Nature, Predictors, and Outcomes of Workers' Longitudinal Workaholism Profiles

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Abstract

This research relies on a combination of variable- and person-centered approaches to help improve our understanding of the dimensionality of the workaholism construct. Our results showed that employees' workaholism ratings simultaneously reflected a global overarching construct co-existing with four specific dimensions (behavioral, motivational, emotional, and cognitive workaholism) among a sample of 432 workers who completed a questionnaire twice over a three-month period. We also examined the profiles taken by workaholism dimensions, and documented their stability over time as well as the associations between these profiles and theoretically-relevant predictors and outcomes. Furthermore, we examined whether these associations differ as a function of working remotely or onsite. Four profiles were identified and found to be highly stable over time: *Unplugged*, *Plugged In*, *Moderately Unplugged with Externalized Workaholism*, and *Moderately Unplugged with Cognitive Workaholism*. Personal life orientation, telepressure, and interpersonal norms regarding work-related messages were related to the likelihood of profile membership. Remote working also reinforced the positive effects of personal life orientation and the negative effects of interpersonal norms regarding work-related messages. Finally, employees' work-to-family guilt, job satisfaction, family satisfaction, and life satisfaction also differed as a function of their profile.

Key words: Workaholism; latent transition analyses; telepressure; job satisfaction; work-to-family guilt; bifactor models

Workaholism has received a fair amount of attention in the organizational sciences (e.g., Clark et al., 2020; Di Stefano & Gaudiino, 2019) due to its undesirable consequences for organizations (e.g., lower levels of performance; Sandrin et al., 2019) and employees (e.g., work-family conflicts; Gillet et al., 2021a). Schaufeli et al. (2009b) defined workaholism as a negative experience encompassing two distinct, yet complementary, components. According to this conception, operationalized through the Dutch Work Addiction Scale (DUWAS; Schaufeli et al., 2009b), working excessively reflects the behavioral component of workaholism and involves spending a great deal of time and effort in work activities while neglecting other spheres of life. In contrast, working compulsively reflects a more emotional and motivational component of workaholism that involves a persistent obsession with work. However, Clark et al. (2020) recently proposed a more comprehensive representation of workaholism, operationalized as part of the Multidimensional Workaholism Scale (MWS), encompassing four facets: (a) an excessive level of work involvement (behavioral), (b) an inner compulsion to work (motivational), (c) the experience of negative emotions when not working (emotional), and (d) persistent thoughts about work (cognitive). Although the DUWAS and the MWS share the same core dimensions (i.e., behavioral, motivational, emotional, and cognitive), this older questionnaire is less precise as it blends multiple facets into the same subfactors (e.g., emotional and motivational workaholism are included in the same working compulsively dimension) and does not seem to encompass the whole range of psychological characteristics that define workaholism (e.g., the cognitive facet). Furthermore, although the DUWAS is arguably the most common measure of workaholism, worrisome psychometric results have been reported in relation to scores obtained on this instrument. For instance, low levels of scale score reliability have been reported for both subscales (e.g., Schaufeli et al., 2009a), and research has not always supported the a priori two-factor structure of this instrument (e.g., Andreassen et al., 2014). In contrast, using the MWS, Clark et al. (2020) demonstrated that their four components were positively correlated, but not redundant, with the working excessively and compulsively facets of the DUWAS. They also demonstrated that each of them tended to present well-differentiated associations with covariates, thus supporting the greater precision afforded by this new multidimensional representation.

However, additional research using the DUWAS has also demonstrated that employees could experience workaholism holistically, as a single global construct (Gillet et al., 2021a; Sandrin et al., 2019). This global representation is supported by the high correlations reported between the different workaholism components assessed in the DUWAS (i.e., working excessively and compulsively; Huyghebaert et al., 2018) and MWS (i.e., motivational, behavioral, emotional, and cognitive workaholism; Clark et al., 2020), and by the demonstration of stronger associations with covariates (i.e., predictors and outcomes) when workaholism is defined as a global dimension (Taris et al., 2012). However, the behavioral, motivational, emotional, and cognitive dimensions of workaholism are also seen as independent from one another (Clark et al., 2020; Schaufeli et al., 2009b), and prior studies have shown that each of these components shared unique associations with predictors and outcomes (e.g., Clark et al., 2020; Huyghebaert et al., 2018). These observations raise a series of important questions regarding: (a) whether the workaholism facets retain specificity beyond the assessment of the overarching workaholism construct; and (b) whether this overarching construct exists as a global entity including specificities mapped by the facets, or whether these facets reflect distinct correlated dimensions without such a common core (Morin et al., 2016b, 2017). The confirmatory factor analytic (CFA) approach has dominated research focusing on the structure of workaholism (e.g., Schaufeli et al., 2009b). However, CFA includes important restrictions that limit its usefulness when the goal is to conduct a complete investigation of the dimensionality of complex psychological constructs (Morin et al., 2016a). Fortunately, alternative approaches exist to support a more thorough investigation of these questions (e.g., Gillet et al., 2017; Tóth-Király et al., 2021).

For instance, person-centered research has started to look at how workaholism components combine within employees (Gillet et al., 2017; Schaufeli et al., 2009a). However, no research has done so while considering all the theoretical facets of workaholism proposed by Clark et al. (2020) and while accounting for the dual global (G; what is common to the workaholism experience across all dimensions) and specific (S; what is unique to each dimension and left unexplained by that global experience) nature of workaholism (Gillet et al., 2018, 2021c). Unfortunately, these prior studies have also resulted in divergent conclusions regarding the relative importance of the different facets of workaholism. Our first aim is thus to identify the workaholism profiles that best characterize a sample of employees who completed the MWS (Clark et al., 2020) by considering the multidimensionality of workaholism through the joint consideration of G- and S- (behavioral, motivational, emotional, and cognitive) factors (Gillet et al., 2018, 2021c Tóth-Király et al., 2021). To the best of our knowledge, only one recent study has adopted a similar approach to investigate employees' workaholism profiles (Gillet et al., 2021c), but has done so while relying on the more restricted DUWAS. Secondly, we also investigate the extent to which the nature of these profiles, their prevalence, and employees' profile membership change over the course of a three-month period. Third, we also seek to document the criterion-related validity of these workaholism profiles by examining their associations with theoretically-relevant predictors and outcomes, whether these associations remain stable over time, and whether these associations differ as a function of working remotely or onsite. We pursued these goals by capitalizing on the theoretical assumptions of self-determination theory (Ryan & Deci, 2017). The global theoretical model tested in the present research, and outlined over the upcoming pages, is illustrated in Figure 1.

Co-Existing Global and Specific Workaholism Components

Recent research (Gillet et al., 2018, 2021c; Tóth-Király et al., 2021) has supported the idea that workaholism can be assessed as a global entity reflecting the commonalities among ratings of all of its specific components (behavioral, motivational, cognitive, and emotional), but that these specific components also retain uniquely relevant specificity remaining unexplained by this global construct. However, the extent to which these results generalize to new samples remains unknown, so that additional investigations are needed to confirm that enough specificity exists at the subscale level in the MWS, once global levels of workaholism are considered. A first objective of this study is thus to verify, as part of preliminary variable-centered analyses, whether these results would be replicated.

Hypothesis 1. Workaholism ratings will be best represented as a bifactor construct including one G-factor (global workaholism) and four S-factors (behavioral, motivational, cognitive, and emotional workaholism).

A Person-Centered Perspective on Global and Specific Components of Workaholism

Despite abundant research supporting the negative consequences of workaholism components (Clark et al., 2016, 2020), a comprehensive assessment of their combined impacts is lacking. To this end, two complementary analytic approaches can be used. On one hand, variable-centered bifactor analyses can properly disaggregate the variance attributed to participants' G/S levels of workaholism, and assess their unique and complementary impact. However, these analyses assume that all employees come from the same population and that results can be summarized by a unique set of "average" parameters. On the other hand, person-centered analyses are specifically designed to identify qualitatively distinct subpopulations of workers presenting distinct configurations on a series of indicators (Meyer & Morin, 2016), such as workaholism components (Gillet et al., 2017). In this study, we combine both approaches to document the nature of workaholism profiles while relying on the optimal (bifactor) measurement structure identified in preliminary variable-centered analyses (Morin et al., 2016b, 2017).

Indeed, employees naturally behave in a variety of ways, so that all of them are likely to present their own workaholism profile combining more than one component of workaholism. For instance, whereas some might display an excessive level of work involvement (behavioral workaholism) without simultaneously experiencing persistent thoughts about work (cognitive workaholism), others might jointly experience both facets of workaholism. Likewise, whereas some might be driven by an inner compulsion to work (motivational workaholism) without experiencing any of the other manifestations of workaholism, others may experience both motivational manifestations and negative emotions (emotional workaholism). Person-centered approaches make it possible to identify the most typical configurations of workaholism observed among distinct types (or profiles) of workers. More generally, person-centered results are naturally aligned with managers and practitioners' tendency to think about employees as members of categories (person-centered) rather than in terms of relations among variables (variable-centered) (Morin et al., 2011). As such, our findings are likely to have important practical implications. Thus, rather than having to decode complex patterns of interrelations and interactions among variables, person-centered results allow managers to consider the combined role of all workaholism components via the identification of types of employees with knowledge about the likely outcomes of corresponding to these various profiles, as well as possible levers of intervention to increase the likelihood of more desirable workaholism profiles.

Person-centered research has started to look at how workaholism components combine within employees (e.g., Kravina et al., 2010; Salanova et al., 2014). Unfortunately, many of those studies relied on a combination of variables not limited to workaholism as profile indicators (work engagement: Innanen et al., 2014; work engagement and job satisfaction: Mäkikangas et al., 2015), making it impossible to isolate the unique effects of workaholism in the definition of the profiles. Among the few studies focusing solely on workaholism, Schaufeli et al. (2009a) identified four profiles (workaholics; nonworkaholics; excessive workers; and compulsive workers). However, this study is limited by its reliance on a sample of medical residents, so that additional studies are needed to see whether these findings generalize to other occupations. Similarly, Gillet et al. (2017) also identified four profiles among two samples of workers from various organizations.

However, these previous studies have all relied on profile indicators ignoring the dual G/S nature of workaholism. Yet, when applying person-centered analyses to indicators known to present a G/S structure, Morin et al. (2016b, 2017) have shown that relying on profile indicators that fail to properly disaggregate these G- and S-factors was likely to result in the erroneous identification of profiles displaying similar levels across indicators (e.g., high or low levels for all dimensions such as the profiles identified by Gillet et al., 2017). Without accounting for this dual global/specific structure, the conceptually-related nature of each workaholism component is likely to result in multicollinearity when all components are used jointly in prediction. For instance, in Clark et al.'s (2020) study, there was a significant difference between regression coefficients and correlations which the authors attributed to multicollinearity. In this situation, bifactor models present a clear advantage as they result in orthogonal (uncorrelated) factors (i.e., the variance shared among all subscales is absorbed by the G-factor). Likewise, by focusing on the identification of distinct subpopulations of workers characterized by qualitatively distinct configurations on all of these workaholism components, person-centered analyses provide a further way to simultaneously consider all components without the limitations traditionally associated with variable-centered analyses (collinearity, impossibility to interpret complex interactions among more than three interacting predictors, etc.). While relying on a bifactor operationalization of workaholism, Gillet et al. (2021c) identified four profiles characterized by different G/S levels of workaholism: (1) Low G/S Workaholism; (2) Average G/S Workaholism; (3) Low Global and Average Specific Workaholism; and (4) High Global and Average Specific Workaholism. Unfortunately, these results have yet to be replicated and extended to the more comprehensive representation of workaholism proposed by Clark et al. (2020).

Theoretical Person-Centered Scenarios

Keeping in mind the importance of disaggregating the G/S components of workaholism, a key challenge for research seeking to understand how these components co-occur among distinct types of employees is related to the lack of previous theorization related to the nature and psychological underpinning of these workaholism profiles. From a purely empirical perspective, it is noteworthy that despite their reliance on a variety of samples, methods, and indicators, the bulk of prior evidence reviewed in the previous section suggests the presence of three to four profiles, generally including a High Workaholism, a Moderate Workaholism, and a Low Workaholism configuration. On this basis, and to partially address the lack of theorization in this area, we thus propose a basic theoretical typology designed to provide a heuristic framework for researchers and practitioners.

A first scenario focuses on ***Unplugged*** employees, displaying low global and specific levels of workaholism. These individuals are assumed to operate in a work environment that fulfills their basic psychological needs, allowing them to display work behaviors that are mainly autonomously regulated (driven by choice, desire, or interest; Ryan & Deci, 2017). Autonomously motivated employees engage in work activities which are in line with what they want to do. Thus, they may volitionally invest many hours in their work because their job is aligned with their personal values and objectives, and because they see it as important and interesting (van Beek et al., 2011). However, although these employees may work hard and be passionate about work, they feel free to enjoy other activities and do not want that their work interferes with their private life or that their physical and psychological health is altered as a result of their work investment (Gillet et al., 2018).

The second scenario characterizes ***Plugged In*** employees, displaying high global and specific levels of workaholism. These individuals are assumed to operate in a work environment that they see as failing to meet their basic psychological needs or as displaying values that are antagonistic to their own (Ryan & Deci, 2017). As a result, their levels of workaholism are primarily driven by internal factors (Clark et al., 2010), such that excessive investment in work is purported to represent a way to decrease their feelings of anxiety, guilt, and shame, and to increase their self-esteem (Porter, 2004). However, their actions might also, to a lesser extent, be driven by external reasons, such as gaining their supervisors' approval, peer admiration, and prestige (Spence & Robbins, 1992). This is evidenced by their tendency to invest efforts in activities that are more likely to lead to promotions, pay rises, or other forms of recognition (Endriulaitienė & Morkevičiūtė, 2020).

A third scenario characterizes ***Moderately Unplugged*** employees, displaying average global and specific levels of workaholism corresponding to neither an *Unplugged*, nor to a *Plugged In*, scenario. These employees do their job according to the organization performance expectations without being role models, and tend to behave in a generally acceptable manner. These employees can be assumed to work in an environment that is generally able to meet their psychological needs, but without offering them particularly stimulating opportunities (i.e., not particularly demanding or challenging). Alternatively, these individuals might also be driven to work for mainly instrumental reasons, and may thus lack the interest for becoming involved in more challenging developmental opportunities. In other words, as long as these individuals are able to achieve a comfortable level of balance and congruence between their own psychological needs and values and those of the organization, they will strive to maintain this balance by avoiding additional involvement opportunities.

Investigation of these preliminary scenarios necessitate person-centered analyses, which should result in important empirical insights into the value of these theoretically-driven scenarios to properly represent the nature of the workaholism configurations typically displayed by employees. However, considering that none of the previous studies used to guide the elaboration of these scenarios has relied on the MWS (Clark et al., 2020), considering that the bifactor approach adopted in this study helps identify profiles displaying clearer qualitative differences (Gillet et al., 2021c), and considering the slightly more distinctive set of profiles identified by Schaufeli et al. (2009a), it also seems reasonable to expect additional profiles characterized by a clearer differentiation among the G/S workaholism components. For instance, one of those profiles may represent employees with an internalized form of workaholism (e.g., dominated by high levels of emotional and cognitive workaholism, corresponding to the working compulsively component of Schaufeli et al.'s, 2009b conceptualization), whereas another one might represent employees with an externalized form of workaholism (e.g., dominated by high levels of behavioral and motivational workaholism, matching the working excessively component of the same conceptualization). However, 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 (Gillet et al., 2017, 2021c), we propose that:

Hypothesis 2. At least four profiles will be identified.

Hypothesis 3. These profiles will minimally include a *Plugged In*, an *Unplugged*, and a *Moderately Unplugged* profile.

Hypothesis 4. At least one profile characterized by a clearer differentiation among the global and specific components of workaholism will be identified.

A Longitudinal Person-Centered Perspective

An additional objective of the present study is to assess the extent to which the workaholism profiles would remain stable over a period of three months. In line with prior research (Hakanen et al., 2018; Huyghebaert et al., 2018), we expected this specific time lag to be suitable because it goes beyond daily fluctuations (e.g., Balducci et al., 2021) but it is still short enough to capture changes that could not be reflected in longer time spans (e.g., Tóth-Király et al., 2021). As noted by Meyer and Morin (2016), it is critical to ascertain the stability of person-centered solutions to support their use as guides for the development of interventions tailored at distinct profiles of employees.

Two distinct forms of longitudinal stability can, and should, be considered (Gillet et al., 2019a; Sandrin et al., 2020). A first form of longitudinal stability, within-sample stability, is related to the nature of the profiles themselves, which could change over time. For example, the number or structure of the profiles could change over time, which would suggest that the profiles have only limited usefulness as intervention guides as they apparently reflect transient phenomena, or that the sample under consideration has recently been exposed to some rather important internal or external changes. Morin et al. (2016c) refer to these two subtypes of within-sample profile stability as configural (same number of profiles) and structural (profiles with the same nature) similarity. In contrast, changing circumstances may alternatively lead to a change in the degree of similarity among members of specific profiles (dispersion similarity), or in the relative size of the profiles (distributional similarity). These two subtypes of within-sample profile stability do not preclude the reliance on person-centered solutions as intervention guides, but simply suggest that the identified profiles show some degree of reactivity to internal or external changes. A second form of longitudinal stability, within-person stability, is related to stability or changes in employees' membership in specific profiles over time (e.g., whether an employee stays in the same profile, or transitions from one profile, such as an *Unplugged* one, to another profile, such as a *Moderately Unplugged* one over time; Gillet et al., 2019a; Sandrin et al., 2020) and can be observed in the absence of within-sample changes.

