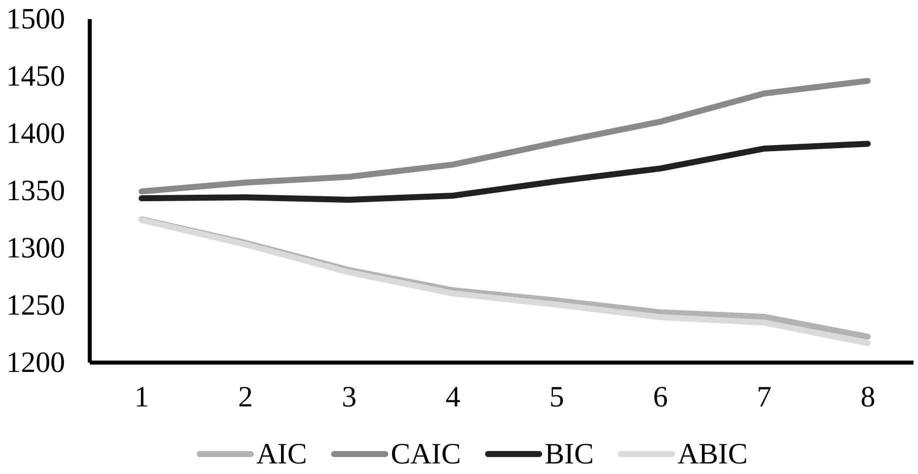

Figure S3a: Onsite Workers, Time 1

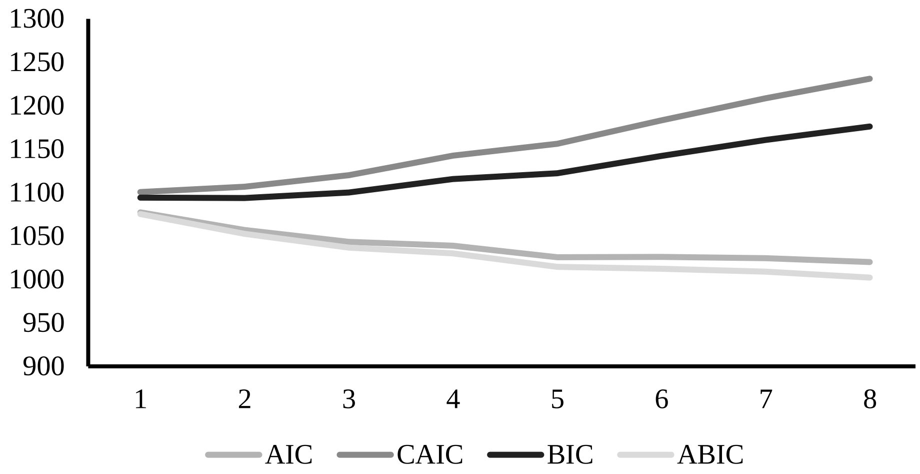

Figure S3b: Onsite Workers, Time 2

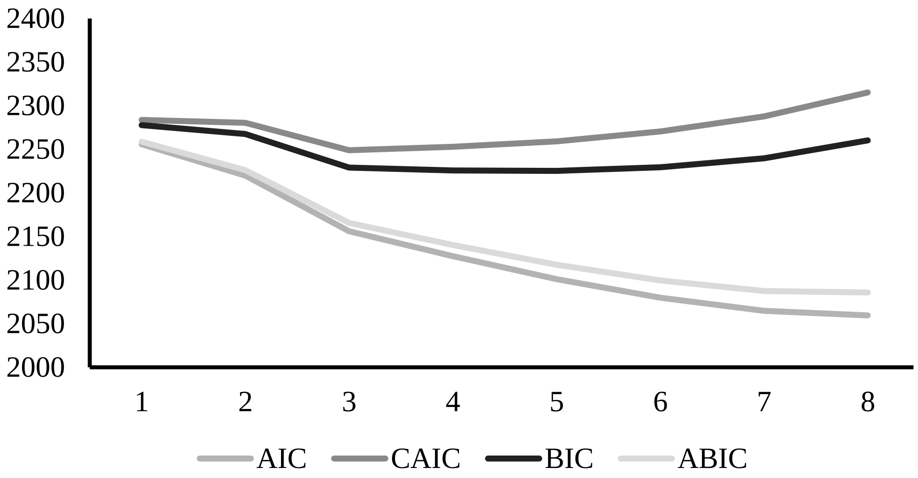

Figure S3c: Remote Workers, Time 1

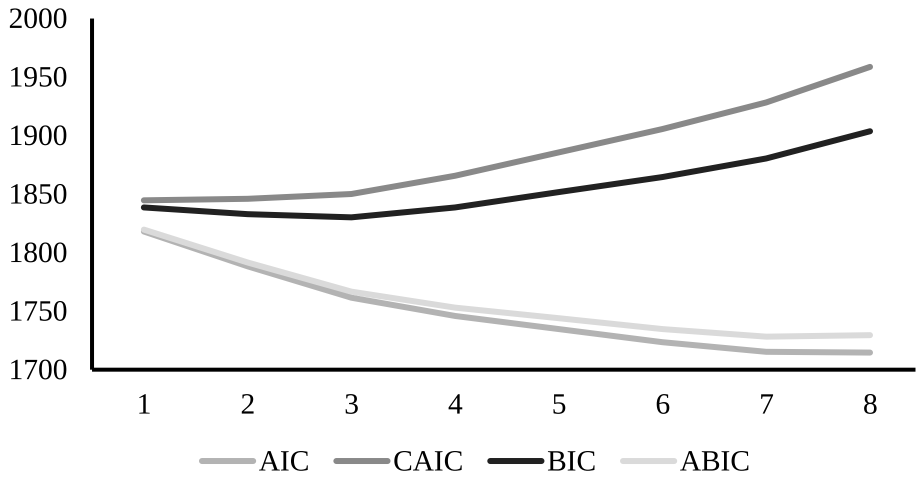

Figure S3d: Remote Workers, Time 2

Figure S3

Elbow Plot for Solutions Estimated Separately among Onsite Workers at Times 1 (S3a) and 2 (S3b) and among Remote Workers at Times 1 (S3c) and 2 (S3d)

Table S10

Results from the Multi-Group Models

Model	LL	#fp	Scaling	AIC	CAIC	BIC	ABIC	Entropy
Multi-Group Tests of Similarity (Time 1)								
Configural Similarity	-1898.475	69	1.140	3934.950	4286.250	4217.250	3998.276	.766
Structural Similarity	-1922.101	54	1.110	3952.203	4227.133	4173.133	4001.762	.760
Dispersion Similarity	-1939.037	39	1.068	3956.073	4154.634	4115.634	3991.866	.730
Distributional Similarity	-1928.186	35	1.022	3926.272	4104.568	4069.568	3958.494	.723
Multi-Group Explanatory Similarity (Time 1)								
