A Longitudinal Perspective on the Nature, Predictors, and Outcomes of Work Recovery Profiles

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Abstract

This person-centered investigation seeks to understand the main configurations taken by four critical dimensions of work recovery experiences (i.e., relaxation, control, mastery, and psychological detachment) among distinct profiles of workers. Capitalizing on a sample of 442 employees who completed the same set of measures two times across a time interval of three months, we further investigate the longitudinal stability of these profiles and of their relations with a series of work-related predictors and well-being indicators. Our results revealed four profiles identical at both time points: Plugged In, Moderately Unplugged, Moderately Plugged In, and Unplugged. These profiles displayed a moderate to high level of within-person stability over time. Workaholism, personal life orientation, and colleagues' norms about the need to rapidly follow up on work-related messages were all found to be associated with profile membership. Levels of emotional exhaustion and somatization also differed across profiles.

Key words: Recovery experiences; latent transition analyses; workaholism; health; burnout

Given its importance for sustaining healthy psychological functioning among employees (Sonnentag & Fritz, 2015), work recovery has recently received a high level of scientific attention in organizational research (e.g., Parker et al., 2020; Sonnentag et al., 2017), as reflected in several recent meta-analyses (e.g., Bennett et al. 2018; Steed et al., 2021). These meta-analyses have mainly focused on correlational patterns of associations between variables (i.e., a variable-centered approach) without considering how different components of work recovery experiences combine among distinct types, or profiles, of employees (i.e., a person-centered approach). In the present investigation, we consider four key components of this complex multifaceted phenomenon (i.e., relaxation, mastery, control, and psychological detachment; Sonnentag & Fritz, 2007), which are defined in Table 1.

These four components are generally conceptualized as distinct, and each of them has been found to share unique relations with a variety of covariates (i.e., predictors and outcomes; e.g., Bosch et al., 2018; Feldt et al., 2013). More generally, although the role of these components has typically been studied in an additive manner, their effects have never been conceptualized as mutually exclusive or simply additive. Indeed, these four recovery experiences are assumed to coexist, vary independently from one another, and even interact with one another (Sonnentag & Fritz, 2007, 2015). Unfortunately, many studies have ignored the inherent multidimensionality of these experiences to combine them into a single global indicator of work recovery (e.g., Halbesleben et al. 2013), making it impossible to detect the active ingredient underlying the observed associations. Although other studies have considered isolated components, or pairs of components, of the work recovery process (e.g., van Wijhe et al., 2013), this piecemeal consideration is unlikely to provide a complete picture of the complex reality of work recovery experiences. In this regard, Sonnentag et al. (2017) noted that the bulk of prior research has mainly focused on psychological detachment, thus overlooking the effects of the other equally critical components of the work recovery process. More generally, research on recovery experiences has primarily adopted a variable-centered approach, focused on the isolated, additive, or interactive associations between recovery experiences, predictors, and outcomes and assuming that these associations would generalize to the whole sample under study.

Fortunately, beyond considering the unique role of different components of work recovery experiences, person-centered studies have recently started to look at how recovery experiences combine within distinct profiles of employees (e.g., Bennett et al., 2016; Chawla et al., 2020; Siltaloppi et al., 2011; for a review, see Gillet et al., 2021). Person-centered analyses are specifically designed to identify quantitatively and qualitatively distinct subpopulations of workers experiencing distinctive configurations of work recovery experiences (Gillet et al., 2021; Kinnunen et al., 2017). Sonnentag et al. (2022) recently concluded that such analyses were highly promising, and were consistent with "the fact that people often pursue multiple activities in combination and enjoy a mix of different recovery experiences" (p. 36). By considering the unique configurations of recovery experiences observed among distinct profiles of employees, this approach will contribute to generate a clearer understanding of work recovery profiles which are most optimal for employees and their organizations. For instance, do workers need to simultaneously display high levels of psychological detachment, relaxation, control, and mastery to maximally benefit from their work recovery experiences? In contrast, are specific types of experiences (e.g., psychological detachment) more critical than others (e.g., mastery) from an outcome perspective? Likewise, this approach should be able to shed light on the key work-related mechanisms (e.g., work demands) and personal characteristics (e.g., workaholism, personal life orientation) involved in the development, maintenance, and change between more or less desirable work recovery profiles rather than separately considering how to separately facilitate diverse forms of work recovery experiences (e.g., psychological detachment, relaxation, mastery, and control). By addressing these questions, this study represents a necessary step in our understanding of how employees jointly experience psychological detachment, relaxation, control, and mastery, of how their exposure to specific characteristics of their occupational reality is likely to impact their overarching work recovery experiences, and of how these distinct profiles of work recovery experiences relate to various components of employees' functioning.

An additional advantage of this approach is that person-centered results have the advantage of being more closely connected to managers and practitioners' natural tendency to think about their employees in terms of categories (person-centered), rather than complex variable associations (variable-centered; Morin et al., 2011). For this reason, our findings are likely to have important implications for practice at a time when many organizations are rethinking the way they can preserve and enhance employees' functioning.

Unfortunately, among emerging person-centered studies of work recovery experiences, few (Chawla et al., 2020; Siltaloppi et al., 2011) have jointly considered psychological detachment, relaxation, control, and mastery, known to represent core components of work recovery (Headrick et al., 2022; Sonnentag & Fritz, 2007). Likewise, although some person-centered studies have jointly considered more than one or two facets of work recovery experiences, most have done so while also incorporating unrelated variables in the profile definition process (e.g., Bennett et al., 2016; Gillet et al., 2021; Kinnunen et al., 2017), thus impeding our ability to understand the unique role played by work recovery experiences. Previous investigations conducted by Siltaloppi et al. (2011) over a period of one year, and by Chawla et al. (2020) over a shorter period of five days, were both able to identify unique work recovery profiles and their associations with predictors and outcomes and thus represent important precursors to the present investigation. The current study expands upon these previous investigations by considering the longitudinal stability of the identified work recovery profiles (through robust tests of within-sample and within-person longitudinal stability; Morin et al., 2016b) across three months, while considering the extent to which their associations with predictors and outcomes remain the same over time.

This study contributes to the extant literature in three important ways. First, we rely on a person-centered approach to identify subpopulations of employees characterized by various configurations of work recovery experiences identified while jointly considering the core components of psychological detachment, relaxation, mastery, and control. Second, we not only document the nature of the work recovery profiles observed among our sample of employees, but also consider the extent to which these profiles (within-sample stability) and individual profile membership (within-person stability) remain stable over a three-month period (Sandrin et al., 2020). Third, we replicate and extend the preliminary findings obtained in past person-centered studies (Chawla et al., 2020; Siltaloppi et al., 2011) conducted among Finnish and USA workers by relying on a sample of employees from the USA and the British Isles, and considering predictors and outcomes not previously examined.

This study specifically aims to: (1) achieve a more refined person-centered understanding of the nature and stability of the work recovery profiles observed among a sample of employees; and (2) document the construct validity of these profiles by examining their associations with theoretically-relevant predictors and outcomes. The three research questions guiding this study are: (a) Can distinct work recovery profiles be identified, and are these profiles consistent with previous research findings (Chawla et al., 2020; Siltaloppi et al., 2011)? (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 work recovery profiles, predictors, and outcomes align with theoretical expectations?

A Theoretically Grounded Perspective on Work Recovery Experiences

Sonnentag et al. (2017) theoretically defined recovery as the “unwinding and restoration processes during which a person’s strain level that has increased as a reaction to a stressor or any other demand returns to its pre-stressor level” (p. 366). This recovery process, when applied to the work role, is theoretically assumed to be contingent on specific activities (e.g., engaging in a hobby) and experiences (e.g., relaxation) occurring during off-work time. This means that research on work recovery can either focus on the activities we engage in during off-work time and which help us to unwind (i.e., what people do during nonwork time) or on one’s underlying psychological experience of recovering from work (i.e., psychological states during nonwork time), although work recovery activities are positively related to work recovery experiences (Sonnentag et al., 2022). For instance, leisurely activities (e.g., reading a book, taking a walk, socializing) have been shown to be positively related to all four work recovery experiences (i.e., relaxation, mastery, control, and psychological detachment; Sonnentag & Fritz, 2007) that are the focal point of the present study by enabling the replenishment of resources and the reversal of strain (e.g., Steed et al., 2021).

These four work recovery experiences are conceptually and empirically distinct (Sonnentag & Fritz 2007) and have been shown to reflect the core functional aspects, or basic psychological experiences, underlying recovery from work during off-job time (Headrick et al., 2022). However, research has yet to comprehensively investigate these four components of work recovery experiences (Chawla et al., 2020). Indeed, thus far, scholars have preferred using a composite score comprising all four work recovery experiences (e.g., Halbesleben et al. 2013) or focusing solely on a subset of these experiences (e.g., psychological detachment and relaxation; van Wijhe et al., 2013). These decisions make it impossible to clearly understand which of the work recovery experiences proposed to be critical by Sonnentag and Fritz (2007) drive recovery, and impede our understanding of the overarching work recovery process truly experienced by different types of employees (e.g., high psychological detachment and relaxation but average mastery and low control; Chawla et al., 2020).

Research focusing on work recovery is typically anchored in three main theoretical frameworks: (a) the effort-recovery model (Meijman & Mulder, 1998), (b) the conservation of resources theory (Hobfoll, 2011), and (c) the job demands-resources model (Bakker & Demerouti, 2007). More specifically, work demands require employees to expand psychological and/or physical efforts in an ongoing manner, which take a toll on exposed employees (Bakker & Demerouti, 2007). Workers exposed to higher levels of work demands also tend to experience feelings of restlessness in their personal life, where they may keep on thinking about work rather than properly recover from it (Kinnunen et al., 2017). Indeed, exposure to work demands generate symptoms of strain (e.g., anxiety, distress, exhaustion) that tend to fade away once the demands have been dealt with as part of normative work recovery experiences. However, when employees are constantly exposed to persistently high levels of demands (or other forms of stressors), recovery cannot take place, leading to an accumulation of strain reactions over time. In contrast, these theoretical models also suggest that a variety of individual and work-related resources can help employees better cope with work demands in a way that facilitates recovery. However, despite these theoretical propositions, longitudinal research able to truly capture the nature of the effects of work demands on work recovery experiences remains limited. Moreover, it remains relatively unclear in these theoretical frameworks which resources are the most likely to maximally support work recovery (Sonnentag et al., 2022). We come back to this issue later, when addressing the predictors considered in this study.

At the core of these theoretical propositions also lies the assumption that positive work recovery experiences are necessary to support psychological and physiological well-being (Bennett et al., 2018; Sonnentag & Fritz, 2007). More precisely, neglecting one's needs for work recovery, and skipping opportunities to recover, are assumed to lead to the emergence of a variety of psychological and physiological health problems (Sonnentag & Fritz, 2015). Indeed, proper work recovery experiences allow employees to recover their energy, and thus to be ready to face another day at work, while also allowing them to maximally enjoy their off-job time. Without that physiological and psychological energy, the upcoming workdays are only likely to keep on draining employees' resources in a way that will make it progressively harder and harder to recover until something gives away (e.g., Hobfoll, 2011). Although research generally supports these theoretical propositions (e.g., Bennett et al., 2016, 2018), it is important to note that the bulk of current evidence remains largely cross-sectional (Sonnentag et al., 2022), while longitudinal research evidence remains inconsistent (Kinnunen & Feldt, 2013; Sonnentag et al., 2010). For instance, psychological detachment was found to be associated with a decrease in emotional exhaustion over time in some studies (Sonnentag et al. 2010), while others have shown that it did not predict change in ill-being over time (Kinnunen & Feldt 2013). We expect these inconsistencies to reflect the piecemeal approach to work recovery adopted in these previous variable-centered studies, suggesting that a more comprehensive understanding of employees' multidimensional work recovery profiles may be needed to achieve greater clarity.

A Person-Centered Perspective on Work Recovery Experiences

Previous person-centered research on work recovery experiences. Although person-centered research has begun to examine how work recovery experiences combine within distinct profiles of workers (for a recent review, see Gillet et al., 2021), most of these studies have solely considered one component of employees' work recovery experiences (e.g., psychological detachment; Gillet et al., 2021; Kinnunen et al., 2017) in combination with other variables, better conceptualized as predictors or outcomes of work recovery experiences (e.g., need for recovery, overcommitment). These studies thus suffer from a circularity that makes it impossible to rely on their results to achieve a clear understanding of how different types of work recovery experiences combine within specific profiles of employees. Likewise, although Bennett et al. (2016) considered the four work recovery experiences that are the focus of our study, they also considered a theoretical predictor (i.e., problem-solving pondering) as a profile indicator. As this variable played a central role in profile definition, their results cannot help isolate the unique role played by these four core components.

Despite the lack of previous research on employees' work recovery profiles, tentative evidence supports the value of a person-centered approach, showing that work recovery experiences cannot be fully understood in isolation. Indeed, the two previous person-centered studies in which all four components of work recovery experiences that are the focus of the present study were considered converged on a five-profile solution (Chawla et al., 2020; Siltaloppi et al., 2011). Both studies identified a profile characterized by low levels across all components (*Plugged In*) and one profile characterized by high levels across all components (*Unplugged*). Both also identified profiles characterized by generally average work recovery experiences across all components (*Moderately Unplugged*). The remaining profiles displayed a configuration dominated by specific recovery experiences: (a) mastery and control (Siltaloppi et al., 2011); (b) high mastery and relaxation with increasing control (Siltaloppi et al., 2011); and (c) moderate or high levels of control, psychological detachment, and relaxation (Chawla et al., 2020). These results suggest that mastery might function in a way that is distinct from the other components, at least in some profiles. However, although the temporality of these two studies is radically different (Chawla et al., 2020: Five days; Siltaloppi et al., 2011: One year), we still need to be cautious about our ability to replicate such results within yet another timeframe (i.e., three months). If we succeed in replicating these results, we will then be able to conclude that the profiles of recovery experiences remain unaffected by the time lag that is considered (Sonnentag et al., 2022).

The need for theory-grounded replication. The divergence between the results obtained in these two studies, conducted among Finnish (Siltaloppi et al., 2011) and US (Chawla et al., 2020) employees, highlights the need for replication. Indeed, person-centered evidence is built from an accumulation of studies conducted among diversified samples of employees (e.g., various occupations, cultures, and countries): Replication is thus critical to differentiate the central set of profiles that emerges consistently across contexts, those specific to some contexts, and those reflecting random sampling variation (Meyer & Morin, 2016).

Beyond replication, the core challenge for research seeking to understand how different types of work experiences may co-occur among distinct types of employees is related to the lack of previous theorization related to the nature and psychological underpinning of these profiles. Indeed, empirically, we can see that despite their reliance on different methods, measures, and samples, the sum of currently available evidence suggests four to five profiles, including at least three profiles characterized by an *Unplugged*, *Moderately Unplugged*, and *Plugged In* configuration across indicators. Yet, these profiles have not yet been theoretically grounded. Inspired by these previous empirical findings, we now turn our attention to the development of a theoretical typology designed to provide a theoretically-grounded heuristic framework to guide future research in this area.

Theoretical person-centered scenarios. A first theoretical scenario characterizes ***Unplugged*** employees, displaying high levels of work recovery experiences across dimensions. These individuals are assumed to operate in a work environment characterized by low demands and high resources (Bakker & Demerouti, 2007). For this reason, these employees should be able to schedule their work to allow more time for recovery activities (Rodriguez-Muñoz et al., 2012). Similarly, the availability of work-related resources, such as autonomy or supervisor support, may reduce their concerns about having to think about work during off-job time, allowing them to experience a smoother recovery (Bakker et al., 2005). These employees can also benefit from personal and family resources (e.g., Park & Fritz, 2015; Xanthopoulou et al., 2007) to fuel their work recovery and replenish their resources (Hobfoll, 2011; Meijman & Mulder, 1998). From the perspective of the job demands-resources model (Bakker & Demerouti, 2007), these employees may possess sufficient personal (e.g., self-efficacy) and professional (e.g., peer support) resources to successfully cope with their work demands.

The second scenario characterizes ***Plugged In*** employees, displaying low levels of recovery experiences across dimensions. These individuals are assumed to operate in a work environment characterized by high demands and low resources (Bakker & Demerouti, 2007) associated with an increased negative activation (e.g., negative affect, work-related rumination; Sonnentag & Fritz, 2015). Negative activation makes it difficult to properly recover from work even after having physically left the workplace. Thus, these employees may continue to be concerned with, and invested in, their work-related tasks when at home, making it harder for them to recover and to rebuild their psychological resources (Hobfoll, 2011; Meijman & Mulder, 1998). These employees may also lack personal, family or work-related resources to help them cope with their work demands (Derks et al., 2015).

A third scenario characterizes ***Moderately Unplugged*** employees, displaying average levels of recovery experiences across dimensions corresponding to neither an *Unplugged*, nor to a *Plugged In*, scenario. These employees perceive their work as moderately demanding, without exposing them to particularly threatening or stimulating opportunities (i.e., not particularly demanding or challenging; Huyghebaert-Zouaghi et al., 2022). These employees may potentially perceive lower levels of work demands than their *Plugged In* colleagues. According to the job demands-resources model (Bakker & Demerouti, 2017), these normative levels of job demands should be easier to incorporate in an ongoing work routine without requiring high levels of adaptation. These individuals should thus be able to allocate their resources, time, and energy across domains in a balanced way, without allowing work to take a disproportionate place in their life (Gillet et al., 2017). This scenario is consistent with person-centered results obtained while focusing on different work-related constructs (e.g., Gillet et al., 2019b; Morin et al., 2017), which has revealed that for a substantial number of employees, work-related experiences do not involve extremes but a more normative routine.