According to Clark et al. (2020), workaholism (at least as operationalized in the MWS) should not be viewed as a stable disposition or as a stable personality trait that someone inherently possesses and that does not fluctuate over time, but rather as a state likely to fluctuate over time as a result of internal or external changes. This perspective is aligned with theory and research suggesting that situational and contextual factors may modify employees' levels of workaholism (Huyghebaert et al., 2018; Ng et al., 2007). However, despite this conceptualization of workaholism as a state (rather than a trait), research on workaholism profiles has been so far cross-sectional. Nevertheless, a variable-centered longitudinal study of employees' workaholism revealed a moderately high level of stability in ratings over three months (Falco et al., 2020). Huyghebaert et al. (2018) also demonstrated similar results over a three-month period. Following interpretation guidelines suggested by Huyghebaert-Zouaghi et al. (2022b), these observations lead us to expect to observe a moderate (≥ 50%) to high (≥ 70%) level of within-person stability, as well as strong evidence of configural, structural, and dispersion within-sample similarity. However, given the lack of longitudinal person-centered evidence, we leave as an open research question whether the size of the profiles (distributional similarity) will change over time, and whether the main transitions will be upward (toward profiles with higher levels of workaholism), downward (toward profiles with lower levels of workaholism), or lateral (toward distinct profiles presenting similar levels of workaholism).

Hypothesis 5. The profiles will display evidence of configural, structural, dispersion, and distribution within-sample similarity.

Hypothesis 6. The profiles will display moderate (≥ 50%) to high (≥ 70%) within-person stability.

A Construct Validation Perspective

Another critical step in the assessment of the construct validity of profiles, especially when relying on a predominantly inductive approach (Morin et al., 2018), is to document their theoretical and practical implications via the examination of their associations with theoretically-relevant predictors and outcomes (Marsh et al., 2009; Meyer & Morin, 2016). Without information on key predictors of workaholism profiles, knowledge regarding the nature of these profiles will be of very limited utility for managers and organizations who also need to know which levers can possibly be used to influence profile membership. Likewise, without information on their outcomes, it remains impossible to clearly assess the positive or negative ramifications of each profile (i.e., whether each profile is associated with positive or negative outcomes), making it hard to decide which profile to target for intervention purposes. In the present study, we consider the role of personal life orientation (PLO), telepressure, and interpersonal norms regarding work-related messages as predictors of workaholism profiles, and work-to-family guilt, job satisfaction, family satisfaction, and life satisfaction as outcomes of these profiles.

Predictors of Profile Membership

The three predictors of workaholism profile membership considered in this study are all individual or environmental characteristics that may hinder (i.e., telepressure and interpersonal norms regarding work-related messages) or facilitate (i.e., PLO) the satisfaction of employees' basic psychological needs, as well as their autonomous motivation (Ryan & Deci, 2017). These factors are thus likely to play a predictive role in relation to employees' likelihood of membership into the various profiles identified in this study (Van den Broeck et al., 2011). These three predictor variables were retained based on previous research showing that they present significant associations with employees' global and specific levels of workaholism (e.g., Barber & Santuzzi, 2015; Grawitch et al., 2018).

PLO. Numerous studies suggest that the desire to organize one's professional and personal lives in a way that makes it possible to have more time to allocate to the latter without interfering too much with the former is becoming more frequent among employees (Korunka et al., 2015; Kubicek & Tement, 2016). In career management research (Hall et al., 2013), the concept of PLO has emerged to reflect this tendency, and to reinforce the idea that employees must succeed at managing the interface between their professional and nonprofessional roles to achieve a sustainable career. PLO is defined as individuals' inclination to allocate enough time to pursue their personal interests (e.g., hobbies, learning, arts) while concurrently engaging in their professional role (Hall et al., 2013). Individuals high in PLO are autonomously motivated by their work and are able to use self-control and self-regulation strategies to psychologically detach from their work and to devote time and energy in nonwork activities (Hirschi et al., 2016). Furthermore, they are not ready to sacrifice other areas of life in pursuit of their work goals and are thus less likely to work too much, beyond what is needed or expected from them (Hirschi et al., 2020). These considerations suggest that higher levels of PLO should be incompatible with workaholism, and that PLO should be associated with a lower risk of membership into profiles presenting higher global levels of workaholism (e.g., *Plugged In*). Given that PLO is associated with better work recovery experiences (e.g., psychological detachment; Sonnentag & Fritz, 2015), individuals high in PLO should also be less likely to display a profile characterized by high specific levels of cognitive workaholism, implying that these employees should find it easier to distance themselves from their work and to stop thinking about it (Clark et al., 2020).

Hypothesis 7. PLO will be associated with a higher likelihood of membership into profiles characterized by lower levels of workaholism (e.g., *Unplugged*) and with a lower likelihood of membership into profiles characterized by higher levels of workaholism (e.g., *Plugged In*), with the Moderately Unplugged profile falling in between.

Telepressure. Past research has supported the role of telepressure (i.e., individual urge to respond quickly to work-related messages at all times) in the prediction of workaholism among a variety of occupations (e.g., Barber & Santuzzi, 2015; Grawitch et al., 2018). Telepressure is associated with need frustration and controlled motivation as employees characterized by high levels of telepressure do not internalize their work in an autonomous and voluntary manner but rather feel pressured to work (Van den Broeck et al., 2011). Indeed, they tend to feel a strong urge to immediately respond to work-related messages, and to become preoccupied when they are unable to do so (Barber et al., 2019). These employees thus tend to have a hard time mentally disengaging from work during nonwork time due to increased levels of negative activation (negative affective arousal). To relieve this negative activation, employees may attempt to immediately deal with the requests expressed in the work-related messages received during nonwork time (Sonnentag & Fritz, 2015). As a result, higher levels of telepressure seem to encourage the emergence of workaholism, leading us to expect telepressure to be associated with a higher probability of membership into profiles presenting higher global levels of workaholism (e.g., *Plugged In*). Given that telepressure is associated with higher levels of controlled motivation and that employees with high specific levels of motivational workaholism tend to work primarily to meet internal and/or external contingencies (Van den Broeck et al., 2011), we also expect telepressure to be associated with a higher likelihood of membership into profiles characterized by higher specific levels of motivational workaholism.

Hypothesis 8. Telepressure will be associated with a higher likelihood of membership into profiles characterized by higher levels of workaholism (e.g., *Plugged In*) and with a lower likelihood of membership into profiles characterized by lower levels of workaholism (e.g., *Unplugged*), with the *Moderately Unplugged* profile falling in between.

Interpersonal Norms Regarding Work-Related Messages. Whereas telepressure reflects employees' preoccupation with the need to respond quickly to work-related messages and the corresponding urge to do so, work-related characteristics may also contribute to nurture and maintain this urge. More precisely, this tendency may be connected with specific interpersonal norms (from supervisors and/or colleagues) regarding the need to respond quickly to work-related messages, even when they occur during off-job time (Derks et al., 2015). In fact, employees' perceptions of interpersonal norms regarding the need to quickly follow up on work-related messages has been found to be detrimental to their psychological detachment and need satisfaction, and may lead to higher levels of workaholism (Mazzetti et al., 2014, 2016). Indeed, employees exposed to such norms may become willing to work overtime for controlled reasons. More specifically, it is important for them to maintain good interpersonal relationships with their supervisors and coworkers (Kang et al., 2017), and to gain their supervisors' approval and the admiration of their peers (Spence & Robbins, 1992). In fact, excessive levels of work investment, such as workaholism, are purported to be a way to decrease employees' feelings of anxiety, guilt, and shame, and to increase their self-esteem (Porter, 2004). We thus expect higher levels of interpersonal norms regarding work-related messages to be associated with a higher likelihood of membership into profiles characterized by higher global levels of workaholism (e.g., *Plugged In*). Moreover, interpersonal norms regarding work-related messages tend to be associated with increases in workload because employees exposed to such norms feel a constant sense of pressure to be responsive, to work in a hurry, and to do more (Derks et al., 2015). As a result, employees who feel being exposed to such norms should be more likely to display a profile characterized by higher specific levels of behavioral workaholism (Clark et al., 2020).

Hypothesis 9. Interpersonal norms regarding work-related messages will be associated with a higher likelihood of membership into profiles characterized by higher levels of workaholism (e.g., *Plugged In*) and with a lower likelihood of membership into profiles characterized by lower levels of workaholism (e.g., *Unplugged*), with the *Moderately Unplugged* profile falling in between.

Outcomes of Profile Membership

Employees characterized by high levels of workaholism devote a lot of time, effort, and cognitive energy to work. Yet, the resources available to support this intense investment for controlled reasons (Van den Broeck et al., 2011) are limited over the long term (Hobfoll, 2002), and eventually become unavailable to support other life domains. Moreover, employees high in workaholism still tend to feel restless when not at work, and to experience difficulties withdrawing from work during off-job time (Clark et al., 2020). In failing to properly stop thinking about work, they often create even more work for themselves, which typically lead them to experience feelings of disappointment and frustration related to their work but also to their life in general (van Wijhe et al., 2014). Indeed, they experience an uncontrollable urge to engage in their work with a rigid persistence that leads them to neglect their other activities, which seems to result from a difficulty in establishing boundaries between their work and other life domains (Clark et al., 2016). As a result, employees high in workaholism have a harder time achieving a satisfactory balance between the demands of, and benefits from, their work and family lives (Gillet et al., 2017). They also tend to experience higher levels of work-to-family guilt (i.e., a negative emotion people experience when their work interferes with their family role; Zhang et al., 2019) and lower levels of family satisfaction (Carlson & Kacmar, 2000).

The lack of previous person-centered studies of workaholism, as conceptualized here (i.e., relying on a proper disaggregation of the G- and S-factors of the MWS), makes it hard to formulate precise hypotheses regarding the nature of the expected associations between the profiles and the outcomes. However, the results obtained from the few previous person-centered studies of workaholism (Gillet et al., 2017, 2021c) and from variable-centered research (Hakanen et al., 2018; Huyghebaert et al., 2018) allow us to hypothesize that profiles presenting higher global levels of workaholism (e.g., *Plugged In*) should be characterized by lower levels of job, family, and life satisfaction, and by higher levels of work-to-family guilt, relative to profiles presenting lower global levels of workaholism (e.g., *Unplugged*). Moreover, because employees with high specific levels of emotional workaholism experience negative emotions when they cannot work, profiles characterized by high levels of emotional workaholism should be more likely to experience frustration and disappointment with their work, as well as guilt when they are unable to perform their work assignments to their self-imposed standards, which can result in lower levels of job satisfaction and higher levels of work-to-family guilt (Clark et al., 2020). These outcomes were selected due to their well-documented associations with work and personal behaviors (Bowling, 2007; Erdogan et al., 2012), as well as their practical relevance for health and work-family balance (Aarntzen et al., 2019; Korabik, 2017).

Hypothesis 10. Profiles characterized by higher levels of workaholism (e.g., *Plugged In*) will be characterized by lower levels of job, family, and life satisfaction, and by higher levels of work-to-family guilt, relative to profiles characterized by lower levels of workaholism (e.g., *Unplugged*).

The Role of Working Remotely or Onsite

By forcing many to work remotely, the COVID-19 pandemic has blurred the boundaries between work and personal lives, making it harder to efficiently manage these boundaries (Kniffin et al., 2021) and thus possibly contributing to workaholism. Previous research has shown variations in workaholism as a function of job settings (e.g., Clark et al., 2016; Gillet et al., 2017), making it important to verify whether the profiles generalize to different contexts. In the present study, we examine whether the identified workaholism profiles generalize across samples of employees working remotely or onsite. These two samples were selected given their high level of differentiation to conduct a robust test of profile similarity. On one hand, working remotely tends to be associated with higher levels of workaholism, emerging from high levels of controlled motivation (Van den Broeck et al., 2011) related to the employees' desire to reciprocate for the increased flexibility and autonomy afforded by their organization (Sherman, 2020). On the other hand, onsite employees typically work according to more normative work schedules and are more autonomously motivated (Gillet et al., 2022). As such, higher levels of workaholism seem to be more likely among the first group of employees (Taris et al., 2012).

In addition, this study was designed to verify whether and how the associations between the workaholism profiles and their predictors (i.e., PLO, telepressure, and interpersonal norms regarding work-related messages) would vary across samples of employees working remotely or onsite (treated as a moderator of the former relations). Indeed, employees have different preferences when it comes to managing the boundaries between their work and nonwork domains (Kossek et al., 2012). These preferences range from integration (i.e., a preference for having no physical, temporal, or behavioral boundaries between their work and personal roles) to segmentation (i.e., a preference for having clear physical, temporal, and behavioral boundaries separating their work role from their personal role). Employees high in PLO who work remotely should feel more in control of when and how they transition between their work and their nonwork roles (Kossek et al., 2012), making it easier for them to schedule their work tasks in a way that is aligned with their PLO. This may allow them to find a better balance between their different life roles and increase the likelihood of membership into an *Unplugged* profile relative to profiles characterized by higher levels of workaholism.

Regarding the effects of telepressure and of interpersonal norms regarding work-related messages on employees' likelihood of profile membership, it seems logical to expect a work context (i.e., remote working) in which the boundaries between the work and nonwork roles are already blurred to increase the impact of these predictors (Wang et al., 2021). Indeed, when employees working remotely perceive high levels of telepressure and interpersonal norms regarding work-related messages, they may become more likely to subject themselves to these pressures (i.e., display higher levels of controlled motivation; Ryan & Deci, 2017), as remote work makes it easier to be constantly connected to work via email or smartphones (Golden et al., 2006). This may contribute to an excessive amount of time and effort devoted to work at the expense of other nonwork roles (e.g., family), and thus increase the likelihood of membership into a *Plugged In* profile relative to profiles characterized by lower levels of workaholism.

We also consider whether and how the associations between the profiles and the outcomes differed as a function of working remotely or onsite. The well-being of employees high in workaholism should suffer in a context (e.g., remote) that limits their ability to work efficiently due to the unavailability of a quiet room to work, to insufficient access to the technologies and support required for their work, and to the interruptions caused by their family life (Gillet et al., 2021b). These interferences may thwart employees' psychological needs for autonomy, competence, and relatedness, increase their controlled motivation, and prevent them from being satisfied at work (Gillet et al., 2019b). In contrast, individuals usually seek to maintain clear boundaries between the life domains that they see as critical to their sense of self (i.e., the work domain for employees high in workaholism), making them more likely to let the demands of their work interfere with their personal life than the other way around (Matthews & Barnes-Farrell, 2010), which is much easier to do when working onsite.

Moreover, employees who experience dissatisfaction in a central role (i.e., work for employees high in workaholism working remotely) may seek to alleviate this dissatisfaction by increasing their involvement in other roles (e.g., family; Hewett et al., 2017). As a result, when facing work difficulties, it might be easier for employees high in workaholism working remotely (relative to those working onsite) to compensate for their frustration in the work domain by enhancing their family involvement, leading to higher levels of family satisfaction (Golden et al., 2006). However, this does mean that organization and managers should increase the difficulty of all work assignments, at the risk of considerably increasing employees' workload and thus contributing to the development of workaholism (Huyghebaert et al., 2018). Remote work may also decrease the saliency of the work role among employees high in workaholism (Thoits, 1992), thus reducing the negative spillover of work-related stressors into their personal life (Edwards & Rothbard, 2000) and making it easier to redistribute their resources across domains (Cheng et al., 2019). In contrast, the negative effects of a *Plugged In* profile on family satisfaction might be exacerbated among onsite employees who work in a setting that makes their family role less salient (Thoits, 1992). For employees in workaholism, working onsite should reinforce their natural tendencies to invest time and energy into their work to the detriment of other roles (e.g., family; Carr et al., 2008), leading to a more pronounced decrease in family satisfaction. Once again, it does mean that working remotely, relative to onsite, is a way to decrease workaholism among all employees, but rather that the detrimental effects of workaholism on family satisfaction might be reduced when employees work remotely (Gillet et al., 2021b).

Despite these speculations, it is important to acknowledge that, due to the lack of prior empirical guidance, we relied on a predominantly inductive approach when studying whether and how these profiles, as well as their associations with these predictors and outcomes, would vary across these two samples of employees (Morin et al., 2018).

Research Question 1. Will the nature of the profiles and their associations with the predictors and outcomes vary across employees working remotely and onsite?

Method

Participants and Procedure

Participants working in the US and UK were invited to complete an online questionnaire twice over a period of three months (Hakanen et al., 2018; Huyghebaert et al., 2018) via the Prolific Academic crowdsourcing platform (https://www.prolific.co). Before completing each questionnaire, participants were informed about the objectives of the research, told that participation was voluntary and confidential, and notified that they could freely withdraw from the project at any time. They were also asked to provide a unique identifier to allow the research team to match their responses over time while maintaining confidentiality. At both time points, participants were compensated £1.75 for completing the questionnaire (15 minutes). The US and UK were not on lockdown (as a result of the COVID pandemic) at Time 1 (T1). The second national lockdown in the UK ended on the day T1 data collection started. At Time 2 (T2), the US was not on national lockdown during data collection, while the third national lockdown in the UK was lifted on March 8th, just a few days after the start of the T2 data collection. However, although our data collection did not occur during these lockdown periods, more than half of the participants who reported working remotely during the study (58.6%) noted that they did not use to work remotely prior to the COVID-19 pandemic.

As this data collection was part of a larger project focusing on the work-family interface (and more specifically to allow us to obtain proper measures of family satisfaction and work-family guilt), recruitment was limited to participants who lived with a spouse or partner. Due to the language of our questionnaire, it was also limited to participants who spoke English as their main language. Lastly, to ensure that participants were able to properly address all work-related questions, and to limit the number of participants who did not work as their main occupation, it was limited to participants who were employed by an organization rather than self-employed. The survey also included two questions assessing participants' attention (e.g., "It is important that you pay attention to our survey, please tick strongly disagree"), and one final question verifying "for scientific reasons", if they really worked in an organization. Only respondents who successfully completed all verifications were included in the study, resulting in a final sample of 432 participants (54.6% females) at T1, and 335 participants (54.0% females), at T2. Of those, 152 reported working onsite, and 280 reported working remotely. Participants lived and worked in the UK (74.3%) or the US (25.7%), and 94.9% held a bachelor degree. They had a mean age of 40.06 years (SD = 10.44) and a mean tenure in their position of 6.27 years (SD = 5.64). A majority held a permanent (93.5%) full-time (89.4%) position. Participants mainly worked in the private sector (60.6%). More precisely, they worked in non-market services (50.0%), market services (35.2%), manufacturing (e.g., chemical, automotive; 10.0%), construction (2.1%), agriculture (0.7%), or other (2.1%). According to the United Nations (2008), non-market services encompass public administration (e.g., public policy researchers, public relations consultants), community (e.g., health educators, community health workers), social services and related activities (e.g., social service managers and assistants), whereas market services include trade, transportation, accommodation, food, and business/administrative services.

