Running Head. Workaholism Dimensionality and Profiles

Complementary Variable- and Person-Centered Approaches to the Dimensionality of Workaholism

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Abstract

This research relies on complementary variable- and person-centered approaches to investigate the underlying dimensionality of the workaholism construct. In three studies (Study 1: *N* = 343 workers; Study 2: *N* = 654 firefighters in Sample 1 and *N* = 247 administrative and technical employees in Sample 2; and Study 3: *N* = 153 nurses in Sample 1 and *N* = 359 educators in Sample 2), the results showed that employees' workaholism ratings simultaneously reflected a global overarching workaholism construct, which co-existed with two specific dimensions (working excessively and compulsively). In Study 1, global levels of self-determined motivation were associated with higher global levels of workaholism, whereas perceived supervisor support was negatively related to global levels of workaholism. We then examined the distinct configurations, or profiles, taken by workaholism dimensions (global workaholism, and specific working excessively and compulsively; Studies 2 and 3) and psychological detachment (Study 3). Studies 2 and 3 also documented the associations between these workaholism profiles, and correlated predictor (e.g., supervisor support, workload) and outcome (e.g., emotional exhaustion, work performance) variables. Three of the four profiles identified were similar across studies (*Low Global and Average Specific Workaholism*, *Average Global and Specific Workaholism*, and *High Global and Average Specific Workaholism*), whereas one profile was different across studies and samples. In both studies, the *High Global and Average Specific Workaholism* profile was associated with the worst correlated outcome variables (e.g., high levels of emotional exhaustion, low levels of job satisfaction).

Key words: Workaholism; latent profiles; supervisor support; job satisfaction; nurses; bifactor models

Workaholism has received a fair amount of attention in the organizational sciences (Clark et al., 2020; Salanova et al., 2014) due to its various undesirable consequences for the organization (e.g., presenteeism; Mazzetti et al., 2019) and the employee (e.g., emotional exhaustion; Clark et al., 2016). Workaholism is defined as a negative experience encompassing two distinct, yet complementary, components (Schaufeli et al., 2009b). The first of those components, working excessively, is behavioral in nature, and refers to spending a great deal of time and effort in work activities while neglecting other spheres of life. The second of those components, working compulsively, is cognitive in nature, and refers to being obsessed with work and to thinking compulsively about work. There is a general recognition (Gillet et al., 2017) that a comprehensive assessment of workaholism should tap into these two components. However, research has also suggested that employees could experience workaholism holistically as a single global construct (Sandrin et al., 2019a). This global representation is supported by the high correlations between ratings of working excessively and compulsively (Huyghebaert et al., 2018a), and by the demonstration of stronger associations with covariates when workaholism is defined as a global dimension (Taris et al., 2012). However, these two dimensions are seen as independent from one another (Schaufeli et al., 2009b), and prior studies have shown that each component shared unique associations with covariates (Huyghebaert et al., 2018a).

These observations raise a series of potentially critical questions regarding: (a) whether the working excessively and compulsively facets really retain meaningful 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 (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. Fortunately, alternative variable- and person-centered approaches exist to support a more thorough investigation of these substantively important questions (Gillet et al., 2017; Tóth-Király et al., 2020). The present research is a substantive-methodological synergy (Gillet et al., 2018) seeking to illustrate the utility of these approaches by showing how they may help to improve our understanding of the dimensionality of workaholism. This research has thus broad relevance for the organizational sciences by providing the illustration of a combined variable- and person-centered framework which helps to understand the underlying structure of a variety of psychological constructs.

More precisely, the present research contributes to our understanding of workaholism by: (a) relying on the variable-centered bifactor modeling framework to account for the multidimensionality of this construct (Studies 1-3); (b) relying on person-centered analyses to assess the nature of employees' workaholism profiles taking into account the globality and specificity of this construct (Studies 2 and 3); (c) verifying the extent to which the profiles identified among samples of firefighters and administrative-technical employees (Study 2) will be replicated among nurses and educators (Study 3) when simultaneously considering employees' psychological detachment, a dimension known to be negatively related to workaholism (Huyghebaert et al., 2018a). The current investigation also seeks to document the criterion-related validity of the workaholism global and specific dimensions (Study 1) and multidimensional profiles (Studies 2 and 3) by examining their associations with theoretically-relevant correlated predictor (i.e., work motivation in Study 1; leader-member exchange – LMX, and psychological need frustration in Study 2; and workload and supervisor support in Study 3) and outcome (i.e., work performance and emotional exhaustion in Study 1; perceived health, stress, and work performance in Study 2; presenteeism; work-family conflicts, emotional exhaustion, job satisfaction, and work performance in Study 3) variables. 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 Components of Workaholism

Recent research (Gillet et al., 2018; Tóth-Király et al., 2020) has demonstrated that workaholism exists both as a global (G) entity reflecting commonalities among ratings of working excessively and compulsively which themselves include relevant specificity (S) remaining unexplained by this global construct. For instance, Tóth-Király et al. (2020) found support for a bifactor model of workaholism including one G-factor (global workaholism) and two S-factors reflecting the working excessively and compulsively facets. However, their results revealed low composite reliability for the working compulsively S-factor, suggesting that this S-factor might not retain much specificity beyond that explained by the G-factor. Similar conclusions were reported by Gillet et al. (2018), who showed that the workaholism G-factor and the working excessively S-factor represented the main sources of variations in item scores, such that ratings of working compulsively mainly served to define the G-factor, while retaining little additional specificity of their own. However, the extent to which these results would generalize beyond the samples used in these previous studies remains unknown. A first objective of the present investigation was thus to verify whether, and how, these results would be replicated across three independent studies involving five distinct samples of employees.

Hypothesis 1. Workaholism ratings will be best represented as a bifactor construct including one G-factor (global workaholism) and two S-factors (working excessively and compulsively).

The Joint Effects of Workaholism Components: A Combined Variable- and Person-Centered Construct Validation Perspective

Despite abundant research supporting the negative consequences of workaholism components (working excessively and compulsively; Schaufeli et al., 2009b), a comprehensive assessment of their combined impacts is lacking. To this end, two complementary analytic approaches can be used. Variable-centered analyses assume that all employees come from the same population to which a unique set of "average" parameters applies. In Study 1, we adopt this approach to identify the optimal measurement structure of workaholism. In contrast, person-centered analyses are designed to identify qualitatively discrete subpopulations of workers presenting distinct configurations of workaholism components (Gillet et al., 2017; Meyer & Morin, 2016). Person-centered analyses are thus specifically designed to account for the joint effect of multiple facets of workaholism, without assuming effects that generalize to the whole population. In Studies 2-3, we adopt this approach to document the nature of workaholism profiles, while relying on the optimal measurement structure identified in Study 1, and replicated in Studies 2-3.

In variable- and person-centered analyses, a critical step is to document the theoretical and practical implications of the identified factors or profiles via the examination of their associations with theoretically-relevant predictor and outcome variables (e.g., Marsh et al., 2009). In Study 1, to ascertain the construct validity of the identified global and specific components of workaholism, we test their associations with work motivation (specified as a correlated predictor), work performance (specified as a correlated outcome), and emotional exhaustion (specified as a correlated outcome). Then, in Studies 2-3, we verify the construct validity of the identified workaholism profiles by investigating their associations with global levels of LMX, need frustration, workload, and supervisor support as correlated predictors of profile membership, and the implications of membership into these profiles in relation to work performance, perceived health, stress, presenteeism, work-family conflicts, emotional exhaustion, and job satisfaction specified as correlated outcomes.

Person-centered results tend to be more naturally aligned with managers and practitioners tendency to think about their employees as corresponding to different categories than in terms of relations observed between a series of variables (Morin et al., 2011). For this reason, our findings are likely to have important implications for practice. For instance, documenting the outcome implications of these profiles will help to decide which should be prioritized from an intervention perspective. Likewise, documenting the role of LMX, need frustration, workload, and supervisor support as possible drivers of profile membership should help identify actionable levers of interventions.

A Person-Centered Perspective on Workaholism

Person-centered research has started to look at how workaholism components combine within employees (Salanova et al., 2014). Unfortunately, many studies relied on a combination of workaholism components and other variables 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 components in the definition of the profiles, at least without first assessing whether the nature of workaholism profiles are robust to the inclusion of these additional variables.

Among the few studies focusing solely on workaholism, Schaufeli et al. (2009a) identified four profiles defined based on the working excessively and compulsively components: (1) Workaholics (16%); (2) Nonworkaholics (29%); (3) Excessive workers (29%); and (4) Compulsive workers (26%). 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. In contrast, Gillet et al. (2017) identified four profiles among two samples of workers from various organizations: (1) Very low levels of working excessively and compulsively; (2) Very high levels of working excessively and compulsively; (3) Moderately high levels of working excessively and compulsively; and (4) Moderately low levels of working excessively and compulsively. Although this second study tested the replicability of their solution across independent samples, their results essentially suggest that there is little value in differentiating the working excessively and compulsively components.

However, all previous studies have relied on indicators ignoring the dual global/specific nature of workaholism. This limitation is particularly important. When applying person-centered analyses to indicators known to present a global/specific structure, relying on profile indicators that confound these global and specific components has been shown by Morin et al. (2016b, 2017) to result in the erroneous estimation of profiles characterized by matching levels across indicators (e.g., such as the profiles identified by Gillet et al., 2017). With this in mind, we propose the following hypothesis.

Hypothesis 2. Four or more profiles will be identified, including a High Workaholism, a Moderate Workaholism, and a Low Workaholism configuration, as well as at least one profile characterized by a clearer differentiation among the global and specific components.

A Person-Centered Perspective on Workaholism and Psychological Detachment

As in Study 2, Study 3 seeks to document the workaholism configurations that best characterize distinct profiles of employees while accounting for the global and specific components of workaholism. In addition, psychological detachment, involving the ability to stop thinking about work during off-job time and to be mentally involved in activities other than the job (Sonnentag & Fritz, 2015), was considered as another psychological mechanism reflecting the logical opposite of workaholism in the definition of the profiles. The inability to stop thinking about work during off-work time, which is a core characteristic of workaholism, has the effect of maintaining employees' psychological systems in a state of activation, thus prohibiting recovery (Bennett et al., 2016). In contrast, psychological detachment helps to turn off these systems, thus helping psychological recovery from accumulated work-related energy expenditure (see Sonnentag & Fritz, 2015, for a review). In this context, it is not surprising to note that psychological detachment has been found to be associated with lower levels of emotional exhaustion and work-family conflicts, and with higher levels of job satisfaction and performance (Fouquereau et al., 2019; Kinnunen et al., 2017).

Prior studies have shown that psychological detachment is intimately related to workaholism. In fact, research has typically considered psychological detachment as either the opposite, or as an outcome, of workaholism, with the expectation that higher levels of workaholism would be strongly associated with lower levels of psychological detachment (Huyghebaert et al., 2018a). Yet, lack of psychological detachment is also likely to play a key role in influencing employees' workaholic behaviors, in turn leading to negative outcomes (Clark et al., 2016). For instance, whereas working excessively and compulsively makes it harder to recover from work and is thus associated with higher levels of emotional exhaustion (Sandrin et al., 2019a), this might be less problematic for employees with high psychological detachment (Sonnentag & Fritz, 2015). In other words, psychological detachment from work during nonwork time may also buffer the negative impact of workaholism.

For these reasons, psychological detachment seemed like a strong candidate variable to incorporate to the definition of the profiles to assess the extent to which their nature would remain unchanged or transformed via the consideration of additional components. Given the observed stability of results observed in previous research relying on various workaholism components (Gillet et al., 2017) or on combinations of workaholism with other related variables (Innanen et al., 2014; Mäkikangas et al., 2015), and the known associations between psychological detachment and the workaholism facets considered here (Huyghebaert et al., 2018a), we do expect a substantial level of stability. Observing stability would also support the idea that the identified profiles tap into some core processes that remain unchanged irrespective of the specific psychological mechanisms that are considered.

Hypothesis 3. Four or more profiles will be identified, including a High Workaholism and Low Psychological Detachment, a Moderate Workaholism and Psychological Detachment, and a Low Workaholism and High Psychological Detachment configuration, as well as at least one profile characterized by a clearer differentiation among the global and specific components of workaholism accompanied by levels of psychological detachment presenting a mirror image to global levels of workaholism (low when high, and vice versa).

Generalizability of the Profiles

Before turning our attention to the various covariates considered in the present study, we first consider another core aspect of the construct validation process of person-centered solutions, which involves the verification of the extent to which a profile solution can be replicated across samples (Morin et al., 2016c). From a practical perspective, evidence of generalizability related to the number (*configural* similarity) and nature (*structural* similarity) of identified profiles makes it possible to devise more generic types of interventions, whereas evidence of variations rather highlights the need for interventions that are specific to each subgroup. Furthermore, observing that the level of inter-individual differences observed among profile members (*dispersion* similarity), or the size of these profiles (*distributional* similarity), is found to differ across samples will help to prioritize the types of employees most likely to benefit from these generic or specific interventions. For instance, previous research has revealed variations in workaholism as a function of work settings, job design, or emotional demands (Gillet et al., 2017; Huyghebaert et al., 2018a; Mazzetti et al., 2019), making it important to verify whether the identified profiles will generalize across work contexts.

In Study 2, we address the replication issue by examining the extent to which the workaholism profiles will generalize across independent samples of firefighters (Sample 1), and of administrative and technical employees (Sample 2). These two samples were selected given their high level of differentiation to conduct a robust test of profile similarity. On the one hand, firefighting is a highly stressful, yet socially critical, occupation, involving a high level of teamwork and challenging work schedules. Furthermore, in this occupation, inadequate work performance also carries a high level of risk for the collectivity, for ones' team-members, and for oneself (Sandrin et al., 2019b). In contrast, administrative and technical (i.e., office) employees more typically work in safer and more individualized conditions, and according to more normative work schedules. As such, higher levels of workaholism seem to be more likely among the first group of employees (Taris et al., 2012).

In Study 3, we address the replication issue by examining the extent to which the workaholism and psychological detachment profiles will generalize across independent samples of nurses (Sample 1) and educators (Sample 2) to extend the range of occupations considered in the present research. Like firefighters, nurses and educators both occupy socially valued occupations in which failure to perform results in important consequences for their patients and students, although none of these occupations shares the hazardous nature of the firefighters' work (Beck & Reilly, 2017). Furthermore, both nurses and educators occupy a position that, despite involving some level of teamwork, requires a substantial level of autonomy (Labrague et al., 2019; Royer & Moreau, 2016). For those reasons, both of these occupations seem to represent a fertile context for the emergence of workaholism (Taris et al., 2012). However, whereas nurses' work schedule is quite demanding (Min et al., 2019) just like that of firefighters (Reinberg et al., 2017), educators work schedule is typically more aligned with that of office workers (de Souza et al., 2014). However, educators also have to accomplish a great variety of highly diversified tasks at work (e.g., leading daily activities, staff meetings, maintaining a safe, hygienic, and inclusive environment, developing routines and schedules; Mertala, 2019).

Lacking prior empirical guidance, we leave open the question of whether and how workaholism profiles will differ across the two samples of employees in each study:

Research Question 1: Will the identified profiles demonstrate evidence of *configural*, *structural*, *dispersion*, and *distributional* similarity across the two samples considered in Studies 2 and 3?

Correlated Predictors of Workaholism Dimensions and Profiles

Supervisor Support and LMX

In Studies 1 and 3, we consider the role played by employees' perceptions of supervisor support. Perceived supervisor support is defined as employees' impression that their supervisors value their contributions and care about their psychological health (Eisenberger et al., 2002). Research has generally shown that supervisor support can have a significant effect on employees' work performance, turnover intentions, and emotional exhaustion (Caesens et al., 2020; Gillet et al., 2020c).

These results are consistent with assumptions from the conservation of resources theory (Hobfoll, 2002). Indeed, access to supervisor support is likely to help workers maintain their psychological and work-related resources, or to develop new ones, thereby helping them to recover more quickly from work (e.g., higher levels of psychological detachment) and protecting them against the undesirable effects of job demands (Spurk et al., 2016). Employees who feel supported at work are also less likely to feel pressured to work extra hours (Mazzetti et al., 2016). Moreover, supervisor support can help nurture employees' feelings of self-determination at work (Fernet et al., 2012), and increase their ability to cope more efficiently with the pressures of their environment (Hakanen & Roodt, 2010). In line with these expectations, previous research has generally supported the idea that employees' perceptions of supervisor support, or of supervisor recognition (a construct closely linked to support; Sandrin et al., 2019a), tended to predict lower levels of workaholism (Gillet et al., 2017, 2018) and higher levels of psychological detachment (Fouquereau et al., 2019).

Hypothesis 4. Supervisor support will be associated with lower global levels of workaholism and with lower specific levels of working compulsively and excessively (Study 1), and with membership into a Low Workaholism and High Psychological Detachment profile (Study 3).

In Study 2, we considered LMX as a correlated predictor variable distinct, and yet conceptually related to supervisor support. Despite the well-documented importance of LMX as a core indicator of the quality of the exchange relationship between a leader and an employee (Liden & Maslyn, 1998), no person-centered research has yet examined the effects of LMX on workaholism profiles. However, the theoretical rationale presented above in relation to the effects of perceived supervisor support, together with results from prior research (Endriulaitienė & Morkevičiūtė, 2020), allow us to formulate the following hypothesis.

Hypothesis 5. Higher levels of LMX will be associated with membership into the Low Workaholism profile, followed by the Moderate Workaholism profile, and then by the High workaholism profile.

Motivation and Need Frustration

In Study 1, we consider the role played by work motivation. Self-determination theory (SDT; Ryan & Deci, 2017) posits that individuals can be motivated for various reasons. Intrinsic motivation represents volitional engagement in an activity for the pleasure and satisfaction that it affords. Identified regulation refers to engagement in an activity that serves a personally-endorsed value or objective. Intrinsic motivation and identified regulation are seen as autonomous (i.e., self-driven) types of motivation. Introjected regulation refers to engagement in an activity driven by internal pressures, such as avoiding shame or guilt, or the pursuit of pride or self-aggrandizement. External regulation refers to engagement in an activity that is controlled by external sources, such as punishments, constraints, or rewards. Introjected and external regulations are seen as controlled (driven by internal or external contingencies) types of motivation. Finally, amotivation refers to a lack of any internally or externally driven motive to pursue an activity.

Past research conducted in the work context has supported the distinct nature of these types of motivation, as well as their different associations with outcomes (Gagné & Deci, 2005). Autonomous types of motivation are generally associated with higher levels of performance, more positive psychological functioning, and fewer undesirable outcomes such as emotional exhaustion or turnover intentions (Howard et al., 2016; Sandrin et al., 2019b). In contrast, controlled motivation and amotivation (the absence of autonomous or controlled motivation) presents the opposite relations with these outcomes (Fernet et al., 2020; Gillet et al., 2016). Overall, research has thus supported SDT propositions regarding the greater desirability of autonomous forms of motivation, and the undesirability of a work approach mainly driven by controlled forms of motivation and amotivation.