However, to support the value of considering these components as distinct from one another, and in accordance with the results obtained by Chawla et al. (2020) and Siltaloppi et al. (2011), it is plausible to expect at least one, perhaps two, additional profiles dominated by a subset of recovery experiences, mastery being the most plausible candidate for this role. Without further knowledge on the nature of these profiles and the number of possible scenarios, it would be premature to elaborate on these possibilities. Rather, we hope that the scenarios proposed here, together with our results, may serve as an impetus for further theoretical developments in this area. Based on these theoretical propositions and empirical evidence, we propose that:

Hypothesis 1. Four to five profiles of work recovery experiences will be identified.

Hypothesis 2. We will identify a minimum of three profiles displaying equivalent levels of work recovery across all four indicators (*Unplugged, Moderately Unplugged, and Plugged In*) corresponding to our three scenarios.

Hypothesis 3. We will identify at least one profile displaying discrepant levels of work recovery across all four indicators.

A Longitudinal Person-Centered Perspective

Meyer and Morin (2016) noted that it is crucial to document how stable over time person-centered results are if we want to be able to use them as guides for intervention. Two forms of stability should be examined in the context of longitudinal studies (Gillet et al., 2019a; Sandrin et al., 2020). Tests of within-sample stability first seek to determine whether the number and nature of the profiles change or remain stable over time (Morin et al., 2016b). In this regard, changes would indicate that the profiles mainly reflect transient phenomena with limited practical utility, unless participants have recently undergone some important changes or transitions. In contrast, changes can occur in relation to the extent to which profile members are similar to one another, and in relation to the size of these profiles. Such changes are consistent with the utility of these profiles as guides for intervention, showcasing the malleability of employees' degree of correspondence to the prototypical configurations reflected in these profiles (within-profile variability) and the fact that changes in profile membership are possible (size of the profiles). Second, within-person stability entails the examination of how stable employees' profile membership remains over time (Gillet et al., 2019a). Within-person stability thus provides more direct evidence of whether profile membership reflects a stable phenomenon at the individual level (i.e., reasonably high rates of stability) and of whether individual changes are possible (i.e., perfect rates of stability suggest that profiles reflect rigid psychological states). This second source of information indicates whether some or all of the profiles are likely to be easier (less stable) or harder (more stable) to modify through intervention, and about whether specific transitions will be easier or harder to support.

So far, research on recovery profiles has been primarily cross-sectional, with two exceptions. First, Siltaloppi et al. (2011) relied on work recovery data collected twice over a period of one year to identify their profiles. More precisely, their profiles were identified while simultaneously taking both time points into account (and thus did not only reflect the configurations of work recovery experiences, but also changes over time in these experiences). This allowed them to conclude that some of their profiles were characterized by changes in work recovery experiences over time, but made it impossible for them to systematically assess the within-sample and within-person stability of their profiles. Second, Chawla et al. (2020) provided tentative evidence of within-sample stability for their five-profile solution, but across a relatively short period of five days. However, if we consider this short time lag, the rates of within-person stability reported by these authors were fairly low, ranging from 43.8% for their *Plugged In* profile to only 2.6% for their *Unplugged* profile, suggesting that the profiles might be more ephemeral than desirable from an intervention perspective.

However, short-term studies are typically designed to maximize temporal variability in self-reports (i.e., relying on short questionnaires allowing employees to recall their previous responses and encouraging them to consider variations in their psychological states) and are thus not optimal for tests of profile stability. Indeed, variable-centered longitudinal studies have typically revealed moderately high levels of stability in recovery experiences over periods of two to three months (Dettmers, 2017; Huyghebaert et al., 2018). Thus, the present study specifically assesses the extent to which the identified profiles will remain stable over a period of three months. In line with prior research (Dettmers, 2017; Huyghebaert et al., 2018), we expected this specific time lag to be suitable because it goes beyond daily fluctuations and is long enough to offset memory biases (Chawla et al., 2020), while remaining short enough to ensure a proper measurement of stability under conditions that can generally be expected to be reasonably stable for most employees (Sonnentag et al., 2010). Based on all of these considerations, we propose that:

Hypothesis 4. The profiles will demonstrate within-sample stability over a three-month period.

Hypothesis 5: The profiles will display a moderate to high level of within-person stability.

Individual and Work-Related Characteristics Likely to Influence Work Recovery Profiles

From the theoretical perspective of the effort-recovery model (Meijman & Mulder, 1998), conservation of resources theory (Hobfoll, 2011), and job demands-resources model (Bakker & Demerouti, 2007), optimal work recovery requires the ability to disconnect from work during one's personal time, and any type of demands or resources likely to interfere with, or support, this disconnection is likely to play a critical role in determining the quality of one's work recovery experiences (e.g., Sonnentag & Fritz, 2007; Sonnentag et al., 2022). In the present study, we first focus on the role played by workaholism, a self-imposed type of work demands (Clark et al., 2020) likely to push employees to invest persistently high levels of efforts and energy in their work, even during off-work hours, and thus to interfere with the quality of their work recovery experiences (Balducci et al., 2021). We also consider the role played by colleagues' norms about the need to follow up quickly on work-related messages, an externally imposed type of work demands that also contributes to increase the pressure placed on employees to maintain a persistent connection to their work (Derks et al., 2015), making it harder to recover the resources expanded during their work hours (Gillet et al., 2022a; Hobfoll, 2011). As a counterbalancing force, we also consider the role played by employees' personal life orientation (Gillet et al., 2022b; Kreiner, 2006), which represents a key personal resource, at least when work recovery experiences are considered, likely to help employees disconnect from work and properly recover from it during their off-work time (Hall et al., 2013; Hobfoll, 2011). The decision to focus on these predictors is anchored in the recognition that contextual factors outside of the control of the employees have traditionally been given much more importance in work recovery research than variables over which employees are likely to have more control (Sonnentag & Fritz, 2007). By focusing on predictors over which employees are likely to have more control, if only in terms of resisting an externally-driven pressure, this focus thus allows us to expand upon previous person-centered studies (Chawla et al., 2020; Siltaloppi et al., 2011).

By considering these different predictors, we seek to identify potential mechanisms which could be leveraged to promote improved recovery experiences for employees and their organizations. For instance, if we demonstrate that personal life orientation is linked to a lower likelihood of membership into work recovery profiles characterized by low levels of recovery experiences (e.g., *Plugged In* profile), then we could then advocate actions seeking to clearly communicate to employees the importance attributed by their organization to their work-life balance.

Workaholism. Clark et al. (2020) recently proposed a comprehensive definition of workaholism encompassing four facets: behavioral, motivational, emotional, and cognitive. Work occupies an overpowering place in the identity of workaholics, who create ever-increasing workloads for themselves (Balducci et al., 2021) and struggle to preserve boundaries between work and their personal lives (Gillet et al., 2017). Rather, workaholics experience an uncontrollable urge to work with a rigid persistence, increasing the likelihood that their work will interfere with their personal life (Huyghebaert et al., 2018) and with their work recovery experiences (Balducci et al., 2021; Sonnentag et al., 2022). To sustain their intense work involvement, workaholics need to remain in a state of constant activation, making it difficult to properly recover from work during off-time hours (Sonnentag & Fritz, 2007; Upadyaya et al., 2016). We thus propose that:

Hypothesis 6. Workaholism will be associated with membership into profiles characterized by lower levels of work recovery experiences (e.g., *Plugged In*) rather than into profiles characterized by higher levels of work recovery experiences (e.g., *Unplugged*).

Colleagues' norms about the need to follow up quickly on work-related messages. Research has shown that strong social norms about the need to remain connected at all time or to quickly respond to work-related messages significantly influenced how employees handle their work-family interface and the quality of their work recovery experiences (e.g., Derks et al., 2014, 2015). When employees experience unwanted intrusions of their work into their family life, they are likely to experience negative outcomes such as poor recovery experiences (Kreiner, 2006). Thus, employees exposed to colleagues' norms about the need to follow up quickly on work-related messages need to remain in a constant state of activation, forcing them to tap into their personal resources to properly cope with these high expectations from their colleagues and making it harder for them to properly recover from work (Braukmann et al., 2018; Hobfoll, 2011; Sonnentag & Fritz, 2007). We thus propose that:

Hypothesis 7. Colleagues' norms about the need to follow up quickly on work-related messages will be associated with membership into profiles characterized by lower levels of work recovery experiences (e.g., *Plugged In*) relative to profiles characterized by higher levels of work recovery experiences (e.g., *Unplugged*).

Personal life orientation. To the best of our knowledge, no study has yet considered how personal life orientation could influence work recovery experiences. However, past studies have shown personal life orientation to be associated with better personal and professional functioning (Hirschi et al., 2016, 2020). Individuals high in personal life orientation are able to prioritize the time and energy allocated to their various life roles and must succeed at managing the interface between their professional and personal roles to achieve a more sustainable career (Hall et al., 2013). They also tend to be strongly involved in their personal roles and are thus more likely to build psychological (e.g., self-esteem), personal (e.g., new skills), and social (e.g., community) resources within these nonwork life domains (Greenhaus & Powell, 2006). In turn, it becomes possible to capitalize on these resources to meet challenges in different life settings (e.g., to maintain high-quality relationships with one's family and friends, but also to increase one's work performance), in turn helping to increase the quality of their work recovery experiences (Sonnentag & Fritz, 2007). We thus propose that:

Hypothesis 8. Personal life orientation will be associated with membership into profiles characterized by higher levels of work recovery experiences (e.g., *Unplugged*) relative to profiles characterized by lower levels of work recovery experiences (e.g., *Plugged In*).

Implications of Work Recovery Profiles for Psychological and Physiological Health Outcomes

The effort-recovery model (Meijman & Mulder, 1998) highlights the critical role of work recovery experiences for the psychological and physiological functioning of employees, an assertion that has generally been supported in research (Chawla et al., 2020; Sonnentag & Fritz, 2007). To properly capture these two layers of consequences, while also complementing prior research (Chawla et al., 2020; Siltaloppi et al., 2011), we thus focus on the implications of the work recovery profiles for employees' emotional exhaustion (psychological outcome) and somatization (physiological outcome). Both outcomes were also selected because they are known to be highly detrimental to employees' performance (e.g., Rivkin et al., 2022; Schaufeli et al., 1996) and linked to multiple undesirable work outcomes (e.g., turnover: Olafsen et al., 2021; absenteeism: Ehrhardt & Ensher, 2021).

Documenting the outcomes of different work recovery profiles is likely to have important theoretical and practical implications. By identifying profiles of employees dominated by a very specific set of recovery experiences (e.g., high levels of psychological detachment and relaxation but low levels of control and mastery), it also becomes possible to better understand the real-life influence of recovery experiences, as these types of experiences rarely occur in a vacuum. In other words, rather than trying to artificially isolate the unique role played by specific recovery experiences, our person-centered approach affords us a more complete, holistic, and realistic view of the reality (Sonnentag et al., 2022). Importantly, profiles are likely to have differentiated effects on various outcomes and contexts, reinforcing the need for a broadband investigation of multiple outcomes across a variety of studies to make sure that there are no unexpected negative implications to profiles who seem more desirable in relation to a very specific set of outcomes in any given study. From a practical perspective, this knowledge is critical to allow managers to identify which profiles of employees should be supported by organizations, and which should be targeted for preventive interventions. Intervention possibilities are often limited in real life settings, and the same action is unlikely to influence all employees and recovery experiences in the same manner (Hahn et al., 2011).

From a theoretical perspective (Meijman & Mulder, 1998; Sonnentag & Fritz, 2007), when unable to properly recover from their work, employees often generate more work for themselves because their poor recovery experiences mean that they will tackle their workload with fewer cognitive, physical, and emotional resources. Without the necessary resources, work often results in feelings of disappointment, frustration, and exhaustion (Gillet et al., 2020). In contrast, adequate recovery experiences allow workers to replenish these resources, making it easier for them to face their work day (Bennett et al., 2018; Sonnentag & Fritz, 2007). It is thus not surprising that Chawla et al. (2020) found that more desirable outcomes were associated with their *Unplugged* profile (e.g., sleep quality, work engagement, and personal initiative), whereas more problematic outcomes occurred in the *Plugged In* one (e.g., emotional exhaustion), with the other profiles falling in between. Bennett et al.'s (2016) *Unplugged* profile also displayed the least somatic symptoms.

It is important to note that whereas psychological detachment and relaxation are two work recovery experiences that contribute to help employees to switch off from work, mastery and control rather seem to be more helpful for helping solve work-related problems (Sonnentag et al., 2022). By switching off from work, employees high in psychological detachment and relaxation may save energy. In contrast, problem-solving may be associated with feelings of strain or exhaustion (Bennett et al., 2016). As a result, the combination of high psychological detachment and relaxation coupled with low control and mastery might be more beneficial from a health perspective than an *Unplugged* profile. We thus propose that:

> *Hypothesis 9.* Profiles characterized by more optimal (e.g., *Unplugged*) or relaxing (e.g., dominated by psychological detachment and relaxation) work recovery experiences will be associated with lower levels of emotional exhaustion and somatic symptoms relative to profiles characterized by more problematic (e.g., *Plugged In*) or problem-solving (e.g., dominated by mastery and control) recovery experiences.

Method

Participants were invited to complete an online questionnaire (including all measures described in Table 1) twice over a period of three months via the Prolific Academic crowdsourcing platform. After raising some preoccupations with the reliance on similar online panels (e.g., MTurk), Landers and Behrend (2015) came to the conclusion that these were "neither better nor worse than other more common convenient samples" (p. 21), and that "if we intend to create theory broadly applicable across organizational contexts, MTurk and similar samples may prove superior to those collected from single convenient organizations" (p. 18). Moreover, when contrasting data collected using Prolific relative to data obtained from undergraduate students recruited via a traditional approach to convenience sampling, Stanton et al. (2022) were able to demonstrate that Prolific data resulted in similar estimates of scale score reliability, and that Prolific represented a successful alternative for convenience sampling seeking to increase ecological validity. In the present study, we relied on Prolific to recruit a sample of working adults from the USA and the British Isles, allowing us to collect data using already validated English versions of these instruments.

Recruitment was limited to participants: (1) for whom English was the main language; (2) who worked for an organization as their main occupation (excluding students, self-employed and unemployed); and (3) who lived with a spouse or partner. The questionnaire included two attention checks (e.g., "It is important that you pay attention to our survey, please tick strongly disagree"), as well as a final question to assess, "for scientific reasons", whether they were truly employed by an organization. Only those who successfully passed all of these checks were retained in the sample.

The final sample included 442 participants (56.6% females) at Time 1, and 356 participants (55.6% females), at Time 2, matching the sex distribution of workers in the USA and British Isles (Bureau of Labor Statistics, 2021). Of those, 158 reported mainly working onsite, and 284 reported mainly working remotely. Participants lived and worked in the British Isles (81.0%) or the USA (19.0%), and 94.1% held a bachelor degree. They had a mean age of 39.52 years (SD = 10.38) and a mean tenure in their position of 6.89 years (SD = 6.03). A majority held a permanent (92.5%) full-time (89.6%) position. Participants mainly worked in the private sector (57.9%). More precisely, participants worked in non-market services (53.2%), market services (33.0%), industry (8.1%), construction (2.3%), agriculture (0.2%), or other sectors (3.2%).

Before participating, participants received information about our objectives (i.e., to better understand the nature of their experiences of recovery from their work-related efforts and the factors that may contribute to these recovery experiences and to their health). They were also told that they could withdraw from the project at any time, and that participation was confidential and voluntary. To ensure their confidentiality, we asked them to come up with a unique identifier, which would allow us to connect their responses over time. Each time, participants received £1.75 for their participation.

Analyses

Preliminary Analyses

We first relied on preliminary factor analyses to verify the psychometric properties of all multi-item measures. The specification of these analyses and their results are reported in Section 1 of the online supplements (including Tables S1 to S6, covering factor structure, composite reliability, measurement invariance over time, and latent correlations). Results revealed that all factors were well-defined and associated with satisfactory composite reliability coefficients: (a) psychological detachment (ω = .895), (b) relaxation (ω = .928), (c) mastery (ω = .910), (d) control (ω = .905), (e) global workaholism (ω = .959), (f) specific motivational (ω = .698), cognitive (ω = .804), emotional (ω = .680), and behavioral (ω = .683) workaholism; (g) personal life orientation (ω = .873), (h) colleagues' norms regarding work-related messages (ω = .899), (i) emotional exhaustion (ω = .950), (j) global somatization (ω = .920), and (k) specific gastrointestinal (ω = .717), fatigue (ω = .538), pain (ω = .434), and cardiovascular (ω = .720) symptoms. All of our main analyses were based on factor scores extracted from saved from these preliminary models in standardized units (*SD* = 1; *M* = 0; e.g., Morin et al., 2016b) and specified as invariant over time to ensure their comparability over time (Millsap, 2011). Factor scores are partially corrected for unreliability (Skrondal & Laake, 2001) and maintain the properties of the measurement model (e.g., invariance) better than scale scores (Morin et al., 2016a). Variable correlations are reported in Table S7 of the online supplements.