Measures

All measures, with the exception of job, family, and life satisfaction, were rated using a five-point response scale ranging from "Strongly Disagree" to "Strongly Agree".

Workaholism (profile indicators). Workaholism was measured using a 16-item scale developed by Clark et al. (2020). This instrument assesses four dimensions of workaholism, each with four items: Motivational (e.g., "I always have an inner pressure inside of me that drives me to work"; α = .85 at T1 and α = .87 at T2), cognitive (e.g., "I feel like I cannot stop myself from thinking about working"; α =

.91 at both T1 and T2), emotional (e.g., "I feel upset if I have to miss a day of work for any reason"; α = .89 at T1 and α = .88 at T2), and behavioral (e.g., "I work more than what is expected of me"; α = .84 at T1 and α = .85 at T2).

PLO (predictor). PLO was measured using a five-item scale (e.g., "Making time for pursuing personal interests is a big priority for me"; α = .88 at both T1 and T2) developed by Hall et al. (2013).

Telepressure (predictor). Telepressure was measured with a six-item scale (e.g., "When using message-based technology for work purposes, I can concentrate better on other tasks once I have responded to my messages"; α = .93 at T1 and α = .94 at T2) created by Barber and Santuzzi (2015).

Interpersonal norms regarding work-related messages (predictor). Work-related interpersonal norms regarding work-related messages were assessed using a 10-item scale (e.g., "My supervisor expects me to respond to work-related messages during my free time after work", "If I do not answer my work-related messages during off job hours, I get comments from my colleagues."; α = .93 at T1 and α = .94 at T2) developed by Derks et al. (2015).

Work-to-family guilt (outcome). Work-to-family guilt was assessed using a four-item scale (e.g., "I regret not being around for my family as much as I would like to"; α = .83 at T1 and α = .85 at T2) developed by Zhang et al. (2019).

Job, family, and life satisfaction (outcomes). Job, family, and life satisfaction were each assessed by one item recommended by Fisher et al. (2016; also see Wanous et al., 1997) as providing an accurate measure of these constructs. These items asked participants to report the extent to which they were satisfied with their current job (r = .78, p < .001 between T1 and T2 measures), family life (r = .63, p < .001 between T1 and T2 measures), and life in general (r = .65, p < .001 between T1 and T2 measures) using a four-point scale (1 "Dissatisfied" to 4 "Satisfied").

Analyses

Preliminary Analyses

The psychometric properties of all multi-item measures were verified as part of preliminary factor analyses. Details on these analyses (factor structure, measurement invariance across groups of employees working onsite or remotely, measurement invariance across groups of US or UK employees, measurement invariance over time, composite reliability, and factor correlations) are reported in the online supplements (Tables S1 to S5). The results support the superiority of the bifactor-CFA solution across samples and over time, thus supporting Hypothesis 1, The main analyses relied on factor scores from these preliminary analyses (Meyer & Morin, 2016; Morin et al., 2016c). To ensure comparability over time, factor scores were obtained from models specified as invariant longitudinally (Millsap, 2011), and estimated in standardized units (SD = 1; M = 0). Factor scores are able to achieve a partial control for unreliability (Skrondal & Laake, 2001) and to preserve the structure of the measurement model (e.g., invariance; Morin et al., 2016b). Attrition analyses revealed no differences between participants who completed one versus two time points.

Model Estimation

Models estimation relied on the maximum likelihood robust (MLR) estimator implemented in Mplus 8.6 (Muthén & Muthén, 2021). Missing responses were handled using full information maximum likelihood procedures, allowing us to estimate longitudinal models using all participants who responded to at least one time point (n = 432) and using all of the available information to estimate each model parameter (without relying on missing data replacement). Latent profile analyses (LPA) are sensitive to the start values used in the model estimation process (Hipp & Bauer, 2006). For this reason, all models were estimated using 5000 sets of random start values allowed 1000 iterations each, and final stage optimization was conducted on the 200 best solutions. These numbers were changed to 10000, 1000, and 500 for the longitudinal analyses. All of our solutions converged on well-replicated solutions, which were maintained even when doubling these values.

Latent Profile Analyses (LPA)

LPA models are designed to examine the multivariate distribution of scores on a set of profile indicators to summarize this distribution via the identification of a finite set of latent profiles of participants characterized by distinct configurations on this set of indicators, while allowing for within-profile variability on all indicators (McLachlan & Peel, 2000). These profiles are similar to prototypes, and called latent to reflect their probabilistic nature (Morin et al., 2018). More precisely, each participant is assigned a probability of membership in each of the latent profiles, which provides a way to assess the LPA model while controlling for classification errors. In this study, time-specific LPA models were first estimated using the five workaholism factors as indicators. At each time point, solutions including one to eight profiles were estimated while allowing the means and variances of the indicators (global workaholism and specific motivational, cognitive, emotional, and behavioral workaholism) to be freely estimated (Morin & Litalien, 2019).

Model Comparison and Selection

The decision of how many profiles to retain relies on a consideration of whether the profiles themselves are meaningful, aligned with theory, and statistically adequate (Marsh et al., 2009; Morin, 2016). Statistical indicators (McLachlan & Peel, 2000) can also be consulted. Thus, a lower value on the Akaïke Information Criterion (AIC), Consistent AIC (CAIC), Bayesian Information Criterion (BIC), and sample-size Adjusted BIC (ABIC) indicate better fitting models. Statistically significant p-values on the adjusted Lo, Mendell and Rubin's (2001) Likelihood Ratio Test (aLMR), and Bootstrap Likelihood Ratio Test (BLRT) suggest better fit relative to a model with one fewer profile[1]. These tests all present a strong sample size dependency (Marsh et al., 2009). For this reason, they often fail to converge on a specific number of profiles. When this happens, it is usually recommended to rely on a graphical display of these indicators, referred to as an elbow plot, in which the observation of a plateau in the decrease in the value of these indicators helps to pinpoint the optimal solution (Morin et al., 2011). Finally, the classification accuracy (from 0 to 1) is summarized by the entropy, which should not be used to select the optimal number of profiles (Lubke & Muthén, 2007).

Longitudinal Tests of Profile Similarity

Assuming that the same number of profiles would be extracted at both time points (Morin & Wang, 2016), the two time-specific LPA solutions will then be combined into a longitudinal LPA for longitudinal tests of within-sample profile similarity. Morin et al.'s (2016c) recommendations, optimized for the longitudinal context by Morin and Litalien (2017), were used to guide these tests. This sequential strategy starts by assessing if each measurement occasion results in the estimation of the same number of profiles. The two time-specific solutions can then be combined in a longitudinal model of *configural* similarity. Equality constraints are then be imposed in sequence on the: (1) within-profile means (*structural* similarity), (2) within-profile variances (*dispersion* similarity), and (3) profile size (*distributional* similarity). The CAIC, BIC, and ABIC can be used to contrast these models so that each form of profile similarity can be considered to be supported as long as at least two of these indices decrease following the integration of equality constraints (Morin et al., 2016c).

Latent Transition Analyses (LTA)

The most similar longitudinal LPA solution will then be re-expressed as a LTA to investigate within-person stability and transitions in profile membership (Collins & Lanza, 2010). This LTA solution, as well as all following analyses, were specified using the manual three-step approach (Asparouhov & Muthén, 2014) outlined by Morin and Litalien (2017). Readers interested in a complete coverage of the technical and practical aspects involved in the estimation of LPA and LTA are referred to Morin and Litalien (2019).

Predictors and Outcomes of Profile Membership

We assessed the extent to which the relations between profiles, predictors (*predictive* similarity), and outcomes (*explanatory* similarity) remained the same over time. Demographics (sex, age, status, sector, and country) were first considered across a series of four models in which their association with profile membership was specified using a multinomial logistic regression link function. First, we estimated a null effects model assuming no relations between these variables and the profiles. Second, the effects of these demographic variables were freely estimated, and allowed to vary over time and as a function of T1 profile membership (to assess the effects on specific profile transitions). Third, predictions were allowed to differ over time only. Finally, a model of *predictive* similarity was estimated by constraining these associations to be equal over time. Relations between the theoretical predictors (work type, PLO, telepressure, and interpersonal norms regarding work-related messages) and profile membership were then assessed in the same sequence.

Time-specific outcome measures (work-to-family guilt as well as job, life, and family satisfaction)

[1] *Statistical research has shown that the BIC, CAIC, ABIC, and BLRT, but not the AIC and aLMR, were efficient at helping to identify the number of latent profiles (for a review, see Diallo et al., 2016, 2017). For this reason, the AIC and aMLR will not be used for purposes of model comparison and selection and are only reported for purposes of transparency.*

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

Results

Latent Profile Analyses (LPA)

The statistical indicators associated with each of the time-specific LPA solutions are reported in Table S6, and graphically displayed in Figures S1 and S2, of the online supplements. These indicators failed to pinpoint a clear dominant solution at both time points. However, the elbow plots revealed a plateau between three and five profiles at both time points. Solutions including three to five profiles were thus carefully examined. This examination revealed that these solutions were highly similar across time points, and that the addition of profiles added meaning to the model up to four profiles. However, adding a fifth profile simply resulted in the splitting of one profile into smaller ones presenting a comparable configuration. On the basis of this examination, which is consistent with Hypothesis 2, we decided to retain the four-profile solution at both time points for further analyses.

The fit indices from all longitudinal models are reported in Table 1. Starting with a model of *configural* similarity including four profiles per time point, equality constraints were then integrated following the sequence proposed by Morin et al. (2016c), starting with the within profile means (*structural* similarity*)*, followed by the within-profile variance (*dispersion* similarity), and finally the profile sizes (*distributional* similarity). The second model or *structural* similarity resulted in lower BIC, CAIC, and ABIC values, and was thus supported by the data. The *dispersion* similarity of the model was also supported by the data, resulting in lower values on these information criteria. Finally, the *distributional* similarity of the solution was supported by the observation of lower values on these information criteria. Supporting Hypothesis 5, the model of *distributional* similarity is graphically represented in Figure 2 and was retained for interpretation. The detailed parameter estimates from this model are reported in Tables S7 and S8 of the online supplements. As shown in Table S8, this solution is associated with a high level of classification accuracy, ranging from 78.5% to 94.3% across T1 profiles, from 75.5% to 90.5% at T2, and summarized in a high entropy value of .696.

Profile 1 displays very low global levels of workaholism, low specific levels of motivational and behavioral workaholism, moderately low specific levels of cognitive workaholism, and average specific levels of emotional workaholism. This *Unplugged* profile characterizes 8.23% of the participants. Profile 2 corresponds to participants reporting high global levels of workaholism, moderately high specific levels of emotional workaholism, and average specific levels of cognitive, motivational, and behavioral workaholism. This *Plugged In* profile characterizes 41.65% of the participants. Profile 3 corresponds to participants reporting low global levels of workaholism, moderately low specific levels of cognitive and emotional workaholism, and moderately high specific levels of motivational and behavioral workaholism. This *Moderately Unplugged with Externalized Workaholism* profile characterizes 28.87% of the participants. Finally, Profile 4 corresponds to participants reporting moderately low global levels of workaholism, moderately low specific levels of motivational and behavioral workaholism, average specific levels of emotional workaholism, and high specific levels of cognitive workaholism. This *Moderately Unplugged with Cognitive Workaholism* profile characterizes 21.26% of the participants. The nature of these profiles partially supports Hypothesis 3, while also being consistent with Hypothesis 4.

Latent Transitions Analyses (LTA)

The transition probabilities are reported in Table 2. Membership into Profiles 2 (*Plugged In*: Stability of 100.0%), 3 (*Moderately Unplugged with Externalized Workaholism*: Stability of 95.8%), and 4 (*Moderately Unplugged with Cognitive Workaholism*: Stability of 92.6%) were the most stable over time. Conversely, Profile 1 (*Unplugged*: Stability of 71.1%) was not as stable. Supporting Hypothesis 6, our results thus reveal a very high level of profile stability that appears to decrease slightly as the global levels of workaholism associated with each profile decrease.

Participants initially presenting very low global levels of workaholism, when they transition to another profile at T2, tend to retain relatively low global levels of workaholism. Indeed, 28.2% of the members of the *Unplugged* profile at T1 transition to the *Moderately Unplugged with Externalized Workaholism* profile at T2. In contrast, only 0.7% of them transition to the *Plugged In* profile at T2, and only 0.1% of them transition to the *Moderately Unplugged with Cognitive Workaholism* profile at T2. For members of the *Moderately Unplugged with Externalized Workaholism* at T1, transitions seem to mainly involve the *Unplugged* profile at T2 (4.2%). Finally, when they transition to a new profile at T2, members of the *Moderately Unplugged with Cognitive Workaholism* profile seem to transition to the *Unplugged* profile (7.4%) at T2.

Predictors of Profile Membership

As shown in Table 1, no associations were found between the demographic variables and participants' likelihood of profile membership (supporting the null effects model), whereas the associations between the theoretical predictors and the profiles generalized over time (i.e., supporting the model of *predictive* similarity). The results from this model are reported in Table 3 and generally support Hypotheses 7, 8, and 9. More precisely, telepressure predicted a decreased likelihood of membership into the *Unplugged* (1) profile relative to the *Moderately Unplugged with Cognitive Workaholism* (4) profile. Telepressure also predicted an increased likelihood of membership into the *Plugged In* (2) profile relative to the *Moderately Unplugged with Externalized Workaholism* (3) and *Unplugged* (1) profiles. Working remotely predicted a decreased likelihood of membership into the *Plugged In* (2) profile relative to the *Moderately Unplugged with Externalized Workaholism* (3) profile. PLO predicted a decreased likelihood of membership into the *Plugged In* (2) profile relative to the *Moderately Unplugged with Cognitive Workaholism* (4), *Moderately Unplugged with Externalized Workaholism* (3), and *Unplugged* (1) profiles. Interpersonal norms regarding work-related messages predicted an increased likelihood of membership into the *Plugged In* (2) profile relative to the *Moderately Unplugged with Cognitive Workaholism* (4), *Moderately Unplugged with Externalized Workaholism* (3), and *Unplugged* (1) profiles.

To investigate whether the role of these predictors differed for employees working onsite (coded 0) or remotely (coded 1) and answer to our Research Question 1, we tested whether the effects of these predictors interacted with work type. The results from these additional analyses revealed few, but noteworthy, statistically significant interaction effects. First, PLO predicted an increased likelihood of membership into the *Unplugged* (1) profile relative to the *Moderately Unplugged with Cognitive Workaholism* (4) profile among employees working remotely [b = .736 (.361), p < .05] but not among employees working onsite [b = -.398 (.372), p = .285]. Second, PLO also predicted a decreased likelihood of membership into the *Plugged In* (2) profile relative to the *Moderately Unplugged with Cognitive Workaholism* (4) profile among employees working onsite [b = -1.140 (.344), p < .01] but not among those working remotely [b = -.260 (.257), p = .311]. Third, interpersonal norms regarding work-related messages predicted a decreased likelihood of membership into the *Unplugged* (1) profile relative to the *Plugged In* (2) profile among employees working remotely [b = -.936 (.378), p < .05] but not among those working onsite [b = -.023 (.333), p = .944].

Outcomes of Profile Membership

The model of *explanatory similarity* resulted in the lowest values on the information criteria and was thus supported by the data (see Table 1). The profile-specific outcome levels, reported in Table 4, revealed clear differences across all profiles but only partially supported Hypothesis 10. The most desirable outcomes (i.e., lowest levels of work-to-family guilt, and highest levels of job, life, and family satisfaction) were associated with Profile 4 (*Moderately Unplugged with Cognitive Workaholism*). Moreover, Profile 1 (*Unplugged*) was associated with lower levels of work-to-family guilt than Profile 2 (*Plugged In*). Profile 1 (*Unplugged*) was also associated with lower levels of job satisfaction than Profiles 2 (*Plugged In*) and 3 (*Moderately Unplugged with Externalized Workaholism*), which did not differ between them. Profile 2 (*Plugged In*) was associated with higher levels of life satisfaction than Profiles 1 (*Unplugged*) and 3 (*Moderately Unplugged with Externalized Workaholism*) which did not differ between them. Finally, Profile 3 (*Moderately Unplugged with Externalized Workaholism*) was associated with lower levels of family satisfaction than Profiles 1 (*Unplugged*) and 2 (*Plugged In*) which did not differ from one another.

The Role of Work Type: Remote or Onsite Work

To investigate how these associations differed as a function of working remotely or onsite (a work type that could change for employees over time) and answer to our Research Question 1, we had to estimate multi-group LPA solutions separately at each time point (with work type as the grouping variable). The results from these additional analyses are reported in Tables S9 and S10 of the online supplements (elbow plots are reported in Figure S3 of the online supplements) and confirmed the superiority of the four-profile solution across groups and time points, as well as the *configural*, *structural*, *dispersion*, and *distributional* similarity of this solution across groups at both T1 and T2. Outcomes were thus integrated separately to the two multi-group solutions of *distributional* similarity. The T1 results supported the *explanatory* similarity of this solution across samples of employees working remotely or onsite, consistent with the presence of outcome associations corresponding to those previously reported which did not differ across groups. Likewise, T2 results also supported the *explanatory* similarity of this solution. However, a detailed examination of the parameter estimates associated with these analyses suggested the presence of differences limited to the work-family guilt outcome. Indeed, when the analyses of *explanatory* similarity were redone using only this outcome, they supported the presence of between-group differences in the associations between profiles and this outcome at T2. Apart from generally supporting the previously reported outcome associations, these results further indicated that, at T2, Profile 1 (*Unplugged*) was associated with lower levels of work-to-family guilt than Profile 4 (*Moderately Unplugged with Cognitive Workaholism*) among employees working onsite (p < .001) but not among those working remotely (p = .232). In addition, Profile 2 (*Plugged In*) was associated with lower levels of work-to-family guilt than Profile 4 (*Moderately Unplugged with Cognitive Workaholism*) among employees working onsite (p < .01) but not among those working remotely (p = .649).