From the perspective of SDT, workaholism is an intensive type of work involvement that appears to be primarily driven by controlled types of motivation (van Beek et al., 2011), which explains why workaholism leads to undesirable outcomes (Ryan & Deci, 2017). Thus, workaholics are assumed to be stimulated by internal and external contingencies, 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). Moreover, for workaholics, excessive investment in work is also purported to represent a way to decrease their feelings of anxiety, guilt, and shame, and to increase their self-esteem (Porter, 2004).

Hypothesis 6. Global self-determined work motivation, autonomous types of motivation, and amotivation will be associated with lower global levels of workaholism and with lower specific levels of working compulsively and excessively, whereas controlled types of motivation will be associated with higher levels of workaholism.

In order to further document the psychological mechanisms underpinning workaholism in Study 2, we once again turn to SDT (Ryan & Deci, 2017), which proposes that controlled types of motivation should mainly emerge from the frustration of employees' basic psychological needs for autonomy (i.e., the need to feel volitional and responsible), competence (i.e., the need to feel efficient when interacting with others and to have opportunities to express one's abilities), and relatedness (i.e., the need to feel socially secure and supported). Competence need frustration is known to be associated with lower feelings of self-worth, possibly leading employees to increase their job involvement in order to prove themselves (Spence & Robbins, 1992). Similarly, autonomy need frustration may lead workers to increase their job involvement to better meet external demands (Ryan & Deci, 2017). Finally, relatedness need frustration may be associated with an increase in employees' workload as they cannot rely on others' help to cope with job requirements (Gillet et al., 2017).

Hypothesis 7. Higher levels of need frustration will be associated with membership into the High Workaholism profile, followed by the Moderate Workaholism profile, and then by the Low workaholism profile.

Workload

In Study 3, we directly tested the role of workload as a correlated predictor of membership into the identified profiles on the basis of previous variable-centered results supporting its association with workaholism (Gillet et al., 2018; Huyghebaert et al., 2018a) and psychological detachment (Bennett et al., 2016; Gillet et al., 2020b). Indeed, employees exposed to higher workloads have to work harder to achieve their objectives, making it more likely for them to think about their work obligations when outside of the work settings, thus leading to high levels of workaholism (Schaufeli et al., 2008). Workload also interferes with employees' need fulfillment and self-actualization (Albrecht, 2015). This is likely to lead to a persistent activation of psychophysiological systems and a persistent negative cognitive activation (Sonnentag & Fritz, 2015) as a result of being unable to attain personal goals (Kinnunen et al., 2017). This persistent activation is thus likely to interfere with the work recovery process and makes it harder to psychologically detach (Sonnentag & Fritz, 2015).

Hypothesis 8. Workload will be associated with a greater likelihood of membership into the High Workaholism and Low Psychological Detachment profile, followed by the Moderate Workaholism and Psychological Detachment profile, and then by the Low Workaholism and High Psychological Detachment.

Correlated Outcomes of Workaholism Dimensions and Profiles

Research generally shows that higher global levels of workaholism or specific levels of working excessively and compulsively tended to be associated with higher levels of emotional exhaustion, work-related stress, presenteeism, and work-family conflicts, and with lower levels of work performance, perceived health, and job satisfaction (Clark et al., 2016; Huyghebaert et al., 2018a; Sandrin et al., 2019a). Results obtained from the few previous person-centered studies of workaholism are also informative. Thus, Gillet et al. (2017) showed that the most desirable outcomes levels (e.g., lower levels of emotional exhaustion, higher levels of perceived health) were associated with the Very Low profile, followed by the Moderately Low profile, then by the Moderately High profile, and finally by the Very High profile. Likewise, Schaufeli et al. (2009a) showed that burnout and presenteeism were lower, and recovery, happiness, and performance higher, in their Nonworkaholic profile.

Indeed, whereas workaholics devote a lot of time, effort, and cognitive energy to work, the resources available to support such an intense investment over the long term are limited (Hobfoll, 2002), and thus rapidly become unavailable to support other spheres of employees' professional or familial lives. Despite this high level of investment, workaholics still tend to feel restless when not at work, and to experience difficulties in withdrawing from work during off-job time. In failing to properly stop thinking about work, they often end up creating even more work for themselves, which then requires even higher levels of investment, and typically leads to feelings of disappointment and frustration (van Wijhe et al., 2014). Workaholics also tend to spend an excessive amount of time and effort at work at the expense of their personal life, which is, in essence, incompatible with work-life balance and thus likely to generate work-family conflicts (Porter, 2004). Moreover, workaholics need to comply with their obsession to work in order to prevent feelings of anxiety, tension, worthlessness, and guilt that occur when they are not working, thus leading them to attend work even when they feel ill (i.e., presenteeism; Mazzetti et al., 2019). Finally, workaholics tend to display lower levels of job satisfaction as they are not freely pursuing goals that are aligned with their own deeply held interests, goals, and values (Clark et al., 2016, 2020). In contrast and consistent with theoretical predictions (Sonnentag & Fritz, 2015), prior variable- and person-centered studies have found that high levels of psychological detachment tended to yield adaptive outcomes (Bennett et al., 2016; Gillet et al., 2020).

Hypothesis 9. (a) In Study 1, global levels of workaholism and specific levels of working excessively and compulsively will be associated with higher levels of emotional exhaustion and with lower levels of work performance. (b) In Studies 2 and 3, the highest levels of emotional exhaustion, stress, presenteeism, and work-family conflicts, and the lowest levels of work performance, perceived health, and job satisfaction will be associated with the High Workaholism (with Low Psychological

Detachment in Study 3) profile, followed by the Moderate Workaholism (with Moderate Psychological Detachment in Study 3) profile, and by the Low Workaholism (with High Psychological Detachment in Study 3) profiles.

Method

Participants and Procedure

In Study 1, a convenience sample of 343 workers (130 men; 213 women) was recruited by trained research assistants in organizations (e.g., public hospitals, industries, sales and services) located in France. Participants had to meet the following criteria: They had to be employed, in France, and to have an immediate supervisor. Respondents were aged between 20 and 62 years (*M* = 42.21, *SD* = 10.88), had an average organizational tenure of 10.96 years (*SD* = 9.67), and an average tenure in the current position of 5.43 years (*SD* = 6.13). A total of 290 participants were full-time workers (84.5%).

The first convenience sample used in Study 2 includes a total of 654 firefighters (598 men and 56 women) working in various French fire stations. Most participants worked full time (87.5%). Respondents were aged between 21 and 63 years (*M* = 41.08, *SD* = 8.28), had been working as firefighters for an average of 21.48 years (*SD* = 8.43), and had an average tenure in their current position of 5.74 years (*SD* = 4.93).

The second convenience sample used in Study 2 includes a total of 247 administrative and technical employees (71 men and 176 women) working in various fire stations located in France. Most participants worked full time (89.1%). Respondents were aged between 24 and 63 years (*M* = 43.28, *SD* = 8.47), had an average tenure in their organization of 13.73 years (*SD* = 7.72), and had an average tenure in their position of 8.64 years (*SD* = 6.24).

The first convenience sample used in Study 3 includes a total of 80 nurses and 73 nursing assistants (14 men and 139 women). Most participants worked full time (81.0%). Respondents were aged between 21 and 64 years (*M* = 42.61, *SD* = 10.46), had an average tenure in their organization of 10.62 years (*SD* = 9.65), and had an average tenure in their position of 6.85 years (*SD* = 6.77).

The second convenience sample used in Study 3 includes a total of 359 educators (88 men and 271 women). Most participants worked full time (89.4%). Respondents were aged between 18 and 63 years (*M* = 38.04, *SD* = 10.34), had an average tenure in their organization of 7.96 years (*SD* = 7.98), and had an average tenure in their position of 5.71 years (*SD* = 6.30).

For all studies, participants contacted organizations located in France to identify those who might be willing to either forward an email to all or some of their employees explaining the nature of the studies and inviting participants to complete an online questionnaire, or to allow us to meet with all or some their employees to recruit them in person. In Studies 1 and 3, the recruitment was done in person: Research assistants explained to potential participants the general purpose of the study and invited them to complete a questionnaire, while stressing the voluntary nature of their participation and their ability to withdraw at any time. Participants were also assured of the anonymity of their responses and provided active consent to participate before completing a paper-based questionnaire. In Study 2, all participants received an e-mail explaining the study purpose and inviting them to complete an online questionnaire. Once online, participants were first asked to complete a consent form in which the anonymous and voluntary nature of their participation was emphasized.

Measures

Workaholism (Studies 1-3) was measured with the Dutch Workaholism Scale (Schaufeli et al., 2009b) along two dimensions: Working compulsively (five items, α = .72 in Study 1, α = .80 in Study 2-Sample 1, α = .74 in Studies 2 and 3-Sample 2, and α = .75 in Study 3-Sample 1; e.g., “I feel that there is something inside me that drives me to work hard”) and excessively (five items, α = .83 in Studies 1 and 2 Sample 2, α = .85 in Study 2-Sample 1, α = .76 in Study 3-Sample 1, and α = .77 in Study 3-Sample 2; e.g., “I find myself continuing to work after my co-workers have called it quits”). Items were rated on a seven-point scale ranging from 1 (never) to 7 (always).

Psychological detachment (Study 3) was assessed with a scale developed by Sonnentag and Fritz (2007). Following a common stem (i.e., “In the evening, after work, and when I am on a weekend/vacation…”), four items (α = .92 in Sample 1 and α = .87 in Sample 2; e.g., “I forget about work”) were rated on a five-point scale ranging from 1 (totally disagree) to 5 (totally agree).

Work motivation (Study 1) was measured with the Gagné et al.’s (2015) Multidimensional Work Motivation Scale. This questionnaire includes 19 items, all rated on a seven-point scale ranging from 1 (does not correspond at all) to 7 (corresponds very strongly). This instrument assesses six dimensions of work motivation: Intrinsic motivation (three items, α = .89; e.g., "Because I have fun engaging in my job"), identified regulation (three items, α = .57; e.g., "Because putting efforts in my job has personal significance to me"), introjected regulation (four items, α = .67; e.g., "Because I have to prove to myself that I can"), external-social regulation (three items, α = .74; e.g., "To avoid being criticized by others"), external-material regulation (three items, α = .64; e.g., "Because others will reward me financially only if I put enough effort in my work"), and amotivation (three items, α = .75; e.g., "I do little because I don't think my job is worth putting efforts into").

Supervisor support (Studies 1 and 3) was assessed using a four-item measure developed by Caesens et al. (2014; α = .89 in Studies 1 and 3-Sample 2, and α = .88 in Study 3-Sample 1; e.g., "My supervisor really cares about my well-being"). All items were rated on a seven-point response scale ranging from "*Strongly Disagree*" to "*Strongly Agree*".

LMX (Study 2) was assessed with a scale (Liden & Maslyn, 1998) assessing the four dimensions of loyalty (four items; e.g., "My supervisor defends my work actions to a superior, even without complete knowledge of the issue in question"), affect (four items; e.g., "I like my supervisor very much as a person"), contribution (four items; e.g., "I do work for my supervisor that goes beyond what is specified in my job description"), and professional respect (four items; e.g., "I admire my supervisor's professional skills"). Items were rated on a five-point scale (1 – strongly disagree; 5 – strongly agree). In line with our objectives, we only rely on the global LMX score (α = .93 in Sample 1 and α = .91 in Sample 2).

Need frustration (Study 2) was assessed with the nine-item Psychological Need Frustration at Work Scale (Gillet et al., 2012). Three items assessed the need for competence (e.g., "It happens that I hear things that make me feel incompetent"), three items assessed the need for autonomy (e.g., "I feel forced to behave in a certain way"), and three items assessed the need for relatedness (e.g., "I think other people hate me"). Responses were rated on a seven-point scale ranging from 1 (strongly disagree) to 7 (strongly agree). In line with our objectives, we only rely on the global need frustration score (α = .88 in Samples 1 and 2).

Workload (Study 3) was assessed with five items (α = .90 in Sample 1 and α = .87 in Sample 2; e.g., "How often does your job require you to work very hard?") developed by Spector and Jex (1998) and rated on a five-point scale ranging from 1 (never) to 5 (always).

Work performance (Studies 1-3) was self-reported by the participants on a single item developed by Kessler et al. (2003) asking them: "On a scale ranging from 1 to 10, how would you rate you work performance over the past four weeks? (with 0 reflecting the worst work performance anyone could have and 10 the performance of a top worker)".

Emotional exhaustion (Studies 1 and 3) was assessed with five items (α = .90 in Study 1, α = .91 in Study 3-Sample 1; α = .87 in Study 3-Sample 2; e.g., "I feel emotionally drained by my work") from the Maslach Burnout Inventory-General Survey (Schaufeli et al., 1996). Items were rated on a 1 (strongly disagree) to 5 (strongly agree) scale.

Perceived stress (Study 2) was assessed with four items (α = .83 in Sample 2; e.g., "How often have you felt that you were unable to control the important things in your life?") developed by Cohen et al. (1983). Reponses are made on a scale ranging from 1 (never) to 5 (often) with reference to the frequency of events over the previous month.

Perceived health (Study 2) was assessed with four items (α = .84 in Sample 2; e.g., "In general, would you say that your health is: 1-poor, 2-fair, 3-good or 4-very good?"; Stewart & Ware, 1992).

Presenteeism (Study 3) was measured with the Stanford Presenteeism Scale (Koopman et al., 2002), which is made of six items (α = .95 in Samples 1 and 2; e.g., "Because of my health problems, the stresses of my job were much harder to handle"). Participants indicated their responses on a five-point Likert-scale ranging from 1 (strongly disagree) to 5 (strongly agree).

Work-family conflicts (Study 3) were measured with three items (α = .87 in Samples 1 and 2; e.g., "My work schedule makes it difficult for me to fulfill my domestic obligations?"; Huyghebaert et al., 2018b) rated on a seven-point scale (1- totally disagree to 7- totally agree).

Job satisfaction (Study 3) was measured with a single item (Shimazu et al., 2015) asking workers to report the extent to which they were satisfied with their job. Responses were made on a four-point scale (1 - unsatisfied to 4 - totally satisfied).

Analyses

Across all three studies, all analyses were realized using the Maximum Likelihood Robust (MLR) estimator available in Mplus 8.3 (Muthén & Muthén, 2019), which provides parameter estimates, standard errors, and goodness-of-fit indices that are robust to the non-normality of the response scales. Full Information Maximum Likelihood (FIML; Enders, 2010) procedures were used to handle the limited amount of missing responses (0 to 6.7% in Study 1; 0 to 0.5% in Study 2-Sample 1; 0 to 2.8% in Study 2-Sample 2; 1.3 to 13.1% in Study 3-Sample 1; and 0.3 to 15.6% in Study 3-Sample 2).

Measurement Models (Studies 1-3)

Following recommendations from past studies (Gillet et al., 2018), a series of a priori CFA and exploratory structural equation modeling (ESEM) solutions were estimated for the workaholism questionnaire, contrasting: (a) two-factor (working compulsively and excessively) CFA (Model 1) and ESEM (Model 2) solutions and (b) bifactor CFA (Model 3) and ESEM (Model 4) solutions including two S-factors (working compulsively and excessively) and one G-factor (global workaholism). In the CFA solution, items were only allowed to define their a priori factors, factors were allowed to correlate, and no cross-loadings were estimated. In the ESEM solution, the factors were defined as in the CFA model, all cross-loadings were freely estimated but assigned a target value of zero using an oblique target rotation procedure. In the bifactor CFA solution, items were allowed to define one a priori S-factor as well as one G-factor, and S-factors were specified as orthogonal (Morin et al., 2020). The bifactor ESEM solution was specified as its bifactor counterpart, although all cross-loadings involving the S-factors were freely estimated but assigned a target value of zero using an orthogonal bifactor target rotation procedure (Morin et al., 2016a). 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 item, factor loadings on G- and S-factors are typically lower than their first-order counterparts (Morin et al., 2020). As such, the critical question 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 at least some meaningful S-factors.

Given the known oversensitivity of the chi-square test of exact fit (χ^2) to sample size and minor model misspecifications (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): Comparative fit index (CFI), Tucker-Lewis index (TLI), and root mean square error of approximation (RMSEA) with 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. As noted by Morin and colleagues (Morin et al., 2016b, 2017, 2020), fit indices are not sufficient to guide the selection of the optimal model given the ability of each alternative model to absorb misfit due to unmodelled parameters (e.g., unmodelled cross-loadings can lead to inflated factor correlations, and an unmodelled G-factor can lead to inflated cross-loadings or factor correlations; Morin et al., 2020). Model comparison should start by contrasting first-order (i.e., non-bifactor) CFA and ESEM solutions. The ESEM solution should be retained when it results in well-defined factors and reduced factor correlations when compared to CFA. The second step involves contrasting the retained CFA or ESEM solution with its bifactor counterpart (Morin et al., 2020). Here, the key elements supporting a bifactor representation are the observation of: (1) an improved level of fit to the data; (2) a well-defined G-factor; and (3) some reasonably well-defined S-factors. Observing multiple cross-loadings higher than .100 or .200 in ESEM that are reduced in bifactor ESEM provides additional evidence favoring the bifactor solution (Morin et al., 2016a).

Once the optimal measurement model was identified, we verified its measurement invariance across samples and studies. The results from these tests are reported in Section 1 of the online supplements. Likewise, preliminary analyses were also conducted to verify the psychometric properties and measurement invariance of the multi-item covariates (correlated predictors or outcomes) used across all three studies. The results from these tests are reported in Section 2 of the online supplements. Across all studies, the profile indicators and the covariates (i.e., correlated predictors and outcomes) were incorporated to the main analyses as factor scores saved from these preliminary analyses. For all variables measured across both samples from a single study, these factor scores were saved from the most invariant measurement model (to ensure comparability across samples) in standardized units (i.e., $M = 0$, $SD = 1$). This approach allowed us to maintain some degree of control for measurement errors and to retain the bifactor properties of the measure (Morin et al., 2016b, 2017).