Latent Profile Analyses

Our main analyses relied on Mplus 8.6 (Muthén & Muthén, 2021), maximum likelihood robust estimation procedures, and full information maximum likelihood estimation (Enders, 2010) to handle missing data. This approach allowed us to estimate all models using the responses from all participants who completed at least one time point (*n* = 442), rather than relying on the problematic listwise elimination of participants who did not complete both time points (*n* = 86). Time-specific latent profile analytic models including one to eight profiles were first estimated while allowing the means and variances of the four recovery experiences factors to be estimated freely across profiles (Morin & Litalien, 2019). These models relied on 5000 sets of random start values, 1000 iterations, and 200 final optimizations (Hipp & Bauer, 2006), while the latter longitudinal models relied on 10000 random starts, 1000 iterations, and 500 final optimizations.

Identifying the optimal number of profiles to retain is a complex decision that needs to be taken while considering multiple sources of information, including (Marsh et al., 2009; McLachlan & Peel, 2000; Morin, 2016): (a) whether each added profile brings a meaningful contribution to the solution; (b) whether each added profile is theoretically consistent; (c) whether each added profile results in a statistically proper (e.g., convergence, lack of negative variance estimates); and (d) a variety of statistical indicators which are available to guide this decision. For these last criteria, a lower value on the Akaïke Information Criterion (AIC), Bayesian Information Criterion (BIC), Consistent AIC (CAIC), and sample-size Adjusted BIC (ABIC) indicate better fitting models. Moreover, a statistically significant Bootstrap Likelihood Ratio Test (BLRT) and adjusted Lo, Mendell and Rubin's (2001) Likelihood Ratio Test (aLMR) both support a model relative to one including fewer profiles. However, statistical research has shown that the BIC, CAIC, ABIC, and BLRT, but not the AIC and aLMR, were efficient at guiding the identification of the optimal number of latent profiles (Diallo et al., 2016, 2017). For this reason, we only report the AIC and aMLR to ensure complete disclosure, and will not use them for purposes of model comparison. In addition, these tests all present a strong sample size dependency (Marsh et al., 2009) and thus often fail to converge on a specific solution. When this happens, scores on the AIC, BIC, CAIC, and ABIC as a function of the number of profiles should be graphically presented in the form of an elbow plot, where the observation of a plateau in the decrease in these values helps to pinpoint the optimal solution (Morin et al., 2011). In practice (e.g., Meyer & Morin, 2016; Morin & Litalien, 2019; Morin et al., 2016a), the statistical indicators are considered first to help pinpoint a range of acceptable solutions, which are then examined to eliminate those that are statistically improper, before being contrasted in terms of meaningfulness and theoretical conformity. Lastly, we also report an indicator of classification accuracy, the entropy, which should not be used to select the optimal number of profiles (Lubke & Muthén, 2007).

Longitudinal Tests of Profile Similarity

As long as the same number of profiles is identified at both time points (Morin & Wang, 2016), the two time-specific solutions can be integrated into a single longitudinal latent profile model. This model can then be used to conduct longitudinal tests of within-sample profile similarity (Morin & Litalien, 2017; Morin et al., 2016b). These tests are realized in sequence, starting by the verification of whether the same number of profiles will be identified over time. Both time-specific solutions are then integrated into a single model of *configural* similarity to which equality constraints are then imposed in sequence on the within-profile means (*structural* similarity), variances (*dispersion* similarity), and size (*distributional* similarity). Model comparisons rely on the BIC, CAIC, and ABIC, and profile similarity is supported when two of these indices decrease in a model relative to the previous one in the sequence (Morin et al., 2016b).

Latent Transition Analyses

A latent transition specification (allowing Time 1 profiles to predict Time 2 profiles) will then be added to the most similar longitudinal solution to investigate within-person stability and transitions (Collins & Lanza, 2010). This solution and all upcoming analyses will be estimated via the manual three-step approach (Asparouhov & Muthén, 2014; Morin & Litalien, 2017).

Predictors and Outcomes of Profile Membership

Before proceeding to the integration of the predictors in our analyses, we initially investigated the need to incorporate demographic characteristics (sex, age, working time, sector, and country) as controlled variables in the upcoming analyses. These variables were first incorporated to the solution through a multinomial logistic regression link function, and four alternative models were contrasted. The first, null effects, model assumed no associations between these demographic characteristics and the profiles. In the second model, the effects of these variables were freely estimated at both time points, and the predictions involving the Time 2 profiles were allowed differ across all Time 1 profiles (i.e., reflecting the effect of these variables on specific transitions). In a third model, these predictions only varied as a function of time. In the last model (*predictive* similarity), these associations were constrained to equality over time. Associations between the profiles and our theoretical predictors (work type, workaholism, personal life orientation, and colleagues' norms regarding work-related messages) were examined using the same model comparison procedures.

Time-specific outcome measures were then incorporated to the solution, and their levels were allowed to differ across profiles and time points. In these analyses, the outcome measures taken at Time 2 are controlled for their variance shared with the Time 1 outcome measures (i.e., stability). A second model of *explanatory* similarity was then estimated by fixing these associations to equality across time points. The statistical significance of between-profile differences in outcome levels was assessed using the multivariate delta method (Raykov & Marcoulides, 2004).

Results

Latent Profile Analyses

The model fit indicators associated with the time-specific latent profile analyses are reported in Table 2, and graphically displayed in Figures S1 and S2 of the online supplements. These indicators failed to pinpoint a clear dominant solution at Time 1, and tentatively supported a solution including six (CAIC), seven (BIC) or eight (ABIC) profiles at Time 2. However, the elbow plots revealed a first plateau at three profiles, and a second plateau at six profiles at both time points. Based on this information, we carefully examined solutions including three to six profiles. This examination revealed that these solutions were already highly similar across time points, and that adding profiles had a heuristic and theoretical contribution to the model up to four profiles. More specifically, the first, third, and fourth profiles included in our final solution (illustrated in Figure 1) were already present in the three-profile solution. Then, adding a fourth profile resulted in the addition of the second profile illustrated in Figure 1 (importantly, this profile displayed levels of relaxation and control that differed significantly from those observed in the third profile, as indicated in Table S8 of the online supplements). However, adding a fifth profile simply resulted in the arbitrary division of one already identified profile into smaller ones with a similar configuration (i.e., a very small profile, similar to Profile 4, and including fewer than 2% of the sample). For these reasons, and in accordance with Hypothesis 1, the four-profile solution was selected at both time points.

The model fit indicators associated with the longitudinal models are reported in Table 3. Following from the model of *configural* similarity, the model or *structural* similarity resulted in lower BIC, CAIC, and ABIC values, and was thus retained. The next models of *dispersion* and *distributional* similarity were also supported by the data. The model of *distributional* similarity was thus selected as our final model, thus supporting Hypothesis 4, and retained for interpretation. The results from this model are graphically displayed in Figure 1 and reported in more details in Tables S8 and S9 of the online supplements. This model was associated with a high classification accuracy (see Table S9: 91.8% to 97.3% at Time 1; 89.6% to 97.1% at Time 2), consistent with the high entropy of .876.

Profile 1 displayed low levels across all types of work recovery experiences. This *Plugged In* profile characterized 18.7% of the participants. Profile 2 represented participants reporting close to average levels of psychological detachment and mastery, and slightly above average levels of relaxation and control. This *Moderately Unplugged* profile corresponded to 42.9% of the participants. Profile 3 represented participants reporting slightly under average levels of psychological detachment and relaxation, average levels of control, and slightly above average levels of mastery. This *Moderately Plugged In* profile corresponded to 18.9% of the participants. Despite the apparent similarity in the shape of these two profiles, our results (see Table S8 of the online supplements) indicate that levels of relaxation and control are both significantly higher (non-overlapping confidence intervals) in Profile 2 than in Profile 3. Finally, Profile 4 represented participants reporting high levels of psychological detachment, relaxation, mastery, and control. This *Unplugged* profile corresponded to 19.5% of the participants. Although the nature of these profiles support Hypothesis 2, they are inconsistent with Hypothesis 3.

Latent Transition Analyses

The transition probabilities are reported in Table 4. Membership into Profiles 1 (*Plugged In*: Stability of 76.5%), 2 (*Moderately Unplugged*: Stability of 69.5%), and 3 (*Moderately Plugged In*: Stability of 69.9%) were the most stable over time. Conversely, membership into Profile 4 (*Unplugged*: Stability of 56.4%) was not as stable. Supporting Hypothesis 5, these results thus reveal a generally high within-person stability that decreases slightly as levels of recovery increase.

Participants initially presenting low levels of recovery experiences, when they transition to another profile at Time 2, retain relatively average levels of recovery experiences. Indeed, 14.2% of the members of the *Plugged In* profile at Time 1 transition to the *Moderately Unplugged* profile, 9.3% of them transition to the *Moderately Plugged In* profile at Time 2, and none of them transition to the *Unplugged* at Time 2. For members of the *Moderately Unplugged* profile at Time 1, transitions involve the *Plugged In* (6.3%), *Moderately Plugged In* (12.4%), and *Unplugged* (11.8%) profiles at Time 2. For members of the *Moderately Plugged In* profile at Time 1, transitions involve the *Plugged In* (6.4%), *Moderately Unplugged* (17.7%), and *Unplugged* (6.0%) profiles at Time 2. Finally, when they transition to a new profile at Time 2, members of the least stable *Unplugged* profile transition to the *Moderately Unplugged* (39.4%) and *Moderately Plugged In* (4.2%) profiles at Time 2.

Predictors of Profile Membership

In relation to the demographic controls, the results reported in Table 3 indicate that all information criteria were at their lowest for the null effects model, indicating a lack of relations between the demographic controls and the profiles at both time points, a conclusion that was also consistent with the parameter estimates from all of these models. For these reasons, demographic controls were not retained for the next stages of analyses. However, in relation to our theoretical predictors, the results reported in Table 3 are consistent with the generalizability of their associations with the profiles over time (i.e., supporting the *predictive* similarity of the solution). The results from this model are reported in Table 5 and revealed that specific levels of cognitive workaholism, global levels of workaholism, and colleagues' norms regarding work-related messages predicted an increased likelihood of membership into the *Plugged In* (1), *Moderately Unplugged* (2), and *Moderately Plugged In* (3) profiles relative to the *Unplugged* (4) profile. Specific levels of cognitive workaholism also predicted an increased likelihood of membership into the *Plugged In* (1) profile relative to the *Moderately Unplugged* (2) and *Moderately Plugged In* (3) profiles, while specific levels of emotional workaholism predicted an increased likelihood of membership into the *Moderately Plugged In* (3) profile relative to the *Unplugged* (4) profile. Moreover, colleagues' norms regarding work-related messages also predicted an increased likelihood of membership into the *Plugged In* (1) profile relative to the

Moderately Unplugged (2) profile. Conversely, personal life orientation predicted a decreased likelihood of membership into the *Plugged In* (1), *Moderately Unplugged* (2), and *Moderately Plugged In* (3) profiles relative to the *Unplugged* (4) profile. Personal life orientation also predicted a decreased likelihood of membership into the *Plugged In* (1) profile relative to the *Moderately Unplugged* (2) and *Moderately Plugged In* (3) profiles, but an increased likelihood of membership into the *Moderately Unplugged* (2) profile relative to the *Moderately Plugged In* (3) profile. Taken together, these findings generally support Hypotheses 6, 7, and 8.

Outcomes of Profile Membership

The lowest values on all information criteria were associated with the model of *explanatory similarity* (i.e., revealing outcome associations that generalized over time), which was retained (see Table 3). The mean level of each outcome in each of the profiles are reported in Table 6. Generally supporting Hypothesis 9, the results revealed clear differentiations across profiles for all outcomes except specific levels of gastrointestinal and pain symptoms. The least desirable outcomes (i.e., the highest levels of emotional exhaustion, specific fatigue symptoms, specific cardio-pulmonary symptoms, and global somatization) were associated with Profile 1 (*Plugged In*). Moreover, Profile 3 (*Moderately Plugged In*) displayed higher levels of emotional exhaustion and global somatization than Profile 4 (*Unplugged*)[1].

Discussion

The current study was designed to contribute to our understanding of the work recovery process through the identification of profiles of employees characterized by distinct configurations of work recovery experiences. Capitalizing on a longitudinal research design, we examined the generalizability of these profiles over time (within-sample stability), and the stability of employees' profile membership (within-person stability) over a time interval of three months. Finally, we investigated the associations between these profiles and a series of theoretically-relevant predictors (i.e., workaholism, personal life orientation, and colleagues' norms regarding work-related messages) and outcomes (i.e., emotional exhaustion and somatization). The present results have theoretical implications related to the effort-recovery model (Meijman & Mulder, 1998), the conservation of resources theory (Hobfoll, 2011), and the job demands-resources model (Bakker & Demerouti, 2007), in addition to their practical implications.

Work Recovery Profiles

One of the main contributions of our study arguably lies in the validation of the theoretical scenarios outlined in the introduction as a guide for future multidimensional research on work recovery experiences. Indeed, our results revealed four distinct work recovery profiles that corresponded closely to the scenarios outlined in the introduction. More precisely, beyond providing support for our *Unplugged* and *Plugged In* scenarios, the *Moderately Unplugged* and *Moderately Plugged In* profiles both shared similarities with our *Moderately Unplugged* scenario. As a result, these profiles provide a novel theoretically-driven heuristic framework to help researchers achieve a more comprehensive understanding of work recovery experiences. Interestingly and supporting their generalizability, these profiles were found to match those identified previously (e.g., Bennett et al., 2016; Chawla et al., 2020; Siltaloppi et al. 2011) and were replicated over time (and across subsamples of remote and onsite employees as part of supplementary analyses reported in Section 2 of the online supplements). This strong evidence of generalizability suggests that these profiles capture some core mechanisms involved in employees' work recovery experiences. This is all the more important that the temporality of each previous study is quite different (e.g., a few days in Chawla et al., 2020; three months in the present research; one year in Siltaloppi et al. 2011). Thus, we might have expected greater differences between our results and those reported by Chawla et al. (2020) based on the assumption that employees' day-to-day recovery experiences are likely to differ from their longer-term recover experiences. The fact that this was not the case gives us greater certainty about the relevance and robustness of these profiles (Sonnentag et al., 2022).

Many have previously highlighted the need to account for multiple, and conceptually distinct, components of work recovery experiences (e.g., mastery, relaxation, psychological detachment, and

[1] Supplementary analyses (see Section 2 of the online supplements) demonstrated that the role of these predictors, as well as the implications of our work recovery profiles in terms of emotional exhaustion and somatization, entirely generalized to remote and onsite employees.

control; Bosch et al., 2018; Feldt et al., 2013). In contrast, our study seems to indicate that there is only limited value in differentiating among these four components, which rather converged with one another within all of our profiles. This conclusion is aligned with previous reports revealing strong correlations between these components (Gillet et al., 2021; Sonnentag & Fritz, 2007), as well as with most of the profiles identified by Chawla et al. (2020) and Siltaloppi et al. (2011). However, these authors also reported two profiles in which at least the levels of mastery deviated from the other components of work recovery experiences. The present results suggest that this last distinction may not be relevant when one seeks to consider relatively stable profiles of work recovery, rather than day-to-day variations in work recovery experiences. From a practical perspective, our results thus suggest that, to achieve a comprehensive picture of employees' work recovery profiles, it may not be necessary to separately consider their levels of relaxation, control, and psychological detachment. In relation to mastery, future research is required to identify the contexts in which it might be worth considering this component as distinct (or not) from the others.

It would also seem important to systematically investigate whether and how similar profiles would be identified across more diversified occupational groups (e.g., service and sale workers, technicians), cultures (e.g., South America, Eastern Europe, Asia), or research designs. For instance, numerous European countries have recently implemented a variety of policies seeking to protect employees' personal lives against the intrusion of the work domain (e.g., flexible work arrangements, accessible and affordable daycare, the right to disconnect; Drobnič et al., 2010) which are likely to support better work recovery experiences (Sonnentag et al., 2016). In contrast, in many Asian countries, work tends to be characterized by long working hours and inflexible workplace policies that do not allow employees to properly recover from their work-related efforts during off-time hours (Zeng & Chen, 2020). It is thus possible that the likelihood of identifying profiles characterized by more positive work recovery experiences (e.g., *Unplugged*) might be lower in these Asian countries than in many European countries. In addition, in some other countries, such as Russia, social policies do not guarantee the same level of freedom and liberty as in other Western or Asian countries (House et al., 2004). Employees working in these more restrictive cultures may thus be more likely to accept an organizational culture promoting presenteeism and/or competition (Simpson, 1998), which in turn might result in profiles characterized by lower recovery experiences (Sonnentag et al., 2022).