Discussion

Prior variable-centered research has demonstrated that the workaholism dimensions proposed by Clark et al. (2020) and assessed via the MWS were moderately-to-strongly inter-correlated, while also presenting well-differentiated associations with various covariates (Clark et al., 2020; Xu & Li, 2021). Anchored in the recognition that employees' workaholism tends to be underpinned by more than one of these dimensions, previous studies have also tried to identify the most commonly occurring configurations, or profiles, of workaholism (e.g., Gillet et al., 2017, 2021c). Despite evidence of consistency related to the nature of the workaholism profiles identified in these studies, only one of them (Gillet et al., 2021c) relied on a bifactor approach to achieve a clear disaggregation of employees' global and specific levels of workaholism, which is known to possibly result in erroneous conclusions in the shape of these profiles (Morin et al., 2016b, 2017).

The present study was designed to contribute to this research area via the identification of workaholism profiles defined based on indicators relying on a proper disaggregation of workers' global levels of workaholism from their specific levels of behavioral, motivational, emotional, and cognitive workaholism. More generally, we relied on a dual variable- and person-centered approach (e.g., Morin et al., 2016b, 2017) to investigate the value of jointly considering global and specific dimensions of workaholism, as measured via the MWS. In doing so, we were able to achieve an improved representation of the structure of workaholism measurement and profiles, expanding upon the results reported by Gillet et al. (2021c) through our reliance on the MWS and our adaption of a longitudinal perspective. Indeed, our longitudinal design allowed us to investigate the within-person and within-sample stability of these profiles (Gillet et al., 2019a; Sandrin et al., 2020). Furthermore, to better document the practical relevance of these profiles, we tested the role of PLO, telepressure, and interpersonal norms regarding work-related messages as predictors of profile membership, as well as the implications of these profiles in terms of work-to-family guilt as well as job, life, and family satisfaction. Finally, we investigated the extent to which these profiles, as well as their associations with the predictors and outcomes, changed as a function of working remotely or onsite.

Workaholism as a Multidimensional Construct

The need to account for the dual nature of workaholism as a global construct (the G-factor) measured from distinct dimensions retaining some degree of specificity of their own (the S-factors) has recently been documented in research relying on Schaufeli et al.'s (2009b) representation of workaholism as encompassing a working excessively and a working compulsively component (Gillet et al., 2018, 2021c; Tóth-Király et al., 2021). However, research had yet to investigate the relevance of such a bifactor structure in relation to Clark et al.'s (2020) improved representation of workaholism as encompassing four distinct dimensions (i.e., behavioral, motivational, emotional, and cognitive). In this regard, our results confirmed our expectations and replicated previous conclusions (Gillet et al., 2018, 2021c; Tóth-Király et al., 2021) supporting the superiority of a bifactor representation of workaholism. This solution revealed co-existing factors representing global levels of workaholism and specific levels of behavioral, motivational, emotional, and cognitive workaholism left unexplained by global levels of workaholism. In this solution, the global factor and the four specific factors were all well-defined, supporting the idea that ratings of behavioral, motivational, emotional, and cognitive workaholism contributed to the assessment of global workaholism levels, while retaining something unique, beyond their contribution to global workaholism levels.

Workaholism Profiles

One of the main contributions of our study arguably lies in the validation of the theoretical workaholism scenarios outlined in the introduction as a guide for future multidimensional research on workaholism. Indeed, our results revealed four distinct workaholism profiles that corresponded closely (i.e., *Plugged-In* and *Unplugged*), or in part (i.e., *Moderately Unplugged with Externalized Workaholism* and *Moderately Unplugged with Cognitive Workaholism*) to the scenarios outlined in the introduction. More precisely, our *Unplugged* scenario seemed to match the *Unplugged* profile identified in this study, which displayed very low to average global and specific levels of workaholism across components. Similarly, the *Plugged In* scenario seemed to correspond to the *Plugged In* profile, which displayed average to high global and specific levels of workaholism across components. In contrast, whereas the *Moderately Unplugged* scenario was conceptualized as displaying average global and specific levels of workaholism, the *Moderately Unplugged with Externalized Workaholism* profile was rather characterized by low global levels of workaholism, moderately low specific levels of cognitive and emotional workaholism, and moderately high specific levels of motivational and behavioral workaholism. Similarly, the *Moderately Unplugged with Cognitive Workaholism* profile was characterized by moderately low global levels of workaholism and specific levels of motivational and behavioral workaholism, average specific levels of emotional workaholism, and high specific levels of cognitive workaholism.

As a result, these profiles provide a novel theoretically-driven heuristic framework to help researchers achieve a more comprehensive understanding of workaholism. Interestingly, prior person-centered studies relying on the working excessively and compulsively facets (e.g., Gillet et al., 2017, 2021c; Schaufeli et al., 2009a) have identified profiles with high levels (similar to our *Plugged In* profile) or low levels (similar to our *Unplugged* profile) of workaholism across both dimensions. This similarity of results, regardless of the questionnaire used (i.e., DUWAS or MWS), reinforces the robustness of our findings and the possible utility of interventions targeting specific profiles of employees. Our results also supported the generalizability of these profiles across time points, as well as across samples of employees working remotely *versus* onsite. These observations suggest that these profiles seem to reflect overarching psychological mechanisms involved in the experience of workaholism, irrespective of the specific facets (or measure) used in its definition.

Our results also supported Gillet et al.'s (2021c) conclusions highlighting the value of disaggregating global and specific components of workaholism prior to the identification of the profiles. Importantly, none of the profiles identified in the present study was characterized by purely matching levels across all five profile indicators (i.e., global workaholism and specific behavioral, motivational, emotional, and cognitive workaholism). In other words, results showed that the four profiles presented a configuration where employees' levels on specific workaholism facets deviated, slightly to more importantly, from their global level of workaholism and from the sample average. This result suggests that workaholism levels are not aligned across dimensions once the variance shared among all components and absorbed into the G-factor is taken into account, which may explain why, contrary to our expectations, we did not identify a profile characterized by moderate and matching levels of workaholism across dimensions (i.e., a pure *Moderately Unplugged* profile). Consequently, although workaholism components are complementary and known to be highly intercorrelated (Clark et al., 2020), our findings demonstrate the value of simultaneously considering global and specific facets of workaholism.

In this regard, our results first showed that employees with high (*Plugged In* profile) global levels of workaholism tended to display a more balanced configuration (specific levels of behavioral, motivational, emotional, and cognitive workaholism showed less pronounced deviations from global levels and from the sample average). Although far more imbalanced than the *Plugged In* profile, it is also noteworthy that the *Unplugged* profile also displayed a generally balanced configuration in relation to the specific cognitive and emotional levels of workaholism (close to the sample average, and thus showing no deviation from the global level). Keeping in mind that the scores obtained on the specific factors reflect the extent to which these dimensions deviate from the globally low levels of workaholism observed in this profile, the specific levels of motivational and behavioral workaholism were thus even lower than these global levels. This suggested that, among *Unplugged* employees, motivational and behavioral signs of workaholism are particularly low.

Conversely, employees characterized by moderately low to low global levels of workaholism (*Moderately Unplugged with Externalized Workaholism* and *Moderately Unplugged with Cognitive Workaholism* profiles) rather tend to be also characterized by higher levels on specific components of workaholism. Thus, rather than identifying one pure *Moderately Unplugged* profile, we identified two of them, one also presenting high levels of *Externalized Workaholism* (i.e., behavioral and motivational) and one presenting high levels of *Cognitive Workaholism*. These two profiles suggest that, at less extreme levels (i.e., moderately low to low), workaholism tends to be dominated either by a clear drive to work excessively, or by a clear tendency to keep thinking about work compulsively. As a result, these profiles provide some support to Schaufeli et al.'s (2009b) representation of workaholism as encompassing a working excessively and a working compulsively component, at least for *Moderately Unplugged* employees. Alternatively, they also indicate that this distinction only appears once their global levels of workaholism, anchored in all four components, are taken into account.

Interestingly, from the perspective of SDT, Gillet et al. (2020) identified six motivation profiles differing from one another both in terms of their global levels of self-determination but also in terms of specific levels of behavioral regulations. More importantly, these six motivation profiles were characterized by well-differentiated configurations, and at least two of them were primarily defined, in part, by their specific levels of introjected and external regulations. In addition, they presented a configuration where employees' specific levels of behavioral regulations deviated from their global level of self-determination and from the sample average. These results thus support SDT assertion (e.g., Ryan & Deci, 2017) that motivation levels are not aligned across dimensions. Yet, motivation has a significant effect on workaholism (Gillet et al., 2021c; Van den Broeck et al., 2011). Thus, it is interesting to note the presence of strong parallels between our results and those obtained by Gillet et al. (2017). Indeed, both studies identified profiles characterized by more or less balanced configurations cross dimensions, both studies identified a profile in which externalized forces seemed to play a dominant role, and both studies identified a profile in which cognitive forces (i.e., introjection) played a key role. All of those observations are consistent with the assumptions of SDT (Ryan & Deci, 2017) according to which different types of persons should be driven by distinct forms of behavioral regulations. Nevertheless, future research should seek to confirm our results and to more clearly capture the mechanisms at play in the determination of the shape of these profiles.

Generalizability over Time and Samples of Remote and Onsite Employees

In terms of within-person stability, our results revealed that membership into the four identified workaholism profiles remained moderately to highly stable (71.1% to 100.0%; Huyghebaert-Zouaghi et al., 2022b) over a three-month period, suggesting that individual profile membership do not change on its own in the absence of a systematic exposure to external changes or interventions. Although exposure to changes or interventions was not assessed in the present study, such changes are unlikely to have affected all participants in a systematic manner, suggesting that most participants probably underwent a more normative work experience over the course of the study. Moreover, these rates of stability are aligned with previous results showing that employees' levels of workaholism tend to be moderately to highly stable over three months (Falco et al., 2020; Huyghebaert et al., 2018). This stability may in part reflect the relatively short time interval considered here (three months *vs.* one-two years). However, the fact that our results also revealed within-person changes suggest that the time interval was sufficient to study changes at the individual level.

More precisely, membership into the *Unplugged* profile was the least stable (71.1%). This observation suggests that it might be easier for interventions to support change among employees characterized by very low levels of workaholism or, rather, that it might be helpful to intervene to help these employees maintain their low levels of workaholism. This observation also implies that it is more difficult to maintain a profile characterized by very low levels of workaholism across all global and specific indicators over time, probably because of the constant chase of efficiency and speed resulting in work intensification (Korunka et al., 2015). Indeed, many employees complain about having to deal with ever-increasing workload and time constraints (e.g., short deadlines, constantly working in a hurry), all of which serve to increase workaholism. This result thus suggests that maintaining very low levels of workaholism may not be sustainable, even in a rather short period of time (i.e., three months), in a society that values hard work (Huyghebaert et al., 2018). Interestingly, most *Unplugged* participants who transitioned to another profile at T2 retained low global levels of workaholism over time (i.e., they mainly transitioned to the *Moderately Unplugged with Externalized Workaholism* profile at T2). In contrast, only 0.7% of them transitioned to the *Plugged In* profile. These results are reassuring because they reveal that only a tiny fraction of employees can see their global levels of workaholism increase drastically over a three-month period. Conversely, global levels of workaholism can still increase over a short period of time (from very low to moderately low), as we pointed out previously, and this increase could potentially be explained, in part, by seasonal variations in sectors of activity that are highly affected by seasonality (e.g., agriculture, promotional periods and sales in commerce). Future research will be required to verify this explanation.

More generally, by providing the first direct source of evidence that workaholism profiles defined according to the recently recommended bifactor operationalization (Gillet et al., 2021c) and the MWS (Clark et al., 2020), generalize over time and across samples of remote and onsite workers, this study represents an important step forward in workaholism research. Indeed, by providing evidence of generalizability, it supports the possibility of devising generic intervention strategies likely to be relevant to many employees without having to worry that the nature of workaholism profiles may change drastically over time and across different types of workers. Our results thus reinforce the idea that the person-centered results do not reflect ephemeral phenomena and can be used as guides for generic interventions seeking to decrease workaholism (e.g., Meyer & Morin, 2016). Yet, it would be particularly important for future investigations to more systematically understand whether and how these profiles would differ across different cultures (e.g., North America, Europe, Asia), as well as whether and how intervention strategies can be devised to nurture more desirable profiles. Our findings also have theoretical implications for workaholism research in demonstrating the value of simultaneously taking into account participants' global levels of workaholism, together with the specificity of each component. The reliance on a more traditional approach (ignoring global levels of workaholism) would have simply resulted in the estimation of profiles revealing little value to consider the unique nature of each workaholism dimension over and above that global level, such as those reported by Gillet et al. (2017). In contrast, our results show that, as expected by Gillet et al. (2021c), both components seem to play a role in the definition of workaholism profiles, and thus bring valuable information to our understanding of workaholism.

Predictors of Workaholism Profiles

By considering the role played by PLO, telepressure, and interpersonal norms regarding work-related messages in the prediction of profile membership, our results provided some practical guidance regarding some of the likely drivers of the distinct workaholism configurations observed among employees. More specifically, PLO was found to be associated with a lower likelihood of membership into the *Plugged In* profile relative to all other profiles, whereas interpersonal norms regarding work-related messages were found to be associated with an increased likelihood of membership into this *Plugged In* profile relative to all other profiles. Furthermore, telepressure was found to associated with an increased likelihood of membership into the *Plugged In* profile relative to the *Moderately Unplugged with Externalized Workaholism* and to the *Unplugged* profiles, as well as into the *Moderately Unplugged with Cognitive Workaholism* profile relative to the *Unplugged* profile. These results thus add further evidence to research supporting the adaptive role of PLO (Hirschi et al., 2016, 2020), as well as the deleterious impact of telepressure (Barber & Santuzzi, 2015; Grawitch et al., 2018) and of interpersonal norms regarding the need to quickly follow up work-related messages (Mazzetti et al., 2014, 2016) for employees.

Although previous research relying on a bifactor operationalization of workaholism has documented the outcomes of participants' global and specific levels of workaholism (Gillet et al., 2018; Huyghebaert-Zouaghi et al., 2022a), the examination of the nomological network of these global and specific factors has rarely considered predictors. As such, the present results add to those previously reported by Gillet et al. (2021c) by demonstrating that job characteristics other than workload (i.e., telepressure and interpersonal norms regarding work-related messages in the present study) also played a role in predicting profile membership. However, further work on the determinants of general and specific levels of workaholism is still required to document their complete nomological network.

To better understand the likely impact of the increasing prevalence of working remotely for employees (Kniffin et al., 2021), we also considered the direct and moderating role played by the remote or onsite nature of employees' work. In this regard, our results first showed that working remotely was associated with a higher likelihood of membership into the *Moderately Unplugged with Externalized Workaholism* profile relative to the *Plugged In* profile. This result supports recent studies showing that workaholism tends to vary as a function of job settings (Clark et al., 2016; Taris et al., 2012), and suggests that working remotely may facilitate the integration of employees' professional and personal roles (Sherman, 2020). Consistent with this idea, the present results add to recently accumulating evidence demonstrating desirable effects of remote working on various outcomes (Kaduk et al., 2019; Kelliher & Anderson, 2010).

Second, our results also indicated that PLO predicted an increased likelihood of membership into the *Unplugged* profile relative to the *Moderately Unplugged with Cognitive Workaholism* profile among employees working remotely but not among employees working onsite. This observation suggests that employees high in PLO who work remotely are less likely to work excessively while neglecting other spheres of life. Indeed, their remote work setting provides them with a greater control on their transitions between their work and their nonwork roles, thus allowing them to schedule their work in a way that is aligned with their PLO (Kossek et al., 2012). In contrast, PLO also predicted a decreased likelihood of membership into the *Plugged In* profile relative to the *Moderately Unplugged with Cognitive Workaholism* profile among employees working onsite but not among those working remotely. This observation thus suggests that the benefits of PLO are not limited to employees working remotely, but rather differ across different types of work. More precisely, whereas PLO seems to help employees' working remotely to display low, relative to moderate, levels of workaholism, it is not sufficient to protect them against the development of very high levels of workaholism, which seems to be limited to employees working onsite. Employees high in PLO tend to prioritize time for themselves (Hall et al., 2013) and their functioning might be weakened in a context (i.e., working remotely) where the boundaries between their work and nonwork lives are blurred (Wang et al., 2021). Indeed, remote workers may have difficulties working efficiently due to insufficient equipment or support required to complete their work, but also due to the interference of their personal life with their work (e.g., family emergencies). As a result, their psychological needs for autonomy, competence, and relatedness may be frustrated (Gillet et al., 2019b), their levels of controlled motivation may increase (Gillet et al., 2018), and they may come to perceive the normative demands of their personal life occurring during their work time as a nuisance. These demands interfere with their ability to meet work requirements promptly and efficiently, which is a condition to be able to switch-off from work and engage in their personal interests. Because of this negative spiral, employees who are high in PLO and who work remotely may come to have an excessive level of work involvement and experience inner compulsions to work as well as negative emotions when not working (Sonnentag & Fritz, 2015). In contrast, given the more natural separation between their work and personal lives, employees working onsite are more likely to satisfy their basic psychological needs, tend to be more autonomously motivated, and seem to be better able to organize their life in a way that is more fully aligned with their PLO (Gillet et al., 2022).

Third, our results showed that interpersonal norms regarding work-related messages predicted an increased likelihood of membership into the *Plugged In* profile relative to the *Unplugged* profile among employees working remotely but not among those working onsite. Indeed, employees working remotely may never be fully detached from work because the temporal (e.g., workdays are interrupted and may extend into the night) and physical (i.e., their workplace is in their home) boundaries of their work are considerably blurred (Sonnentag & Fritz, 2015). More generally, our results indicate that remote working seems to act as a double-edged sword (Gillet et al., 2021b) by reinforcing the positive effects of PLO but also the negative effects of interpersonal norms regarding work-related messages. It would be important for future research to consider the mechanisms responsible for the associations observed in this study, as well as to investigate the various work-related characteristics involved in the emergence of these specific workaholism configurations.