Predictive Analyses (Study 1)

In Study 1, predictive analyses involved the estimation of the direct effects of work motivation and supervisor support on employees' global levels of workaholism and specific levels of working excessively and compulsively, and of the direct effects of the workaholism G- and S-factors on employees' levels of emotional exhaustion and work performance. We also allowed work motivation and supervisor support to directly predict emotional exhaustion and work performance in order to avoid error propagation (i.e., forcing these unmodelled paths to be absorbed in order parts of the model) based on preliminary analyses indicating the need to incorporate these direct paths. To avoid the problems identified by Koch et al. (2018) for models in which covariates (i.e., work motivation and supervisor support) are used to predict bifactor constructs (i.e., workaholism), we relied on factor scores reflecting the global and specific facets of workaholism. For work motivation, we relied on a bifactor ESEM model in line with recent organizational studies (Fernet et al., 2020; Gillet et al., 2020c) demonstrating that bifactor ESEM made it possible to obtain a direct estimate of employees' global levels of self-determined work motivation and an equally direct estimate of the unique quality associated with each specific regulation in a way that matched SDT theoretical proposition (Fernet et al., 2020). Emotional exhaustion and supervisor support were specified as latent CFA factors (see Section 2 of the online supplements), whereas work performance was assessed with a single item.

Latent Profile Analyses (LPA; Studies 2 and 3)

In Studies 2 and 3, LPA were estimated using 5000 random sets of start values, 1000 iterations, and 200 final optimizations (Hipp & Bauer, 2006), and allowing the means and variances of the indicators to be freely estimated in all profiles (Diallo et al., 2016). These values were increased to 10000, 1000, and 500 for the multi-sample analyses. LPA solutions including one to eight profiles were first estimated separately in both samples from each study using the three workaholism factors (i.e., global workaholism, specific working excessively, and specific working compulsively), as well as psychological detachment in Study 3, to verify if the same number of profiles would be identified across samples.

To select the optimal number of profiles in each sample, we considered the theoretical conformity, meaning, and statistical adequacy of the alternative solutions (Marsh et al., 2009). Statistical indicators were also consulted (McLachlan & Peel, 2000). Lower values on the Bayesian Information Criterion (BIC), sample-size Adjusted BIC (ABIC), Akaïke Information Criterion (AIC), and Consistent AIC (CAIC) indicate a better fitting model. In addition, a statistically significant p-value on the Lo, Mendel, and Rubin (2001) Likelihood Ratio Test (aLMR) and on the Bootstrap Likelihood Ratio Test (BLRT) supports a solution relative to one including one fewer profile. Statistical studies support the accuracy of the CAIC, BIC, ABIC, and BLRT, but not that of the AIC and aLMR (Diallo et al., 2016, 2017). We thus report these indicators (AIC and aLMR) for complete disclosure, but do not use them to guide our decision. Furthermore, all indicators remain influenced by sample size, and often keep on suggesting the addition of profiles without converging on a specific model (Marsh et al., 2009). In this situation, the point at which the decrease in the value of these indicators reaches a plateau, on a graphical display called an elbow plot, can be used to suggest the optimal solution (Morin et al., 2011). Finally, the entropy (from 0 to 1) indicates the precision with which the cases are classified into the profiles, but should not be used to guide model selection.

Tests of Profile Similarity (Studies 2 and 3)

In both studies, once the optimal number of profiles has been selected in each sample, we integrated the two LPA solutions (one per sample) into a multigroup LPA to conduct systematic tests of profile similarity. These tests were conducted in the sequential strategy proposed by Morin et al. (2016c). The first step, corresponding to the sample-specific LPA, verifies if the same number of profiles can be identified in each sample (*configural* similarity). In the second step, the *structural* similarity of the profiles is verified by including equality constraints across samples on the means of the profile indicators to test whether the profiles retain the same shape across samples. The third step tests the *dispersion* similarity of the profiles by including equality constraints on the variances of the profile indicators to verify whether the within-profile variability remains comparable across samples. The fourth step tests the *distributional* similarity of the profiles by constraining the class probabilities to equality across samples to ascertain whether the relative size of the profiles remains unchanged.

Correlated Predictor Variables of Profile Membership (Studies 2 and 3)

Relations between the correlated predictor variables (LMX and need frustration in Study 2, and workload and supervisor support in Study 3) and profile membership were assessed using multinomial logistic regressions. In these analyses, the correlated predictor variables were directly integrated into the most similar multigroup LPA solution identified previously, and used to predict the likelihood of profile membership. Three alternative models were contrasted (Morin et al., 2016c) to test whether relations existed between correlated predictor variables and the profiles, and whether these relations could be assumed to generalize across samples. In the first model, the effects were fixed to be zero (null effects). In the second model, the effects were freely estimated across samples. In the third model, the effects were fixed to equality across samples (*predictive* similarity).

Correlated Outcome Variables of Profile Membership (Studies 2 and 3)

In Study 2, measures of the correlated outcomes were only available in Sample 2. Levels on these correlated outcomes (perceived stress, perceived health, and work performance) were thus contrasted across profiles using the three-step approach (Vermunt, 2010) implemented using Mplus' Auxiliary (DU3STEP) function (Asparouhov & Muthén, 2014). In contrast, correlated outcome measures were available in both samples in Study 3, making it possible to test of explanatory similarity (i.e., equivalence of associations between the profiles and the correlated outcomes across samples). To this end, the correlated outcomes (presenteeism, work-family-conflicts, emotional exhaustion, job satisfaction, and work performance) were directly incorporated into the most similar LPA solution, and used to contrast models in which the relations between profile membership and the correlated outcomes levels were either constrained to be equal (explanatory similarity) or not across samples (Morin et al., 2016c). The Mplus' MODEL CONSTRAINT function was used to test mean-level differences across profiles using the multivariate delta method (Raykov & Marcoulides, 2004).

Results

Measurement Models for Workaholism (Studies 1-3)

The goodness-of-fit results from the alternative models used to represent the workaholism measure in Studies 1 to 3 are reported in Table 1. The results support the superiority of the bifactor ESEM solution across all studies and samples, thus supporting Hypothesis 1. More details regarding the comparison between these alternative models are reported in the Studies 1 to 3 sections of the online supplements. Model-based coefficients of composite reliability (McDonald's, 1970 omega coefficient) also proved to be acceptable in this bifactor ESEM solution (global workaholism ω = .870 to .915; specific working excessively ω = .537 to .730; and specific working compulsively ω = .535 to .623; see Table 2). Importantly, the previous caveat regarding bifactor results also applies to estimates of reliability. Indeed, because construct-relevant (i.e., true score) variance is divided into two components (G- and S-), factor-specific reliability estimates (calculated as the ratio of true score variance by the total variance) will necessarily be lower in bifactor models, leading some (Perreira et al., 2018) to suggest more lenient interpretation guidelines (e.g., $\omega \geq .500$) for the S-factors.

Predictive Models (Study 1)

The goodness-of-fit indices from the predictive model were satisfactory [χ^2 (df) = 548.564 (321), CFI = .946, TLI = .917, and RMSEA = .045 (.039; .052)]. The results from this model are reported in Table 3. These results failed to support Hypothesis 6, showing that global levels of self-determination were associated with higher global levels of workaholism and that specific levels of external-material regulation were associated with lower specific levels of working excessively. Partially supporting Hypothesis 4, supervisor support was found to be associated with lower global levels of workaholism and emotional exhaustion, but not with specific levels of working compulsively and excessively. Global levels of workaholism were also associated with higher levels of emotional exhaustion, and specific levels of working compulsively were found to be associated with higher levels of performance, thus providing partial support for Hypothesis 9a. Finally, scores on the amotivation S-factor were associated with lower levels of performance and higher levels of emotional exhaustion.

Latent Profile Analyses (LPA; Studies 2 and 3)

The fit indices associated with the various LPA solutions, and their examination process, are reported in Section 3 of the online supplements. This examination supported the superiority of a four-profile solution across both samples from Study 2, as well as across both samples from Study 3, thus providing evidence of *configural* similarity across samples in both studies. The results from the multi-sample tests of profile similarity conducted on the basis of these four-profile solutions are reported in Table 4 (Study 2). Starting from the model of *configural* similarity, in Study 2, the next model of *structural* similarity resulted in lower CAIC, BIC, and ABIC values and was thus supported. Similarly, the next model of *dispersion* similarity also resulted in lower values on the CAIC, BIC, and ABIC, and was supported by the data. Finally, the model of *distributional* similarity resulted in lower values on the CAIC and BIC, indicating that the size of the profiles was similar across samples.

In Study 3, however, the model of *structural* similarity resulted in higher BIC and ABIC values relative to the previous model of *structural* similarity, and was thus not supported by the data. However, following a detailed examination of the parameter estimates from the previous model of *configural* similarity, an alternative model of partial *structural* similarity (in which the means from a single profile were allowed to differ across samples) was supported. From this model of partial *structural* similarity, the next model of *dispersion* similarity resulted in lower values on the CAIC, BIC, and ABIC, and was supported by the data. Finally, the model of *distributional* similarity resulted in lower values on the CAIC and BIC, indicating that the size of the profiles was similar across samples.

This model of *distributional* similarity (built from a model of partial *structural* similarity in Study 3) was thus retained for interpretation in both studies, thus answering our Research Question 1 by demonstrating the similarity of all (Study 2) or most (Study 3) of the identified profiles across samples. The results from this model are illustrated in Figure 2, and generally support Hypotheses 2 and 3. A first set of three profiles proved to be common to both studies. A first profile (Profile 2 in Study 2 and Profile 1 in Study 3) characterized employees with close to average global levels of workaholism, and specific levels of working excessively and compulsively, accompanied by average levels of psychological detachment in Study 3. This *Average Global and Specific Workaholism* profile corresponded to 37.99% of the sample in Study 2 and to 29.56% of the employees in Study 3. A second profile (Profile 4 in Study 2 and Profile 2 in Study 3) characterized employees with moderately high to high global levels of workaholism, average specific levels of working excessively, moderately low (Study 3) to average (Study 2) specific levels of working compulsively, and low levels of psychological detachment (Study 3). This *High Global and Average Specific Workaholism* profile corresponded to 49.10% of the sample in Study 2 and 15.10% of the employees in Study 3. A third profile (Profile 3 in both studies) characterized employees with low global levels of workaholism, average specific levels of working excessively and compulsively, and moderately high levels of psychological detachment (Study 3). This *Low Global and Average Specific Workaholism* profile corresponded to 7.95% of the sample in Study 2 and 27.26% of the employees in Study 3.

One additional profile only emerged in Study 2 (Profile 1), and characterized employees with very low global levels of workaholism, low specific levels of working compulsively, and moderately low specific levels of working excessively. This *Low Global and Specific Workaholism* profile was the smallest, corresponding to 4.96% of the sample in Study 2. In contrast, in Study 3, the last profile (Profile 4) was found to differ between samples of nurses and educators. Among nurses, this profile characterized those with moderately low levels of global workaholism, moderately high levels of specific working excessively and compulsively, and high levels of psychological detachment. In contrast, among educators, this profile characterized those with average levels of global workaholism and specific working compulsively, moderately low levels of specific working excessively, and low levels of psychological detachment. This *Low Global Workaholism/High Specific Workaholism and Psychological Detachment* (Sample 1: Nurses) and *Average Global Workaholism/Low Specific Workaholism and Psychological Detachment* (Sample 2: Educators) corresponded to 28.08% of the employees in both samples in Study 3.

Correlated Predictors of Profile Membership (Studies 2 and 3)

As shown in Table 4, the analyses related to the associations between the correlated predictor variables (global levels of LMX and need frustration in Study 2, and workload and supervisor support in Study 3) and participants' likelihood of profile membership are consistent with the presence of associations between these variables that generalize across samples in Study 2 (i.e., the model of *predictive* similarity resulted in the lowest values for the CAIC, BIC, and ABIC), but that differ across samples in Study 3 (i.e., the model allowing for the free estimation of these associations across samples resulted in the lowest AIC, BIC, and ABIC values when compared to the alternative models). The results from these models are reported in Table 5.

In Study 2, these results first support Hypothesis 5 by revealing that perceptions of global LMX predicted an increased likelihood of membership into the *High Global and Average Specific Workaholism* relative to the *Low Global and Specific Workaholism* and to the *Low Global and Average Specific Workaholism* profiles, as well as into the *Average Global and Specific Workaholism* profile relative to the *Low Global and Specific Workaholism* profile. In addition, global levels of need frustration predicted an increased likelihood of membership into the *High Global and Average Specific Workaholism* profile relative to all other profiles, thus partially supporting Hypothesis 7.

In Study 3, some of the associations involving workload proved to generalize across samples and provided support for Hypothesis 8. Thus, higher workload perceptions predicted a decreased likelihood of membership into the *Low Global and Average Specific Workaholism* profile relative to the *Average Global and Specific Workaholism*, *High Global and Average Specific Workaholism*, *Low Global Workaholism/High Specific Workaholism and Psychological Detachment* (Sample 1), and *Average Global Workaholism/Low Specific Workaholism and Psychological Detachment* (Sample 2) profiles across samples. Furthermore, in Sample 2, higher workload perceptions also increased the likelihood of membership into the *Average Global and Specific Workaholism* and *High Global and Average Specific Workaholism* profiles relative to the *Average Global Workaholism/Low Specific Workaholism and Psychological Detachment* profile, as well as into the *High Global and Average Specific Workaholism* profile relative to the *Average Global and Specific Workaholism* profile.

Still in Study 3, in relation to perceptions of supervisor support, our results failed to support Hypothesis 4, and revealed widespread associations with profile membership in Sample 1, but no associations with profile membership in Sample 2. Thus, in Sample 1, perceptions of supervisor support predicted a decreased likelihood of membership into the *Low Global and Average Specific Workaholism* profile relative to the *Average Global and Specific Workaholism*, *High Global and Average Specific Workaholism*, and *Low Global Workaholism/High Specific Workaholism and Psychological Detachment* profiles. In addition, perceived supervisor support predicted a decreased likelihood of membership into the *High Global and Average Specific Workaholism* and *Low Global and Average Specific Workaholism* profiles relative to the *Low Global Workaholism/High Specific Workaholism and Psychological Detachment* profile, and an increased likelihood of membership into the *Average Global and Specific Workaholism* profile relative to the *High Global and Average Specific Workaholism* and *Low Global and Average Specific Workaholism* profiles.

Correlated Outcomes of Profile Membership (Studies 2 and 3)

The results of the associations between participants' profile membership and their levels on the various correlated outcome variables considered in Study 2-Sample 2 are reported in Figure 3a (see also Table S10 in Section 4 of the online supplements). First, participants' perceived health levels were found to be lower in the *Low Global and Specific Workaholism* and *High Global and Average Specific Workaholism* profiles, which did not differ from one another, in comparison to the *Average Global and Specific Workaholism* and *Low Global and Average Specific Workaholism* profiles, which also did not differ from one another. Second, participants' levels of perceived stress were found to be lower in the *Low Global and Specific Workaholism* and *Average Global and Specific Workaholism* profiles, which did not differ from one another, in comparison to the *Low Global and Average Specific Workaholism* and *High Global and Average Specific Workaholism* profiles, which also did not differ from one another. Finally, participants' levels of work performance were found to be lower in the *Low Global and Specific Workaholism* and *Average Global and Specific Workaholism* profiles, which did not differ from one another, in comparison to the *High Global and Average Specific Workaholism* profile, while the *Low Global and Average Specific Workaholism* profile did not differ from the *Low Global and Specific Workaholism* and *Average Global and Specific Workaholism* profiles.

As shown in the bottom section of Table 4, the analyses related to the associations between profile membership and the correlated outcome variables considered in Study 3 failed to support a model of complete *explanatory* similarity. However, they supported a model of partial *explanatory* similarity in which profile-specific outcomes levels were found to be similar across samples for Profiles 1 to 3, but differed across samples for Profile 4 (which has a distinct structure across samples). The results from this solution are reported in Figure 3b (see also Table S11 in Section 4 of the online supplements). Turning first our attention to comparisons between the first three profiles, in both samples, participants' levels of presenteeism, work-family-conflicts, and emotional exhaustion were found to be the highest in the *High Global and Average Specific Workaholism* profile, followed by the *Average Global and Specific Workaholism* profile, and finally by the *Low Global and Average Specific Workaholism* profile. Conversely, participants' levels of work performance and job satisfaction were found to be the highest in the *Low Global and Average Specific Workaholism* profile, followed by the *Average Global and Specific Workaholism* profile, and finally by the *High Global and Average Specific Workaholism* profile.

In Study 3-Sample 1, participants' levels of presenteeism, work-family-conflicts, and emotional exhaustion were found to be the lowest in the *Low Global Workaholism/High Specific Workaholism and Psychological Detachment* profile. Conversely, participants' levels of work performance were found to be the highest in the *Low Global Workaholism/High Specific Workaholism and Psychological*

Detachment profile. In addition, participants' levels of job satisfaction were found to be the highest in the *Low Global Workaholism/High Specific Workaholism and Psychological Detachment Low Global Workaholism/High Specific Workaholism and Psychological Detachment* but the *Low Global Workaholism/High Specific Workaholism and Psychological Detachment* and *Low Global and Average Specific Workaholism* profiles did not differ from one another.

In Study 3-Sample 2, the *Average Global and Specific Workaholism* and *Average Global Workaholism/Low Specific Workaholism and Psychological Detachment* profiles did not differ from one another on presenteeism, work-family conflicts, emotional exhaustion, work performance, and job satisfaction. In addition, the *Low Global and Average Specific Workaholism* and *Average Global Workaholism/Low Specific Workaholism and Psychological Detachment* profiles did not differ from one another on work performance. Participants' levels of work performance were also found to be higher in the *Average Global Workaholism/Low Specific Workaholism and Psychological Detachment* profile relative to the *High Global and Average Specific Workaholism* profile.

Finally, still in Study 3, presenteeism, work-family conflicts, and emotional exhaustion were higher in the *Average Global Workaholism/Low Specific Workaholism and Psychological Detachment* profile in Sample 2 relative to the *Low Global Workaholism/High Specific Workaholism and Psychological Detachment* profile in Sample 1. Conversely, work performance was lower in the *Average Global Workaholism/Low Specific Workaholism and Psychological Detachment* profile in Sample 2 relative to the *Low Global Workaholism/High Specific Workaholism and Psychological Detachment Low Global Workaholism/High Specific Workaholism and Psychological Detachment* profile in Sample 1. Moreover, the *Low Global Workaholism/High Specific Workaholism and Psychological Detachment* profile in Sample 1 and *Average Global Workaholism/Low Specific Workaholism and Psychological Detachment* profile in Sample 2 did not differ from one another on job satisfaction. Taken together, these results generally provided support for Hypothesis 9.

Discussion

The present research adopts a dual variable- and person-centered approach, as proposed by Morin et al. (2017), to specifically investigate the value of jointly considering global and specific dimensions of the workaholism construct. Through the application of this framework, we were able to achieve an improved representation of the structure of employees' workaholism measurement and profiles. A Table summarizing our main hypotheses and their level of support is provided in the Appendix.