In terms of within-person stability, profile membership appeared to be moderately to highly stable over time (56.4% to 76.5%). These stability rates match previous reports showing that work recovery experiences appear moderately to highly stable over comparable time intervals (e.g., three months; Dettmers, 2017; Huyghebaert et al., 2018). These stability rates support the value of profile-based interventions, suggesting that the current set of work recovery profiles neither capture rigid conditions, nor entirely ephemeral tendencies (Hahn et al., 2011; Meyer & Morin, 2016), as already demonstrated by Siltaloppi et al. (2011) over a one-year period. In other words, even if an employee displays a work recovery profile associated with negative consequences at a given point in time, it is possible to envisage actions that could help this employee to rapidly develop improved recovery experiences, thus supporting the emergence of a more adaptive profile. Beyond supporting the possible relevance of interventions by highlighting that change is possible, the moderately high levels of stability of the profiles identified in the present study also highlights that change in unlikely to occur on its own for a majority of employees, which further reinforces the importance of interventions, and the value of these profiles as guides for intervention.

Membership into the *Unplugged* profile was the least stable over time (56.4%). This observation stands in contrast with Siltaloppi et al.'s (2011) results revealing a rather high level of stability in their *Unplugged* profile. Nevertheless, it is noteworthy that Siltaloppi et al. (2011) relied on different statistical methods, extracting profiles while jointly considering two time points, which is likely to force the extraction of profiles displaying a stronger consistency. In contrast, we separately estimated our profiles at each time point, systematically tested their similarity over time, and then tested the extent to which participants' membership was stable over time without letting that assessment influences the nature and shape of our profiles. Although further studies are needed to confirm our findings, the present results suggest that it might be hard to maintain high levels of work recovery experiences over time (even for a period as short as three months). Although our results do not formally test this possibility, other research suggests that the difficulty associated with maintaining high levels of work recovery 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., 2022), as well as to the increasingly blurred work-family boundaries to which workers are now exposed (Kreiner, 2006). Given the desirability of this profile, it would be important for organizations to consider intervening to help employees with more desirable profiles to maintain these profiles over time, possibly via their consultation to identify which practices seem particularly helpful (or harmful) in this regard. Such interventions may subsequently be expanded to help employees optimize their work recovery experiences.

Predictors of Work Recovery Profiles

Our results demonstrated that work recovery profiles were independent from employees' demographic characteristics (sex, age, working time, sector, and country), thus reinforcing the value of considering the possible role of individual and work-related variables likely to change over time. In this regard, by considering the role played by workaholism, personal life orientation, and colleagues' norms regarding work-related messages in the prediction of profile membership, our results provide some practical guidance regarding some of the likely drivers of the profiles identified in this study.

Our results first showed that global levels of workaholism as well as specific levels of cognitive and emotional workaholism seemed to decrease the likelihood of experiencing proper work recovery experiences, as these dimensions were all negatively related to membership into the *Unplugged* profile, while specific levels of cognitive workaholism were positively related to membership into the *Plugged In* profile. These observations support previous evidence showcasing the detrimental role of workaholism (Balducci et al., 2021; Huyghebaert et al., 2018), in addition to reinforcing the need to consider specific facets of workaholism beyond participants' global levels of workaholism (e.g., Gillet et al., 2022c). In line with the assumptions of the effort-recovery model (Meijman & Mulder, 1998), these results are in harmony with the idea that employees with high levels of workaholism invest a lot of their energy and resources at work at the expense of their personal life, decreasing their ability to properly recover from work during off-job time (Gillet et al., 2017).

However, specific levels of motivational and behavioral workaholism shared no association with profile membership on their own, while specific levels of emotional workaholism only predicted an increased likelihood of membership into the *Moderately Plugged In* profile relative to the *Unplugged* profile. In this regard, Howard et al. (2022) also found that cognitive workaholism was the sole facet of workaholism to share associations with mindfulness, whereas Clark et al. (2020) noted that this facet of workaholism was particularly important to consider for the prediction of poor work-related health outcomes (e.g., work-related rumination, depression). Taken together, these results suggest that this component of workaholism (and to a lesser extent specific emotional workaholism) might be particularly relevant to consider when trying to understand employees' work recovery experiences, their health outcomes, and more generally the ability to enjoy the present moment without worrying too much about work. These observations are coherent with the nature of this cognitive dimension of workaholism, which entails experiencing persistent thoughts about work (Clark et al., 2020). As such, it shares a natural connection with psychological detachment (Bennett et al., 2018; Sonnentag & Fritz, 2007), a core component of employees' work recovery experiences, as well as with work-related rumination (Gillet et al., 2021; Kinnunen et al., 2017), another known driver of poor recovery experiences. Thus, reducing the automaticity of the relentless work-related thoughts that characterize this specific facet of workaholism should be a priority for interventions seeking to facilitate recovery (Meijman & Mulder, 1998).

Exposure to colleagues' norms regarding work-related messages was also positively related to poorer work recovery experiences, thereby confirming prior reports of negative relations between this form of work-related pressure and work recovery (Derks et al., 2014, 2015). In line with the assumptions of the job demands-resources model (Bakker & Demerouti, 2007), these relations could be linked to the fact that employees feeling pressured to quickly respond to work demands at all times or at least perceiving high expectations of being constantly available and responsive should be more likely to succumb to that pressure, pushing them to personal sacrifices designed to help enhance their work performance, to struggle in withdrawing from work during off-job time, and to feel restless when not at work (Braukmann et al., 2018; Sonnentag & Fritz, 2007).

In contrast, personal life orientation was related to better work recovery experiences, thus also supporting prior results highlighting the benefits of having a life orientation that values personal time and activities (Hall et al., 2013). Indeed, because they tend to be more highly invested in their nonwork roles, employees high in personal life orientation are more likely to experience higher levels of positive affect when involved in these roles, in turn helping them to build extra resources within these roles (Greenhaus & Powell, 2006). In line with the assumptions of the conservation of resources theory (Hobfoll, 2011), these resources then become available to support their functioning across all of their life roles, thus directly contributing to more positive work recovery experiences (Sonnentag & Fritz, 2007). Importantly, personal life orientation was also found to be related to a lower likelihood of membership into the *Moderately Plugged In* profile relative to the similar but slightly more desirable *Moderately Unplugged* profile, thus supporting the idea that the benefits of personal life orientation apply to all levels of work recovery experiences. This last result is important, as we have demonstrated that personal life orientation predicted membership into profiles that primarily differ in two components (i.e., relaxation and control). These results thus suggest that the effects of personal life orientation on recovery experience may be limited to these two dimensions, so that practitioners wishing to facilitate relaxation and control could capitalize on improving personal life orientation.

Outcomes of Profile Membership

Our results finally revealed that the profiles shared clear associations with the outcomes. Thus, the *Plugged In* profile displayed the most problematic outcomes (i.e., the highest levels of emotional exhaustion, global somatization, specific fatigue symptoms, and specific cardio-pulmonary symptoms). Conversely, the *Unplugged* profile displayed lower levels of emotional exhaustion and global somatization than the *Moderately Plugged In* profile. These observations support the previously reported benefits of work recovery experiences (e.g., Bennett et al., 2018; Sonnentag & Fritz, 2007). Moreover, they are consistent with the assumptions of the conservation of resources theory (Hobfoll, 2011) suggesting that employees who are unable to properly recover from their work-related efforts exhaust their personal resources, generating a downward spiral of resource depletion likely to interfere with their ability to meet the demands of their work and personal lives and leading to detrimental physical and psychological health outcomes (Gillet et al., 2021).

It is noteworthy that the four profiles did not differ in their specific levels of gastrointestinal and pain symptoms, whereas the *Unplugged*, *Moderately Unplugged*, and *Moderately Plugged In* profiles did not differ in their specific levels of fatigue and cardio-pulmonary symptoms. Furthermore, although the *Moderately Unplugged* profile did not differ from the *Moderately Plugged In* and *Unplugged* profiles on emotional exhaustion and global somatization, the *Moderately Plugged In* profile was associated with higher scores on these two outcomes relative to the *Unplugged* profile. First, these results suggest that the effects of the work recovery profiles are different depending on the nature of the outcomes considered, in line with prior studies showing that psychological detachment, relaxation, mastery, and control have differential effects on fatigue and vigor (Bennett et al., 2018) or on sleep quality, emotional exhaustion, work engagement, helping behavior, and personal initiative (Chawla et al., 2020).

Second, these findings confirm the need to better differentiate the *Moderately Plugged In* and *Moderately Unplugged* profiles which, although similar, still differ from one another in their global level of recovery experiences, and particularly in terms of relaxation and control, as well as in relation to their aforementioned associations with personal life orientation. The fact that they did not differ from one another in terms of outcomes highlights the need to consider a broader range of outcomes in future studies to more clearly investigate similarities and differences between these two profiles. Their differential associations with personal life orientation, which was our only variable unrelated to the work-context or to physical health suggests that these profiles may be primarily differentiated by what happens outside of the work context. Future studies are needed to investigate this possibility.

In fact, our results suggest that psychological detachment and mastery may not be sufficient to counteract the deleterious effects of the moderately low levels of relaxation and control observed in the *Moderately Plugged In* profile for outcomes related to emotional exhaustion and global somatization. Thus, the slightly lower levels of relaxation and control displayed by employees within the *Moderately Plugged In* profile seem particularly important in the prediction of higher levels of emotional exhaustion and global somatization relative to the *Unplugged* profile. Indeed, not all recovery experiences may be equally important for everyone, so that employees may differ in their preferences for specific types of recovery experiences (ten Brummelhuis & Trougakos, 2014). Yet, according to Sonnentag et al. (2022), only recovery experiences that actually match one's preferences should be beneficial.

Interestingly, past research has also shown that relaxation was the most important predictor of sleep quality (Chawla et al., 2020). Conversely, control had the strongest effects on vigor (Bennett et al., 2018). This might be explained by the fact that relaxation helps generate more positive affect (Stone et al., 1995). Similarly, the benefits of control are in line with the numerous studies (Sandrin et al., 2019, 2022) showing a positive effect of autonomous motivation (i.e., actions are driven by pleasure and choice). Thus, the degree to which someone can decide what to do during off-job time, as well as when and how to do it, may be associated with better health outcomes because of the effects of this sense of control on the positive reevaluation of potentially stressful situations and the experience of more positive affect (Lazarus & Folkman, 1984; van Steenberger et al., 2021). Clearly, future research will be needed to better unpack these mechanisms, and to achieve a clearer differentiation between the nature of the two moderate profiles identified in this study. To do this, it could be interesting to consider outcomes (e.g., sleep, engagement) already identified as likely to be influenced by the dimensions that most differentiate these two profiles, namely relaxation and control.

Limitations and Future Directions

Limitations of the present study need to be acknowledged. First, our sole reliance on self-report measures is accompanied by a risk that self-report and social desirability biases may play a role in our results. To reduce this concern, future studies should consider the incorporation of informant ratings (e.g., supervisor, customers, colleagues) and objective measures (e.g., official data about performance, turnover, or absenteeism). Second, we relied on a mixed sample of employees who lived and worked in the British Isles or the USA, and who were recruited via a crowdsourcing platform. Despite the incorporation of quality checks in our data collection procedure, further research will be needed to test the replicability of our results to different work settings, countries, languages, and cultures, as well as to samples recruited using different methods. Moreover, our study occurred during a national lockdown due to a global pandemic which might have significantly impacted individuals' functioning (Huyghebaert-Zouaghi et al., 2022), which could also have influenced our results.

Third, we measured the stability of our work recovery profiles over a period of three months, during which no specific transition or systematic change occurred for most participants. Both countries were also on national lockdown (COVID-19) during data collection, which may have made it more difficult for some participants to experience work recovery through outdoor activities. Moreover, recovery experiences may be more difficult at certain times of the year (e.g., fall or winter) because there are fewer activities that can be done during off-job time due to weather constraints. For these reasons, stability could be smaller if longer time intervals (e.g., one year), or intervals encompassing interventions, changes or transitions, and different seasons were considered. In addition, there might be interindividual differences in the speed with which changes in recovery experiences occur (Sonnentag et al., 2022). Finally, workaholism, personal life orientation, and colleagues’ norms regarding work-related messages were the only predictors considered in our research. It would be valuable for future investigations, to consider the role of other personal characteristics (e.g., self-efficacy, resilience) as well as that of challenge (e.g., role complexity, responsibilities) and hindrance (e.g., role overload, role conflict, role ambiguity) demands relate to work recovery profiles. Likewise, additional negative (e.g., turnover, absenteeism, depression) and positive (e.g., creativity, performance) outcomes could be included to better document the implications of the work recovery profiles.

Implications for Practice

Our results suggest that organizations and managers should be particularly careful to monitor the emergence of any type of norm, be it formal and informal, highlighting the need for employees to remain responsive to work-related messages outside of their work hours, and take action to support employees’ right to disconnect. Employees displaying high levels of workaholism and/or low levels of personal life orientation might be particularly vulnerable to these norms, and to poor work recovery experiences, and should also be a focus for intervention. Indeed, our results show that workers exposed to these three characteristics were the least likely to be display an *Unplugged* profile and most likely to display a *Plugged In* profile. For instance, workplace could support employees’ personal life orientation by offering enabling work-life policies and work environments that support and value well-being (Bourdeau et al., 2019), as well as by encouraging employees to adopt healthier lifestyles and developing norms that clearly support the importance of work-life segmentation (Kreiner, 2006). Coaching and counseling interventions might also be needed for employees displaying high levels of workaholism, who might have difficulties in reaching a more balanced lifestyle on their own (Van Gordon et al., 2017). Serious attempts to achieve a sustainable workload reduction are themselves likely to contribute to address all three issues (Derks et al., 2015), as well as any policies supporting employees' right to enjoy their personal life (Huyghebaert-Zouaghi et al., 2022). Indeed, and despite our focus on some individual predictors of work recovery experiences, it remains important to keep in mind that job stressors, demands, and pressures remain the most likely theoretical drivers of poor work recovery experience, and deserve a focal role in intervention in their own right (Sonnentag et al., 2022).

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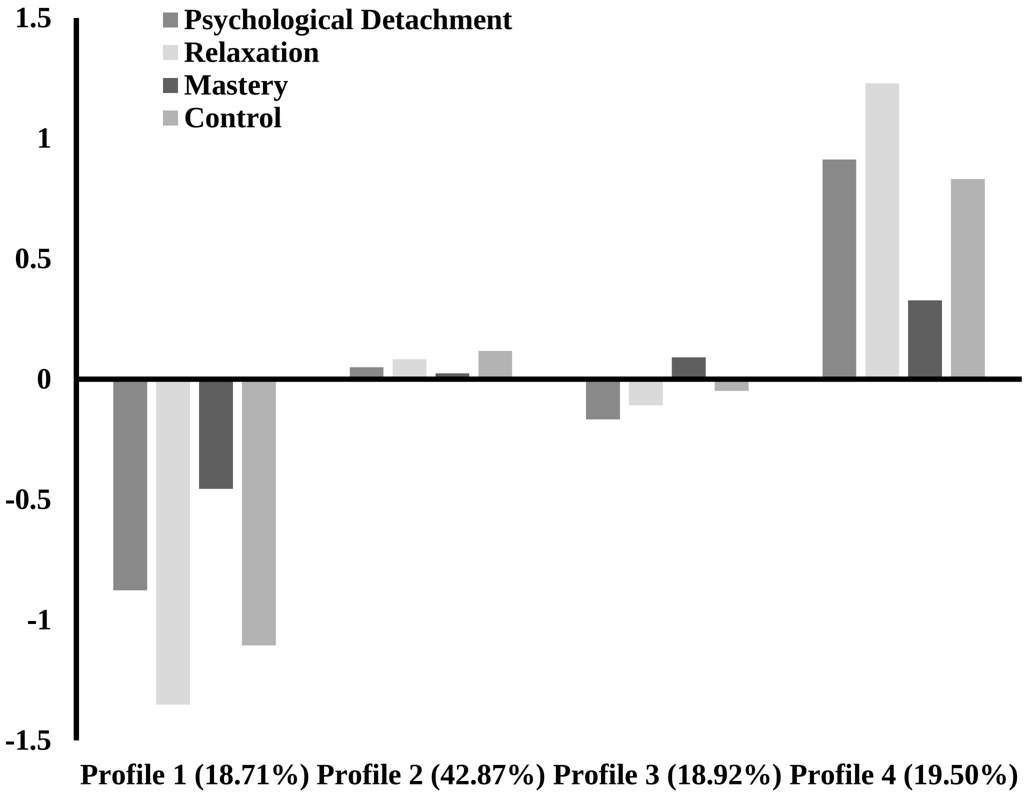

Figure 1. Final Four-Profile Solution
Note. Profile 1: Plugged In; Profile 2: Moderately Unplugged; Profile 3: Moderately Plugged In; Profile 4: Unplugged; the Y-axis refers to scores on the profile indicators, which are all factor scores estimated with a mean of 0 and a standard deviation of 1.