Outcomes of Profile Membership

Our results finally revealed well-differentiated associations between the workaholism profiles and outcomes. More specifically, the *Moderately Unplugged with Cognitive Workaholism* profile was associated the most positive outcomes (i.e., the lowest levels of work-to-family guilt, and the highest levels of job, life, and family satisfaction). These results suggest that employees who are invested in, and cognitively activated by, their work, even during off-job time, can sometimes experience positive outcomes. Work takes an important place in the life of these employees, but without resulting in excessive behaviors, this importance seems more beneficial in terms of functioning than when accompanied by such behaviors or than a complete lack of investment. These results are consistent with those from prior research showing that problem-solving pondering (i.e., a proactive and constructive search for solutions to work-related problems during off-job time; Junker et al., 2020) may sometimes may be associated with more positive feelings about work (e.g., job satisfaction), and with an improved functioning when solutions can be found (Greenhaus & Powell, 2006).

In contrast, the *Unplugged* profile was also associated with lower levels of work-to-family guilt than the *Plugged In* profile. Taken together, these findings confirm the detrimental effects of global levels of workaholism (e.g., Clark et al., 2016, 2020), as well as the utility of accounting for both global and specific facets of workaholism. Indeed, although global levels of workaholism might be a core driver of employees' functioning (Clark et al., 2016), at least in relation to the outcomes considered here, it does not appear sufficient to consider these global levels without also considering the specific facets. For instance, employees characterized by a *Plugged In* profile displayed higher levels of family and life satisfaction, but also higher levels of work-to-family guilt, than those corresponding to the *Moderately Unplugged with Externalized Workaholism* profile. Thus, although the *Plugged In* profile was characterized by higher global levels of workaholism, the lower specific levels of motivational and behavioral workaholism coupled with the higher specific levels of cognitive and emotional workaholism displayed by workers corresponding to this profile, in comparison to the *Moderately Unplugged with Externalized Workaholism* one, seemed to carry some benefits from an outcome perspective. Due to our bifactor operationalization of workaholism, these unexpected findings suggest that pure low levels of motivational and behavioral workaholism (i.e., working excessively) might buffer the negative effects of more widespread global workaholism.

On the one hand, these observations confirm that global levels of workaholism are not necessarily associated with low levels of satisfaction across various life domains (Burke, 2001; Burke et al., 2008). Interestingly, Stoeber et al. (2013) also found that workaholism was associated with higher levels of autonomous motivation, which is known to be positively related to satisfaction in matching domains (Ryan & Deci, 2017). The fact that family and life satisfaction constitute indicators of hedonic well-being may contribute to explain this result, as hedonic well-being is defined as the positive feelings associated with getting what one wants (Deci & Ryan, 2008). Because individuals high in workaholism tend to be primarily driven by internal pressures and, to a lesser extent, by some external pressures, they may experience more positive emotions (e.g., pride) when able to successfully face these pressures by displaying high levels of workaholism. They can also experience positive emotions because the simple act of working can be a real source of interest and pleasure for them (Stoeber et al., 2013). These positive emotions may spillover to their evaluations of their life in general, in the form of more positive assessments regarding their family and life satisfaction. On the other hand, benefits did not come without a cost, as shown by the fact that the *Plugged In* profile was also found to be associated with the highest levels of work-to-family guilt.

The *Unplugged* profile was found to associated with the lowest levels of job and life satisfaction (although the level of life satisfaction observed in this profile did not differ from that observed in the *Moderately Unplugged with Externalized Workaholism* profile). These results thus suggest that there might be limits to the benefits of displaying very low levels of workaholism. Although these results seem to contradict the negative relations reported between workaholism and job or family life satisfaction in previous studies (Gillet et al., 2021a; Huyghebaert-Zouaghi et al., 2022a), it is important to acknowledge that these variable-centered results focus on the average relations observed among a sample, and thus are not directly comparable to the present person-centered results focusing on distinctive configurations of workaholism. These unexpected findings could be explained by the fact that employees presenting very low levels of workaholism might also display high levels of work disengagement and boredom. Yet, boredom and disengagement also represent a state of low arousal (Danckert et al., 2018; Matthews et al., 2016) that is not conductive to positive outcomes. Thus, possibly as a result of this suboptimal level of arousal, *Unplugged* employees seem more likely to experience detrimental outcomes (Sousa & Neves, 2020). However, beyond these negative outcomes, it remains important to keep in mind that this *Unplugged* profile still presented one of the lowest levels of work-to-family guilt (even if the *Moderately Unplugged with Cognitive Workaholism* profile displayed even lower levels) and higher levels of family satisfaction than the *Moderately Unplugged with Externalized Workaholism* profile. These results are consistent with our expectations and confirm that employees with low levels of workaholism do not spend an excessive amount of time and effort at work at the expense of their personal life, thus promoting their work-life balance and decreasing their chances of experiencing work-family conflicts (Carlson & Kacmar, 2000).

We also considered how these associations differed as a function of working remotely or onsite. Our results revealed some differences that were limited to the work-to-family guilt outcome at T2. More specifically, the *Unplugged* and *Plugged In* profiles were associated with lower levels of work-to-family guilt than the *Moderately Unplugged with Cognitive Workaholism* profile among employees working onsite but not among those working remotely. Contrary to our previous suggestions, these results indicate that moderately low global levels of workaholism do not always carry more benefits than very low or high global (i.e., more extreme) levels of workaholism (Gillet et al., 2019b, 2021c) for onsite workers. More importantly, they also reinforce the importance of considering job settings when examining the implications of workaholism. Indeed, because the work context is critical to the self-concept of employees high in workaholism (Gillet et al., 2021b), they may not want to let the demands of their work interfere with their personal life (Matthews & Barnes-Farrell, 2010), which is much easier to achieve when working onsite. In contrast, the negative effects of workaholism on work-to-family guilt may be reduced when work is accomplished in a setting (i.e., remote) that makes the work role less salient (Thoits, 1992), and makes it harder to benefit from supportive social interactions with their supervisor and colleagues (Kirk & Belovics, 2006), known to be negatively associated with work-family conflicts (Gillet et al., 2018; Sandrin et al., 2020). Conversely, employees low in workaholism are not motivated by controlled reasons, are not ready to spend an excessive amount of effort at work at the expense of their other roles (e.g., family) and tend to expand most of their personal resources outside of the work setting. Thus, they may adopt defensive strategies (e.g., psychologically disengage from work) to protect these resources when working onsite (Hobfoll, 2002), resulting in lower levels of work-to-family guilt. In contrast, they may not experience differences in work-to-family guilt when working remotely, as this context can blur the temporal boundaries between their work and personal lives, resulting in higher levels of need frustration, and a decrease in their autonomous motivation, personal time, and control in the prioritization of the time and energy allocated to their various roles (Gillet et al., 2022; Wang et al., 2021).

Limitations and Future Directions

Although the present research offers the first investigation of the nature, stability, predictors, and outcomes of workaholism profiles defined while accounting for employees' global levels of workaholism properly disaggregated from the specific levels of behavioral, motivational, emotional, and cognitive workaholism, it has some limitations. First, the fact that this study relied solely on self-report measures increases the risk of social desirability and self-report biases. To alleviate these concerns, it would be useful for future studies to consider the incorporation of objective measures (e.g., organizational data on work performance and absenteeism) and informant ratings of employees' functioning (e.g., colleagues, supervisors, spouse). Furthermore, job, family, and life satisfaction were each assessed with a single item. Although, participants' answers to these items were reasonably stable over a three-month period, thus supporting their test-retest reliability, single-item measures still tend to be less reliable and less comprehensive than multi-item measures. It would thus be informative to replicate our findings using with more comprehensive measurement of satisfaction. Second, the present study was conducted solely among a sample of mixed employees working in the UK or the US. Further research is thus needed to generalize the current results in different countries, languages, and cultures. Third, we did not assess the causes (e.g., whether it was voluntary, whether it was always part of the job or caused by the pandemic) or context (e.g., access to childcare or to a proper home office) of remote work. It would thus be important for future research to consider how these characteristics might influence the likely impact of remote work for employees. Moreover, although our data collection did not occur during periods of national lockdowns, it still occurred in the midst of a global pandemic which significantly affected individuals' psychological and social functioning, as well as their work and family experiences (Huyghebaert-Zouaghi et al., 2022b; Wang et al., 2021). This context could have influenced our results, whose generalizability should thus be verified.

Fourth, the time interval between the two measurement waves was relatively short (three months), suggesting that the stability of the workaholism profiles could be attenuated over a longer time period. The present study thus suggests that a three-month period might not be a sufficient time interval to a full consideration of stability and change in profile membership, while still suggesting that at least some within-person changes did occur over such a short period. The current research also assessed the stability of workaholism profiles over a three-month period, which was not characterized by any specific or systematic change or transition for most participants. Clearly, estimates of stability reported in the current investigation could be reduced if continuity and change were assessed across more meaningful transitions (e.g., promotion) or interventions (e.g., professional training). Future studies should thus examine the extent to which our findings would generalize to longer periods of time and social changes. Finally, PLO, telepressure, and interpersonal norms regarding work-related messages were the only predictors of interest in our research. Yet, it would be interesting to examine how other personal characteristics (e.g., type-A personality, perfectionism, performance-based self-esteem, preference for onsite versus remote work) as well as hindrance (e.g., role conflict, overload, and ambiguity) and challenge (e.g., role responsibility and complexity) demands relate to employees' workaholism, and their interplay with remote and onsite working. It would be equally important to assess whether the observed associations between the predictors and the profiles can be considered as causal or simply correlational in nature, and to verify the possible confounding role of personality in these associations. Likewise, it would be interesting for future research to incorporate a broader range of positive (e.g., organizational citizenship behaviors, creativity) and negative (e.g., absenteeism, counterproductive behaviors) outcomes to better understand the full implications of these profiles.

Practical Implications

Our findings suggest that managers should be particularly attentive to workers exposed to telepressure and interpersonal norms regarding the need to respond quickly to work-related messages (Derks et al., 2015), and to those who struggle to efficiently manage the interface between their professional and nonprofessional roles (i.e., low PLO; Hall et al., 2013). Indeed, our results showed that these employees were more likely to be members of the *Plugged In* profile (associated with the highest levels of work-to-family guilt) and less likely to be members of the *Moderately Unplugged with Cognitive Workaholism* profile (associated with the most positive outcomes). Therefore, changes designed to increase workers' PLO and reduce telepressure and interpersonal norms regarding the need to respond quickly to work-related messages seemed to be associated with better functioning.

For instance, PLO could be encouraged at the organizational level by stating clear segmentation norms and encouraging balanced and healthier lifestyles (Kreiner et al., 2006), by creating well-being-oriented work environments, and by offering enabling versus enclosing work-life policies (Bourdeau et al., 2019). PLO could also be promoted through coaching or counseling (e.g., developing new habits and replacing one's old malfunctioning behaviors; Van Gordon et al., 2017). It might also be useful to encourage more efficient work recovery processes to protect employees' professional well-being and to facilitate positive spillover between their work and personal roles (Demsky et al., 2014). Individuals high in PLO are not ready to focus their entire life on work. They prefer to distance themselves from work and take time to do other things alone or with their family (Hall et al., 2013). Conversely, individuals low in PLO might place too much emphasis on work in their daily life, resulting in a lack of time and energy to devote to other non-work activities (Sonnentag & Fritz, 2015). In addition, these employees may also experience increased levels of workaholism, as an excessive investment in work and an inability to detach from work are two characteristics of workaholism (Schaufeli et al., 2009). These employees may then face a depletion of their resources (Hobfoll, 2002), as they do not take the time to recover from the efforts made at work (Barber et al., 2019), which may expose them to health problems and impaired functioning (Clark et al., 2016).

Efficient work recovery can be developed and trained, and interventions have proved to be efficient in previous studies. For instance, participants involved in a recovery training program (e.g., time management techniques, self-reflection) displayed better recovery experiences (e.g., relaxation) and higher levels of sleep quality after the training, in comparison to those not involved in this training (Hahn et al., 2011). Mindfulness-based interventions are also useful to increase recovery during off-job time (Hülsheger et al., 2015). However, caution is needed in relation to the implementation of interventions seeking to increase PLO or decrease interpersonal norms regarding work-related messages, as high levels of PLO and low levels of interpersonal norms regarding work-related messages seem to be associated with less desirable workaholism profiles among some employees.

Although few differences were identified between remote and onsite workers, PLO predicted an increased likelihood of membership into the *Unplugged* profile only among employees working remotely, but also a decreased likelihood of membership into the *Plugged In* only among employees working onsite. Furthermore, interpersonal norms regarding work-related messages predicted a decreased likelihood of membership into the *Unplugged* profile only among employees working remotely. These results suggest that it might be particularly useful to increase PLO and to decrease interpersonal norms regarding the need to follow up quickly on work-related messages among remote workers to reinforce their likelihood of membership into a profile characterized by low levels of workaholism across dimensions, in turn leading to lower levels of work-family guilt. Similarly, interventions seeking to increase PLO seem particularly interesting for onsite workers as a way to reduce their likelihood of membership into a profile characterized by high global levels of workaholism associated with the highest levels of work-to-family guilt. More generally, as recently suggested, organizations and managers should rethink work and propose different interventions to better support onsite and remote workers (Kniffin et al., 2021).

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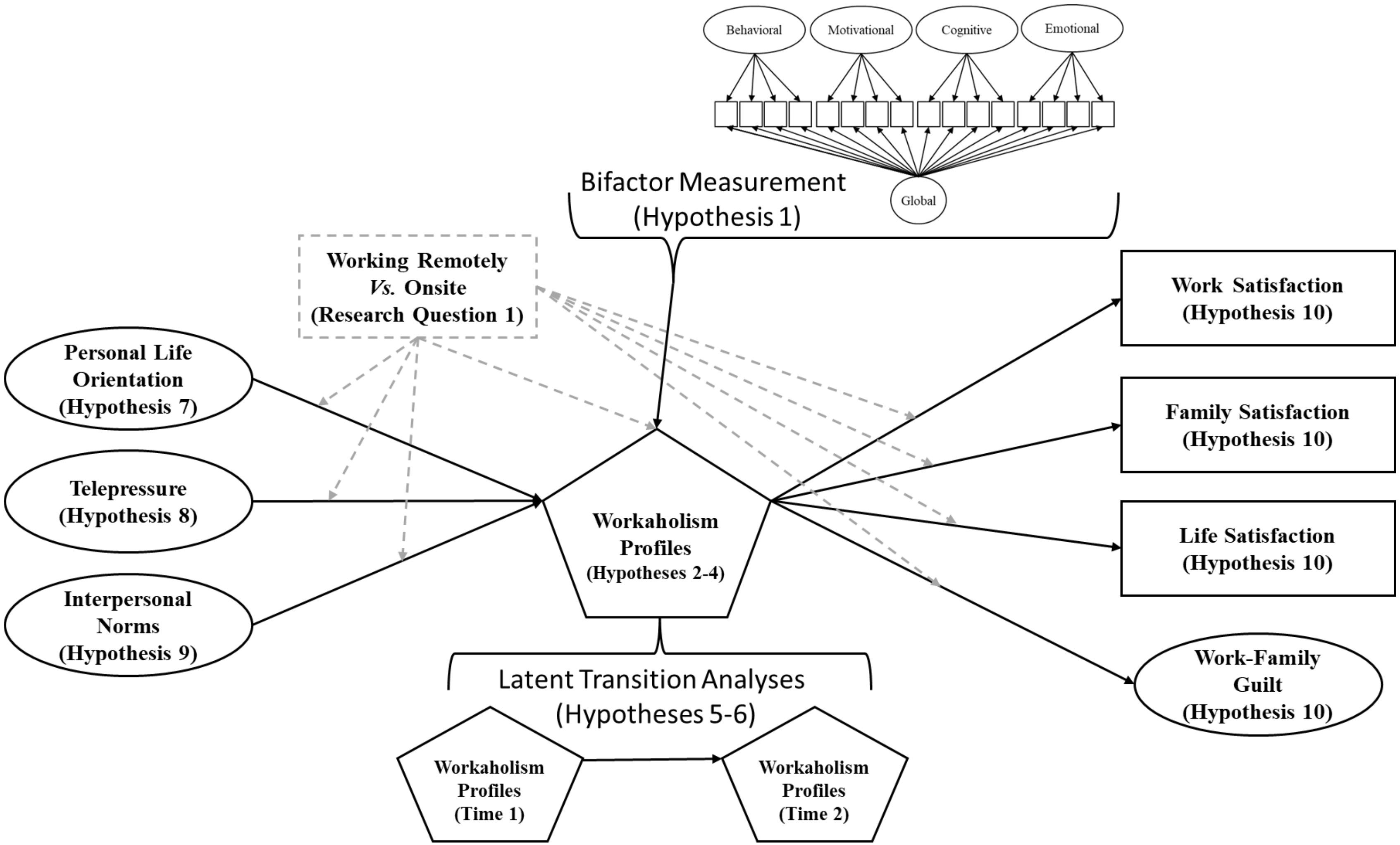

Figure 1. Theoretical Model Tested in the Present Research.
Note. Ovals represent latent continuous constructs (i.e., latent factors estimated from their indicators for Hypothesis 1, and factor scores incorporated into the main analyses for the other hypotheses); the pentagon represents the latent categorical construct (i.e., the latent profiles estimated at both time points); rectangles reflect observed scores; arrows reflect directional associations; greyscale arrows are linked to our Research Question.