Free Relations with Outcomes	-6108.008	77	1.025	12370.015	12762.046	12685.046	12440.684	.818
Equal Relations with Outcomes	-6127.332	42	1.004	12338.664	12552.499	12510.499	12377.211	.815
Multi-Group Tests of Similarity (Time 2)								
Configural Similarity	-1550.518	69	.923	3239.035	3575.405	3506.405	3287.506	.695
Structural Similarity	-1568.425	54	1.031	3244.851	3508.097	3454.097	3282.785	.704
Dispersion Similarity	-1581.879	39	1.126	3241.758	3431.880	3392.880	3269.154	.665
Distributional Similarity	-1589.935	35	1.032	3249.869	3420.492	3385.492	3274.456	.688
Multi-Group Explanatory Similarity (Time 2)								
Free Relations with Outcomes	-4858.076	77	1.139	9870.153	10245.048	10168.522	9924.243	.816
Equal Relations with Outcomes	-4892.586	42	1.121	9869.173	10073.920	10031.920	9898.677	.801

Note. LL: Model loglikelihood; #fp: Number of free parameters; Scaling: Scaling correction factor associated with robust maximum likelihood estimates; AIC: Akaïke information criteria; CAIC: Constant AIC; BIC: Bayesian information criteria; and ABIC: Sample size adjusted BIC.