Workaholism as a Multidimensional Construct

The need to take into account the working excessively and working compulsively components of workaholism has long been acknowledged (Schaufeli et al., 2009b). Likewise, recent research has supported a bifactor operationalization of workaholism, allowing of a representation of workaholism as a global entity reflecting commonality among ratings of working excessively and compulsively, but also for a direct estimation of the specificity remaining at the level of each specific subscale (Gillet et al., 2018; Tóth-Király et al., 2020). However, questions remained regarding whether each of those components retained a meaningful level of specificity allowing them to bring added value to the understanding of associations between workaholism and other constructs. The present research was designed to further investigate this issue.

In the present research, our results confirmed our expectations and replicated the conclusions from previous studies (Gillet et al., 2018; Tóth-Király et al., 2020) in supporting the superiority of a bifactor representation of workaholism across five independent samples of employees. This solution revealed co-existing factors representing global levels of workaholism and specific levels of working excessively and compulsively left unexplained by global levels of workaholism. In this solution, the global factor (workaholism) and the specific working excessively factors both appeared to be well-defined, supporting the idea that ratings of working excessively contributed to the assessment of global workaholism levels while retaining something unique beyond their contribution to global workaholism levels. This unique contribution could, logically, come to reflect excessive work that sometimes tends to happen in disconnection from workaholism. In contrast, the working compulsively S-factor was more weakly defined, suggesting that ratings of working compulsively mainly served to define global workaholism levels without retaining a lot of unicity beyond these global levels. This suggest that working compulsively rarely happens in disconnection from workaholism.

In terms of criterion-related validity, the results obtained in Study 1 revealed that the relations between work motivation, supervisor support, emotional exhaustion, and work performance, and the workaholism components mainly involved employees' global levels of workaholism. More specifically, in accordance with prior research (Gillet et al., 2018; Tóth-Király et al., 2020), the workaholism G-factor was found to predict higher levels of emotional exhaustion, whereas none of the remaining S-factors (working excessively and compulsively) further contributed to this prediction. Likewise, perceived supervisor support and employees' global levels of self-determined work motivation were both significantly related to employees' global levels of workaholism.

Although the negative effects of perceived supervisor support on employees' global levels of workaholism matched our expectations (Gillet et al., 2018; Sandrin et al., 2019a), the positive effects of employees' global levels of self-determined work motivation on their global levels of workaholism were not aligned with our expectations. However, although the bulk of prior research does support the idea that workaholism tends to be mainly driven by controlled types of motivation (van Beek et al., 2011), other studies have also revealed, like Study 1, positive associations between self-determined work motivation and workaholism (Endriulaitienė & Morkevičiūtė, 2020). These results thus suggest that the motivational pattern that underpins workaholism might be more complex than previously thought, and might involve a combination of autonomous and controlled forms of motivation (Van den Broeck et al., 2011). Indeed, workers may volitionally invest many hours in their jobs because their work is aligned with their personal values and objectives, and because they see it as important and interesting (van Beek et al., 2011). However, they may also be strongly motivated by gaining supervisors' approval, peer admiration, and prestige (Spence & Robbins, 1992) and decreasing their feelings of anxiety, guilt, and shame (Porter, 2004). The present results, showing that workaholism was mainly predicted by the global self-determination G-factor, underpinned by employees' ratings of all types of motivation, but not by any specific type of autonomous or controlled motivation, seems to match this hypothesis. Additional studies will be needed to better understand the complex mechanisms underlying the role played by work motivation in workaholism (Clark et al., 2020).

More generally, the results from Study 1 support the criterion-related validity of the workaholism G-factor but call into question the need to consider the specific levels of working excessively and compulsively, once employees' global levels of workaholism are considered. Yet, these results suggest that, at least as far as perceived supervisor support, global self-determined motivation, emotional exhaustion, and work performance are concerned, these specific components do not play a role in prediction once global workaholism levels are considered, with one exception. Indeed, the results also showed that specific levels of working compulsively helped increase work performance, in a way that suggests that working compulsively might carry some benefits in terms of performance, despite the emotional toll taken by global levels of workaholism. Studies 2 and 3 sought to further verify this assertion while relying on a more holistic person-centered approach.

Workaholism Profiles

The results showed that four profiles best summarized the workaholism configurations presenting clear qualitative differences that were fully replicated across samples in Study 2: (1) *Low Global and Specific Workaholism*, (2) *Average Global and Specific Workaholism*, (3) *Low Global and Average Specific Workaholism*, and (4) *High Global and Average Specific Workaholism*. This evidence of replication thus provides a first source of evidence suporting the construct validity of these profiles. In Study 3, we investigated the extent to which these four profiles would be replicated using a more stringent approach involving the incorporation of an additional profile indicator (psychological detachment). Supporting the robustness of the identified profiles to the incorporation of additional indicators, results led to the identification of three profiles corresponding to the last three profiles identified in Study 2. Importantly, these three profiles were characterized by matching levels across all three (Study 2) or four (Study 3) profile indicators, and displaying a *High Global and Average Specific Workaholism*, *Average Global and Specific Workaholism*, and *Low Global and Average Specific Workaholism* configuration. The observation of matching levels across indicators is consistent with the complementarity of these four components, and with the previous reports of high correlations among them (Huyghebaert et al., 2018a). In addition, the replication of these profiles across studies, despite the added consideration of psychological detachment in Study 3, supports the idea, advanced in the introduction of Study 3, that these profiles reflect some overarching psychological mechanisms likely to be associated with the workaholism process irrespective of the specific mechanisms considered in their definition. This conclusion also matches the similarity in workaholism profiles identified in previous person-centered studies (Gillet et al., 2017; Schaufeli et al., 2009a), while allowing us to separately consider the role played by global and specific workaholism components, a distinction which was not considered in these previous investigations. Likewise, this observation also reinforces the generalizability of these processes to different samples of employees, and thus their potential utility as guides to the development of generic interventions seeking to impede the workaholism process (Meyer & Morin, 2016).

However, the fourth profile identified in Study 3 did not correspond to the *Low Global and Specific Workaholism* profile identified in Study 2. Rather, this fourth profile appeared to be characterized by moderately low levels of global workaholism, moderately high levels of specific working excessively and compulsively, and high levels of psychological detachment (*Low Global Workaholism/High Specific Workaholism and Psychological Detachment*) in the nurses sample, and by average levels of global workaholism and specific working compulsively, moderately low levels of specific working excessively, and low levels of psychological detachment (*Average Global Workaholism/Low Specific Workaholism and Psychological Detachment*) in the educators sample, possibly reflecting the greater level of work investment required by nursing and education relative to the occupations covered in Study 2 (Taris et al., 2012). In addition, this last profile was found to display a distinct configuration among nurses and educators, thus supporting the idea that the work context does seem to have an influence on the emergence of specific workaholism profiles (Clark et al., 2016).

Among this profile of non-workaholic nurses able to psychologically detach from work, at least some level of excessive work and of compulsive thinking about work might be required as part of the job. In contrast, among educators, this profile describes employees presenting more balanced specific levels of working excessively and compulsively. Interestingly, both profiles seemed to describe roughly a fourth of each sample in Study 3. Thus, when we consider the whole set of results, it seems that roughly 50% of the nurses can be considered to correspond to a non-workaholic profile (i.e., *Low Global and Average Specific Workaholism* and *Low Global Workaholism/High Specific Workaholism and Psychological Detachment* profiles), relative to only 27% of the educators (*Low Global and Average Specific Workaholism* profile). In contrast, globally average levels of workaholism seem to be more frequent among educators (58%: *Average Global and Specific Workaholism* and *Average Global Workaholism/Low Specific Workaholism and Psychological Detachment* profiles) than among nurses (30%). These findings are aligned with prior research suggesting that levels of workaholism tend to be higher, and those of psychological detachment lower, among educators (Gu et al., 2020; Nie & Sun, 2016) because of their constant exposition to job demands (e.g., regular instructional duties, time demands, behavioral management) that deplete their resources (Hobfoll, 2002). Indeed, under high levels of job demands, educators have a harder time mentally disengaging from work during nonwork time due to increased negative activation (negative affect). This negative activation can also result in attempts to deal with the job demands or involvement in additional work tasks (e.g., helping an isolated child who has been victimized) during nonwork time (Sonnentag & Fritz, 2015).

More generally, the identification of this profile highlights the often-noted importance of replication in person-centered analyses in order to be able to identify the core set of profiles that will tend to emerge across all situations, as well as the secondary set of profiles that will tend to appear only in specific situations (Meyer & Morin, 2016). Yet, it would appear particularly important for future investigations to consider additional profile indicators (e.g., work engagement, work-related rumination) and to more systematically understand the work-related characteristics at play in the emergence of these specific profiles, as well as the additional specific occupational groups among which those profiles might emerge more frequently.

Although the identified profiles were mainly differentiated in relation to employees' global levels of workaholism, which seems to argue against the added value of simultaneously considering the working excessively and compulsively S-factors, some of our results still highlight the value of jointly considering global and specific facets of workaholism. When interpreting these results, the bifactor nature of the workaholism S-factors needs to be taken into account. Indeed, these S-factors do not reflect the extent to which employees tend to work excessively or compulsively, but rather the extent to which scores on these dimensions deviate from employees' global levels of workaholism. As such, a score of 0 illustrates a perfect alignment with the workaholism G-factor, whereas positive and negative scores reflect some degree of imbalance.

More precisely, our results revealed that employees with low (*Low Global and Average Specific Workaholism* and *Low Global Workaholism/High Specific Workaholism and Psychological Detachment* profiles) or high (*High Global and Average Specific Workaholism* profile) displayed a more imbalanced configuration where specific levels of working excessively and compulsively tended to show more pronounced deviations from the global levels of workaholism observed in these profiles. Conversely, employees characterized by the *Low Global and Specific Workaholism* and *Average Global Workaholism/Low Specific Workaholism and Psychological Detachment* profiles displayed a more balanced configuration. This is also the case for the *Average* profile (i.e., close to average with well-aligned global and specific levels of workaholism). In particular, the identification of this profile suggests that global levels of workaholism remain minimal and aligned across dimensions for nearly a third of the sample in Studies 2 and 3. This finding is aligned with results from past studies of work engagement (Gillet et al., 2019a, 2020a), well-being and psychological health (Morin et al., 2016b, 2017), interactional justice (Fouquereau et al., 2020), emotional labor (Fouquereau et al., 2019) or need satisfaction (Gillet et al., 2019b), in which a similarly average profile was also found to characterize a significant proportion of employees.

More generally, although specific levels of working excessively and compulsively seemed to matter more for our profiles than they did in the Gillet et al.'s (2017) study, they remained secondary to the role played by global levels of workaholism. Nevertheless, as in Study 1, results from Studies 2 and 3 suggest that distinguishing between global and specific facets of workaholism does help us to achieve a slightly better understanding of workaholism, but only for a subset of employees.

Correlated Predictor Variables of Workaholism Profiles

The results also provided some practical guidance by documenting the relations between profile membership and psychological need frustration, LMX, supervisor support, and workload. Interestingly, these results identified psychological need frustration as a core correlated predictor variable of profile membership in Study 2. More specifically, in alignment with SDT (Ryan & Deci, 2017), which assumes that psychological need frustration is associated with higher levels of controlled motivation, the present results first showed that global need frustration predicted an increased likelihood of membership into the *High Global and Average Specific Workaholism* profile relative to all other profiles. These results lend additional support to previous research having demonstrated the detrimental role of need frustration for employees (Gillet et al., 2017).

Workload was also found to predict a decreased likelihood of membership into the *Low Global and Average Specific Workaholism* profile relative to the *Average Global and Specific Workaholism, High Global and Average Specific Workaholism, Low Global Workaholism/High Specific Workaholism and Psychological Detachment* (nurses sample in Study 3), and *Average Global Workaholism/Low Specific Workaholism and Psychological Detachment* (educators sample in Study 3) profiles. These results are generally aligned with those from previous studies showing that job demands tend to be associated with higher levels of workaholism and lower levels of psychological detachment (Gillet et al., 2017; Sonnentag & Fritz, 2015). This association has been explained by the fact that job demands tend to require effortful regulatory processes (Hobfoll, 2002) likely to disrupt workers' concentration and to increase their feelings of rumination. Job demands may thus directly increase the time spent at work or dedicated to work during off-job time (Huyghebaert et al., 2018a).

Furthermore, employees' perceptions of global LMX predicted a decreased likelihood of membership into the *Low Global and Specific Workaholism* profile relative to the *Average Global and Specific Workaholism* and *High Global and Average Specific Workaholism* profiles, as well as into the *Low Global and Average Specific Workaholism* profile relative to the *High Global and Average Specific Workaholism* profile. Study 3's results also revealed that supervisor support predicted an increased likelihood of membership into the profiles characterized by average levels of workaholism relative to profiles characterized by more extreme levels (high or low) of workaholism, but only among nurses. To better understand this result, Liu et al. (2011) suggested that employees' LMX perceptions (or supervisor support) may depend on the way they perceive the quality of their colleagues' exchange relationships with their supervisors (i.e., their colleagues' LMX). Thus, perceived equity in terms of LMX may moderate the impact of LMX (or supervisor support), such that the effects of LMX (or supervisor support) on workaholism profiles might be stronger when an employee feels being favored relative to his or her coworkers. This form of favorable inequity might reflect a more personal relationship (Boies & Howell, 2006), leading employees to value this relationship more, thus leading them to invest even more time and energy at work as a way to preserve this relationship. These results are particularly interesting given that the bulk of prior research has generally positioned LMX or supervisor support as positive drivers of work-related correlated outcome variables in a "the more, the better" perspective (Caesens et al., 2014; Liden & Maslyn 1998). Furthermore, our findings are aligned with previous studies showing that constructive leadership behaviors may be associated with negative outcomes (Caesens et al., 2020; Carnevale et al., 2020), and match results previously reported by Gillet et al. (2017) regarding associations between supervisor support and membership into profiles characterized by higher levels of workaholism.

Our results thus seem to advocate a more nuanced view of the desirability of perceived supervisor support and LMX, suggesting that the benefits of these types of leadership characteristics might not generalize to all correlated outcome variables (Caesens et al., 2020), or might follow curvilinear relationships where "just enough" might be better than "too much" (Carnevale et al., 2020). Interestingly, these interpretations also help to make sense of the apparent discrepancy in results obtained across Studies 1 and 3 in relation to the role played by supervisor support, and suggest that some of these unexpected associations might only emerge in the context of person-centered analyses in which all workaholism components are simultaneously considered. However, it would be interesting for future research to devote more attention to unpacking the mechanisms involved in the effects of LMX and supervisor support, as well as those of other forms of other positive types of leadership behaviors in order to achieve a clearer understanding of the conditions under which they might lead to more, or less, desirable correlated outcome variables.

Correlated Outcome Variables of Profile Membership

Our results finally revealed well-differentiated associations between the workaholism profiles and correlated outcome variables. In both studies, the profiles characterized by low to very low global levels of workaholism were associated with the most adaptive correlated outcome variables (e.g., low levels of perceived stress, emotional exhaustion, and work-family conflicts). These findings confirm the detrimental effects of global levels of workaholism (Clark et al., 2016) and the positive effects of psychological detachment (Sonnentag & Fritz, 2015). Indeed, workers presenting low levels of workaholism and high levels of psychological detachment are generally described as joyful and satisfied, which in turn increase their likelihood of experiencing desirable correlated outcome variables (Clark et al., 2020). More generally, our results confirm the utility of taking into account both global and specific facets of workaholism coupled with psychological detachment when studying the outcome implications of workaholism profiles.

Indeed, in relation to the outcomes' implications of the three profiles characterized by different global and specific levels of workaholism (*Low Global and Average Specific Workaholism*, *Low Global Workaholism/High Specific Workaholism and Psychological Detachment*, and *High Global and Average Specific Workaholism* profiles), it does not appear to be sufficient to consider the global levels without also considering the specific facets. For instance, employees characterized by a *Low Global and Average Specific Workaholism* profile displayed higher levels of presenteeism, work-family conflicts, and emotional exhaustion, as well as lower levels of work performance than those within the *Low Global Workaholism/High Specific Workaholism and Psychological Detachment* profile. Yet, although these two profiles are characterized by similarly low levels of global workaholism, they still differ in their specific levels of working excessively and compulsively. More specifically, the *Low Global and Average Specific Workaholism* profile characterized employees with average levels of specific working excessively and compulsively, whereas the *Low Global Workaholism/High Specific Workaholism and Psychological Detachment* profile is characterized by moderately high levels of specific working excessively and compulsively. Importantly, this difference appears to be associated with slightly lower levels of psychological detachment in the *Low Global and Average Specific Workaholism* profile, in turn leading to less desirable correlated outcomes levels (Sonnentag & Fritz, 2015). This observation is aligned with the results obtained in Study 1 showing that specific levels of working compulsively were associated with higher levels of work performance.

It is noteworthy that our results seem to support the idea that the *Average Global and Specific Workaholism* profile may be associated with positive correlated outcome variables. This conclusion is consistent with the SDT research litterature (Gillet et al., 2019b), which has often shown (when focusing on need satisfaction: Sheldon & Niemiec, 2006) the benefits of having a more equilibrated (or balanced) approach to work (i.e., close to average and well-aligned levels of global and specific workaholism) rather than a more extreme (low or high) and imbalanced configuration. Therefore, balance across workaholism facets may stem from a more thoughtful allocation of work resources, which may in turn limit work-related stress and conflicts, thus leading to more adaptive functioning.

More generally, the present results also suggest that the combined role played by global and specific facets of workaholism and psychological detachment may differ as a function of the correlated outcome variables under study. This observation reinforces the importance for future research to incorporate a broader range of positive (e.g., organizational citizenship behaviors, creativity) and negative (e.g., absenteeism, counterproductive behaviors) correlated outcome variables to better understand the mechanisms underlying these different relations.

Practical Implications

From an intervention perspective, our findings demonstrate that managers should be particularly attentive to employees exposed to, or rather perceiving being exposed to, high levels of workload, and even more importantly high levels of psychological need frustration. Indeed, our results showed that these workers were more likely to experience higher global levels of workaholism, in turn leading them to experience negative correlated outcome variables. Consequently, changes designed to reduce workload and need frustration sustainably might decrease workaholism in the long run. Among possible ways to achieve this objective, supervisors might promote a supportive culture, for instance, by promoting fairness in the application of policies (Eisenberger et al., 2002). Informal mentoring activities and social events might also help to build a stronger workplace support climate among employees (Newman et al., 2012). The endpoint of these strategies is to create a workplace characterized by supportive and positive interactions among colleagues (Newman et al., 2012). However, caution is needed in relation to the implementation of interventions seeking to increase the provision of supervisor support or to the development of high levels of LMX, as high levels on these dimensions seem to be associated with less desirable workaholism profiles among specific employees.