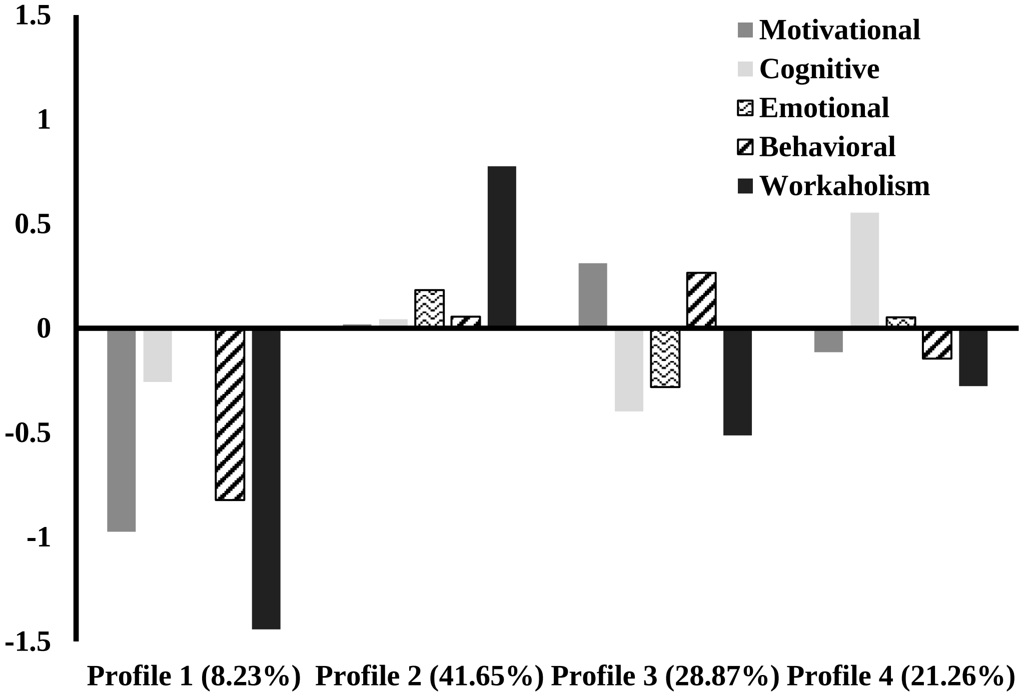

Figure 2. Final Four-Profile Solution
Note. Profile 1: Unplugged; Profile 2: Plugged In; Profile 3: Moderately Unplugged with Externalized Workaholism; Profile 4: Moderately Unplugged with Cognitive Workaholism; the Y-axis refers to scores on the profile indicators, which are all factor scores estimated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

Table 1

Results from the Time-Specific and Longitudinal Models

Model	LL	#fp	Scaling	AIC	CAIC	BIC	ABIC	Entropy
Final Latent Profile Analyses								
Time 1	-2501.192	43	1.179	5088.385	5306.327	5263.327	5126.869	.696
Time 2	-2451.795	43	1.191	4989.590	5207.533	5164.533	5028.075	.765
Longitudinal Latent Profile Analyses								
Configural Similarity	-4952.988	86	1.185	10077.975	10573.860	10427.860	10154.944	.731
Structural Similarity	-4976.739	66	1.343	10085.479	10419.995	10353.995	10144.958	.686
Dispersion Similarity	-4990.478	46	1.603	10072.956	10306.103	10260.103	10114.125	.682
Distributional Similarity	-4990.645	43	1.688	10067.291	10285.233	10242.233	10105.775	.682
Predictive Similarity: Demographics								
Null Effects Model	-2432.842	35	.777	4935.684	5113.079	5078.079	4967.008	.874
Profile-Specific Free Relations with Predictors	-2388.951	125	.659	5027.901	5661.454	5536.454	5139.775	.875
Free Relations with Predictors	-2400.000	65	.835	4930.000	5259.448	5194.448	4988.175	.886
Equal Relations with Predictors	-2421.955	50	.830	4943.909	5197.331	5147.331	4988.659	.877
Predictive Similarity: Predictors								
Null Effects Model	-4039.434	59	1.044	8196.868	8495.905	8436.905	8249.672	.874
Profile-Specific Free Relations with Predictors	-3954.025	131	.713	8170.051	8834.014	8703.014	8287.295	.877
Free Relations with Predictors	-3976.215	83	1.017	8118.431	8539.110	8456.110	8192.715	.884
Equal Relations with Predictors	-3993.636	71	1.073	8129.272	8489.130	8418.130	8192.816	.869
Explanatory Similarity								
Free Relations with Outcomes	-4557.703	55	1.435	9225.406	9504.170	9449.170	9274.631	.883
Equal Relations with Outcomes	-4563.577	39	1.788	9205.154	9402.823	9363.823	9240.059	.879

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

Table 2

Transitions Probabilities

	To Profile 1 at T2	To Profile 2 at T2	To Profile 3 at T2	To Profile 4 at T2
From Profile 1 at T1	.711	.007	.282	.001
From Profile 2 at T1	.000	1.000	.000	.000
From Profile 3 at T1	.042	.000	.958	.000
From Profile 4 at T1	.074	.000	.000	.926

Note. Profile 1: Unplugged; Profile 2: Plugged In; Profile 3: Moderately Unplugged with Externalized Workaholism; Profile 4: Moderately Unplugged with Cognitive Workaholism.

Table 3

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
Personal life orientation	.316 (.265)	1.372	-.592 (.223)**	.553	-.046 (.238)	.955
Interpersonal norms	-.227 (.261)	.797	.398 (.158)*	1.489	-.147 (.188)	.863
Workplace telepressure	-.645 (.223)**	.525	.291 (.197)	1.337	-.348 (.191)	.706
Work type	.433 (.421)	1.542	-.092 (.344)	.912	.571 (.395)	1.770
	Profile 1 vs 3		Profile 2 vs 3		Profile 1 vs 2	
Predictors	Coef. (SE)	OR	Coef. (SE)	OR	Coef. (SE)	OR
Personal life orientation	.362 (.230)	1.436	-.546 (.173)**	.579	.908 (.250)**	2.480
Interpersonal norms	-.080 (.244)	.923	.545 (.148)**	1.724	-.625 (.247)*	.535
Workplace telepressure	-.297 (.182)	.743	.639 (.162)**	1.894	-.936 (.210)**	.392
Work type	-.138 (.365)	.871	-.663 (.324)*	.515	.526 (.385)	1.691

Note. * $p < .05$; ** $p < .01$; SE: Standard error of the coefficient; OR: Odds ratio; 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; personal life orientation, workplace telepressure, and interpersonal norms regarding 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: Unplugged; Profile 2: Plugged In; Profile 3: Moderately Unplugged with Externalized Workaholism; Profile 4: Moderately Unplugged with Cognitive Workaholism.

Table 4

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
Work-to-family guilt	-.085 [-.592; .423]	.605 [.307; .902]	.230 [-.362; .821]	-.629 [-.773; -.484]	4 < 1 < 2; 1 = 3; 2 = 3; 4 < 3
Job satisfaction	1.964 [1.518; 2.410]	2.963 [2.656; 3.270]	2.628 [2.206; 3.050]	3.468 [3.242; 3.694]	1 < 2 = 3 < 4
Life satisfaction	2.682 [2.389; 2.974]	3.216 [3.001; 3.431]	2.376 [1.936; 2.817]	3.645 [3.439; 3.852]	1 = 3 < 2 < 4
Family satisfaction	3.217 [2.853; 3.581]	3.477 [3.315; 3.639]	2.551 [2.124; 2.979]	3.755 [3.571; 3.940]	3 < 1 = 2 < 4

Note. M: Mean; CI: 95% confidence interval; the indicator of work-to-family guilt is estimated from factor scores with a mean of 0 and a standard deviation of 1; Profile 1: Unplugged; Profile 2: Plugged In; Profile 3: Moderately Unplugged with Externalized Workaholism; Profile 4: Moderately Unplugged with Cognitive Workaholism.

Online Supplements for:

Nature, Predictors, and Outcomes of Workers' Longitudinal Workaholism 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.

Preliminary Measurement Models

Due to the complexity of the longitudinal models underlying all constructs assessed in the present study, preliminary analyses were conducted separately for the workaholism variables and the predictor (personal life orientation, workplace telepressure, and interpersonal norms regarding work-related messages) and outcome (work-to-family guilt) variables. These longitudinal measurement models were estimated using Mplus 8.6 (Muthén & Muthén, 2021) using the maximum likelihood robust (MLR) estimator, which provides parameter estimates, standard errors, and goodness-of-fit that are robust to the non-normality of the response scales used in the present study. These models were estimated in conjunction with full information maximum likelihood (FIML; Enders, 2010) to handle missing data.

As noted in the main manuscript, accumulating research evidence supports the idea that workaholism ratings are best represented by a bifactor operationalization (Gillet et al., 2018; Tóth-Király et al., 2021) making it possible to simultaneously assess respondents' global levels of workaholism (G-factor) together with non-redundant estimates of the specificity remaining at the levels of each workaholism subscale (S-factors) over and above these global levels (Morin et al., 2016). In bifactor models, all workaholism items are used to define an overarching workaholism G-factor, whereas all subscale-specific items are simultaneously used to define the S-factors reflecting the unique quality associated with each workaholism facet left unexplained by the G-factor. Importantly, research in which these two layers of measurement cannot be properly disentangled carries the risk of leading to an overly similar assessment of the relative contribution of each workaholism component, making it impossible to clearly identify the unique contribution of each of them over and above that of participants' global levels of workaholism (Tóth-Király et al., 2021).

A bifactor-confirmatory factor analytic (CFA) model including one workaholism G-factor and four orthogonal S-factors (motivational, cognitive, emotional, and behavioral) was estimated at both Time 1 (T1) and Time 2 (T2). We also contrasted this solution to a simpler CFA solution in which items were only allowed to load on their a priori dimension, allowing all factors to correlate. Given the known oversensitivity of the chi-square test of exact fit (χ^2) to sample size and minor model misspecifications (e.g., Marsh et al., 2005), we relied on sample-size independent goodness-of-fit indices to describe the fit of the alternative models (Hu & Bentler, 1999): The comparative fit index (CFI), the Tucker-Lewis index (TLI), as well as the root mean square error of approximation (RMSEA) and its 90% confidence interval. Values greater than .90 for the CFI and TLI indicate adequate model fit, although values greater than .95 are preferable. Values smaller than .08 or .06 for the RMSEA respectively support acceptable and excellent model fit.

The goodness-of-fit results from all workaholism models are reported in Table S1. These results clearly support the adequacy of the a priori bifactor-CFA model underlying the workaholism measure (with all CFI and TLI $\geq$ .90, and all RMSEA $\leq$ .08) and its superiority relative to the CFA model (ΔCFI = .024 at T1 to .026 at T2; ΔTLI = .021 at T1 to .027 at T2; ΔRMSEA = .009 at T1 to .015 at T2). This solution was thus retained for sequential tests of measurement invariance (Millsap, 2011): (1) configural invariance; (2) weak invariance (loadings); (3) strong invariance (loadings and intercepts); (4) strict invariance (loadings, intercepts, and uniquenesses); (5) invariance of the latent variance-covariance matrix (loadings, intercepts, uniquenesses, correlated uniquenesses, and latent variances-covariances); and (6) latent means invariance (loadings, intercepts, uniquenesses, correlated uniquenesses, latent variances-covariances, and latent means). These tests were first conducted across groups of employees working remotely or onsite at T1, and then at T2, before being conducted for the total sample across measurement occasions (longitudinal invariance). These tests were also conducted across groups of employees working in the US or UK at T1, and then at T2. Like the chi square, chi square difference tests are oversensitive to sample size and minor misspecifications. For this reason, invariance was assessed by considering changes in CFI and RMSEA (Chen, 2007; Cheung & Rensvold, 2002). A ΔCFI/TLI of .010 or less and a ΔRMSEA of .015 or less between a more restricted model and the previous one support the invariance hypothesis.

The results from these tests, reported in Table S1, supported the configural, weak, strong, strict, latent variance-covariance, and latent means invariance of the model across groups (working remotely or onsite; US or UK) and time points. These results thus show that the measurement models underlying workaholism ratings can be considered to be fully equivalent across groups and over time, leading to the estimation of similar constructs, and consistent with a lack of latent means differences across groups or over time. Factor scores used in the main analyses were extracted from the final longitudinal model of latent means invariance. Parameter estimates from this final longitudinal model of latent means invariance are reported in Table S2. When interpreting bifactor-CFA results, it is important to keep in mind that, because bifactor models rely on two factors to explain the covariance present at the item level for each specific item, factor loadings on G- and S-factors are typically lower than their first-order counterparts (e.g., Morin et al., 2016). As such, the critical question when interpreting a bifactor solution is whether the G-factor really taps into a meaningful amount of covariance shared among all items, and whether there remains sufficient specificity at the subscale level unexplained by the G-factor to result in the estimation of meaningful S-factors.

Composite reliability coefficients associated with each of the a priori factors are calculated from the model standardized parameters using McDonald (1970) omega (ω) coefficient:

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

where $|\lambda_i|$ are the standardized factor loadings associated with a factor in absolute values, and δi, the item uniquenesses. Omega coefficients of composite reliability can be interpreted in the same manner as alpha coefficients of scale score reliability and reflect the proportion of the total variance in item responses that can be attributed to the factors (themselves reflecting true score variance, i.e., reliable variance). Thus, just like for alpha coefficients, omega is positively influenced by the number of items included in a subscale (e.g., Streiner, 2003), and should minimally be higher than .600, although coefficients higher than .700 or .800 are even better. However, given that bifactor models divide true score variance in two factors, omega tends to be much lower for bifactor S-factors than for their first-order correlated factors (Morin et al., 2020). As a result, it has been suggested that omega value as low as .50 could be considered acceptable for S-factors (Perreira et al., 2018).

The results from the bifactor-CFA solution revealed a well-defined G-factor over time (ω = .955) with strong positive loadings from the motivational (λ = .512 to .853), cognitive (λ = .592 to .747), emotional (λ = .683 to .744), and behavioral (λ = .543 to .644) items. Over and above this G-factor, items associated with the motivational (λ = .033 to .574, ω = .670), cognitive (λ = .372 to .608, ω = .802), emotional (λ = .367 to .404, ω = .638), and behavioral (λ = .270 to .608, ω = .688) S-factors all retained a satisfactory level of specificity.

A CFA model was also estimated for the multi-item predictor and outcome variables at both T1 and T2, and included a total of four factors (personal life orientation, workplace telepressure, interpersonal norms regarding work-related messages, and work-to-family guilt) at each time point. All factors were freely allowed to correlate. The goodness-of-fit results for these models are reported in Table S3. These results support the adequacy of the a priori model (with all CFI/TLI ≥ .90 and all RMSEA ≤ .08). Although the fit of the multi-group models (but not of the longitudinal models from which the factor scores were extracted from the main analyses) is suboptimal, the results support the configural, weak, strong, strict invariance of this model across groups (working remotely or onsite; US or UK) and time points, as well as the invariance of the latent variances-covariances, and latent means (ΔCFI ≤ .010; ΔTLI ≤ .010; and ΔRMSEA ≤ .015). These results show that the parameter estimates can be considered to be fully equivalent across groups and time waves. The parameter estimates and composite reliability scores obtained from the most invariant longitudinal measurement models (latent means invariance) are reported in Table S4. These results show that all factors are well-defined by satisfactory factor loadings (λ = .462 to .921), resulting in satisfactory composite reliability coefficients, ranging from ω = .850 to .937. Factor scores were saved from this most invariant measurement model and used as predictor and outcome indicators in the main research. The correlations between all variables are reported in Table S5.

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Table S1

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

Description	χ^2 (*df*)	CFI	TLI	RMSEA	90% CI	CM	$\Delta\chi^2$ (*df*)	ΔCFI	ΔTLI	ΔRMSEA
Workaholism										
CFA Time 1	399.395 (98)*	.918	.900	.084	[.076; .093]	-	-	-	-	-
Bifactor-CFA Time 1	301.298 (88)*	.942	.921	.075	[.066; .084]	-	-	-	-	-
CFA Time 2	269.879 (98)*	.940	.927	.072	[.062; .083]	-	-	-	-	-
Bifactor-CFA Time 2	184.806 (88)*	.966	.954	.057	[.046; .069]	-	-	-	-	-
Workaholism: Multi-Group (Remote vs. Onsite) Invariance T1										
M1. Configural invariance	455.442 (176)*	.928	.902	.086	[.076; .095]	-	-	-	-	-
M2. Weak invariance	452.602 (203)*	.936	.924	.075	[.066; .085]	M1	19.261 (27)	+.008	+.022	-.011
M3. Strong invariance	467.486 (214)*	.935	.927	.074	[.065; .083]	M2	13.504 (11)	-.001	+.003	-.001
M4. Strict invariance	495.347 (230)*	.931	.929	.073	[.064; .082]	M3	29.391 (16)	-.004	+.002	-.001
M5. Variance-covariance invariance	498.395 (235)*	.932	.931	.072	[.063; .081]	M4	3.280 (5)	+.001	+.002	-.001
M6. Latent means invariance	504.111 (240)*	.932	.932	.071	[.063; .080]	M5	5.514 (5)	.000	+.001	-.001
Workaholism: Multi-Group (Remote vs. Onsite) Invariance T2										
M7. Configural invariance	282.103 (176)*	.965	.952	.060	[.047; .073]	-	-	-	-	-
M8. Weak invariance	307.094 (203)*	.965	.959	.055	[.042; .068]	M7	26.970 (27)	.000	+.007	-.005
M9. Strong invariance	319.408 (214)*	.965	.961	.054	[.041; .066]	M8	11.721 (11)	.000	+.002	-.001
M10. Strict invariance	352.236 (230)*	.959	.958	.056	[.044; .068]	M9	31.099 (16)	-.006	-.003	+.002
M11. Variance-covariance invariance	364.063 (235)*	.957	.956	.057	[.045; .069]	M10	14.239 (5)	-.002	-.002	+.001
M12. Latent means invariance	367.260 (240)*	.958	.958	.056	[.044; .067]	M11	3.193 (5)	+.001	+.002	-.001
Workaholism: Longitudinal Invariance										
M13. Configural invariance	756.031 (391)*	.954	.942	.046	[.042; 051]	-	-	-	-	-
M14. Weak invariance	785.167 (418)*	.954	.945	.045	[.040; .050]	M13	28.625 (27)	.000	+.003	-.001
M15. Strong invariance	791.831 (429)*	.955	.948	.044	[.039; .049]	M14	5.208 (11)	+.001	+.003	-.001
M16. Strict invariance	798.437 (445)*	.956	.951	.043	[.038; .048]	M15	11.652 (16)	+.001	+.003	-.001
M17. Variance-covariance invariance	801.026 (450)*	.956	.952	.042	[.038; .047]	M16	2.371 (5)	.000	+.001	-.001
M18. Latent means invariance	810.143 (455)*	.956	.952	.043	[.038; .047]	M17	9.141 (5)	.000	.000	+.001
Workaholism: Multi-Group (US vs. UK) Invariance T1										
M19. Configural invariance	424.319 (176)*	.937	.914	.081	[.071; .091]	-	-	-	-	-
M20. Weak invariance	469.637 (203)*	.932	.920	.078	[.069; .087]	M19	45.684 (27)*	-.005	+.006	-.003
M21. Strong invariance	485.448 (214)*	.931	.922	.077	[.068; .086]	M20	14.519 (11)	-.001	+.002	-.001
M22. Strict invariance	483.648 (230)*	.935	.933	.071	[.063; .080]	M21	9.638 (16)	+.004	+.011	-.006
M23. Variance-covariance invariance	487.140 (235)*	.936	.934	.070	[.062; .079]	M22	2.950 (5)	+.001	+.001	-.001
M24. Latent means invariance	504.574 (240)*	.933	.933	.071	[.063; .080]	M23	19.926 (5)*	-.003	-.001	+.001
Workaholism: Multi-Group (US vs UK) Invariance T2										
M25. Configural invariance	297.306 (176)*	.960	.946	.064	[.051; .077]	-	-	-	-	-
M26. Weak invariance	333.977 (203)*	.957	.949	.062	[.050; .074]	M25	37.531 (27)	-.003	+.003	-.002
M27. Strong invariance	341.841 (214)*	.958	.953	.060	[.048; .071]	M26	6.818 (11)	+.001	+.004	-.002
M28. Strict invariance	378.400 (230)*	.951	.949	.062	[.051; .073]	M27	34.529 (16)*	-.007	-.004	+.002
M29. Variance-covariance invariance	391.024 (235)*	.949	.948	.063	[.052; .074]	M28	12.883 (5)*	-.002	-.001	+.001
M30. Latent means invariance	402.042 (240)*	.947	.947	.063	[.052; .074]	M29	10.761 (5)	-.002	-.001	.000