Table 1

Definitions and Operationalization of the Variables Measured in the Present Study

Variable	Definition	# items	Sample item	Alpha (α)	Response	Reference
Work Recovery Experiences (Profile Indicators)						
Psychological detachment	The ability to stop thinking about work during off-job time	4	*I distance myself from my work*	T1: .89 T2: .90	1- *Strongly Disagree* to 5- *Strongly Agree*	Sonnentag & Fritz (2007)
Relaxation	A sense of peacefulness, positive emotions, and low levels of activation during nonwork time	4	*I do relaxing things*	T1: .92 T2: .93	1- *Strongly Disagree* to 5- *Strongly Agree*	Sonnentag & Fritz (2007)
Control	The degree to which employees can freely decide what to do, and how to do it, during off-job time	4	*I decide my own schedule*	T1: .90 T2: .90	1- *Strongly Disagree* to 5- *Strongly Agree*	Sonnentag & Fritz (2007)
Mastery	The experience of a sense of proficiency and competence during nonwork time	4	*I seek out intellectual challenges*	T1: .90 T2: .92	1- *Strongly Disagree* to 5- *Strongly Agree*	Sonnentag & Fritz (2007)
Workaholism (Predictor)						
Motivational	An inner compulsion to work	4	*I always have an inner pressure inside of me that drives me to work*	T1: .88 T2: .89	1- *Strongly Disagree* to 5- *Strongly Agree*	Clark et al. (2020)
Cognitive	Persistent thoughts about work	4	*I feel like I cannot stop myself from thinking about working*	T1: .92 T2: .91	1- *Strongly Disagree* to 5- *Strongly Agree*	Clark et al. (2020)
Emotional	The experience of negative emotions when not working	4	*I feel upset if I have to miss a day of work for any reason*	T1: .86 T2: .88	1- *Strongly Disagree* to 5- *Strongly Agree*	Clark et al. (2020)
Behavioral	An excessive level of work involvement	4	*I work more than what is expected of me*	T1: .86 T2: .87	1- *Strongly Disagree* to 5- *Strongly Agree*	Clark et al. (2020)
Other Predictors						
Personal life orientation	Individuals' inclination to allocate enough time, in their lives, to pursue their own personal interests while concurrently engaging in a professional career	5	*Making time for pursuing personal interests is a big priority for me*	T1: .86 T2: .88	1- *Strongly Disagree* to 5- *Strongly Agree*	Hall et al. (2013)
Colleagues' norms	Colleagues' norms about the need to remain connected at all times or to quickly respond to work-related messages	6	*If I do not answer my work-related messages during off job hours, I get comments from my colleagues*	T1: .90 T2: .89	1- *Strongly Disagree* to 5- *Strongly Agree*	Derks et al. (2015)
Somatic Symptoms (Outcomes)						
Gastrointestinal	Symptoms involving the gastrointestinal tract	3	*Stomach pain*	T1: .74 T2: .75	1- *Not Bothered* to 3- *Very Bothered*	Pedersen et al. (2019)
Fatigue	A lack of energy	2	*Trouble sleeping*	T1: .66 T2: .66	1- *Not Bothered* to 3- *Very Bothered*	Pedersen et al. (2019)
Pain	An unpleasant sensory and emotional experience	3	*Headaches*	T1: .52 T2: .43	1- *Not Bothered* to 3- *Very Bothered*	Pedersen et al. (2019)
Cardio-Pulmonary	A range of disorders that affect the heart and lungs	5	*Shortness of breath*	T1: .71 T2: .63	1- *Not Bothered* to 3- *Very Bothered*	Pedersen et al. (2019)
Other Outcome						
Emotional Exhaustion	A state of feeling emotionally worn-out and drained	5	*Working all day is really a strain for me*	T1: .95 T2: .95	1- *Never* to 7- *Everyday*	Schaufeli et al. (1996)

Table 2

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	-2436.009	8	1.096	4888.017	4928.748	4920.748	4895.359	Na	Na	Na
2 Profiles	-2151.273	17	1.022	4336.546	4423.098	4406.098	4352.148	.979	< .001	< .001
3 Profiles	-1904.788	26	1.125	3861.577	3993.951	3967.951	3885.439	.954	< .001	< .001
4 Profiles	-1794.905	35	1.157	3659.809	3838.005	3803.005	3691.931	.896	.025	< .001
5 Profiles	-1686.399	44	1.284	3460.798	3684.816	3640.816	3501.180	.895	.095	< .001
6 Profiles	-1622.270	53	1.128	3350.540	3620.380	3567.380	3399.182	.875	.001	< .001
7 Profiles	-1587.662	62	1.156	3299.323	3614.984	3552.984	3356.225	.865	.048	< .001
8 Profiles	-1542.134	71	1.087	3226.268	3587.751	3516.751	3291.429	.874	.056	< .001
Time 2										
1 Profile	-2355.418	8	1.175	4726.836	4767.567	4759.567	4734.178	Na	Na	Na
2 Profiles	-2057.419	17	1.120	4148.837	4235.389	4218.389	4164.439	.943	< .001	< .001
3 Profiles	-1845.305	26	1.513	3742.610	3874.984	3848.984	3766.472	.939	.135	< .001
4 Profiles	-1735.198	35	1.096	3540.397	3718.593	3683.593	3572.519	.872	< .001	< .001
5 Profiles	-1670.451	44	1.079	3428.902	3652.919	3608.919	3469.284	.891	.002	< .001
6 Profiles	-1609.554	53	1.018	3325.107	3594.947	3541.947	3373.749	.864	< .001	< .001
7 Profiles	-1580.740	62	1.129	3285.479	3601.141	3539.141	3342.381	.872	.191	< .001
8 Profiles	-1565.249	71	1.051	3272.497	3633.980	3562.980	3337.659	.856	.126	< .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.

Table 3

Results from the Time-Specific and Longitudinal Models

Model	LL	#fp	Scaling	AIC	CAIC	BIC	ABIC	Entropy
Final Latent Profile Analyses								
Time 1	-1794.905	35	1.157	3659.809	3838.005	3803.005	3691.931	.896
Time 2	-1735.198	35	1.096	3540.397	3718.593	3683.593	3572.519	.872
Longitudinal Latent Profile Analyses								
Configural Similarity	-3530.103	70	1.126	7200.206	7556.598	7486.598	7264.450	.884
Structural Similarity	-3534.300	54	1.231	7176.600	7451.531	7397.531	7226.160	.882
Dispersion Similarity	-3556.459	38	1.437	7188.918	7382.388	7344.388	7223.793	.876
Distributional Similarity	-3557.673	35	1.508	7185.346	7363.542	7328.542	7217.468	.876
Predictive Similarity: Demographics								
Null Effects Model	-2560.142	35	.963	5190.284	5368.480	5333.480	5222.406	.865
Profile-Specific Free Relations with Predictors	-2513.184	125	.683	5276.368	5912.782	5787.782	5391.089	.893
Free Relations with Predictors	-2534.790	65	.997	5199.580	5530.515	5465.515	5259.235	.869
Equal Relations with Predictors	-2547.685	50	.970	5195.370	5449.935	5399.935	5241.258	.866
Predictive Similarity: Predictors								
Null Effects Model	-6887.224	167	1.198	14108.447	14958.696	14791.696	14261.715	.865
Profile-Specific Free Relations with Predictors	-6705.837	311	1.206	14033.673	15617.071	15306.071	14319.100	.905
Free Relations with Predictors	-6770.432	215	1.169	13970.864	15065.495	14850.495	14168.184	.876
Equal Relations with Predictors	-6785.941	191	1.180	13953.882	14926.322	14735.322	14129.176	.871
Explanatory Similarity								
Free Relations with Outcomes	-5550.862	75	1.091	11251.723	11633.571	11558.571	11320.556	.899
Equal Relations with Outcomes	-5561.604	51	1.295	11225.209	11484.866	11433.866	11272.015	.899

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 4

Transitions Probabilities

	Profile 1	Profile 2	Profile 3	Profile 4
Profile 1	.765	.142	.093	.000
Profile 2	.063	.695	.124	.118
Profile 3	.064	.177	.699	.060
Profile 4	.000	.394	.042	.564

Note. Profile 1: Plugged In; Profile 2: Moderately Unplugged; Profile 3: Moderately Plugged In; Profile 4: Unplugged.

Table 5

Results from the Predictive Analyses

	Profile 1 vs 4		Profile 2 vs 4		Profile 3 vs 4	
Predictors	Coef. (SE)	OR	Coef. (SE)	OR	Coef. (SE)	OR
S-Motivational	.248 (.246)	1.282	.042 (.157)	1.043	-.043 (.188)	.958
S-Cognitive	1.357 (.228)**	3.886	.613 (.174)**	1.847	.797 (.204)**	2.220
S-Emotional	.256 (.227)	1.291	.303 (.180)	1.355	.423 (.209)*	1.527
S-Behavioral	-.059 (.232)	.942	-.148 (.132)	.863	.003 (.171)	1.003
G-Workaholism	.659 (.208)**	1.934	.540 (.170)**	1.716	.489 (.193)*	1.631
Personal life orientation	-1.102 (.219)**	.332	-.377 (.154)*	.686	-.737 (.172)**	.479
Colleagues' norms	.847 (.230)**	2.333	.431 (186)*	1.538	.516 (.219)*	1.675
Work type	.017 (.328)	1.017	.215 (.238)	1.240	.289 (.286)	1.336
	Profile 1 vs 3		Profile 2 vs 3		Profile 1 vs 2	
Predictors	Coef. (SE)	OR	Coef. (SE)	OR	Coef. (SE)	OR
S-Motivational	.291 (.198)	1.338	.085 (.143)	1.088	.206 (.215)	1.229
S-Cognitive	.560 (.172)**	1.751	-.184 (.139)	.832	.744 (.164)**	2.105
S-Emotional	-.168 (.177)	.846	-.120 (.143)	.887	-.048 (.169)	.953
S-Behavioral	-.062 (.205)	.940	-.150 (.145)	.861	.088 (.211)	1.092
G-Workaholism	.170 (.167)	1.186	.051 (.140)	1.052	.119 (.161)	1.127
Personal life orientation	-.366 (.164)*	.694	.360 (.130)**	1.433	-.725 (.192)**	.484
Colleagues' norms	.331 (.176)	1.393	-.085 (.153)	.918	.416 (.164)*	1.516
Work type	-.272 (.277)	.762	-.074 (.241)	.928	-.198 (.284)	.821

Note. * $p < .05$; ** $p < .01$; SE: Standard error of the coefficient; OR: Odds ratio; S: Specific; G: Global; the coefficients and OR reflect the effects of the predictors on the likelihood of membership into the first listed profile relative to the second listed profile; motivational, cognitive, emotional, behavioral, and global workaholism, as well as personal life orientation, and norms of colleagues about work-related messages are estimated from factor scores with a standard deviation of 1 and a mean of 0; work type was coded 0 for onsite workers and 1 for remote workers; Profile 1: Plugged In; Profile 2: Moderately Unplugged; Profile 3: Moderately Plugged In; Profile 4: Unplugged.

Table 6

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]	Summary of Statistically Significant Differences
Emotional exhaustion	.854 [.660; 1.047]	-.239 [-.376; -.102]	-.066 [-.259; .127]	-.427 [-.635; -.218]	1 > 2 = 4; 1 > 3 > 4; 2 = 3
S-Gastrointestinal symptoms	.017 [-.107; .140]	.063 [-.014; .140]	.088 [-.026; .202]	.028 [-.065; .121]	1 = 2 = 3 = 4
S-Fatigue symptoms	.255 [.128; .383]	-.144 [-.233; -.055]	-.031 [-.132; .070]	-.094 [-.183; -.004]	1 > 2 = 3 = 4
S-Pain symptoms	-.008 [-.135; .119]	.016 [-.059; .091]	.114 [.017; .211]	.049 [-.049; .147]	1 = 2 = 3 = 4
S-Cardio-pulmonary symptoms	.265 [.089; .440]	.023 [-.045; .091]	.007 [-.071; .084]	.005 [-.052; .062]	1 > 2 = 3 = 4
G-Somatization	.759 [.599; .920]	-.084 [-.205; .037]	.012 [-.151; .174]	-.239 [-.377; -.101]	1 > 2 = 4; 1 > 3 > 4; 2 = 3

Note. M: Mean; CI: 95% confidence interval; S: Specific; G: Global; the indicators of emotional exhaustion and somatization as well as gastrointestinal, fatigue, pain, and cardio-pulmonary symptoms are estimated from factor scores with a mean of 0 and a standard deviation of 1; Profile 1: Plugged In; Profile 2: Moderately Unplugged; Profile 3: Moderately Plugged In; Profile 4: Unplugged.

Online Supplements for:

A Longitudinal Perspective on the Nature, Predictors, and Outcomes of Work Recovery Profiles

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.

Section 1:
Preliminary Measurement Models

Analyses

Given our reliance on complex longitudinal models involving multiple constructs, some of which are multidimensional, we conducted preliminary analyses separately for the: (1) recovery experiences and (2) predictors (workaholism, personal life orientation, and colleagues' norms about work-related messages) and emotional exhaustion (outcome). These preliminary analyses relied on Mplus 8.6 (Muthén & Muthén, 2021) and the maximum likelihood robust (MLR) estimator. We also relied on full information maximum likelihood (FIML; Enders, 2010) to deal with missing data, allowing us to save factor scores including no missing data. Since responses to the somatization questionnaire were provided using a three-point scale, it was necessary to rely on a different estimator (and separate measurement models) which takes into account the ordinal responses associated with this type of response scale (Finney & DiStephano, 2013). However, because the somatization measure relied on a three-point rating scale, it was necessary to rely on an alternative estimator (and on a separate measurement model) to account for this ordinal type of rating. Somatization was thus modelled with a robust weighted least square mean and variance (WLSMV) adjusted estimator. Since this estimator is not as efficient in handling missing data (Asparouhov & Muthén, 2010), we did not rely on this estimator to estimate missing values for employees who responded to only one data collection, as the FIML process used in our main analyses is more efficient (Enders, 2010).

As the chi-square test of exact fit (χ^2) is oversensitive to minor misspecifications, omitted variables, and sample size (e.g., Marsh et al., 2005), models were assessed and compared using sample-size independent fit indices (Hu & Bentler, 1999): The Tucker-Lewis index (TLI), comparative fit index (CFI), and root mean square error of approximation (RMSEA) coupled with its 90% confidence interval. Values above .90 are acceptable for TLI and CFI, although values above .95 are recommended. Values less than .08 are acceptable for the RMSEA, although values less than .05 are preferred. Likewise, tests of measurement invariance relied on changes in fit indices (Chen, 2007; Cheung & Rensvold, 2002). A ΔCFI/TLI of .010 or less and a ΔRMSEA of .015 or less between a model and the previous model indicates that the invariance is supported. We also report composite reliability coefficients (omega: ω) calculated from the standardized parameters (McDonald, 1970):

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

In this formular, $|\lambda_i|$ reflects the standardized factor loadings, and δi, the item uniquenesses.

For work recovery, we relied on a four-factor (control, mastery, psychological detachment, and relaxation) correlated factors confirmatory factor analytic (CFA) model at Times 1 (T1) and 2 (T2). All items were used to assess their a priori factor, with no cross-loading or correlated uniqueness.

Many studies have demonstrated that ratings of workaholism follow a bifactor representation (Gillet et al., 2018; Tóth-Király et al., 2021). A bifactor model implies the joint estimation of employees' global levels of workaholism (G-factor) and of the (non-redundant, orthogonal) specificity associated with each workaholism facet (S-factors) beyond these global levels (Morin et al., 2016). The workaholism G-factor is defined based on all items, whereas subscale-specific items are also used to define the S-factors. Research failing to separate these G- and S- factors is likely to erroneously conclude that each dimension plays a similar role, without truly capturing their truly unique nature beyond what they share with the other components (Tóth-Király et al., 2021). Consequently, the model used to represent the multi-items predictors and emotional exhaustion included a total of nine factors (G-workaholism, S-motivational workaholism, S-behavioral workaholism, S-emotional workaholism, S-cognitive workaholism, personal life orientation, colleagues' norms about work-related messages, and emotional exhaustion) at T1 and T2. The factors were defined solely by their a priori items (both the G- and S-factors for the workaholism items), with no cross-loading or correlated uniqueness. Although the G- and S-factors from the bifactor part of this solution were defined as orthogonal (uncorrelated) according to traditional bifactor specifications (Morin et al., 2016), these G- and S- factors could freely correlate with the CFA factors (personal life orientation, colleagues' norms about work-related messages, and emotional exhaustion), which were also allowed to freely correlate with one another.

As for workaholism, a bifactor-CFA model with one somatization G-factor and four symptoms-specific S-factors (gastrointestinal, pain, fatigue, and cardiovascular symptoms) was tested at T1 and

T2. As this structure represents a novel way to represent the ratings obtained on this scale, we contrasted this a priori solution with a more traditional correlated factors CFA. Both solutions included no cross-loading or correlated uniqueness.

We then sequentially tested the invariance of these solutions over time (Millsap, 2011): (i) configural invariance; (ii) weak (loadings) invariance; (ii) strong (MLR: loadings and intercepts; WLSMV: loadings and thresholds) invariance; (iv) strict (loadings, intercepts/thresholds, and uniquenesses) invariance; (v) invariance of the latent variance-covariance matrix; and (vi) latent means invariance.

Results

The model fit of all work recovery models is presented in Table S1, and confirms the adequacy of the CFA model underlying all recovery experiences, as well as the configural, weak, strong, strict, latent variances-covariances, and latent means invariance of this solution over time. For our main analyses, factor scores were saved from this final model (latent means invariance), for which parameter estimates are reported in Table S2. These results revealed that psychological detachment (λ = .708 to .909, ω = .895), relaxation (λ = .800 to .941, ω = .928), mastery (λ = .798 to .881, ω = .910), and control (λ = .801 to .880, ω = .905) were all well-defined by satisfactory factor loadings and composite reliability coefficients.