In terms of research implications, our results thus suggest that at least three profiles seem to routinely emerge across various types of occupations (*Low Global and Average Specific Workaholism*, *Average Global and Specific Workaholism*, and *High Global and Average Specific Workaholism*). The nature of these profiles seems to remain essentially unchanged when additional variables are taken into account in the analytic process (i.e., psychological detachment). In addition, three additional profiles seem to emerge within more specific occupational groups (*Low Global and Specific Workaholism*: Firefighters and office workers; *Low Global Workaholism/High Specific Workaholism and Psychological Detachment:* Nurses; *Average Global Workaholism/Low Specific Workaholism and Psychological Detachment:* Educators). As such, the present studies represent a first step toward the identification of the most commonly observed workaholism configurations. However, more research would be needed to more systematically understand the work-related characteristics at play in the emergence of these specific profiles, as well as the additional specific occupational groups among which those profiles might emerge more frequently.

In terms of psychological assessment, our results indicate that a bifactor approach is required to avoid obtaining workaholism estimates capturing a confusing blend of variance attributed to global and specific components likely to be contaminated by multicollinearity. Indeed, failure to account for this form of multidimensionality is likely to mistakenly suggest that the working excessively and compulsively facets of workaholism are reasonably distinct constructs without a common core and yet displaying comparable associations with correlated outcome variables (Morin et al., 2016b, 2017). This erroneous conclusion would stem from the unmodelled role played by global workaholism levels, and serve to obscure the important role played by specific workaholism components. Ignoring this duality will thus result in a biased, and far more limited, view of the complex reality of the workaholism construct. This conclusion reinforces the value of latent variable methods. However, although latent variable methodologies are straightforward to apply in a research context, these approaches do not naturally lend themselves to the requirements of practitioners who want to obtain manifest scores on workaholism measures. For such purposes, scoring procedures will need to be developed using calculations similar to those used to generate factor scores (Perreira et al, 2018), possibly via the development of online calculators. Scores obtained using this approach will be naturally standardized and easy to interpret in relation to the sample means and variances, at least pending the formal development of more representative interpretative norms.

Limitations and Future Directions

Although the present research offers the first investigation of the characteristics, and of the correlated predictor and outcome variables, of employees' workaholism and workaholism profiles defined using global and specific workaholism levels, it has some limitations. First, this research capitalized on self-report measures, which may have been influenced by self-reported biases and social desirability. For instance, the inconsistent findings regarding the effects of global and specific facets of workaholism on work performance might be linked to the self-report assessment of work performance used in the present research. Indeed, past studies have already demonstrated a positive effect of workaholism on work performance by relying on supervisor ratings of employees' performance through the company's established performance appraisal system (Balducci et al., 2020). In contrast, prior research has shown that workaholism was negatively related to work performance assessed with a self-report measure (Shimazu & Schaufeli, 2009). Upcoming studies should thus incorporate more objective indicators of organizational and individual functioning (e.g., absenteeism), as well as ratings obtained from multiple informants (e.g., supervisors' ratings of performance) to explain the effects of workaholism on various correlated outcome variables. Second, this research involved five samples of mixed workers, administrative and technical employees, firefighters, nurses, and educators. Other variable- and person-centered studies are still needed to confirm the generalizability of the results demonstrated here and their relations with a broader range of correlated predictor and outcome variables across a variety of countries, cultures, and occupations (e.g., teachers, sales employees, managers) (Morin et al., 2016c).

Third, we examined variables considered to be predictors or outcomes on the basis of theoretical and empirical considerations (Clark et al., 2016; Ryan & Deci, 2017). Although our approach made it possible to rule out possible effects of these predictors on workaholism components, our study design and the limitations inherent to our analytical method did not allow us to assess possible spurious associations, reversed causality, or reciprocal influence, nor the eventuality of workaholism impacting variations in the outcomes. The cross-sectional nature of our study is why we referred to these covariates as correlated predictor and outcome variables, rather than simply as predictors and outcomes. Consequently, additional longitudinal research would gain from studying the direction of the relations between predictor and outcome variables and workaholism. Longitudinal research would also make it possible to confirm that the workaholism profiles identified here are similar in terms of number, size, characteristics, variability, and associations with predictors and outcomes over time, and to test whether profile membership remains stable over time for specific employees. For instance, it would be interesting to test in a diary study whether a profile characterized by low global and specific levels of workaholism is more or less stable than a profile characterized by low global and specific levels of workaholism coupled with high levels of psychological detachment. Indeed, Chawla et al. (2020) examined the dynamic nature of profiles of daily recovery experiences and found a high variation in profile membership stability across days. To the best of our knowledge, no person-centered research has yet examined the stability of workaholism profiles over time but this represents a promising avenue for future studies. Finally, we only considered five correlated predictor variables (LMX, need frustration, motivation, workload, and supervisor support). It would be worthwhile for future studies to consider a greater variety of work-related (e.g., other leadership behaviors) or individual (e.g., perfectionism, job crafting) correlated predictor variables.

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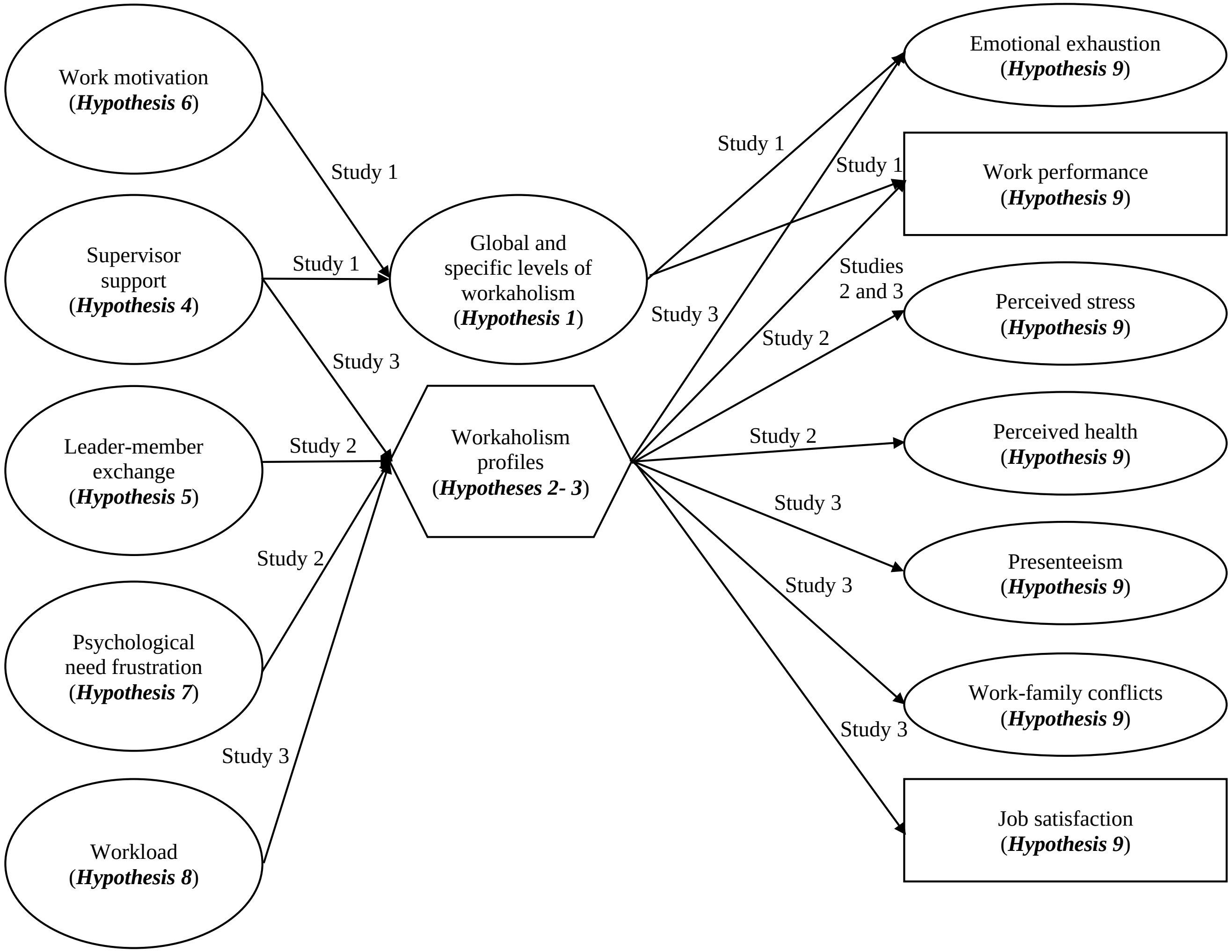

Figure 1. Theoretical Model Tested in the Present Research.
Note. Ovals represent latent continuous constructs (i.e., latent factors estimated from their indicators, and incorporated into the analyses as factor scores with the exception of work motivation, supervisor support, and emotional exhaustion incorporated as fully latent factors in Study 1); the hexagon represents a latent categorical construct (i.e., the latent profiles estimated in Studies 2 and 3); rectangles reflect observed scores; arrows reflect directional associations.

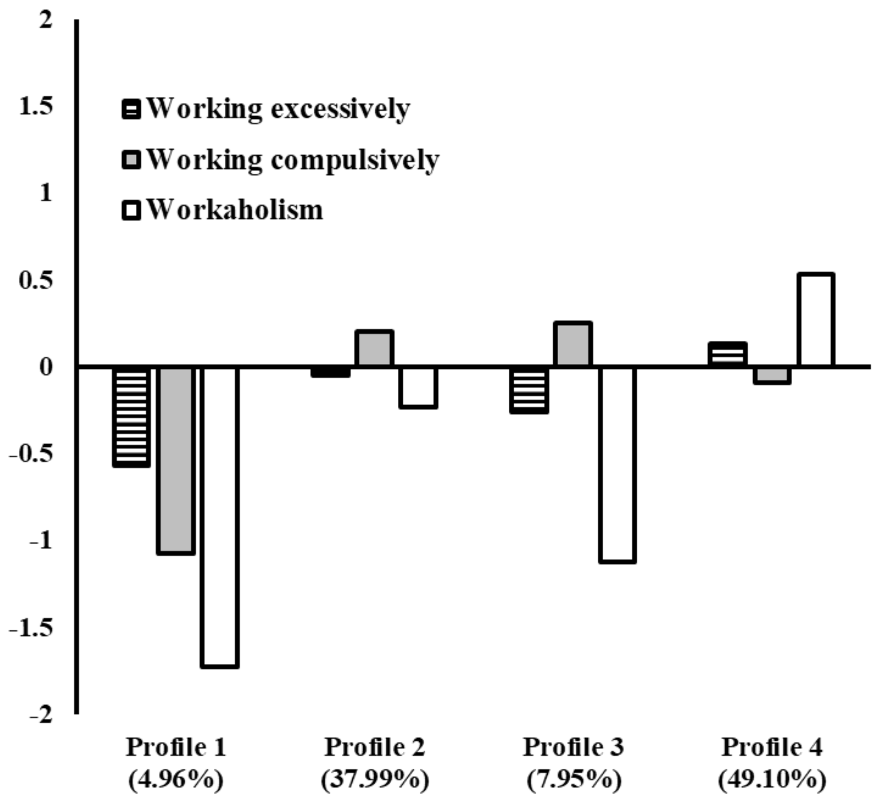

Figure 2a.
Profile 1: *Low Global and Specific Workaholism*; Profile 2: *Average Global and Specific Workaholism*; Profile 3: *Low Global and Average Specific Workaholism*; and Profile 4: *High Global and Average Specific Workaholism*.

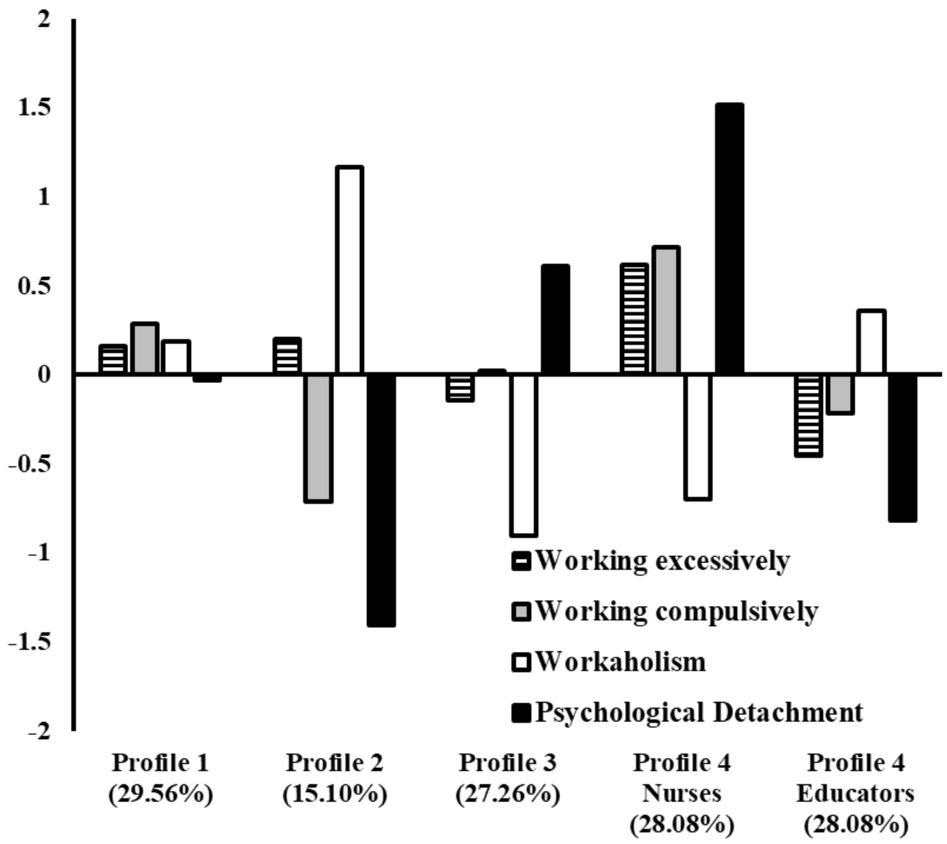

Figure 2b.
Profile 1: *Average Global and Specific Workaholism*; Profile 2: *High Global and Average Specific Workaholism*; Profile 3: *Low Global and Average Specific Workaholism*; Profile 4 (Nurses): *Low Global Workaholism/High Specific Workaholism and Psychological Detachment;* and Profile 4 (Educators): *Average Global Workaholism/Low Specific Workaholism and Psychological Detachment*.

Figure 2. Final 4-Profile Solution of Distributional Similarity across Samples for Studies 2 (Figure 2a) and 3 (Figure 2b).
Note. Profile indicators are estimated from factor scores with a mean of 0 and a standard deviation of 1.

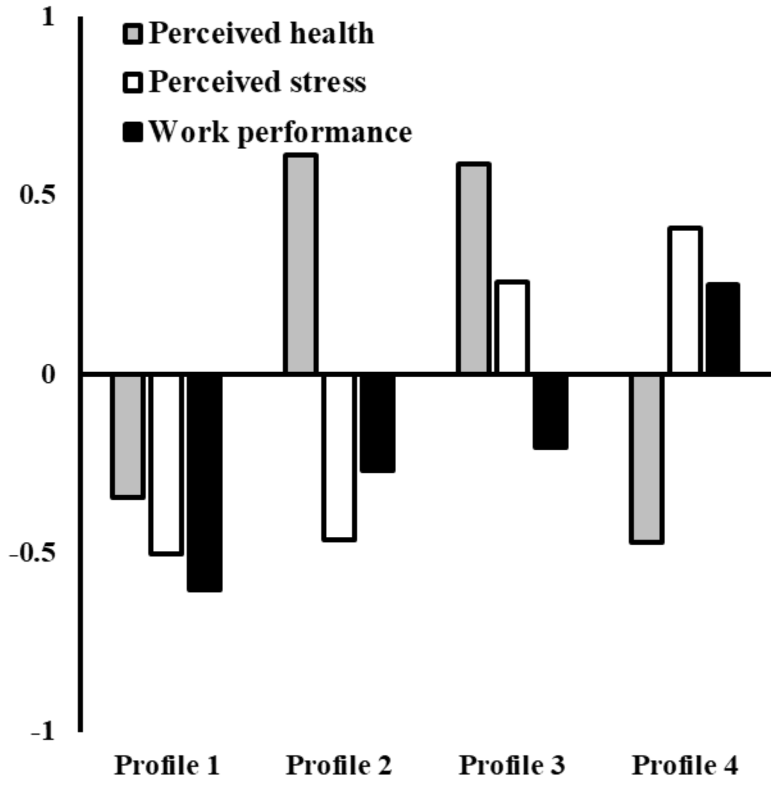

Figure 3a.
Profile 1: *Low Global and Specific Workaholism*; Profile 2: *Average Global and Specific Workaholism*; Profile 3: *Low Global and Average Specific Workaholism*; and Profile 4: *High Global and Average Specific Workaholism*.

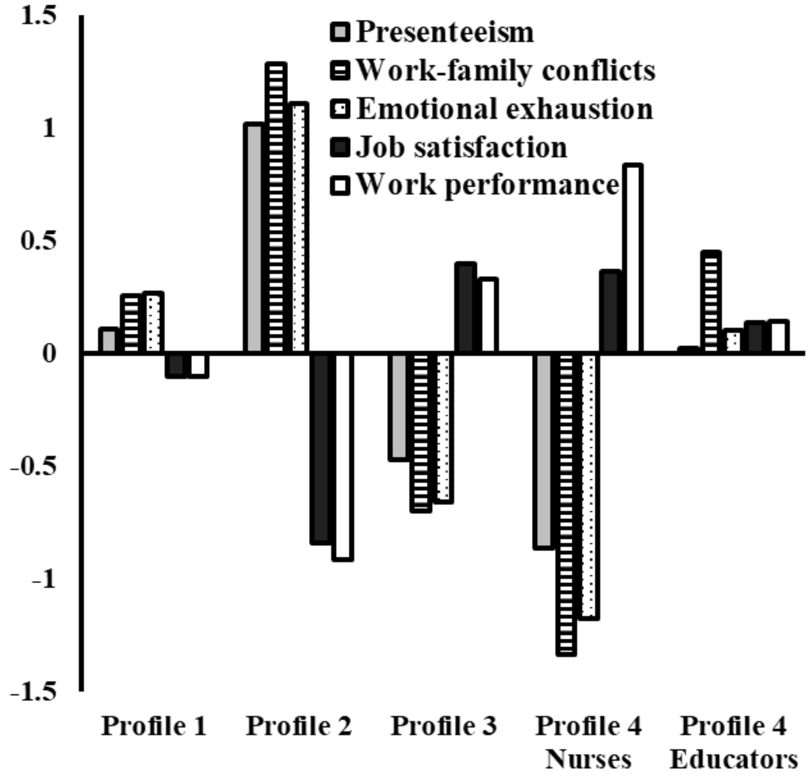

Figure 3b.
Profile 1: *Average Global and Specific Workaholism*; Profile 2: *High Global and Average Specific Workaholism*; Profile 3: *Low Global and Average Specific Workaholism*; Profile 4 (Nurses): *Low Global Workaholism/High Specific Workaholism and Psychological Detachment;* and Profile 4 (Educators): *Average Global Workaholism/Low Specific Workaholism and Psychological Detachment*.