Note. * $p < .01$; CFA: Confirmatory factor analysis; 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)

Items	G-Workaholism λ	S-Motivational λ	S-Cognitive λ	S-Emotional λ	S-Behavioral λ	δ
Motivational						
Item 1	.512	.574				.408
Item 2	.623	.527				.334
Item 3	.853	*.033*				.271
Item 4	.718	.474				.261
Cognitive						
Item 1	.592		.576			.317
Item 2	.670		.543			.257
Item 3	.747		.372			.305
Item 4	.648		.608			.210
Emotional						
Item 1	.683			.367		.398
Item 2	.741			.385		.302
Item 3	.744			.404		.284
Item 4	.706			.382		.356
Behavioral						
Item 1	.543				.270	.632
Item 2	.622				.591	.264
Item 3	.644				.414	.414
Item 4	.576				.608	.299
ω	.955	.670	.802	.638	.688	

Note. G = Global factor estimated as part of a bifactor model; S = Specific factor estimated as part of a bifactor model; λ: Factor loading; δ: Item uniqueness; ω: Omega coefficient of 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										
CFA Time 1	786.960 (269)*	.914	.904	.067	[.061; .072]	-	-	-	-	-
CFA Time 2	751.931 (269)*	.913	.903	.073	[.067; .079]	-	-	-	-	-
Predictors and Outcome: Multi-Group (Remote vs. Onsite) Invariance T1										
M1. Configural invariance	1140.431 (538)*	.905	.894	.072	[.066; .078]	-	-	-	-	-
M2. Weak invariance	1163.819 (559)*	.905	.898	.071	[.065; .076]	M1	24.153 (21)	.000	+.004	-.001
M3. Strong invariance	1200.524 (580)*	.903	.899	.070	[.065; .076]	M2	36.040 (21)	-.002	+.001	-.001
M4. Strict invariance	1258.235 (605)*	.897	.898	.071	[.065; .076]	M3	55.173 (25)	-.006	-.001	+.001
M5. Variance-covariance invariance	1263.533 (615)*	.898	.901	.070	[.064; .075]	M4	5.345 (10)	+.001	+.003	-.001
M6. Latent means invariance	1278.365 (619)*	.896	.900	.070	[.065; .076]	M5	15.408 (4)	-.002	-.001	.000
Predictors and Outcome: Multi-Group (Remote vs. Onsite) Invariance T2										
M7. Configural invariance	1148.640 (538)*	.897	.886	.082	[.076; .089]	-	-	-	-	-
M8. Weak invariance	1195.294 (559)*	.893	.885	.082	[.076; .089]	M7	46.594 (21)	-.004	-.001	.000
M9. Strong invariance	1254.458 (580)*	.887	.883	.083	[.077; .090]	M8	60.011 (21)	-.006	-.002	+.001
M10. Strict invariance	1292.983 (605)*	.884	.885	.082	[.076; .089]	M9	44.684 (25)	-.003	+.002	-.001
M11. Variance-covariance invariance	1305.447 (615)*	.884	.887	.082	[.076; .088]	M10	11.314 (10)	.000	+.002	.000
M12. Latent means invariance	1312.055 (619)*	.884	.887	.082	[.076; .088]	M11	6.577 (5)	.000	.000	.000
Predictors and Outcome: Longitudinal Invariance										
M13. Configural invariance	2160.202 (1122)*	.925	.918	.046	[.043; .049]	-	-	-	-	-
M14. Weak invariance	2190.626 (1143)*	.924	.919	.046	[.043; .049]	M7	30.748 (21)	-.001	+.001	.000
M15. Strong invariance	2211.317 (1164)*	.924	.920	.046	[.043; .049]	M8	18.712 (21)	.000	+.001	.000
M16. Strict invariance	2255.001 (1189)*	.923	.920	.046	[.043; .048]	M9	45.065 (25)*	-.001	.000	.000
M17. Variance-covariance invariance	2259.143 (1199)*	.923	.921	.045	[.042; .048]	M10	4.021 (10)	.000	+.001	-.001
M18. Latent means invariance	2262.507 (1203)*	.923	.922	.045	[.042; .048]	M11	3.162 (4)	.000	+.001	.000
Predictors and Outcome: Multi-Group (US vs UK) Invariance T1										
M19. Configural invariance	1150.968 (538)*	.904	.893	.073	[.067; .078]	-	-	-	-	-
M20. Weak invariance	1173.136 (559)*	.904	.897	.071	[.066; .077]	M19	21.978 (21)	.000	+.004	-.002
M21. Strong invariance	1206.865 (580)*	.902	.899	.071	[.065; .076]	M20	33.296 (21)*	-.002	+.002	.000
M22. Strict invariance	1206.883 (605)*	.906	.907	.068	[.062; .073]	M21	25.738 (25)	+.004	+.008	-.003
M23. Variance-covariance invariance	1229.155 (615)*	.904	.906	.068	[.062; .074]	M22	22.223 (10)*	-.002	-.001	.000
M24. Latent means invariance	1257.593 (619)*	.900	.903	.069	[.064; .075]	M23	29.617 (4)*	-.004	-.003	+.001
Predictors and Outcome: Multi-Group (Remote vs. Onsite) Invariance T2										
M25. Configural invariance	1145.686 (538)*	.898	.887	.082	[.076; .089]	-	-	-	-	-
M26. Weak invariance	1167.109 (559)*	.898	.891	.081	[.074; .087]	M25	22.453 (21)	.000	+.004	-.001
M27. Strong invariance	1197.937 (580)*	.897	.893	.080	[.073; .086]	M26	30.169 (21)	-.001	+.002	-.001
M28. Strict invariance	1222.451 (605)*	.897	.898	.078	[.072; .084]	M27	35.240 (25)	.000	+.005	-.002
M29. Variance-covariance invariance	1233.181 (615)*	.897	.899	.077	[.071; .084]	M28	28.777 (10)*	.000	+.001	-.001
M30. Latent means invariance	1248.982 (619)*	.895	.898	.078	[.072; .084]	M29	5.977 (5)	-.002	-.001	+.001

Note. * $p < .01$; CFA: Confirmatory factor analysis; 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)

Items	Personal life orientation λ	Workplace telepressure λ	Interpersonal norms λ	Work-to-family guilt λ	δ
Personal life orientation					
Item 1	.726				.474
Item 2	.780				.391
Item 3	.820				.328
Item 4	.773				.402
Item 5	.792				.373
Workplace telepressure					
Item 1		.720			.481
Item 2		.759			.424
Item 3		.838			.298
Item 4		.899			.191
Item 5		.921			.151
Item 6		.908			.175
Interpersonal norms					
Item 1			.884		.219
Item 2			.844		.288
Item 3			.863		.255
Item 4			.772		.405
Item 5			.635		.597
Item 6			.688		.527
Item 7			.673		.547
Item 8			.758		.426
Item 9			.663		.560
Item 10			.908		.176
Work-to-family guilt					
Item 1				.462	.786
Item 2				.868	.247
Item 3				.855	.269
Item 4				.832	.308
ω	.885	.937	.937	.850	
Factor Correlations	Personal life orientation	Workplace telepressure	Interpersonal norms	Work-to-family guilt	
Personal life orientation					
Workplace telepressure	*.003*				
Interpersonal norms	-.104	.249			
Work-to-family guilt	-.206	.276	.457		

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

Table S5

Correlations between Variables

	M	SD	1	2	3	4	5	6	7	8	9	10	11	12	13	14
1. Sex	.450	.498	-													
2. Age	40.060	1.441	.126**	-												
3. Status	.110	.309	-.149**	.008	-											
4. Sector	.390	.489	-.163**	.004	.106*	-										
5. Country	.260	.437	.220**	-.064	-.151**	-.116*	-									
6. S-Motivational (T1)†	-.006	.805	-.163**	.020	.055	.031	-.097*	-								
7. S-Cognitive (T1)†	-.015	.862	-.129**	-.076	.004	.063	-.086	-.080	-							
8. S-Emotional (T1)†	.020	.782	-.034	.007	.061	.022	-.117*	-.099*	-.009	-						
9. S-Behavioral (T1)†	-.015	.857	-.023	.012	-.015	-.018	-.049	.233**	-.087	-.202**	-					
10. G-Workaholism (T1)†	.013	.963	-.040	.018	-.063	-.039	-.008	.069	.102*	.129**	.083	-				
11. Personal life orientation (T1)†	.020	.949	.041	-.108*	-.096*	-.017	.111*	.049	-123*	-.080	-.025	-.222**	-			
12. Interpersonal norms (T1)†	-.003	.977	-.018	-.059	-.012	-.123*	.133**	-.072	.233**	.013	.091	.349**	-.130**	-		
13. Telepressure (T1)†	.001	.969	-.016	-.099*	-.049	-.017	.085	.044	.235**	.072	-.028	.334**	.013	.261**	-	
14. Work-to-family guilt (T1)†	-.019	.946	-.062	-.036	.041	.030	-.102*	-.014	.324**	.050	.112*	.298**	-.246**	.510**	.290**	-
15. Job satisfaction (T1)	3.070	.875	-.019	.099*	-.053	-.053	.050	.164**	-.174**	.036	.092	.230**	-.039	-.174**	-.009	-.251**
16. Life satisfaction (T1)	3.220	.736	-.112*	-.039	-.061	.013	-.001	.131**	-.096*	.062	-.022	.118*	.047	-.117*	-.003	-.266**
17. Family satisfaction (T1)	3.380	.724	-.118*	-.075	-.015	.055	-.067	.089	-.096*	.054	-.041	.010	.062	-.080	-.023	-.185**
18. Work type (T1)	.640	.480	.106*	-.024	-.072	-.113*	.062	.060	.015	-.093	.016	-.002	.034	-.049	.151**	-.053
19. S-Motivational (T2)†	-.008	.816	-.083	.023	.035	.043	-.056	.828**	-.214**	-.137**	.331**	.040	.100*	-.081	-.020	-.083
20. S-Cognitive (T2)†	.013	.833	-.116*	-.101*	.023	.045	-.125**	.080	.822**	.133**	.062	.117*	-.157**	.193**	.215**	.339**
21. S-Emotional (T2)†	-.009	.760	-.100*	.026	.096*	.026	-.139**	.185**	-.159**	.841**	-.087	.136**	-.037	-.037	.081	.030
22. S-Behavioral (T2)†	.018	.819	.022	.041	-.016	-.020	-.027	.108*	-.126**	-.177**	.881**	.116*	.019	.084	-.053	.083
23. G-Workaholism (T2)†	-.018	.906	-.091	.020	-.040	-.057	-.002	.118*	.193**	.150**	.134**	.805**	-.223**	.349**	.298**	.257**
24. Personal life orientation (T2)†	-.021	.887	.033	-.132**	-.054	-.002	.127**	.038	-.089	-.029	-.038	-.223**	.782**	-.080	.044	-.170**
25. Interpersonal norms (T2)†	-.003	.955	-.049	-.067	.000	-.120*	.078	-.034	.243**	.017	.118*	.347**	-.167**	.904**	.228**	.516**
26. Telepressure (T2)†	-.002	.923	-.110*	-.116*	.004	.006	.014	.071	.300**	.136**	.034	.292**	-.052	.205**	.729**	.265**
27. Work-to-family guilt (T2)†	.018	.908	-.082	-.030	.034	.040	-.104*	.009	.343**	.065	.098*	.286**	-.206**	.466**	.327**	.827**
28. Job satisfaction (T2)	2.990	.930	-.011	.091	-.038	-.072	.093	.186**	-.187**	.025	.114*	.174**	-.032	-.193**	-.013	-.240**
29. Life satisfaction (T2)	3.160	.734	-.122*	-.078	-.015	.052	.031	.146**	-.138*	.071	-.007	.094	-.003	-.108*	-.028	-.217**
30. Family satisfaction (T2)	3.410	.690	-.109*	-.082	-.035	.050	-.040	.115*	-.106	.028	-.022	.029	.014	-.049	-.065	-.094
31. Work type (T2)	.670	.469	.104	-.045	-.091	-.109*	.057	.032	.040	.024	.002	-.009	.023	-.036	.062	-.126*

	15	16	17	18	19	20	21	22	23	24	25	26	27	28	29	30	31
15. Job satisfaction (T1)	-																
16. Life satisfaction (T1)	.466**	-															
17. Family satisfaction (T1)	.248**	.703**	-														
18. Work type (T1)	.059	.030	-.010	-													
19. S-Motivational (T2)†	.179**	.126**	.090	.049	-												
20. S-Cognitive (T2)†	-.164**	-.108*	-.109*	.010	-.116*	-											
21. S-Emotional (T2)†	.102*	.109*	.075	-.073	-.024	.028	-										
22. S-Behavioral (T2)†	.060	-.059	-.056	.002	.273**	-.042	-.152**	-									
23. G-Workaholism (T2)†	.216**	.116*	.037	-.037	.095*	.110*	.098*	.087	-								
24. Personal life orientation (T2)†	-.057	-.027	.014	.040	.096*	-.123*	-.008	-.007	-.220**	-							
25. Interpersonal norms (T2)†	-.174**	-.103*	-.073	-.044	-.063	.216**	-.021	.086	.398**	-.105*	-						
26. Telepressure (T2)†	-.020	-.001	-.009	.055	.003	.314**	.105*	-.010	.368**	-.009	.262**	-					
27. Work-to-family guilt (T2)†	-.251**	-.248**	-.191**	-.046	-.090	.377**	.049	.048	.288**	-.205**	.496**	.326**	-				
28. Job satisfaction (T2)	.783**	.370**	.173**	.063	.206**	-.182**	.080	.096	.215**	-.044	-.209**	-.045	-.299**	-			
29. Life satisfaction (T2)	.401**	.654**	.499**	.040	.154**	-.136*	.111*	-.060	.109*	-.050	-.091	-.020	-.279**	.486**	-		
30. Family satisfaction (T2)	.242**	.547**	.628**	-.016	.077	-.137	.097	-.055	.063	-.047	-.012	-.060	-.147**	.243**	.697**	-	
31. Work type (T2)	.119*	.102	-.007	.644**	.067	.029	-.010	-.008	-.009	.040	-.033	.046	-.120*	.085	.095	.021	-

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

Table S6

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

Model	LL	#fp	Scaling	AIC	CAIC	BIC	ABIC	Entropy	aLMR	BLRT
Time 1										
1 Profile	-2715.511	10	1.032	5451.022	5501.706	5491.706	5459.972	Na	Na	Na
2 Profiles	-2613.615	21	1.239	5269.230	5375.666	5354.666	5288.024	.676	.001	< .001
3 Profiles	-2537.778	32	1.198	5139.555	5301.745	5269.745	5168.195	.777	.002	< .001
4 Profiles	-2501.192	43	1.179	5088.385	5306.327	5263.327	5126.869	.696	.178	< .001
5 Profiles	-2471.392	54	1.113	5050.784	5324.479	5270.479	5099.113	.750	.052	< .001
6 Profiles	-2450.687	65	1.120	5031.375	5360.822	5295.822	5089.549	.785	.558	< .001
7 Profiles	-2416.659	76	1.044	4985.317	5370.518	5294.518	5053.336	.758	.061	< .001
8 Profiles	-2404.632	87	1.006	4983.265	5424.218	5337.218	5061.129	.826	.157	< .001
Time 2										
1 Profile	-2648.600	10	1.050	5317.199	5367.884	5357.884	5326.149	Na	Na	Na
2 Profiles	-2553.559	21	1.174	5149.117	5255.554	5234.554	5167.912	.950	.005	< .001
3 Profiles	-2493.119	32	1.124	5050.238	5212.428	5180.428	5078.878	.753	< .001	< .001
4 Profiles	-2451.795	43	1.191	4989.590	5207.533	5164.533	5028.075	.765	.074	< .001
5 Profiles	-2410.427	54	.984	4928.855	5202.550	5148.550	4977.184	.801	.121	< .001
6 Profiles	-2390.450	65	1.020	4910.900	5240.347	5175.347	4969.074	.729	.836	< .001
7 Profiles	-2370.073	76	1.120	4892.145	5277.345	5201.345	4960.164	.762	.644	< .001
8 Profiles	-2349.952	87	1.113	4873.905	5314.858	5227.858	4951.769	.803	.139	< .001