The model fit of the models including the predictors and emotional exhaustion is presented in Table S3 and confirms the adequacy of these measurement models (with all CFI/TLI ≥ .90 and all RMSEA ≤ .08), as well as their configural, weak, strong, strict, latent variances-covariances, and latent means invariance over time. For our main analyses, factor scores were saved from this final model (latent means invariance), for which parameter estimates are reported in Table S4. When interpreting results from a bifactor model, we must remember that this type of modeling relies on two factors to explain the item-level covariance. Factor loadings on the G- and S-factors are thus generally lower than their first-order counterparts (e.g., Morin et al., 2016). In this context, the main question is whether the G-factor captures a meaningful amount of covariance shared among all items, and whether there is sufficient specificity remaining in each S-factor. For workaholism, we found a strong G-factor (ω = .959) well-defined by the motivational (λ = .667 to .780), cognitive (λ = .641 to .707), emotional (λ = .604 to .683), and behavioral (λ = .636 to .669) items. The motivational (λ = .001 to .582, ω = .698), behavioral (λ = .161 to .673, ω = .683), cognitive (λ = .424 to .568, ω = .804), and emotional (λ = .350 to .511, ω = .680) S-factors also retained a satisfactory level of specificity. The CFA factors representing personal life orientation (λ = .707 to .800, ω = .873), colleagues' norms about work-related messages (λ = .701 to .876, ω = .899), and emotional exhaustion (λ = .828 to .931, ω = .950) were also well-defined by satisfactory factor loadings and composite reliability coefficients.

The model fit of the somatization models is presented in Table S5 and confirms the adequacy of the bifactor-CFA model (with all CFI and TLI ≥ .95, and all RMSEA ≤ .05) and its superiority in comparison with the CFA model (ΔCFI = .010 to .019; ΔTLI = .012 to .023; ΔRMSEA = .009 to .017). This bifactor-CFA model was then submitted to tests of measurement invariance, which supported the configural, weak, strong, strict, latent variances-covariances, and latent means invariance of the model over time. For our main analyses, factor scores were saved from this final model (latent means invariance), for which parameter estimates are reported in Table S6. Once again, we identified a strong G-factor (ω = .920) well-defined by the gastrointestinal (λ = .604 to .649), fatigue (λ = .543 to .755), pain (λ = .500 to .656), and cardiovascular (λ = .543 to .666) symptoms items. The gastrointestinal (λ = .428 to .570, ω = .717), fatigue (λ = .400 to .512, ω = .538), pain ($|\lambda|$ = .196 to .607, ω = .434), and cardiovascular (λ = .375 to .658, ω = .720) S-factors also retained a satisfactory level of specificity. Correlations among all variables are shown in Table S7.

Section 2:
The Role of Work Type: Remote versus Onsite Work

This research contributes to the paucity of research examining the unique work experiences of remote workers (Huyghebaert-Zouaghi et al., 2022), relative to that of onsite workers. This is an important concern as work settings have changed rapidly and substantially since the COVID-19 outbreak (Wang et al., 2021). Thus, research into the nature of remote workers' work recovery experiences is vital if organizations are to create workplace environments that afford remote employees the same opportunities for positive work experiences as their onsite counterparts (Charalampous et al., 2019). This study specifically aims to determine whether the nature and stability of the profiles, as well as their associations with predictors and outcomes, differ as a function of working remotely or onsite.

Thus far, research has uncovered that work recovery experiences tend to vary as a function of employees' work setting (Bennett et al., 2018; Sonnentag et al., 2017). In the present investigation, we rely on a more inductive approach to examine whether and how the work recovery profiles and the way they relate to predictors and outcomes, generalize across subsamples of remote or onsite employees. Working remotely tends to be associated with guilt and overcommitment emerging from workers s' desire to pay back the organization for providing them with a higher level of autonomy and flexibility (Sherman, 2020). Conversely, employees working onsite often benefit from more normative schedules, making it easier for them to recover (Charalampous et al., 2019).

For present purposes, working remotely means that the boundaries between one's professional and personal lives are already distorted in a way that could either enhance or decrease the undesirable effects of self- (i.e., workaholism) or others- (i.e., colleagues' norms about the need to follow up quickly on work-related messages) forms of work-related pressures on the quality of one's work recovery experiences (Wang et al., 2021). On the one hand, the flexibility afforded by a remote work setting (Biron & van Veldhoven, 2016) makes it far easier for employees to organize their schedule in a way that allows them to devote more time and energy to their work in a way that could amplify the negative impact of these two forms of pressures. On the other hand, the detrimental effects of these two forms of pressures on work recovery experiences could also be diminished when one works remotely, as this setting helps decrease the saliency of the work role (Wang et al., 2021). Likewise, by providing employees with higher levels of flexibility and autonomy (Biron & van Veldhoven, 2016), a remote work setting helps them to feel more in control about when to transition between roles (Park et al., 2020) and to distribute their resources more evenly across domains (Wan et al., 2019).

Employees with a high personal life orientation may see working remotely as a threat to their ability to manage the boundaries between their work and personal lives and may thus experience a sense of losing control in their prioritization of the time and energy to allocate to their various roles (Hall et al., 2013). Although they value their personal life, they may come to perceive its normative demands as interfering with their ability to meet work requirements promptly and efficiently, which is necessary to be able to recover properly from work. Alternatively, remote employees with a high personal life orientation should be able to schedule their work leaves them more time to dedicate to their personal life, thus increasing their ability to balance their different life roles and their likelihood of corresponding to the *Unplugged* profile (Sonnentag & Fritz, 2007).

In terms of outcomes, the health of remote employees could be impaired when working remotely makes it harder for them to find a peaceful workspace, limits their access to valuable resources, leads to more frequent interruptions, and increases their likelihood of experiencing work-family conflicts (e.g., Allen et al., 2020; Charalampous et al., 2019; Page et al., 2021). In contrast, it should be easier for onsite employees to maintain clearer boundaries between work and their personal lives, increasing their likelihood of experiencing more positive personal experiences (Wang et al., 2021). These positive experiences should help them build more resources, thereby increasing their ability to meet their professional objectives and to experience desirable health outcomes (i.e., lower emotional exhaustion and somatic symptoms; Hobfoll, 2011; Wayne et al., 2019).

Analyses and Results

We proceed to test the measurement invariance of each of the previous identified solutions across subsamples of remote or onsite workers at T1, and then at T2. The model fit of all work recovery models is presented in Table S1, and confirms the adequacy of the CFA model underlying all recovery experiences, as well as the configural, weak, strong, strict, latent variances-covariances, and latent means invariance of this solution across groups. The fit of the models including the predictors and emotional exhaustion is presented in Table S3 and confirms the adequacy of these measurement models (with all CFI/TLI $\geq$ .90 and all RMSEA $\leq$ .08), as well as their configural, weak, strong, strict, latent variances-covariances, and latent means invariance across groups. The bifactor-CFA somatization model was submitted to tests of measurement invariance, which supported the configural, weak, strong, strict, latent variances-covariances, and latent means invariance of the model across groups (see Table S5).

To further investigate the implications of work recovery profiles for emotional exhaustion and somatization between subsamples of remote or onsite employees (a work setting that can change over time), we had to estimate distinct multi-group latent profile analyses (working remotely or onsite was the grouping variable) at each time point. These additional analyses are reported in Tables S10-S11 and Figure S3. These additional results supported the superiority of the four-profile solution in both subsamples at both time points. They also confirmed the *configural*, *structural*, *dispersion*, and *distributional* similarity of the model solution in both subsamples across time points. The outcomes were then included to these solutions of *distributional* similarity at each time point, and the results were again consistent with the generalizability of these associations (*explanatory* similarity) across subsamples and time points. We finally examined if the role of predictors varied between remote (coded 1) and onsite (coded 0) employees by incorporating interactions between work type and these predictors to the final model. The null effects model was associated with the lowest values on all information criteria, supporting a lack of interactions between the predictors and work type (see the last section of Table S11).

Discussion

Our findings supported the generalizability of our results across subsamples of remote and onsite employees. These results stand in contrast with previous studies suggesting that work recovery experiences may vary as a function of job settings (Bennett et al., 2018; Sonnentag & Fritz, 2007), or with the idea that working remotely may buffer the undesirable effects of job demands and problematic individual characteristics on employees' professional and personal functioning (e.g., Gillet et al., 2022). However, these results are aligned with prior research demonstrating the generalizable adaptive effects of profiles characterized by high work recovery experiences on a various set of work-related indicators of behaviors and of well- and ill-being among employees working in very distinct settings (Chawla et al., 2020). More generally, by providing evidence of generalizability over time and across these two samples of employees, our results represent an important step forward in work recovery research by supporting the idea that generic interventions could be devised in a way that will be relevant across a variety of work settings.

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Table S1

Goodness-of-Fit Statistics for the Estimated Models (Recovery Experiences)

Description	χ^2 (*df*)	CFI	TLI	RMSEA	90% CI	CM	$\Delta\chi^2$ (*df*)	ΔCFI	ΔTLI	ΔRMSEA
Recovery Experiences										
Time 1	395.742 (98)*	.920	.902	.083	[.074; .092]	-	-	-	-	-
Time 2	296.874 (98)*	.941	.927	.076	[.066; .085]	-	-	-	-	-
Recovery: Multi-Group Invariance T1										
M1. Configural invariance	501.919 (196)*	.919	.901	.084	[.075; .093]	-	-	-	-	-
M2. Weak invariance	521.649 (208)*	.917	.904	.083	[.074; .091]	M1	20.243 (12)	-.002	+.003	-.001
M3. Strong invariance	537.122 (220)*	.916	.908	.081	[.072; .089]	M2	12.018 (12)	-.001	+.004	-.002
M4. Strict invariance	519.328 (236)*	.925	.924	.074	[.065; .082]	M3	8.027 (16)	+.009	+.016	-.007
M5. Variance-covariance invariance	528.437 (246)*	.925	.927	.072	[.064; .081]	M4	7.868 (10)	.000	+.003	-.002
M6. Latent means invariance	532.990 (250)*	.925	.928	.072	[.063; .080]	M5	3.340 (4)	.000	+.001	.000
Recovery: Multi-Group Invariance T2										
M7. Configural invariance	411.597 (196)*	.939	.925	.079	[.068; .089]	-	-	-	-	-
M8. Weak invariance	437.133 (208)*	.935	.925	.079	[.068; .089]	M7	25.495 (12)*	-.004	.000	.000
M9. Strong invariance	457.118 (220)*	.933	.926	.078	[.068; .088]	M8	18.895 (12)	-.002	+.001	-.001
M10. Strict invariance	461.932 (236)*	.936	.935	.073	[.063; .083]	M9	16.185 (16)	+.003	+.009	-.005
M11. Variance-covariance invariance	479.371 (246)*	.934	.935	.073	[.063; .083]	M10	17.558 (10)	-.002	.000	.000
M12. Latent means invariance	484.787 (250)*	.933	.936	.073	[.063; .082]	M11	5.025 (4)	-.001	+.001	.000
Recovery: Longitudinal Invariance										
M13. Configural invariance	979.208 (420)*	.935	.923	.055	[.050; 059]	-	-	-	-	-
M14. Weak invariance	983.267 (432)*	.936	.927	.054	[.049; .058]	M13	6.085 (12)	+.001	+.004	-.001
M15. Strong invariance	995.061 (444)*	.936	.929	.053	[.049; .057]	M14	9.243 (12)	.000	+.002	-.001
M16. Strict invariance	1012.921 (460)*	.936	.931	.052	[.048; .056]	M15	25.442 (16)	.000	+.002	-.001
M17. Variance-covariance invariance	1024.029 (470)*	.936	.932	.052	[.047; .056]	M16	10.044 (10)	.000	+.001	.000
M18. Latent means invariance	1033.083 (474)*	.935	.932	.052	[.047; .056]	M17	9.133 (4)	-.001	.000	.000

Note. * $p < .05$; 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 M18 Solution (Longitudinal Latent Means Invariance Recovery Experiences)

Items	Detachment λ	Relaxation λ	Mastery λ	Control λ	δ
Detachment					
Item 1	.909				.174
Item 2	.888				.211
Item 3	.784				.386
Item 4	.708				.499
Relaxation					
Item 1		.835			.303
Item 2		.913			.167
Item 3		.941			.114
Item 4		.800			.360
Mastery					
Item 1			.798		.363
Item 2			.862		.257
Item 3			.881		.224
Item 4			.846		.284
Control					
Item 1				.801	.359
Item 2				.869	.245
Item 3				.880	.226
Item 4				.807	.348
ω	.895	.928	.910	.905	
Factor Correlations	**Detachment**	**Relaxation**	**Mastery**	**Control**	
Detachment					
Relaxation	.540				
Mastery	*.094*	.239			
Control	.390	.611	.225		

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

Table S3

Goodness-of-Fit Statistics for the Estimated Models (Predictors and Outcome)

Description	χ^2 (*df*)	CFI	TLI	RMSEA	90% CI	CM	$\Delta\chi^2$ (*df*)	ΔCFI	ΔTLI	ΔRMSEA
Predictors and Outcome										
Time 1	1098.690 (430)*	.927	.916	.059	[.055; .064]	-	-	-	-	-
Time 2	943.681 (430)*	.933	.923	.058	[.053; .063]	-	-	-	-	-
Predictors and Outcome: Multi-Group Invariance T1										
M1. Configural invariance	1601.454 (860)*	.922	.909	.062	[.058; .067]	-	-	-	-	-
M2. Weak invariance	1656.919 (900)*	.920	.912	.062	[.057; .066]	M1	57.419 (40)*	-.002	+.003	.000
M3. Strong invariance	1699.320 (924)*	.918	.912	.062	[.057; .066]	M2	42.318 (24)*	-.002	.000	.000
M4. Strict invariance	1727.611 (956)*	.918	.915	.060	[.056; .065]	M3	40.319 (32)	.000	+.003	+.002
M5. Variance-covariance invariance	1748.472 (982)*	.919	.918	.059	[.055; .064]	M4	21.422 (26)	+.001	+.003	-.001
M6. Latent means invariance	1760.630 (990)*	.918	.918	.059	[.055; .064]	M5	12.141 (8)	-.001	.000	.000
Predictors and Outcome: Multi-Group Invariance T2										
M7. Configural invariance	1560.181 (860)*	.914	.900	.068	[.062; .073]	-	-	-	-	-
M8. Weak invariance	1585.759 (900)*	.916	.907	.065	[.060; .071]	M7	34.673 (40)	+.002	+.007	-.003
M9. Strong invariance	1627.344 (924)*	.913	.907	.065	[.060; .071]	M8	41.566 (24)*	-.003	.000	.000
M10. Strict invariance	1687.331 (956)*	.910	.907	.066	[.060; .071]	M9	58.657 (32)*	-.003	.000	+.001
M11. Variance-covariance invariance	1701.535 (982)*	.911	.910	.064	[.059; .069]	M10	16.503 (26)	+.001	+.003	-.002
M12. Latent means invariance	1720.370 (990)*	.910	.910	.064	[.059; .069]	M11	18.762 (8)*	-.001	.000	.000
Predictors and Outcome: Longitudinal Invariance										
M13. Configural invariance	3015.989 (1788)*	.939	.931	.039	[.037; .042]	-	-	-	-	-
M14. Weak invariance	3047.970 (1828)*	.939	.933	.039	[.036; .041]	M13	34.273 (40)	.000	+.002	.000
M15. Strong invariance	3077.784 (1852)*	.939	.933	.039	[.036; .041]	M14	29.295 (24)	.000	.000	.000
M16. Strict invariance	3105.127 (1884)*	.939	.935	.038	[.036; .041]	M15	35.316 (32)	.000	+.002	-.001
M17. Variance-covariance invariance	3139.979 (1910)*	.938	.935	.038	[.036; .041]	M16	34.813 (26)	-.001	.000	.000
M18. Latent means invariance	3147.357 (1918)*	.939	.935	.038	[.036; .040]	M17	6.882 (8)	.000	.000	.000

Note. * $p < .01$; χ^2: Scaled chi-square test of exact fit; *df*: Degrees of freedom; CFI: Comparative fit index; TLI: Tucker-Lewis index; RMSEA: Root mean square error of approximation; 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 M18 Solution (Longitudinal Latent Means Invariance Predictors and Outcome)

Items	G-Workahol. λ	S-Motiv. λ	S-Cognit. λ	S-Emot. λ	S-Behav. λ	PLO λ	CN λ	EE λ	δ
Motivational workaholism									
Item 1	.667	.582							.216
Item 2	.688	.493							.283
Item 3	.780	*.001*							.392
Item 4	.754	.498							.183
Cognitive workaholism									
Item 1	.641		.553						.284
Item 2	.684		.535						.246
Item 3	.707		.424						.320
Item 4	.689		.568						.202
Emotional workaholism									
Item 1	.604			.440					.441
Item 2	.670			.511					.291
Item 3	.683			.469					.314
Item 4	.671			.350					.428
Behavioral workaholism									
Item 1	.636				.161				.569
Item 2	.637				.673				.140
Item 3	.668				.379				.410
Item 4	.669				.524				.279
Personal life orientation									
Item 1						.773			.403
Item 2						.776			.398
Item 3						.800			.360
Item 4						.707			.500
Item 5						.743			.448
Colleagues' norms									
Item 1							.776		.398
Item 2							.794		.369
Item 3							.716		.488
Item 4							.768		.410
Item 5							.701		.509
Item 6							.876		.233
Emotional exhaustion									
Item 1								.919	.155
Item 2								.931	.134
Item 3								.925	.145
Item 4								.845	.286
Item 5								.828	.315
ω	.959	.698	.804	.680	.683	.873	.899	.950	
Correlations	**G-Workahol.**	**S-Motiv.**	**S-Cognit.**	**S-Emot.**	**S-Behav.**	**PLO**	**CN**	**EE**	
G-Workahol.	-								
S-Motiv.	.000	-							
S-Cognit.	.000	.000	-						
S-Emot.l	.000	.000	.000	-					
S-Behav.	.000	.000	.000	.000	-				
PLO	-.129	*.030*	*-.079*	-.182	*-.088*	-			
CN	.475	-.187	.188	*-.076*	*.068*	-.171	-		
EE	.154	*.030*	.444	*-.085*	*.092*	*.015*	.317	-	

Note. λ: Factor loading; δ: Item uniqueness; ω: Omega coefficient of composite reliability; G: Global; S: Specific; PLO: Personal life orientations; CN: Colleagues' norms about work-related messages; EE: Emotional exhaustion; the non-significant parameters (p > .05) are marked in italics.