Figure 3. Profile-Specific Levels of the Correlated Outcomes in Study 2-Sample 2 (Figure 3a) and across Samples (Explanatory Similarity) in Study 3 (Figure 3b)
Note. Indicators of presenteeism, work-family conflicts, and emotional exhaustion are estimated from factor scores with a mean of 0 and a standard deviation of 1; work performance and job satisfaction scores were also standardized prior to drawing this histogram.

Table 1

Goodness-of-Fit Statistics of the Preliminary Measurement Models (Workaholism)

Description	χ^2 (*df*)	CFI	TLI	RMSEA	90% CI
Study 1					
CFA	161.976 (34)*	.873	.832	.105	[.089; .121]
ESEM	129.427 (26)*	.898	.823	.108	[.090; .127]
Bifactor-CFA	67.752 (25)*	.958	.924	.071	[.051; .091]
Bifactor-ESEM	54.219 (18)*	.964	.910	.077	[.054; .100]
Study 2 Sample 1					
CFA	310.872 (34)*	.873	.832	.112	[.100; .123]
ESEM	683.546 (26)*	.699	.479	.197	[.184; .210]
Bifactor-CFA	160.316 (25)*	.938	.888	.091	[.078; .105]
Bifactor-ESEM	69.053 (18)*	.977	.942	.066	[.050; .083]
Study 2 Sample 2					
CFA	167.987 (34)*	.814	.754	.126	[.108; .146]
ESEM	130.764 (26)*	.855	.748	.128	[.106; .150]
Bifactor-CFA	72.194 (25)*	.935	.882	.087	[.064; .111]
Bifactor-ESEM	25.953 (18)	.989	.972	.042	[.000; .076]
Study 3 Sample 1					
CFA	107.640 (34)*	.817	.758	.120	[.095; .146]
ESEM	57.339 (26)*	.922	.865	.090	[.058; .121]
Bifactor-CFA	51.378 (25)*	.934	.882	.084	[.051; .116]
Bifactor-ESEM	27.381 (18)	.977	.942	.059	[.000; .101]
Study 3 Sample 2					
CFA	184.509 (34)*	.842	.791	.112	[.097; .129]
ESEM	142.675 (26)*	.877	.788	.113	[.095; .132]
Bifactor-CFA	96.715 (25)*	.925	.864	.091	[.072; .110]
Bifactor-ESEM	49.675 (18)*	.967	.917	.071	[.048; .095]

Note. * $p < .01$; χ^2: Robust chi-square test of exact fit; *df*: Degrees of freedom; CFI: Comparative fit index; TLI: Tucker-Lewis index; RMSEA: Root mean square error of approximation; 90% CI: 90% confidence interval..

Table 2

Standardized Factor Loadings (λ) and Uniquenesses (δ) from the Retained Bifactor-ESEM Solution (Workaholism)

	Study 1				Study 2 Sample 1				Study 2 Sample 2				Study 3 Sample 1				Study 3 Sample 2			
	G	S-WE	S-WC		G	S-WE	S-WC		G	S-WE	S-WC		G	S-WE	S-WC		G	S-WE	S-WC	
Items	λ	λ	λ	δ	λ	λ	λ	δ	λ	λ	λ	δ	λ	λ	λ	δ	λ	λ	λ	δ
WE																				
Item 1	**.626**	**.522**	*-.014*	.335	**.640**	**.375**	*-.064*	.446	**.590**	**.404**	-.169	.460	**.479**	**.384**	*.210*	.579	**.508**	**.569**	*.029*	.418
Item 2	**.538**	**.437**	*-.069*	.515	**.553**	**.394**	.125	.524	**.365**	**.707**	*-.012*	.367	**.462**	**.430**	*.019*	.601	**.426**	**.308**	.110	.712
Item 3	**.524**	**.573**	.162	.370	**.595**	**.563**	.133	.311	**.504**	**.609**	.285	.294	**.381**	**.586**	*.137*	.492	**.440**	**.494**	*.052*	.560
Item 4	**.682**	***.126***	*-.030*	.518	**.698**	**.267**	*-.043*	.440	**.569**	**.329**	*-.034*	.567	**.665**	***-.020***	*.145*	.536	**.610**	***.173***	-.154	.574
Item 5	**.655**	**.299**	*-.028*	.481	**.719**	**.235**	-.107	.417	**.649**	**.354**	*-.031*	.452	**.531**	**.357**	.269	.519	**.528**	**.532**	*.018*	.438
WC																				
Item 1	**.443**	*-.053*	**.541**	.508	**.573**	-.095	**.716**	*.150*	**.480**	*-.038*	**.619**	.384	**.526**	*.166*	**.241**	.638	**.422**	*-.073*	**.901**	.004
Item 2	**.599**	*.073*	**.306**	.542	**.568**	.263	**.364**	.477	**.425**	.202	**.493**	.535	**.505**	.351	**.319**	.521	**.610**	.131	**.284**	.530
Item 3	**.742**	*.072*	**.173**	.415	**.697**	*.014*	**.240**	.456	**.653**	*-.039*	**.353**	.447	**.770**	*-.159*	**.595**	*.027*	**.655**	.234	**.121**	.502
Item 4	**.583**	-.099	**-.275**	.575	**.754**	-.101	**-.257**	.355	**.726**	*-.021*	**-.262**	.404	**.510**	*-.007*	**-.249**	.678	**.571**	*-.024*	***-.093***	.665
Item 5	**.645**	*-.025*	**-.397**	.425	**.760**	*-.037*	**-.163**	.394	**.714**	*-.037*	***-.190***	.453	**.866**	*-.160*	**-.471**	.003	**.800**	-.235	***-.242***	*.246*
ω	.886	.633	.537		.915	.611	.623		.881	.730	.623		.876	.537	.535		.870	.615	.580	

Note. G = Global factor estimated as part of a bifactor model; S = Specific factor estimated as part of a bifactor model; λ: Factor loading (bold: Target factor loadings); δ: Item uniqueness; ω: Omega coefficient of model-based composite reliability; WE = Working excessively; WC = Working compulsively; non-significant parameters ($p \geq .05$) are marked in italics; WE Item 1: *I seem to be in a hurry and racing against the clock*; Item 2: *I find myself continuing to work after my coworkers have called it quits*; Item 3. *I stay busy and keep many irons in the fire*; Item 4: *I spend more time working than on socializing with friends, on hobbies, or on leisure activities*; and Item 5: *I find myself doing two or three things at one time such as eating lunch and writing a memo, while taking on the telephone*; WC Item 1: *It is important to me to work hard even when I do not enjoy what I am doing*; Item 2: *I feel that there is something inside me that drives me to work hard*; Item 3. *I feel obliged to work hard, even when it is not enjoyable*; Item 4: *I feel guilty when I take time off work*; and Item 5: *It is hard for me to relax when I am not working.*

Table 3

Results from the Predictive Model (Study 1)

	Global self-determination			Intrinsic motivation			Identified regulation			Introjected regulation		
Correlated outcome variables	*b*	*SE*	β	*b*	*SE*	β	*b*	*SE*	β	*b*	*SE*	β
Global workaholism	.267	.113*	.286	-.245	.303	-.262	-.102	.525	-.109	.063	.093	.068
Working excessively	.160	.084	.208	.040	.188	.052	-.166	.369	-.217	-.150	.078	-.196
Working compulsively	.113	.079	.148	-.074	.214	-.098	.047	.371	.061	-.035	.094	-.046
Emotional exhaustion	-.164	.108	-.107	-.442	.229	-.289	-.014	.244	-.009	.116	.106	.076
Work performance	.167	.139	.120	.065	.217	.046	.043	.291	.031	-.058	.126	-.042

	External-social regulation			External-material regulation			Amotivation			Supervisor support		
Correlated outcome variables	*b*	*SE*	β	*b*	*SE*	β	*b*	*SE*	β	*b*	*SE*	β
Global workaholism	.209	.118	.224	.047	.105	.051	.001	.127	.001	-.255	.110*	-.273
Working excessively	-.070	.093	-.091	-.186	.067**	-.243	-.111	.064	-.144	-.152	.087	-.198
Working compulsively	-.024	.083	-.031	-.029	.066	-.038	-.035	.058	-.046	.109	.057	.143
Emotional exhaustion	.037	.099	.024	.003	.118	.002	.238	.083**	.156	-.351	.120**	-.299
Work performance	-.015	.106	-.011	.019	.149	.014	-.239	.109*	-.171	.035	.120	.025

	Global workaholism			Working excessively			Working compulsively		
Correlated outcome variables	*b*	*SE*	β	*b*	*SE*	β	*b*	*SE*	β
Emotional exhaustion	.688	.209**	.420	.257	.164	.129	-.301	.163	-.150
Work performance	-.101	.125	-.068	-.159	.125	-.087	.239	.100*	.130

Note. * $p < .05$; ** $p < .01$; *b*: Unstandardized regression coefficient; SE: Standard error of the coefficient; β: Standardized regression coefficient

Table 4

Fit Results from the Multi-Group Tests of Profile Similarity (Studies 2 and 3)

	LL	#fp	SC	AIC	CAIC	BIC	ABIC	Entropy
Study 2								
Multi-Group Similarity								
Configural Similarity	-3779.233	55	1.073	7668.467	7987.660	7932.660	7757.989	.765
Structural Similarity	-3797.979	43	.886	7681.957	7931.508	7888.508	7751.947	.775
Dispersion Similarity	-3812.012	31	1.121	7686.025	7865.933	7834.933	7736.482	.751
Distributional Similarity	-3819.726	28	1.093	7695.452	7857.950	7829.950	7741.027	.743
Correlated Predictor Variables								
Null effects model	-3819.726	4	1.000	7647.452	7670.666	7666.666	7653.963	.743
Effects freely estimated across samples	-3782.636	16	.991	7597.271	7690.127	7674.127	7623.314	.758
Predictive similarity	-3786.693	10	1.018	7593.386	7651.421	7641.421	7609.662	.757
Study 3								
Multi-Group Similarity								
Configural Similarity	-2638.038	71	.995	5418.077	5789.998	5718.998	5493.633	.877
Structural Similarity	-2690.561	55	1.036	5491.121	5779.229	5724.229	5549.651	.872
Partial Structural Similarity	-2669.748	59	1.052	5457.497	5766.558	5707.558	5520.283	.831
Dispersion Similarity	-2691.212	43	1.132	5468.425	5693.673	5650.673	5514.184	.865
Distributional Similarity	-2697.023	40	1.146	5474.046	5683.579	5643.579	5516.613	.824
Correlated Predictor Variables								
Null effects model	-2697.023	4	1.000	5402.046	5422.999	5418.999	5406.303	.824
Effects freely estimated across samples	-2586.399	16	1.011	5204.797	5288.610	5272.610	5221.824	.864
Predictive similarity	-2606.091	10	1.018	5232.182	5284.565	5274.565	5242.823	.850
Correlated Outcome Variables								
Associations freely estimated across samples	-5418.904	49	1.229	10935.809	11192.487	11143.487	10987.953	.892
Explanatory similarity	-5510.195	29	1.176	11078.390	11230.301	11201.301	11109.251	.892
Partial similarity (Profiles 1-2-3 vs. 4)	-5463.016	34	1.134	10994.032	11172.135	11138.135	11030.213	.876

Note. LL = Loglikelihood; #fp = Number of free parameters; Scaling: Scaling correction factor; AIC = Akaïke information criterion; BIC = Bayesian information criterion; CAIC = Consistent AIC; ABIC = Sample-size adjusted BIC.

Table 5

Results from Multinomial Logistic Regressions for the Effects of the Correlated Predictor Variables on Profile Membership (Study 2: Predictive Similarity)

	Profile 1 vs. Profile 4		Profile 2 vs. Profile 4		Profile 3 vs. Profile 4		Profile 1 vs. Profile 3		Profile 2 vs. Profile 3		Profile 1 vs. Profile 2	
	Coef. (SE)	OR	Coef. (SE)	OR	Coef. (SE)	OR	Coef. (SE)	OR	Coef. (SE)	OR	Coef. (SE)	OR
Study 2: Predictive Similarity												
LMX	-.706 (.217)**	.493	-.200 (.147)	.819	-.366 (.187)*	.693	-.340 (.243)	.712	.166 (.192)	1.181	-.506 (.212)**	.603
Frustration	-1.237 (.267)**	.290	-.816 (.158)**	.442	-.999 (.241)**	.368	-.238 (.325)	.788	.183 (.260)	1.201	-.421 (.272)	.656
Study 3: Free across Samples												
Sample 1												
Workload	-.133 (.292)	.876	.365 (.415)	1.441	-2.532 (.537)**	.079	2.400 (.480)**	11.019	2.898 (.605)**	18.134	-.498 (.387)	.608
Supervisor support	-.412 (.273)	.662	-1.446 (.372)**	.236	-1.662 (.368)**	.190	1.250 (.340)**	3.490	.216 (.378)	1.241	1.034 (.374)**	2.811
Sample 2												
Workload	1.843 (.363)**	6.318	3.047 (.461)**	21.062	-.518 (.218)*	.595	2.362 (.404)**	1.610	3.566 (.497)**	35.369	-1.204 (.279)**	.300
Supervisor support	.298 (.263)	1.347	.098 (.343)	1.103	-.024 (.202)	.976	.322 (.265)	1.380	.122 (.336)	1.130	.200 (.213)	1.222

Note. * $p < .05$; ** $p < .01$; SE: Standard error of the coefficient; OR: Odds ratio; the coefficients and OR reflects the effects of the correlated predictor variables on the likelihood of membership into the first listed profile relative to the second listed profile; correlated predictor variables are estimated from factor scores with a mean of 0 and a standard deviation of 1; For Study 2: Profile 1 (*Low Global and Specific Workaholism)*; Profile 2 (*Average Global and Specific Workaholism)*; Profile 3 (*Low Global and Average Specific Workaholism)*; and Profile 4 (*High Global and Average Specific Workaholism)*; For Study 3: Profile 1 (*Average Global and Specific Workaholism)*; Profile 2 (*High Global and Average Specific Workaholism)*; Profile 3 (*Low Global and Average Specific Workaholism)*; Profile 4-Nurses (*Low Global Workaholism/High Specific Workaholism and Psychological Detachment);* Profile 4-Educators (*Average Global Workaholism/Low Specific Workaholism and Psychological Detachment)*.

Appendix

Summary of our Main Hypotheses

Hypotheses	Studies	Support	Key results
Hypothesis 1. Workaholism ratings will be best represented as a bifactor construct including one G-factor (global workaholism) and two S-factors (working excessively and compulsively).	Study 1 Study 2 (Samples 1 and 2) Study 3 (Samples 1 and 2)	Supported	A bifactor representation of workaholism was supported, and found to be invariant, across all studies and samples.
Hypothesis 2. Four or more profiles will be identified, including a High Workaholism, a Moderate Workaholism, and a Low Workaholism configuration, as well as at least one profile characterized by a clearer differentiation among the global and specific components.	Study 2 (Samples 1 and 2)	Supported	1: *Low Global and Specific Workaholism* (4.96%). 2: *Average Global and Specific Workaholism* (37.99%). 3: *Low Global and Average Specific Workaholism* (7.95%). 4: *High Global and Average Specific Workaholism* (49.10%).
Hypothesis 3. Four or more profiles will be identified, including a High Workaholism and Low Psychological Detachment, a Moderate Workaholism and Psychological Detachment, and a Low Workaholism and High Psychological Detachment configuration, as well as at least one profile characterized by a clearer differentiation among the global and specific components of workaholism accompanied by levels of psychological detachment presenting a mirror image to global levels of workaholism (low when high, and vice versa).	Study 3 (Samples 1 and 2)	Supported	1: *Average Global and Specific Workaholism* (29.56%). 2: *High Global and Average Specific Workaholism* (15.10%). 3: *Low Global and Average Specific Workaholism* (27.26%). 4 (Nurses): *Low Global Workaholism/High Specific Workaholism and Psychological Detachment* (28.08%). 4 (Educators): *Average Global Workaholism/Low Specific Workaholism and Psychological Detachment* (28.08%).
Research Question 1: Will the identified profiles demonstrate evidence of *configural*, *structural*, *dispersion*, and *distributional* similarity across the two samples considered in Studies 2 and 3?	Study 2 (Samples 1 and 2) Study 3 (Samples 1 and 2)	Study 2: Yes Study 3: Partially	<u>Study 2</u>: The profiles were fully replicated across samples. <u>Study 3</u>: One profile was found to differ across samples (see the results associated with Hypothesis 3).
Hypothesis 4. Supervisor support will be associated with lower global levels of workaholism and with lower specific levels of working compulsively and excessively (Study 1), and with membership into a Low Workaholism and High Psychological Detachment profile (Study 3).	Study 1 Study 3 (Samples 1 and 2)	Study 1: Partially Supported Study 3: Not Supported	<u>Study 1</u>: Supervisor support was associated with lower global levels of workaholism, but not with specific levels of working compulsively and excessively. <u>Study 3-Sample 2</u>: Supervisor support was not associated with profile membership. <u>Study3-Sample 1</u>: Supervisor support predicted a decreased likelihood of membership into the *Low Global and Average Specific Workaholism* profile relative to profiles characterized by higher workaholism and lower psychological detachment.