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

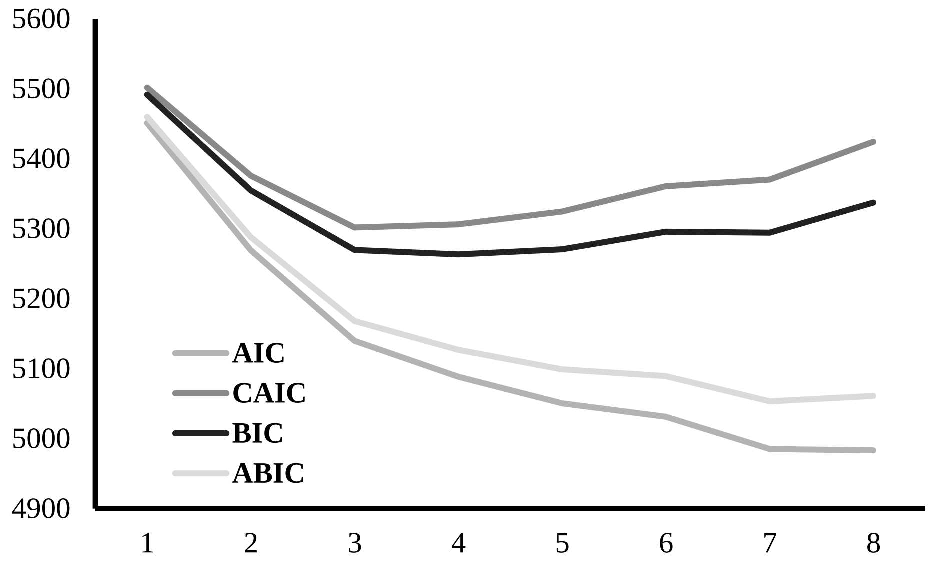

Figure S1
Elbow Plot of the Value of the Information Criteria for Solutions Including Different Numbers of Latent Profiles at Time 1

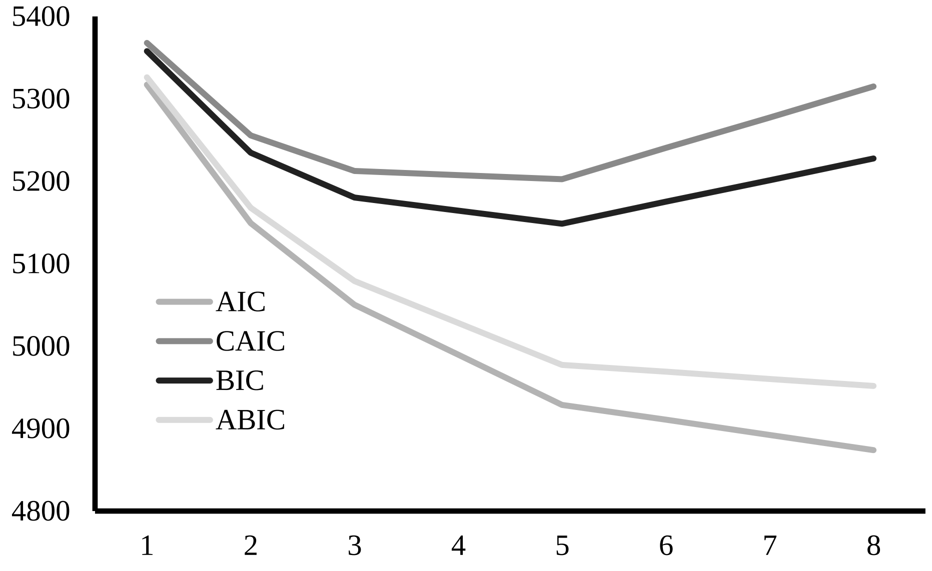

Figure S2
Elbow Plot of the Value of the Information Criteria for Solutions Including Different Numbers of Latent Profiles at Time 2

Table S7

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

	Profile 1 Mean [CI]	Profile 2 Mean [CI]	Profile 3 Mean [CI]	Profile 4 Mean [CI]
S-Motivational	-.974 [-1.252; -.695]	.019 [-.067; .106]	.311 [.080; .542]	-.114 [-.473; .245]
S-Cognitive	-.258 [-.333; -.183]	.043 [-.100; .185]	-.398 [-.517; -.279]	.553 [.189; .917]
S-Emotional	-.004 [-.109; .100]	.183 [.043; .323]	-.282 [-.435; -.128]	.052 [-.187; .291]
S-Behavioral	-.823 [-1.015; -.631]	.056 [-.041; .153]	.266 [.057; .475]	-.145 [-.479; .189]
G-Workaholism	-1.442 [-1.491; -1.393]	.776 [.641; .911]	-.514 [-.647; -.380]	-.277 [-.590; .037]
	Profile 1 Variance [CI]	Profile 2 Variance [CI]	Profile 3 Variance [CI]	Profile 4 Variance [CI]
S-Motivational	.412 [.042; .782]	.223 [.166; .279]	.812 [.601; 1.024]	.873 [.664; 1.082]
S-Cognitive	.058 [.031; .085]	.815 [.674; .956]	.179 [.076; .283]	.962 [.601; 1.324]
S-Emotional	.088 [.020; .157]	.791 [.574; 1.009]	.310 [.177; .443]	.611 [.091; 1.131]
S-Behavioral	.193 [.044; .342]	.282 [.186; .378]	.881 [.704; 1.058]	1.090 [.707; 1.474]
G-Workaholism	.023 [.010; .037]	.436 [.327; .544]	.207 [.156; .257]	.540 [.259; .821]

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: Unplugged; Profile 2: Plugged In; Profile 3: Moderately Unplugged with Externalized Workaholism; and Profile 4: Moderately Unplugged with Cognitive Workaholism.

Table S8

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

	Profile 1	Profile 2	Profile 3	Profile 4
Time 1				
Profile 1	.943	.001	.030	.026
Profile 2	.000	.867	.043	.091
Profile 3	.002	.067	.785	.146
Profile 4	.005	.112	.078	.805
Time 2				
Profile 1	.905	.000	.053	.042
Profile 2	.000	.868	.042	.090
Profile 3	.014	.090	.755	.141
Profile 4	.001	.142	.078	.779

Note. Profile 1: Unplugged; Profile 2: Plugged In; Profile 3: Moderately Unplugged with Externalized Workaholism; and Profile 4: Moderately Unplugged with Cognitive Workaholism.

Table S9

Results from the Latent Profile Analysis Models estimated separately across Groups and Time Points

Model	LL	#fp	Scaling	AIC	CAIC	BIC	ABIC	Entropy	aLMR	BLRT
Onsite Workers: Time 1										
1 Profile	-974.161	10	1.022	1968.322	2008.692	1998.692	1967.040	Na	Na	Na
2 Profiles	-925.653	21	1.046	1893.306	1978.082	1957.082	1890.613	.911	.001	< .001
3 Profiles	-890.298	32	1.117	1844.597	1973.779	1941.779	1840.494	.850	.075	< .001
4 Profiles	-868.534	43	1.042	1823.067	1996.656	1953.656	1817.555	.798	.136	.091
5 Profiles	-849.158	54	.965	1806.317	2024.312	1970.312	1799.394	.794	.184	< .001
6 Profiles	-835.241	65	1.037	1800.483	2062.885	1997.885	1792.150	.862	.454	.333
7 Profiles	-819.928	76	.947	1791.856	2098.665	2022.665	1782.113	.875	.760	.217
8 Profiles	-805.796	87	.904	1785.591	2136.806	2049.806	1774.438	.909	.409	.133
Onsite Workers Time 2										
1 Profile	-709.515	10	1.027	1439.030	1475.943	1465.943	1434.345	Na	Na	Na
2 Profiles	-666.862	21	.938	1375.723	1453.242	1432.242	1365.884	.994	.037	< .001
3 Profiles	-633.539	32	.763	1331.077	1449.200	1417.200	1316.085	.997	.093	< .001
4 Profiles	-610.151	43	.914	1306.303	1465.031	1422.031	1286.156	.863	.031	< .001
5 Profiles	-591.700	54	.878	1291.400	1490.732	1436.732	1266.099	.837	.194	< .001
6 Profiles	-578.616	65	.798	1287.232	1527.169	1462.169	1256.777	.875	.093	< .001
7 Profiles	-564.660	76	.847	1281.321	1561.863	1485.863	1245.713	.863	301	< .001
8 Profiles	-548.564	87	.871	1271.128	1592.275	1505.275	1230.366	.890	.160	.042
Remote Workers: Time 1										
1 Profile	-1735.543	10	1.041	3491.085	3537.361	3527.361	3495.652	Na	Na	Na
2 Profiles	-1665.053	21	1.162	3372.107	3469.287	3448.287	3381.698	.704	.051	< .001
3 Profiles	-1615.507	32	1.159	3295.014	3443.098	3411.098	3309.630	.776	.022	< .001
4 Profiles	-1582.593	43	1.158	3251.186	3450.174	3407.174	3270.826	.819	.225	< .001
5 Profiles	-1561.717	54	1.127	3231.434	3481.326	3427.326	3256.098	.758	.617	.021
6 Profiles	-1543.443	65	.911	3216.885	3517.681	3452.681	3246.573	.851	.132	< .001
7 Profiles	-1518.918	76	1.063	3189.836	3541.535	3465.535	3224.547	.839	.576	< .001
8 Profiles	-1498.579	87	.930	3171.157	3573.760	3486.760	3210.893	.833	.369	< .001
Remote Workers Time 2										
1 Profile	-1423.892	10	.990	2867.784	2911.990	2901.990	2870.297	Na	Na	Na
2 Profiles	-1367.605	21	1.079	2777.209	2870.041	2849.041	2782.486	.939	.015	< .001
3 Profiles	-1338.308	32	1.120	2740.616	2882.073	2850.073	2748.657	.872	.081	< .001
4 Profiles	-1316.692	43	1.002	2719.383	2909.466	2866.466	2730.189	.905	.061	.004
5 Profiles	-1296.930	54	.997	2701.860	2940.569	2886.569	2715.429	.908	.441	< .001
6 Profiles	-1280.285	65	.938	2690.570	2977.905	2912.905	2706.904	.808	.694	< .001
7 Profiles	-1262.655	76	.945	2677.310	3013.270	2937.270	2696.408	.835	.186	.077
8 Profiles	-1248.542	87	.952	2671.084	3055.670	2968.670	2692.946	.846	.104	.172

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

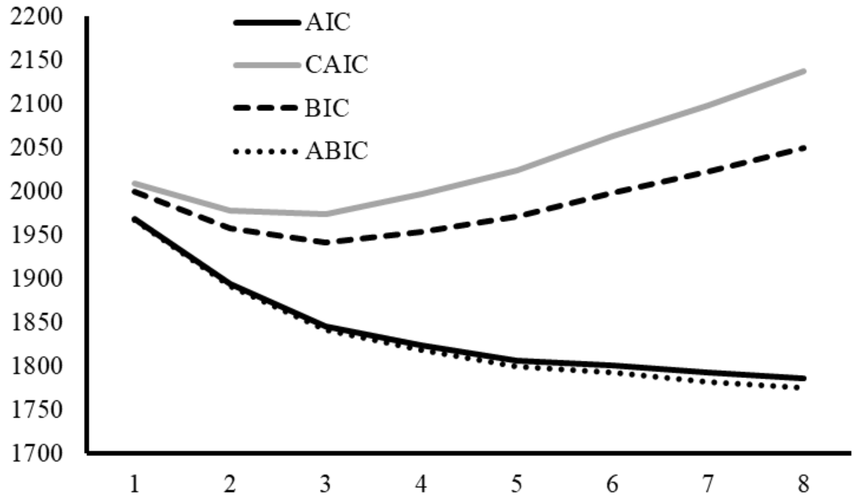

Figure S3a: Onsite Workers, Time 1

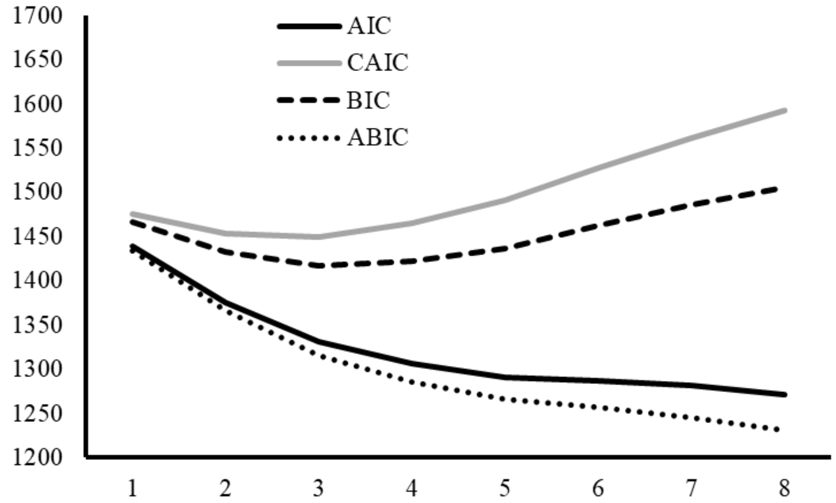

Figure S3b: Onsite Workers, Time 2

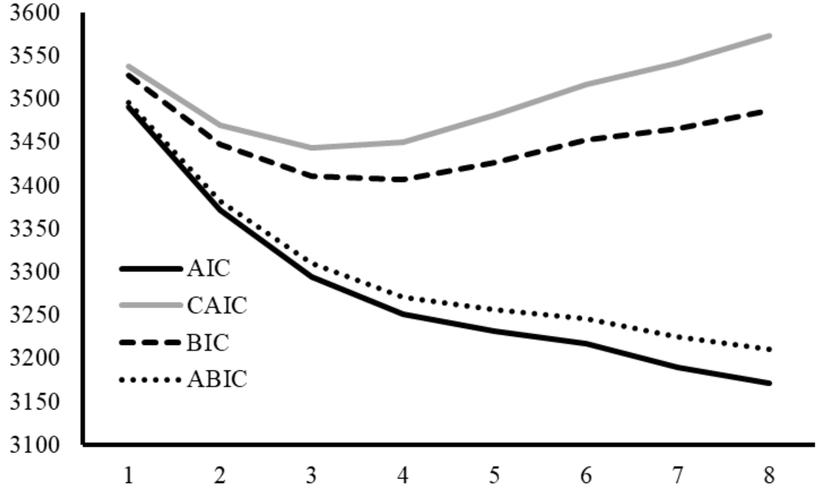

Figure S3c: Remote Workers, Time 1

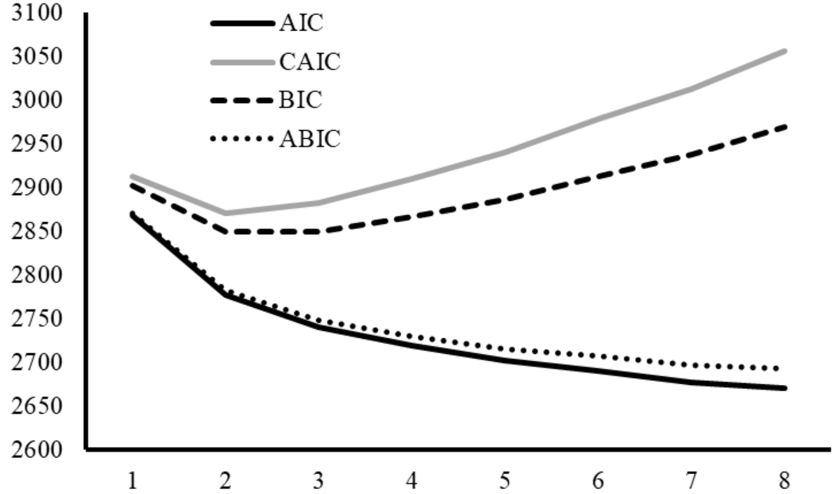

Figure S3d: Remote Workers, Time 2

Figure S3

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

Table S10

Results from the Multi-Group Models

Model	LL	#fp	Scaling	AIC	CAIC	BIC	ABIC	Entropy
Multi-Group Tests of Similarity (Time 1)								
Configural Similarity	-2731.739	87	1.056	5637.479	6078.432	5991.432	5715.343	.812
Structural Similarity	-2762.719	67	1.058	5659.439	5999.023	5932.023	5719.403	.815
Dispersion Similarity	-2781.382	47	1.171	5656.763	5894.979	5847.979	5698.828	.698
Distributional Similarity	-2782.583	44	1.175	5653.166	5876.176	5832.176	5692.545	.696
Multi-Group Explanatory Similarity (Time 1)								
Free Relations with Outcomes	-4778.243	36	1.689	9628.486	9810.949	9774.949	9660.706	.803
Equal Relations with Outcomes	-4782.871	20	1.229	9605.742	9707.110	9687.110	9623.641	.802
Multi-Group Explanatory Similarity (Time 1): Work-Family Guilt Only								
Free Relations with Outcomes	-3354.057	9	1.030	6726.115	6771.73	6762.730	6734.169	.702
Equal Relations with Outcomes	-3354.556	5	.972	6719.113	6744.455	6739.455	6723.588	.702
Multi-Group Tests of Similarity (Time 2)								
Configural Similarity	-2136.363	87	.938	4446.726	4865.555	4778.555	4502.582	.912
Structural Similarity	-2160.742	67	.877	4455.484	4778.031	4711.031	4498.500	.807
Dispersion Similarity	-2187.176	47	1.118	4468.352	4694.616	4647.616	4498.527	.777
Distributional Similarity	-2187.259	44	1.109	4462.518	4674.340	4630.340	4490.768	.776
Multi-Group Explanatory Similarity (Time 2)								
Free Relations with Outcomes	-3741.249	36	1.140	7554.499	7727.807	7691.807	7577.612	.810
Equal Relations with Outcomes	-3765.001	20	1.094	7570.002	7646.285	7646.285	7582.843	.808
Multi-Group Explanatory Similarity (Time 2): Work-Family Guilt Only								
Free Relations with Outcomes	-2611.180	9	1.020	5240.360	5283.687	5274.687	5246.138	.794
Equal Relations with Outcomes	-2623.115	5	.982	5256.231	5280.301	5275.301	5259.441	.781

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.