Table S5

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

Description	χ^2 (*df*)	CFI	TLI	RMSEA	90% CI	CM	$\Delta\chi^2$ (*df*)	ΔCFI	ΔTLI	ΔRMSEA
Somatization										
Time 1 CFA	103.676 (49)*	.970	.960	.050	[.037; .064]	-	-	-	-	-
Time 1 Bifactor-CFA	63.317 (43)*	.989	.983	.033	[.012; .049]					
Time 2 CFA	81.918 (49)*	.977	.969	.043	[.026; .060]					
Time 2 Bifactor-CFA	61.208 (43)*	.987	.981	.034	[.010; .053]	-	-	-	-	-
Somatization: Multi-Group Invariance T1										
M1. Configural invariance	115.118 (86)*	.985	.977	.039	[.016; .057]	-	-	-	-	-
M2. Weak invariance	135.750 (104)*	.984	.980	.037	[.016; .054]	M1	22.574 (18)	-.001	+.003	-.002
M3. Strong invariance	146.579 (111)*	.982	.979	.038	[.018; .054]	M2	11.867 (7)	-.002	-.001	+.001
M4. Strict invariance	165.848 (123)*	.978	.977	.040	[.022; .054]	M3	21.981 (12)*	-.004	-.002	+.002
M5. Variance-covariance invariance	153.199 (128)	.987	.987	.030	[.000; .046]	M4	2.797 (5)	+.009	+.010	-.010
M6. Latent means invariance	152.020 (133)	.990	.990	.025	[.000; .043]	M5	2.179 (5)	+.003	+.003	-.005
Somatization: Multi-Group Invariance T2										
M7. Configural invariance	108.212 (86)	.985	.977	.038	[.000; .059]	-				
M8. Weak invariance	118.122 (104)	.990	.988	.028	[.000; .049]	M7	13.890 (18)	+.005	+.011	-.010
M9. Strong invariance	123.867 (111)	.991	.990	.026	[.000; .047]	M8	6.355 (7)	+.001	+.002	-.002
M10. Strict invariance	132.920 (123)	.993	.993	.021	[.000; .044]	M9	9.997 (12)	+.002	+.003	-.005
M11. Variance-covariance invariance	131.612 (128)	.998	.997	.013	[.000; .039]	M10	3.040 (5)	+.005	+.004	-.008
M12. Latent means invariance	137.757 (133)	.997	.997	.014	[.000; .039]	M11	5.813 (5)	-.001	.000	+.001
Somatization: Longitudinal Invariance										
M13. Configural invariance	242.079 (193)*	.990	.986	.024	[.013; 033]	-				
M14. Weak invariance	256.213 (211)*	.991	.988	.022	[.010; .031]	M13	16.630 (18)	+.001	+.002	-.002
M15. Strong invariance	259.631 (218)*	.992	.990	.021	[.007; .030]	M14	3.675 (7)	+.001	+.002	-.001
M16. Strict invariance	267.059 (230)*	.993	.991	.019	[.002; .028]	M15	10.600 (12)	+.001	+.001	-.002
M17. Variance-covariance invariance	266.000 (235)	.994	.993	.017	[.000; .027]	M16	3.368 (5)	+.001	+.002	-.002
M18. Latent means invariance	286.218 (240)*	.991	.989	.021	[.009; .030]	M17	22.617 (5)*	-.003	-.005	+.004

Note. * $p < .05$; 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 S6

Standardized Factor Loadings (λ) and Uniquenesses (δ) for the M18 Solution (Longitudinal Latent Means Invariance Somatization)

Items	G-Somatization Λ	S-Gastrointestinal λ	S-Fatigue λ	S-Pain λ	S-Cardiovascular λ	δ
Gastrointestinal						
Item 1	.604	.428				.453
Item 2	.649	.570				.254
Item 3	.643	.569				.263
Fatigue						
Item 1	.755		.400			.271
Item 2	.543		.512			.443
Pain						
Item 1	.500			.196		.711
Item 2	.618			.607		*.249*
Item 3	.656			-.256		.504
Cardiovascular						
Item 1	.551				.658	.262
Item 2	.543				.375	.565
Item 3	.666				.521	.285
Item 4	.605				.441	.439
ω	.920	.717	.538	.434	.720	

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

Table S7

Correlations between Variables

	1	2	3	4	5	6	7	8	9	10	11	12	13	14
1. Sex	-													
2. Age	.039	-												
3. Working time	-.134**	.008	-											
4. Sector	-.238**	.106*	.025	-										
5. Country	.146**	-.040	-.071	-.098*	-									
6. S-Motivational (T1)†	-.139**	.025	-.078	.025	-.088	-								
7. S-Cognitive (T1)†	-.094*	-.042	-.052	-.003	-.079	-.156**	-							
8. S-Emotional (T1)†	-.041	-.072	.075	-.007	-.011	-.121*	-.023	-						
9. S-Behavioral (T1)†	.042	.024	-.038	-.038	-.049	.130**	-.135**	-.263**	-					
10. G-Workaholism (T1)†	-.095*	.043	-.080	-.088	-.031	.105*	.117*	.091	.102*	-				
11. Personal life orientation (T1)†	.008	-.130**	-.099*	.026	.040	.019	-.005	-.176**	-.030	-.215**	-			
12. Colleagues' norms (T1)†	-.006	-.010	.036	-.100*	.030	-.211**	.255**	-.131**	.052	.507**	-.170**	-		
13. Emotional exhaustion (T1)†	-.074	-.172**	-.119*	-.024	-.020	.009	.577**	-.041	.131**	.135**	.054	.331**	-	
14. S-Gastrointestinal (T1)†	-.009	.033	-.036	.006	.046	.063	.055	-.082	.064	.045	.033	-.040	-.012	-
15. S-Fatigue (T1)†	-.008	-.048	.013	-.020	.060	-.042	.256**	-.044	-.001	.012	-.042	.128**	.294**	-.226**
16. S-Pain (T1)†	-.045	.103*	-.006	-.018	-.024	.055	-.072	.077	.013	.076	-.012	-.038	-.036	-.005
17. S-Cardiovascular (T1)†	-.022	.000	-.050	.023	-.051	-.061	.111*	.036	-.040	.051	-.045	.028	.100*	-.154*
18. G-Somatization (T1)†	-.314**	-.092	-.011	.026	-.039	.054	.346**	.040	.047	.127**	-.021	.206**	.439**	.176**
19. Psychological detachment (T1)†	.169**	.026	.050	.044	.025	.056	-.526**	.004	-.063	-.559**	.219**	-.521**	-.422**	-.014
20. Relaxation (T1)†	.115*	.000	-.033	-.002	.086	.010	-.275**	-.117*	.041	-.276**	.399**	-.281**	-.234**	.097*
21. Mastery (T1)†	.033	.066	-.023	-.001	.157**	-.038	-.111*	-.013	-.054	.062	.159**	.057	-.123**	.033
22. Control (T1)†	-.080	-.039	-.012	.028	.048	.015	-.290**	-.085	.005	-.166**	.388**	-.214**	-.239**	.067
23. Work type (T1)	.092	-.086	-.055	-.034	.000	-.010	.055	-.084	-.026	-.118*	.087	-.046	-.014	.009
24. S-Motivational (T2)†	-.151**	.007	-.072	.033	-.047	.706**	.069	-.013	.064	.154**	.175**	-.086	.106*	.024
25. S-Cognitive (T2)†	-.126**	-.064	-.029	.032	-.098*	-.100*	.829**	-.062	-.121*	.049	-.070	.195**	.440**	.039
26. S-Emotional (T2)†	-.018	-.050	.072	-.016	-.028	-.031	-.024	.802**	-.238**	.062	-.158**	.017	-.033	-.011
27. S-Behavioral (T2)†	-.022	.097*	-.048	.001	-.057	.051	.007	-.309**	.770**	.141**	.005	.041	.118*	.105*
28. G-Workaholism (T2)†	-.103*	-.007	-.105*	-.078	-.401	.063	.121*	.121*	.098	.915**	-.152**	.513**	.211**	.016
29. Personal life orientation (T2)†	.046	-.131**	-.056	.008	.072	-.005	-.062	-.064	.031	-.155**	.832**	-.144**	.065	.024
30. Colleagues' norms (T2)†	-.055	-.062	.037	-.089	.024	-.162**	.214**	-.050	.011	.488**	-.184**	.849**	.311**	-.094*
31. Emotional exhaustion (T2)†	-.108*	-.172**	-.121*	.029	-.042	.030	.572**	-.012	.094*	.087	.049	.318**	.886**	-.033
32. S-Gastrointestinal (T2)†	-.063	-.004	-.069	-.009	.076	.029	.122*	-.074	.037	.106*	.093	.083	.056	.498**
33. S-Fatigue (T2)†	-.054	-.024	.047	-.035	-.040	-.020	.136*	-.064	.153**	.071	-.066	.231**	.292**	.004
34. S-Pain (T2)†	-.031	.177**	.004	.018	-.009	.050	-.070	.018	-.015	.089	.010	-.003	-.052	.046
35. S-Cardiovascular (T2)†	-.006	-.024	-.015	.049	-.067	-.011	.151**	.022	-.114*	-.032	-.043	.005	.137**	-.160**
36. G-Somatization (T2)†	-.296**	-.050	.006	-.021	-.058	.027	.356**	.035	.003	.142**	-.043	.285**	.455**	.109*
37. Psychological detachment (T2)†	.209**	.040	.038	.025	.069	.089	-.531**	.000	-.009	-.522**	.232**	-.500**	-.415**	.003
38. Relaxation (T2)†	.124**	-.014	.005	-.029	.108*	.051	-.305**	-.088	.063	-.302**	.350**	-.344**	-.293**	.089
39. Mastery (T2)†	.028	.084	-.051	.018	.115*	-.063	-.146**	-.004	.006	.086	.142**	.026	-.134**	.075
40. Control (T2)†	-.058	-.002	.012	.058	.035	.037	-.300**	-.087	.041	-.170**	.288**	-.241**	-.239**	.074
41. Work type (T2)	.090	-.047	-.114*	.014	.061	-.026	.006	-.089	-.048	-.122*	.118*	-.093	-.100	-.013

Table S7 (continued)

Correlations between Variables

	15	16	17	18	19	20	21	22	23	24	25	26	27	28	29
15. S-Fatigue (T1)†	-														
16. S-Pain (T1)†	-.157**	-													
17. S-Cardiovascular (T1)†	-.107*	-.090	-												
18. G-Somatization (T1)†	.257**	.085	.215**	-											
19. Psychological detachment (T1)†	-.194**	-.003	-.116*	-.322**	-										
20. Relaxation (T1)†	-.136**	.011	-.096*	-.278**	.556**	-									
21. Mastery (T1)†	-.096*	-.003	.016	-.030	.076	.267**	-								
22. Control (T1)†	-.168**	.030	-.077	-.198**	.414**	.662**	.279**	-							
23. Work type (T1)	.038	.027	.046	.004	.078	.049	-.011	.042	-						
24. S-Motivational (T2)†	.054	.026	-.007	.124**	-.044	-.033	.033	.039	-.003	-					
25. S-Cognitive (T2)†	.201**	-.084	.097*	.285**	-.470**	-.273**	-.161**	-.290**	.125**	-.067	-				
26. S-Emotional (T2)†	-.088	.035	.017	.059	-.011	-.122*	-.013	-.136**	-.033	-.075	.048	-			
27. S-Behavioral (T2)†	.053	.002	-.007	.077	-.079	.027	-.077	-.030	-.061	.086	-.056	-.232**	-		
28. G-Workaholism (T2)†	.033	.035	.036	.144**	-.542**	-.272**	.061	-.180**	-.116*	.118*	.067	.080	.091	-	
29. Personal life orientation (T2)†	-.060	-.021	-.050	-.044	.175**	.361**	.162**	.357**	.087	.094*	-.163**	-.177**	-.041	-.102*	-
30. Colleagues’ norms (T2)†	.151**	.021	.022	.161**	-.462**	-.247**	-.030	-.214**	-.076	-.161**	.198**	.026	.066	.533**	-.202**
31. Emotional exhaustion (T2)†	.299**	-.047	.092	.437**	-.378**	-.235**	-.160**	-.249**	-.024	.104*	.444**	-.075	.108*	.201**	.005
32. S-Gastrointestinal (T2)†	-.080	.188**	-.136*	.211**	-.121*	.001	-.038	.032	.016	.060	.098	-.034	.028	.134*	.031
33. S-Fatigue (T2)†	.537**	-.063	-.084	.257**	-.205**	-.143**	-.141**	-.112*	-.074	-.001	.092	-.090	.131*	.101	.000
34. S-Pain (T2)†	-.122*	.440**	-.098	.005	-.024	.004	.046	-.007	-.006	-.005	-.080	.019	-.019	.079	-.012
35. S-Cardiovascular (T2)†	.024	-.090	.518**	.233**	-.112*	-.135*	-.001	-.106*	.014	.027	.166**	-.069	-.097	-.023	-.076
36. G-Somatization (T2)†	.192**	.086	.175**	.757**	-.303**	-.292**	-.081	-.204**	-.091	.110*	.299**	.023	.056	.186**	-.099
37. Psychological detachment (T2)†	-.191**	.017	-.133**	-.303**	.835**	.486**	.104*	.352**	.059	.051	-.549**	-.021	-.071	-.561**	.220**
38. Relaxation (T2)†	-.138**	.032	-.111*	-.291**	.448**	.699**	.212**	.559**	.040	.047	-.329**	-.098*	.019	-.334**	.337**
39. Mastery (T2)†	-.108*	.054	-.013	-.050	.043	.258**	.739**	.242**	.022	-.027	-.177**	-.011	-.028	.090	.170**
40. Control (T2)†	-.162**	.026	-.060	-.209**	.346**	.506**	.150**	.752**	.005	.082	-.345**	-.147**	-.005	-.213**	.284**
41. Work type (T2)	.038	.080	.053	-.021	.106*	.109*	.054	.137**	.794**	-.017	.049	-.087	-.084	-.138**	.112*

Table S7 (continued)

Correlations between Variables

	30	31	32	33	34	35	36	37	38	39	40	41
30. Colleagues' norms (T2)†	-											
31. Emotional exhaustion (T2)†	.353**	-										
32. S-Gastrointestinal (T2)†	.086	.064	-									
33. S-Fatigue (T2)†	.172**	.324**	-.140**	-								
34. S-Pain (T2)†	.046	-.046	.008	-.151**	-							
35. S-Cardiovascular (T2)†	-.050	.128*	-.192**	-.121*	-.148**	-						
36. G-Somatization (T2)†	.252**	.527**	.187**	.335**	.041	.226**	-					
37. Psychological detachment (T2)†	-.539**	-.422**	-.130*	-.192**	-.024	-.122*	-.331**	-				
38. Relaxation (T2)†	-.369**	-.309**	-.067	-.149**	.023	-.093	-.326**	.600**	-			
39. Mastery (T2)†	-.028	-.183**	.023	-.147**	.141**	-.064	-.116*	.123**	.262**	-		
40. Control (T2)†	-.281**	-.272**	-.042	-.118*	.001	-.077	-.235**	.446**	.655**	.214**	-	
41. Work type (T2)	-.096	-.090	.026	-.082	.029	.006	-.095	.104	.093	.060	.063	-

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; working time 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.