Hypotheses	Studies	Support	Key results
Hypothesis 5. Higher levels of LMX will be associated with membership into the Low Workaholism profile, followed by the Moderate Workaholism profile, and then by the High workaholism profile.	Study 2 (Samples 1 and 2)	Supported	LMX predicted an increased likelihood of membership into the *High Global and Average Specific Workaholism* profile relative to profiles characterized by lower workaholism.
Hypothesis 6. Global self-determined work motivation, autonomous types of motivation, and amotivation will be associated with lower global levels of workaholism and with lower specific levels of working compulsively and excessively, whereas controlled types of motivation will be associated with higher levels of workaholism.	Study 1	Not Supported	Global levels of self-determination were associated with higher global levels of workaholism, and specific levels of external-material regulation were associated with lower specific levels of working excessively.
Hypothesis 7. Higher levels of need frustration will be associated with membership into the High Workaholism profile, followed by the Moderate Workaholism profile, and then by the Low workaholism profile.	Study 2 (Samples 1 and 2)	Partially Supported	Global levels of need frustration predicted an increased likelihood of membership into the *High Global and Average Specific Workaholism* profile relative to all other profiles.
Hypothesis 8. Workload will be associated with a greater likelihood of membership into the High Workaholism and Low Psychological Detachment profile, followed by the Moderate Workaholism and Psychological Detachment profile, and then by the Low Workaholism and High Psychological Detachment.	Study 3 (Samples 1 and 2).	Supported	Workload predicted a decreased likelihood of membership into the *Low Global and Average Specific Workaholism* profile relative to profiles with higher workaholism and lower psychological detachment. Workload also predicted an increased likelihood of membership into the *High Global and Average Specific Workaholism* profile relative to the *Average Global and Specific Workaholism* profile.
Hypothesis 9a. Global levels of workaholism and specific levels of working excessively and compulsively will be associated with higher levels of emotional exhaustion and with lower levels of work performance.	Study 1	Partially Supported	Global levels of workaholism were associated with higher levels of emotional exhaustion, and specific levels of working compulsively were associated with higher levels of performance.
Hypothesis 9b. The highest levels of emotional exhaustion, stress, presenteeism, and work-family conflicts, and the lowest levels of work performance, perceived health, and job satisfaction will be associated with the High Workaholism (with Low Psychological Detachment in Study 3) profile, followed by the Moderate Workaholism (with Moderate Psychological Detachment in Study 3) profile, and by the Low Workaholism (with High Psychological Detachment in Study 3) profiles.	Study 2 (Samples 1 and 2) Study 3 (Samples 1 and 2).	Supported	The most adaptive outcomes (e.g., low perceived stress, presenteeism, work-family-conflicts, and emotional exhaustion) were associated with the profiles characterized by low levels of workaholism and high levels of psychological detachment relative to profiles characterized by higher levels of workaholism and lower levels of psychological detachment.

Section 1
Preliminary Measurement Models for Workaholism

Study 1

The goodness-of-fit results from the preliminary measurement models used to investigate the optimal measurement structure for the workaholism questionnaire are reported in Table 1 in the main manuscript. Starting with an examination of the first-order CFA and ESEM solutions, neither of those solutions was able to achieve an acceptable level of fit to the data. However, the correlation between the two workaholism factors was substantially reduced in the ESEM (r = .545) relative to the CFA (r = .874) solution, thus supporting the added value of ESEM. Starting from this ESEM solution, the subsequent bifactor-ESEM solution was able to achieve a satisfactory level of fit to the data, and resulted in generally satisfactory parameter estimates. More precisely, this solution revealed a well-defined G-factor (λ = .443 to .742, M_{λ} = .604). Similarly, with the exception of a few items which mainly reflect the G-factor rather than their own a priori S-factors, the S-factors also retained a meaningful degree of specificity over and above employees' global levels of workaholism (λ = .126 to .573, M_{λ} = .391 for working excessively; |λ| = .173 to .541, $M_{|\lambda|}$ = .338 for working compulsively). Finally, although multiple cross-loadings were statistically significant (thus supporting again the need to incorporate them to the model), they all remained reasonable in magnitude (|λ| = .014 to .162, $M_{|\lambda|}$ = .063) and smaller than their ESEM counterparts (|λ| = .009 to .512, $M_{|\lambda|}$ = .257), and did not detract from a meaningful interpretation of the factors. Thus, these results support the superiority of the bifactor ESEM solution.

Study 2

The goodness-of-fit results from the preliminary measurement models used to investigate the optimal measurement structure for the workaholism questionnaire are reported in Table 1 in the main manuscript. Starting with an examination of the first-order CFA and ESEM solutions, the two alternative solutions were not able to achieve an acceptable level of fit to the data in both samples. However, the factor correlations were substantially reduced in the ESEM (r = .508 in Sample 1 and r = .479 in Sample 2) relative to the CFA (r = .884 in Sample 1 and r = .763 in Sample 2) solutions, thus supporting the added-value of ESEM. Starting from this ESEM solution, the subsequent bifactor-ESEM solution was able to achieve a satisfactory level of fit to the data, and resulted in generally satisfactory parameter estimates. In addition, in this study, the bifactor CFA solutions failed to achieve an acceptable level of fit to the data.

In both samples, the bifactor ESEM solution (see Table 2 in the main manuscript) reveal a well-defined G-factor (λ = .553 to .760, M_{λ} = .656 in Sample 1; and λ = .365 to .726, M_{λ} = .568 in Sample 2). Similarly, with the exception of a few items which mainly reflect the global workaholism G-factor rather than their own a priori S-factors, the S-factors also retained a meaningful degree of specificity over and above employees' global levels of workaholism (λ = .235 to .563, M_{λ} = .367 for specific working excessively; |λ| = .163 to .716, M_{λ} = .348 for specific working compulsively in Sample 1; and λ = .329 to .707, M_{λ} = .481 for specific working excessively; |λ| = .190 to .619, M_{λ} = .383 for specific working compulsively in Sample 2). In both samples, multiple cross-loadings were statistically significant, although they all remained reasonable in magnitude (|λ| = .014 to .263, $M_{|\lambda|}$ = .098 in Sample 1; and |λ| = .012 to .285, $M_{|\lambda|}$ = .087 in Sample 2) and did not detract from a meaningful interpretation of the factors. Thus, as in Study 1, these results support the superiority of the bifactor ESEM solution.

Study 3

The goodness-of-fit results from the preliminary measurement models used to investigate the optimal measurement structure for the workaholism questionnaire are reported in Table 1 in the main manuscript. Starting with an examination of the first-order CFA and ESEM solutions, the two alternative solutions were not able to achieve an acceptable level of fit to the data in both samples. However, the factor correlations were substantially reduced in the ESEM (r = .396 in Sample 1 and r = .537 in Sample 2) relative to the CFA (r = .906 in Sample 1 and r = .816 in Sample 2) solutions, thus supporting the added-value of ESEM. Starting from this ESEM solution, the subsequent bifactor-ESEM solution was able to achieve a satisfactory level of fit to the data, and resulted in generally satisfactory parameter estimates. In addition, as in Study 2, the bifactor CFA solutions failed to achieve an acceptable fit to the data.

Moreover, in both samples, the bifactor ESEM solution (see Table 2 in the main manuscript) reveal a well-defined G-factor (λ = .381 to .866, M_{λ} = .570 in Sample 1; and λ = .422 to .800, M_{λ} = .557 in Sample 2). Similarly, with the exception of a few items which mainly reflect the global workaholism

G-factor rather than their own a priori S-factors, the S-factors also retained a meaningful degree of specificity over and above employees' global levels of workaholism ($|\lambda|$ = .020 to .586, M_{λ} = .355 for specific working excessively; $|\lambda|$ = .241 to .595, M_{λ} = .375 for specific working compulsively in Sample 1; and λ = .173 to .569, M_{λ} = .415 for specific working excessively; $|\lambda|$ = .093 to .901, M_{λ} = .328 for specific working compulsively in Sample 2). In both samples, multiple cross-loadings were statistically significant, although they all remained reasonable in magnitude ($|\lambda|$ = .007 to .351, $M_{|\lambda|}$ = .162 in Sample 1; and $|\lambda|$ = .018 to .235, $M_{|\lambda|}$ = .106 in Sample 2) and did not detract from a meaningful interpretation of the factors. Thus, as in Study 1, these results once again support the superiority of the bifactor ESEM solution.

Measurement Invariance

The bifactor ESEM solution was thus retained for all samples. Tests of measurement invariance were then conduct to verify the equivalence of this solution across (a) the total samples from Studies 1 and 2; (b) both samples from Study 2; (c) the combined samples from Studies 1 and 2 and the combined samples from Study 3; (d) both samples from Study 3. These tests were conducted in the following sequence (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, and latent variances and covariances); and (6) latent means invariance (loadings, intercepts, uniquenesses, latent variances and covariances, and latent means). Changes (Δ) in goodness-of-fit indices were used in tests of measurement invariance. More precisely, a ΔCFI of .010 or less, a ΔTLI of .010 or less, and a ΔRMSEA of .015 or less between a model and the previous one were taken to support the invariance hypothesis (Marsh et al., 2005).

The results from these tests are reported in Table S1 of the online supplements. These results support the configural, weak, partial strong (equality constraints had to be relaxed on the intercepts of two out of five of the working excessively items which were scored slightly higher in Study 2), strict, and latent variance-covariance invariance of this solution across Studies 1 and 2. These results also revealed that participants from Study 2 had higher latent mean levels than participants from Study 1 on the working excessively S-factor. The results also supported the configural, weak, partial strong (equality constraints had to be relaxed on the intercepts of two out of five of the working excessively items which were scored slightly higher in Sample 1), strict, latent variance-covariance, and latent means invariance of this solution across both samples from Study 2. Factor scores (estimated in standardized units: M = 0, SD = 1) from this model of latent means invariance (across samples from Study 2) were used in the main analyses.

Moreover, the results supported the configural, weak, partial strong (equality constraints had to be relaxed on the intercepts from two out of five of the working excessively items which were scored slightly higher in Studies 1 and 2 than in Study 3), partial strict (equality constraints had to be relaxed on the uniqueness of one working excessively item which was slightly higher in Study 3), and latent variance-covariance invariance of this solution across the three studies. These results also revealed that participants from Study 3 had higher latent mean levels than participants from Studies 1 and 2 on the working excessively S-factor. Finally, the results supported the configural, weak, partial strong (equality constraints had to be relaxed on the intercepts from two out of five of the working excessively items which were scored slightly higher in Sample 2), partial strict (equality constraints had to be relaxed on the uniqueness of one working excessively item which was slightly higher in Sample 1), latent variance-covariance, and latent means invariance across both samples from Study 3.

References

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Table S1

Goodness-of-Fit Statistics of the Tests of Measurement Invariance (Workaholism)

Description	χ^2 (*df*)	CFI	TLI	RMSEA	90% CI	CM	$\Delta\chi^2$ (*df*)	ΔCFI	ΔTLI	ΔRMSEA
Multi-Group Tests of Invariance (Studies 1 vs. 2)										
M1. Configural invariance	136.697 (36)*	.974	.936	.067	[.055; .079]	-	-	-	-	-
M2. Weak invariance	176.780 (57)*	.970	.952	.058	[.049; .068]	M1	43.607 (21)*	-.004	+.016	-.009
M3. Strong invariance	290.395 (64)*	.943	.919	.075	[.067; .084]	M2	130.340 (7)*	-.027	-.033	+.017
M3’. Partial strong invariance	207.075 (62)*	.963	.947	.061	[.052; .071]	M2	28.829 (5)*	-.007	-.005	+.003
M4. Strict invariance	233.822 (72)*	.959	.949	.060	[.052; .069]	M3’	27.152 (10)*	-.004	+.002	-.001
M5. Latent variance-covariance invariance	239.640 (78)*	.959	.953	.058	[.049; .066]	M4	5.826 (6)	.000	+.004	-.002
M6. Latent means invariance	449.344 (81)*	.906	.896	.086	[.078; .093]	M5	339.927 (3)*	-.053	-.057	+.028
Multi-Group Tests of Invariance (Study 2: Samples 1 vs. 2)										
M1. Configural invariance	96.723 (36)*	.980	.949	.061	[.047; .076]	-	-	-	-	-
M2. Weak invariance	127.366 (57)*	.976	.963	.052	[.040; .065]	M1	31.362 (21)	-.004	+.014	-.009
M3. Strong invariance	180.494 (64)*	.961	.945	.064	[.053; .075]	M2	62.500 (7)*	-.015	-.018	+.012
M3’. Partial strong invariance	147.592 (62)*	.971	.958	.055	[.044; .067]	M2	23.337 (5)*	-.005	-.005	+.003
M4. Strict invariance	176.586 (72)*	.965	.956	.057	[.046; .067]	M3’	28.967 (10)*	-.006	-.002	+.002
M5. Latent variance-covariance invariance	187.270 (78)*	.963	.958	.056	[.046; .066]	M4	11.039 (6)	-.002	+.002	-.001
M6. Latent means invariance	197.696 (81)*	.961	.956	.057	[.047; .067]	M5	10.366 (3)	-.002	-.002	+.001
Multi-Group Tests of Invariance (Studies 1/2 vs. 3)										
M1. Configural invariance	222.188 (36)*	.964	.911	.077	[.067; .087]	-	-	-	-	-
M2. Weak invariance	281.976 (57)*	.957	.932	.067	[.060; .075]	M1	64.757 (21)*	-.007	+.021	-.010
M3. Strong invariance	462.873 (64)*	.924	.893	.085	[.077; .092]	M2	193.643 (7)*	-.033	-.039	+.018
M3’. Partial strong invariance	296.212 (62)*	.955	.935	.066	[.058; .073]	M2	15.485 (5)*	-.002	+.003	-.001
M4. Strict invariance	364.558 (72)*	.944	.930	.068	[.061; .075]	M3’	69.259 (10)*	-.011	-.005	+.002
M4’. Partial strict invariance	339.994 (71)*	.949	.935	.066	[.059; .073]	M3’	43.816 (9)*	-.006	.000	.000
M5. Latent variance-covariance invariance	353.934 (77)*	.947	.938	.064	[.058; .071]	M4’	13.423 (6)	-.002	+.003	-.002
M6. Latent means invariance	579.400 (80)*	.905	.893	.085	[.078; .091]	M5	379.047 (3)*	-.042	-.045	+.021
Multi-Group Tests of Invariance (Study 3: Samples 1 vs. 2)										
M1. Configural invariance	89.188 (36)*	.961	.902	.077	[.057; .097]	-	-	-	-	-
M2. Weak invariance	120.919 (57)*	.953	.925	.067	[.050; .084]	M1	36.281 (21)	-.008	+.023	-.010
M3. Strong invariance	152.803 (64)*	.934	.908	.074	[.059; .090]	M2	34.198 (7)*	-.019	-.017	+.007
M3’. Partial strong invariance	137.523 (62)*	.944	.919	.070	[.054; .086]	M2	16.983 (5)*	-.009	-.006	+.003
M4. Strict invariance	166.324 (72)*	.930	.913	.072	[.058; .087]	M3’	28.982 (10)*	-.014	-.006	+.002
M4’. Partial strict invariance	155.355 (71)*	.938	.921	.069	[.054; .084]	M3’	17.785 (9)	-.006	+.002	-.001
M5. Latent variance-covariance invariance	164.560 (77)*	.933	.923	.067	[.053; .082]	M4’	8.872 (6)	-.005	+.002	-.002
M6. Latent means invariance	182.898 (80)*	.924	.914	.072	[.058; .085]	M5	18.642 (3)*	-.009	-.009	+.005

Note. * $p < .01$; χ^2: Robust chi-square test of exact fit; *df*: Degrees of freedom; CFI: Comparative fit index; TLI: Tucker-Lewis index; RMSEA: Root mean square error of approximation; 90% CI: 90% confidence interval; CM: Comparison model; Δ: Change in fit relative to the CM

Section 2
Preliminary Measurement Models for the Covariates

Study 1

In Study 1, latent factors representing the multi-items correlated predictor (i.e., motivation and supervisor support) and outcome (emotional exhaustion) variables, were directly included the final predictive model. For work motivation, we relied on a bifactor ESEM model in line with recent organizational studies (Fernet et al., 2020; Gillet et al., 2020c) demonstrating that bifactor ESEM made it possible to obtain a direct estimate of employees' global levels of self-determined work motivation and an equally direct estimate of the unique quality associated with each specific regulation in a way that matched SDT theoretical proposition (Fernet et al., 2020). Emotional exhaustion and supervisor support were specified as latent CFA factors. The parameter estimates from these models are reported in Table S2 of the online supplements. These results revealed a reliable (ω = .881) G-factor well-defined by factor loadings matching the SDT continuum from intrinsic (λ between .623 and .723, *M* = .667), identified (λ between .556 and .692, *M* = .601), introjected (λ between .269 and .633, *M* = .443), external-social (λ between .201 and .348, *M* = .289), external-material (λ between .008 and .250, *M* = .139), and amotivation (λ between -.197 and -.213, *M* = -.207) items. Likewise, the S-factors related to intrinsic motivation (λ = .447-.510, *M* = .483; ω = .736), external-social regulation (λ = .566-.682, *M* = .620; ω = .740), external-material regulation (λ = .379-.775, *M* = .585; ω = .671), and amotivation (λ = .455-.820, *M* = .640; ω = .728) were also generally well-defined. Finally, although the remaining S-factors appeared to be more weakly defined then the previous ones, the S-factor associated with introjected regulation (λ = -.161 to .723, *M* = .346; ω = .566), but not identified regulation (λ = -.206 to .268, *M* = -.016; ω = .194), still appeared to retain a meaningful level of specificity (associated with ω values greater than .500; see Perreira et al., 2018; Morin et al., 2020) once the variance explained by the G-factor was taken into account. Finally, the CFA factors associated with supervisor support (λ = .740-.896, *M* = .809; ω = .897) and emotional exhaustion (λ = .720-.849, *M* = .807; ω = .904) also appeared to be well-defined.

Study 2

For the correlated predictor variables, our goal was to obtain a single estimate of employees' global levels of LMX and need frustration, while accounting for the subscale specificity present in these instruments. A bifactor approach seemed to be naturally suited to this objective. However, for comparison purposes, we also considered first-order alternatives and, as for the measure of workaholism, we contrasted ESEM and CFA solutions. Importantly, in bifactor models, separate sets of global and specific orthogonal factors were specified for the LMX and need frustration measures (so that LMX items did not contribute to define the global need frustration factor, and vice versa), and correlations were freely estimated between the LMX and need frustration factors. Similarly, ESEM and bifactor-ESEM solutions relied on distinct sets of ESEM factors, allowing for cross-loadings between the LMX items, between the need frustration items, but not across the two sets of factors.