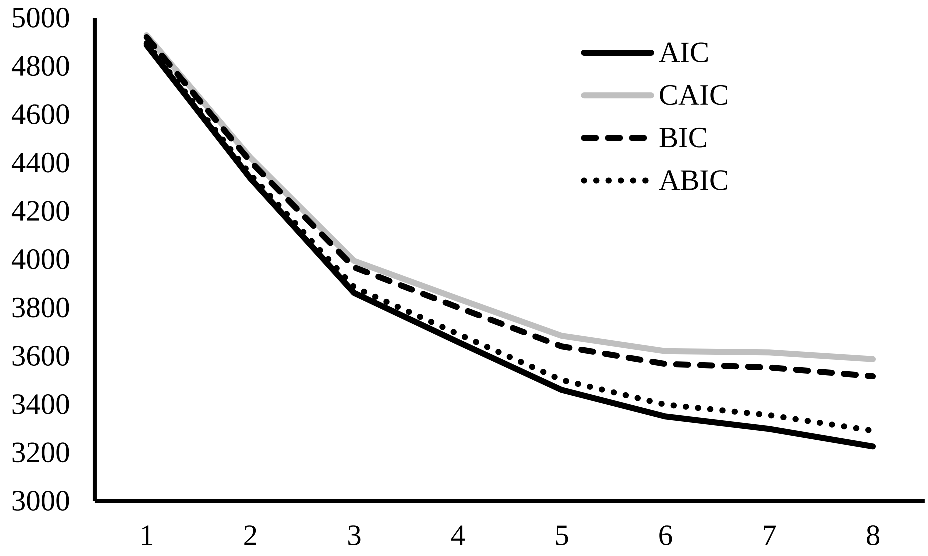

Figure S1
Elbow Plot of the Value of the Information Criteria for Solutions Including Different Numbers of Latent Profiles at Time 1

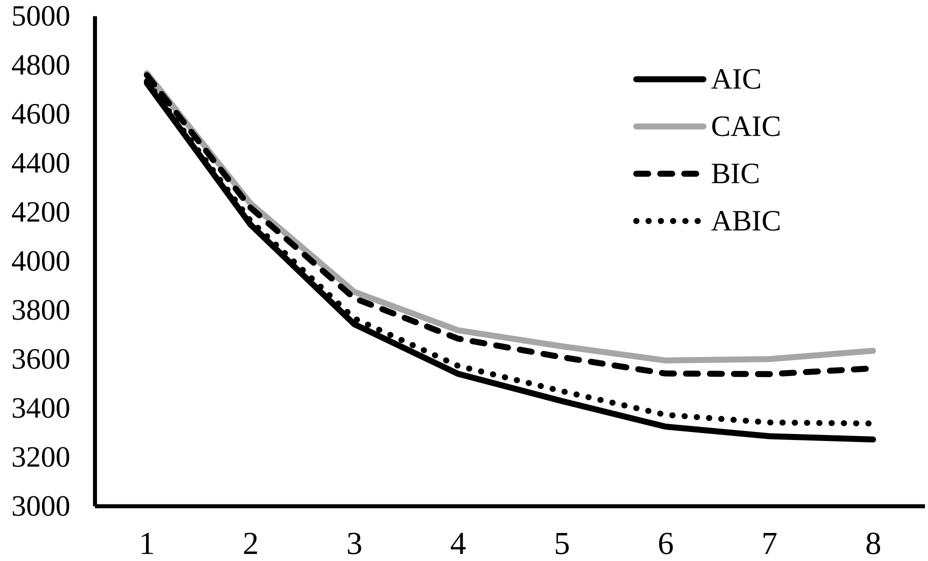

Figure S2
Elbow Plot of the Value of the Information Criteria for Solutions Including Different Numbers of Latent Profiles at Time 2

Table S8

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

	Profile 1 Mean [CI]	Profile 2 Mean [CI]	Profile 3 Mean [CI]	Profile 4 Mean [CI]
Detachment	-.877 [-1.090; -.663]	.050 [-.080; .181]	-.167 [-.320; -.014]	.912 [.756; 1.068]
Relaxation	-1.351 [-1.648; -1.054]	.083 [-.005; .171]	-.108 [-.119; -.097]	1.228 [1.211; 1.246]
Mastery	-.456 [-.682; -.229]	.025 [-.087; .137]	.091 [-.055; .237]	.328 [.131; .524]
Control	-1.106 [-1.373; -.840]	.117 [-.013; .247]	-.049 [-.054; -.044]	.831 [.705; .956]
	Profile 1 Variance [CI]	Profile 2 Variance [CI]	Profile 3 Variance [CI]	Profile 4 Variance [CI]
Detachment	.698 [.483; .913]	.618 [.524; .713]	.552 [.428; .675]	.384 [.210; .558]
Relaxation	.858 [.618; 1.099]	.219 [.132; .307]	.002 [.001; .004]	.003 [.002; .005]
Mastery	.965 [.764; 1.166]	.690 [.587; .792]	.591 [.468; .715]	1.159 [.926; 1.392]
Control	1.115 [.770; 1.461]	.532 [.436; .628]	.001 [.000; .001]	.307 [.213; .402]

Note. CI = 95% confidence interval; the profile indicators are estimated from factor scores with a mean of 0 and a standard deviation of 1; Profile 1: Plugged In; Profile 2: Moderately Unplugged; Profile 3: Moderately Plugged In; and Profile 4: Unplugged.

Table S9

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
Time 1				
Profile 1	.919	.081	.000	.000
Profile 2	.064	.918	.006	.012
Profile 3	.001	.026	.973	.000
Profile 4	.000	.031	.000	.969
Time 2				
Profile 1	.896	.104	.000	.000
Profile 2	.058	.928	.012	.002
Profile 3	.003	.052	.945	.000
Profile 4	.000	.029	.000	.971

Note. Profile 1: Plugged In; Profile 2: Moderately Unplugged; Profile 3: Moderately Plugged In; and Profile 4: Unplugged.

Table S10

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	-876.897	8	1.021	1769.794	1802.294	1794.294	1768.971	Na	Na	Na
2 Profiles	-778.505	17	1.118	1591.010	1660.261	1643.074	1589.261	.973	.001	< .001
3 Profiles	-685.581	26	1.147	1423.162	1528.789	1502.789	1420.487	.969	.005	< .001
4 Profiles	-639.323	35	1.025	1348.646	1490.837	1455.837	1345.045	.914	.001	< .001
5 Profiles	-599.038	44	1.039	1286.077	1464.831	1420.831	1281.550	.923	.102	< .001
6 Profiles	-570.201	53	.948	1246.403	1461.720	1408.720	1240.950	.913	.013	< .001
7 Profiles	-554.428	62	1.003	1232.856	1484.737	1422.737	1226.478	.918	.123	.098
8 Profiles	-517.851	71	.962	1177.702	1466.146	1395.146	1170.397	.922	.003	< .001
Onsite Workers Time 2										
1 Profile	-744.775	8	.932	1505.550	1536.241	1528.241	1502.942	Na	Na	Na
2 Profiles	-643.251	17	.986	1320.503	1385.720	1368.720	1314.960	.963	< .001	< .001
3 Profiles	-571.461	26	1.054	1194.921	1294.665	1268.665	1186.445	.965	.012	< .001
4 Profiles	-526.334	35	.966	1122.667	1256.937	1221.937	1111.256	.954	.010	< .001
5 Profiles	-491.547	44	1.162	1071.094	1239.891	1195.891	1056.749	.920	.480	< .001
6 Profiles	-463.979	53	1.078	1033.958	1237.281	1184.281	1016.679	.916	.484	< .001
7 Profiles	-446.612	62	1.009	1017.224	1255.073	1193.073	997.010	.927	.439	< .001
8 Profiles	-441.244	71	1.040	1024.488	1296.864	1225.864	1001.340	.907	.423	.217
Remote Workers: Time 1										
1 Profile	-1556.638	8	1.147	3129.276	3166.467	3158.467	3133.099	Na	Na	Na
2 Profiles	-1359.944	17	1.010	2753.888	2832.921	2815.921	2762.013	.982	< .001	< .001
3 Profiles	-1208.423	26	1.099	2468.846	2589.719	2563.719	2481.272	.951	< .001	< .001
4 Profiles	-1136.180	35	1.189	2342.360	2505.074	2470.074	2359.088	.886	.105	< .001
5 Profiles	-1068.957	44	1.423	2225.914	2430.469	2386.469	2246.944	.892	.494	< .001
6 Profiles	-1026.478	53	1.092	2158.955	2405.351	2352.351	2184.286	.876	.083	< .001
7 Profiles	-991.688	62	1.029	2107.376	2395.612	2333.612	2137.008	.885	.001	< .001
8 Profiles	-955.368	71	1.125	2052.735	2382.813	2311.813	2086.669	.920	.119	< .001
Remote Workers Time 2										
1 Profile	-1208.200	8	1.300	2432.399	2467.904	2459.904	2434.458	Na	Na	Na
2 Profiles	-1033.299	17	1.181	2100.599	2176.046	2159.046	2105.166	.946	< .001	< .001
3 Profiles	-906.527	26	1.108	1865.054	1980.444	1954.444	1872.040	.945	< .001	< .001
4 Profiles	-862.100	35	1.141	1794.200	1949.533	1914.533	1803.604	.857	.137	< .001
5 Profiles	-835.509	44	1.237	1759.018	1954.293	1910.293	1770.840	.835	.489	< .001
6 Profiles	-807.289	53	1.077	1720.577	1955.795	1902.795	1734.817	.853	.145	< .001
7 Profiles	-786.377	62	.935	1696.754	1971.915	1909.915	1713.412	.902	.231	.140
8 Profiles	-772.428	71	.916	1686.855	2001.959	1930.959	1705.932	.898	.017	< .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.

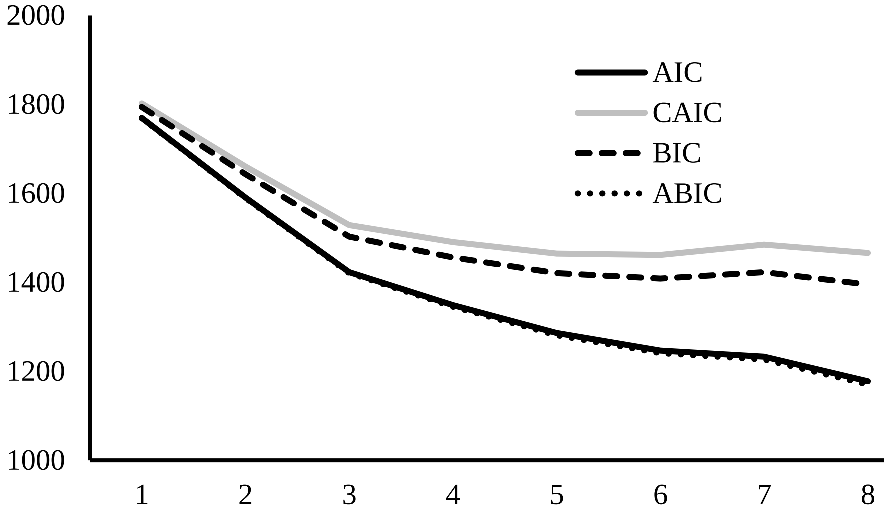

Figure S3a: Onsite Workers, Time 1

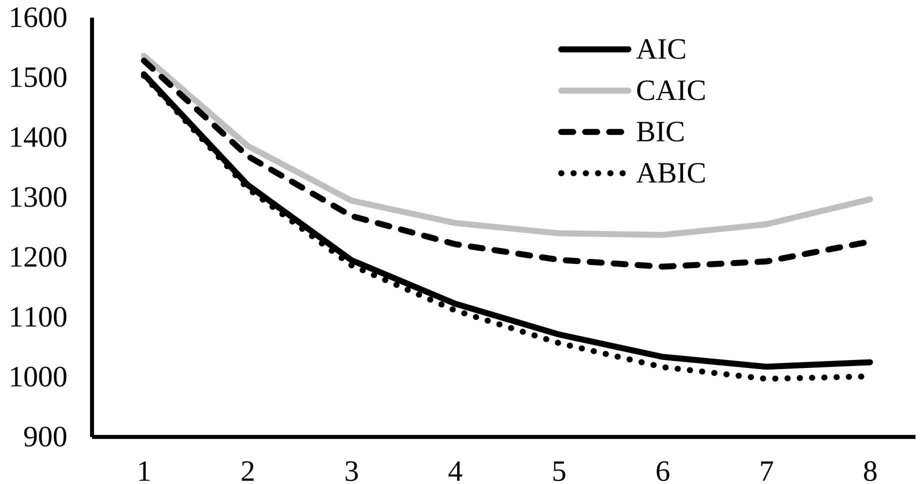

Figure S3b: Onsite Workers, Time 2

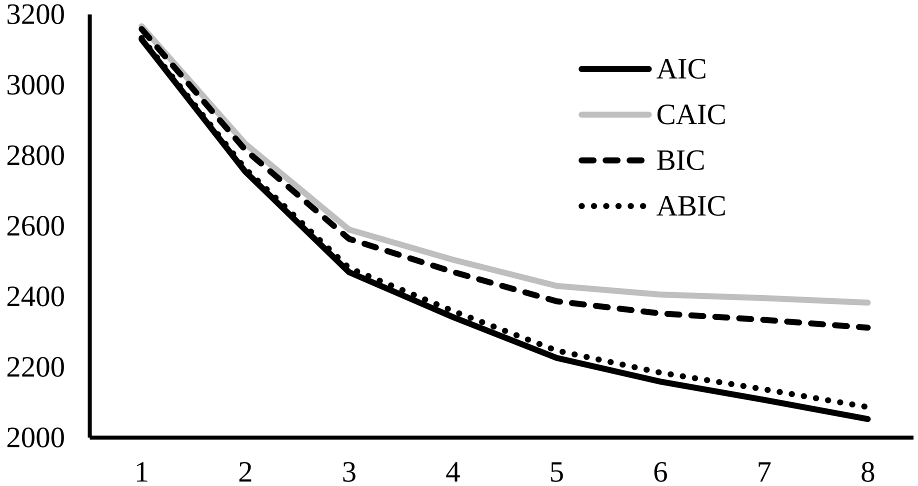

Figure S3c: Remote Workers, Time 1

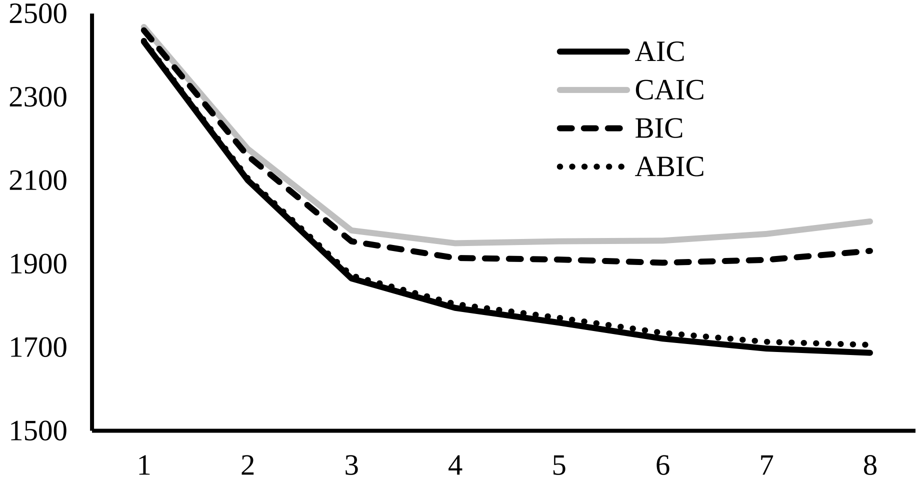

Figure S3d: Remote Workers, Time 2

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 S11

Results from the Multi-Group Models

Model	LL	#fp	Scaling	AIC	CAIC	BIC	ABIC	Entropy
Multi-Group Tests of Similarity (Time 1)								
Configural Similarity	-2068.669	71	1.083	4279.337	4640.820	4569.820	4344.499	.895
Structural Similarity	-2075.603	55	1.221	4261.206	4541.228	4486.228	4311.683	.908
Dispersion Similarity	-2082.256	39	1.131	4242.513	4441.074	4402.074	4278.306	.896
Distributional Similarity	-2083.065	36	1.152	4238.130	4421.417	4385.417	4271.170	.896
Multi-Group Explanatory Similarity (Time 1)								
Free Relations with Outcomes	-4571.484	54	1.075	9250.968	9525.899	9471.899	9300.528	.907
Equal Relations with Outcomes	-4581.231	30	1.096	9222.461	9375.200	9345.200	9249.994	.905
Multi-Group Tests of Similarity (Time 2)								
Configural Similarity	-1624.133	71	1.067	3390.267	3736.387	3665.387	3440.143	.888
Structural Similarity	-1642.761	55	1.028	3395.522	3663.643	3608.643	3434.159	.920
Dispersion Similarity	-1651.546	39	1.131	3381.093	3571.215	3532.215	3408.490	.888
Distributional Similarity	-1657.328	36	1.147	3386.656	3562.154	3526.154	3411.946	.889
Multi-Group Explanatory Similarity (Time 2)								
Free Relations with Outcomes	-3620.744	54	1.118	7349.488	7612.735	7558.735	7387.422	.896
Equal Relations with Outcomes	-3629.667	30	1.151	7319.334	7475.582	7435.582	7340.408	.894
Predictive Similarity: Predictors x Work Type								
Null Effects Model	-8772.376	534	1.372	18612.753	21331.512	20797.512	19102.842	.871
Profile-Specific Free Relations with Predictors	-8637.455	780	1.014	18834.910	22806.132	22026.132	19550.771	.928
Free Relations with Predictors	-8757.974	600	1.364	18715.948	21770.734	21170.734	19266.610	.884
Equal Relations with Predictors	-8787.907	555	1.356	18685.814	21511.491	20956.491	19195.177	.873

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.