Goodness-of-fit indices associated with each of these four measurement models in each sample are reported in Table S3 of the online supplements. Starting with an examination of the first-order CFA and ESEM solutions, only the ESEM solutions were able to achieve an acceptable level of fit to the data in both samples. The decision was thus made to retain an ESEM representation of the data, a decision that was also supported by an examination of the bifactor alternatives (i.e., the bifactor CFA solutions failed to achieve an acceptable level of fit to the data in both samples). Examination of the parameter estimates associated with the bifactor ESEM solution, reported in Table S4 of the online supplements, shows well-defined LMX (λ =.255 to .846, M_λ =.726 in Sample 1; and |λ| =.055 to .860, M_λ =.678 in Sample 2) and need frustration (λ =.426 to .850, M_λ =.647 in Sample 1; and λ =.424 to .868, M_λ =.625 in Sample 2) G-factors. However, with the exception of relatedness need frustration (λ = .439 to .610, M_λ = .516 in Sample 1; and λ = .365 to .476, M_λ = .434 in Sample 2) and autonomy need frustration (λ = .385 to .567, M_λ = .533 in Sample 1; and λ = .507 to .647, M_λ = .598 in Sample 2), the other S-factors do not retain sufficient specificity over and above participants' global levels of LMX and need frustration, supporting our decision to rely only on the G-factors (Sample 1: λ = .068 to .357, M_λ = .186 for affect; |λ| = .149 to .351, M_λ = .217 for loyalty; |λ| = .068 to .490, M_λ = .217 for contribution; |λ| = .007 to .592, M_λ = .234 for professional respect; and |λ| = .101 to .410, M_λ = .285 for competence need frustration; Sample 2: |λ| = .130 to .408, M_λ = .223 for affect; |λ| = .125 to .513, M_λ = .282 for loyalty; |λ| = .073 to .135, M_λ = .110 for contribution; |λ| = .010 to .789, M_λ = .321 for professional respect; and |λ| = .023 to

.039, M_λ = .027 for competence need frustration).

Tests of measurement invariance were conducted on this bifactor ESEM solution across both samples from Study 2. The results from these tests, reported in Table S3 from the online supplements, supported the configural, weak, strong, strict, latent variance-covariance, and latent means invariance of the correlated predictor variables' model across samples in Study 2.

For the correlated outcome variables in Sample 2, a two-factor CFA was specified to reflect ratings of perceived stress and health. Each item was only allowed to load on the factor it was assumed to measure and all factors were allowed to freely correlate. This model included a priori correlated uniquenesses to account for the negative wording of two of the items (Marsh et al., 2010). Goodness-of-fit indices associated with this measurement model are reported in Table S3 of the online supplements. This CFA solution was able to achieve an acceptable level of fit to the data. Examination of the parameter estimates associated with this solution shows well-defined perceived stress (λ =.255 to .846, M_λ = .726) and health (λ =.426 to .850, M_λ = .647) factors (see Table S5 of the online supplements). Factor scores (estimated in standardized units with M = 0 and SD = 1) were saved from this models (CFA for the correlated outcome variables in Study 2, latent means invariance for the correlated predictor variables) and were used in the main analyses.

Study 3

Tests of invariance were conducted on a complete measurement model including workaholism (ESEM solution), and correlated CFA factors reflecting psychological detachment, workload, supervisor support, presenteeism, emotional exhaustion, and work-family conflicts. The results from these tests, reported in Table S6 of the online supplements, supported the configural, weak, partial strong (equality constraints had to be relaxed on the intercepts of one working excessively item and one emotional exhaustion item, which were both scored higher in Sample 2), partial strict (equality constraints had to be relaxed on the uniqueness of one working excessively item which was slightly lower in Study 2), latent variance-covariance, and partial latent means (equality constraints had to be relaxed on the latent means of psychological detachment factor which was slightly lower in Sample 2, and of the work-family conflicts factor which was slightly higher in Sample 2) invariance of this solution across both samples from Study 3. Examination of the parameter estimates associated with this solution shows well-defined global workaholism (λ =.432 to .714, M_λ = .569 in Sample 1; λ =.469 to .714, M_λ = .576 in Sample 2), specific working excessively (λ =.082 to .755, M_λ = .347 in Sample 1 and M_λ = .358 in Sample 2), specific working compulsively (λ =.037 to .441, M_λ = .289), psychological detachment (λ =.728 to .886, M_λ = .811), workload (λ =.724 to .822, M_λ = .771), supervisor support (λ =.726 to .901, M_λ = .810), presenteeism (λ =.838 to .892, M_λ = .873), emotional exhaustion (λ =.662 to .824, M_λ = .777), and work-family conflicts (λ =.749 to .875, M_λ = .829) factors (see Table S7 of the online supplements). Factor scores (estimated in standardized units with M = 0 and SD = 1) from this model of partial means invariance were used in the main analyses.

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Table S2

Standardized Factor Loadings (λ) and Uniquenesses (δ) for the Covariates (Study 1)

Items	Global SD (G-λ)	IM (S-λ)	IDR (S-λ)	INR (S-λ)	EXSRS (S-λ)	EXMR (S-λ)	AMO (S-λ)	SUP	EE	δ
IM										
Item 1	**.623**	**.510**	*-.033*	*-.111*	*-.086*	*-.075*	-.134			.307
Item 2	**.723**	**.501**	*-.078*	-.102	-.137	*-.105*	*-.069*			.175
Item 3	**.655**	**.447**	-.161	-.114	-.103	-.099	-.170			.282
IDR										
Item 1	**.556**	*-.212*	***.268***	*.010*	.227	*.090*	*.039*			.513
Item 2	**.692**	.440	***-.110***	*-.002*	-.192	*-.090*	*-.008*			.271
Item 3	**.556**	*.112*	***-.206***	*.072*	*-.024*	*-.011*	*-.011*			.630
INR										
Item 1	**.556**	*-.310*	.449	***-.161***	.317	*.117*	.115			*.240*
Item 2	**.633**	*-.131*	*-.062*	***-.099***	.216	*.031*	*-.004*			.521
Item 3	**.269**	*-.160*	*.143*	**.723**	.318	*.071*	.123			*.238*
Item 4	**.427**	-.255	*-.119*	**.415**	.201	.158	*.036*			.499
EXSR										
Item 1	**.317**	*-.169*	*.116*	*-.069*	**.566**	.221	*.072*			.478
Item 2	**.348**	*-.088*	*.027*	*.035*	**.682**	*.073*	.188			.364
Item 3	**.201**	*-.005*	*.005*	.419	**.612**	*.098*	.170			.371
EXMR										
Item 1	***.080***	*.008*	*.167*	*-.019*	*.047*	**.601**	*.149*			*.580*
Item 2	**.250**	*-.022*	*-.074*	*.048*	.154	**.775**	*.109*			*.294*
Item 3	***.086***	-.326	*-.017*	.184	.231	**.379**	*.129*			.638
AMO										
Item 1	**-.211**	*-.054*	*.035*	*-.048*	.139	*.074*	**.820**			*.253*
Item 2	**-.213**	*-.055*	*-.041*	*.090*	.150	.119	**.644**			.491
Item 3	**-.197**	-.220	*.026*	.147	*.138*	.188	**.455**			.629
SUP										
Item 1								.876		.232
Item 2								.791		.374
Item 3								.896		.198
Item 4								.740		.453
EE										
Item 1									.849	.279
Item 2									.788	.379
Item 3									.838	.297
Item 4									.842	.291
Item 5									.720	.482
ω	.881	.736	.194	.566	.740	.671	.728	.897	.904	

Note. λ: Factor loading; δ: Item uniqueness; ω: Omega coefficient of model-based composite reliability; G: Global factor from the bifactor model; S: Specific factors from the bifactor model; SD: Self-determination; IM: Intrinsic motivation; IDR: Identified regulation; INR: Introjected regulation; EXSR: External-social regulation; EXMR: External-material regulation; AMO: Amotivation; SUP: Supervisor support; EE: Emotional exhaustion; target factor loadings are indicated in bold; non-significant parameters ($p \geq .05$) are marked in italics.

Table S3

Goodness-of-Fit Statistics for the Estimated Correlated Predictor and Outcome Variables Measurement Models (Study 2)

Description	χ^2 (*df*)	CFI	TLI	RMSEA	90% CI	CM	$\Delta\chi^2$ (*df*)	ΔCFI	ΔTLI	ΔRMSEA
Correlated Predictor Variables in Sample 1										
CFA	875.522 (168)*	.899	.874	.080	[.075; .086]	-	-	-	-	-
ESEM	200.241 (132)*	.990	.984	.028	[.020; .036]	-	-	-	-	-
B-CFA	776.997 (148)*	.910	.873	.081	[.075; .086]	-	-	-	-	-
B-ESEM	162.867 (110)*	.992	.986	.027	[.018; .036]	-	-	-	-	-
Correlated Predictor Variables in Sample 2										
CFA	466.315 (168)*	.886	.857	.085	[.076; .084]	-	-	-	-	-
ESEM	150.636 (132)*	.993	.989	.024	[.000; .040]	-	-	-	-	-
B-CFA	416.984 (148)*	.897	.854	.086	[.076; .096]	-	-	-	-	-
B-ESEM	113.542 (110)*	.999	.997	.011	[.000; .035]	-	-	-	-	-
Multi-Group Tests of Invariance (Correlated Predictor Variables)										
M1. Configural invariance	265.131 (220)*	.995	.991	.021	[.009; .030]	-	-	-	-	-
M2. Weak invariance	344.090 (275)*	.993	.989	.024	[.014; .031]	M1	79.140 (55)	-.002	-.002	+.003
M3. Strong invariance	377.522 (287)*	.991	.986	.026	[.018; .033]	M2	115.460 (12)*	-.002	-.003	+.002
M4. Strict invariance	412.717 (308)*	.989	.985	.027	[.020; .034]	M3	36.284 (21)	-.002	-.001	+.001
M5. Latent variance-covariance invariance	477.772 (353)*	.987	.985	.028	[.021; .034]	M4	63.137 (45)	-.002	.000	+.001
M6. Latent means invariance	509.512 (362)*	.985	.982	.030	[.024; .036]	M5	23.329 (9)*	-.002	-.003	+.002
Correlated Outcome Variables in Sample 2										
CFA	33.187 (17)*	.976	.961	.062	[.029; .093]					

Note. * $p < .01$; χ^2: Robust chi-square test of exact fit; *df*: Degrees of freedom; CFI: Comparative fit index; TLI: Tucker-Lewis index; RMSEA: Root mean square error of approximation; 90% CI: 90% confidence interval; CM: Comparison model; Δ: Change in fit relative to the CM.

Table S4

Standardized Factor Loadings (λ) and Uniquenesses (δ) from the B-ESEM Solution (Correlated Predictor Variables, Means Invariance, Study 2)

Items	Global LMX (G-λ)	AFF (S-λ)	LOY (S-λ)	CON (S-λ)	PRO (S-λ)	Global NF (G-λ)	RNF (S-λ)	ANF (S-λ)	CNF (S-λ)	δ
Affect										
Item 1	**.794**	***.131***	.273	*-.021*	*.003*					.278
Item 2	**.740**	**.380**	-.127	*-.011*	*-.007*					.292
Item 3	**.188**	***-.039***	*-.019*	*.073*	.563					.641
LOY										
Item 1	**.821**	.308	**-.172**	*.048*	*.022*					.199
Item 2	**.832**	-.143	**-.151**	*-.041*	*-.086*					.256
Item 3	**.809**	*.060*	**.382**	*-.089*	*-.017*					.187
CON										
Item 1	**.854**	*-.150*	*-.104*	***-.072***	*-.135*					.214
Item 2	**.836**	.181	-.144	***.063***	*-.021*					.243
Item 3	**.729**	*-.056*	*-.067*	***.569***	*.165*					*.111*
PRO										
Item 1	**.792**	-.201	*-.088*	*.033*	***-.068***					.319
Item 2	**.415**	*-.086*	-.085	.220	**.594**					.413
Item 3	**.758**	*.048*	.231	*-.007*	***.152***					.346
RNF										
Item 1						**.617**	.061	**.598**	*-.011*	.259
Item 2						**.528**	-.100	**.508**	.106	.442
Item 3						**.480**	.054	**.478**	.072	.533
ANF										
Item 1						**.662**	**.407**	*.029*	-.089	.387
Item 2						**.584**	**.562**	*-.008*	*-.008*	.343
Item 3						**.425**	**.669**	*.045*	*.021*	.370
CNF										
Item 1						**.851**	*.039*	-.171	**-.263**	.176
Item 2						**.813**	*-.038*	.099	***-.066***	.323
Item 3						**.818**	-.055	*.051*	***.475***	*.100*
ω	.955	.200	.436	.466	.381	.894	.709	.670	.519	

Note. λ: Factor loading; δ: Item uniqueness; ω: Omega coefficient of model-based composite reliability; G: Global factor from the bifactor model; S: Specific factors from the bifactor model; AFF: Affect; LOY: Loyalty; CON: Contribution; PRO: Professional respect; RNF: Relatedness need frustration; ANF: Autonomy need frustration; CNF: Competence need frustration; target factor loadings are indicated in bold; non-significant parameters ($p \geq .05$) are marked in italics.

Table S5

Standardized Factor Loadings (λ) and Uniquenesses (δ) from the CFA Solution (Correlated Outcome Variables, Study 2, Sample 2)

Items	Perceived stress (λ)	Perceived health (λ)	δ
Perceived stress			
Item 1	.777		.396
Item 2	.667		.556
Item 3	.745		.445
Item 4	.740		.453
Perceived health			
Item 1		.801	.358
Item 2		.718	.485
Item 3		.784	.386
Item 4		.698	.513
ω	.823	.838	

Note. λ: Factor loading; δ: Item uniqueness; ω: Omega coefficient of model-based composite reliability.

Table S6

Goodness-of-Fit Statistics for the Estimated Measurement Models (Study 3)

Description	χ^2 (*df*)	CFI	TLI	RMSEA	90% CI	CM	$\Delta\chi^2$ (*df*)	ΔCFI	ΔTLI	ΔRMSEA
Multi-Group Tests of Invariance (Samples 1 and 2)										
M1. Configural invariance	2048.713 (1158)*	.914	.901	.055	[.051; .059]	-	-	-	-	-
M2. Weak invariance	2121.632 (1200)*	.911	.901	.055	[.051; .059]	M1	73.002 (42)*	-.003	.000	.000
M3. Strong invariance	2216.109 (1228)*	.905	.897	.056	[.052; .060]	M2	96.829 (28)*	-.006	-.004	+.001
M3'. Partial strong invariance	2192.667 (1226)*	.907	.900	.055	[.052; .059]	M2	71.851 (26)*	-.004	-.001	.000
M4. Strict invariance	2248.116 (1263)*	.905	.900	.055	[.051; .059]	M3'	59.971 (37)*	-.002	.000	.000
M4'. Partial strict invariance	2234.348 (1262)*	.906	.901	.055	[.051; .059]	M3'	51.539 (36)	-.001	+.001	.000
M5. Latent variance-covariance invariance	2308.591 (1307)*	.903	.901	.055	[.051; .058]	M4'	74.202 (45)*	-.003	.000	.000
M6. Latent means invariance	2378.847 (1316)*	.897	.896	.056	[.053; .060]	M5	71.620 (9)*	-.006	-.005	+.001
M6'. Partial latent means invariance	2347.470 (1314)*	.900	.900	.055	[.052; .059]	M5	39.226 (7)*	-.003	-.001	.000

Note. * $p < .01$; χ^2: Robust chi-square test of exact fit; *df*: Degrees of freedom; CFI: Comparative fit index; TLI: Tucker-Lewis index; RMSEA: Root mean square error of approximation; 90% CI: 90% confidence interval; CM: Comparison model; Δ: Change in fit relative to the CM

Table S7

Standardized Factor Loadings (λ) and Uniquenesses (δ) from the Partial Latent Means Invariance Model (Study 3)

Items	Global W (G-λ)	WE (S-λ)	WC (S-λ)	PD (λ)	WOR (λ)	SUP (λ)	PRE (λ)	WFC (λ)	EE (λ)	δ
WE										
Item 1	**.486**	**.755**	*.029*							.193
Item 2	**.469**	**.244**	*.010*							.720
Item 3	**.432/.518**	**.282/.338**	.196/.235							.695/.562
Item 4	**.634**	***.082***	-.156							.566
Item 5	**.553**	**.373**	*.068*							.550
WC										
Item 1	**.490**	*.001*	**.309**							.665
Item 2	**.714**	*.010*	**.396**							.333
Item 3	**.686**	.155	***.037***							.504
Item 4	**.517**	*-.031*	**-.264**							.662
Item 5	**.704**	-.119	**-.441**							.296
PD										
Item 1				.886						.215
Item 2				.862						.256
Item 3				.728						.470
Item 4				.767						.412
WOR										
Item 1					.724					.476
Item 2					.822					.325
Item 3					.761					.422
Item 4					.757					.427
Item 5					.793					.372
SUP										
Item 1						.901				.188
Item 2						.746				.443
Item 3						.867				.248
Item 4						.726				.473
PRE										
Item 1							.877			.230
Item 2							.872			.240
Item 3							.883			.220
Item 4							.875			.234
Item 5							.892			.205
Item 6							.838			.298
WFC										
Item 1								.875		.234
Item 2								.749		.439
Item 3								.864		.254
EE										
Item 1									.797	.365
Item 2									.778	.395
Item 3									.823	.323
Item 4									.824	.321
Item 5									.662	.561
ω	.862/.868	.525/.553	.460	.886	.880	.886	.951	.870	.885	

Note. λ: Factor loading; δ: Item uniqueness; ω: Omega coefficient of model-based composite reliability; G: Global factor from the bifactor model; S: Specific factors from the bifactor model; W: Workaholism; WE: Working excessively; WC: Working compulsively; PD: Psychological detachment; WOR: Workload; SUP: Supervisor support; PRE: Presenteeism; WFC: Work-family conflicts; EE: Emotional exhaustion; target factor loadings are indicated in bold; non-significant parameters ($p \geq .05$) are marked in italics.

Section 3
Latent Profile Analyses

Study 2

The results from the latent profile solutions estimated in Study 2 are reported in Table S8 of the online supplements, while those from the models estimated in Study 3 are reported in Table S9 of these same supplements. These results are graphically illustrated using elbow plots, reported in Figures S1 (Study 2-Sample 1), S2 (Study 2-Sample 2), S3 (Study 3-Sample 1), and S4 (Study 3-Sample 2) of the online supplements.

In Study 2 Sample 1, the CAIC reached its lowest point for the two-profile solution, the BIC reached its lowest point for the three-profile solution, and the ABIC reached its lowest point for the six-profile solution. In Sample 2, the CAIC and BIC reached their lowest point for the one-profile solution, whereas the ABIC reached its lowest point for the eight-profile solution. Examination of the elbow plots was more informative, suggesting a plateau in the decrease of the value of the various information criteria occurring after the three- or four-profile solutions in Sample 1, and a plateau in the decrease of the value of the AIC and ABIC occurring after the three-profile solution (matching a slight decrease in the value of the CAIC and BIC) in Sample 2.

In Study 3 Sample 1, the CAIC reached its lowest point for the six-profile solution, the BIC reached its lowest point for the seven-profile solution, and the ABIC reached its lowest point for the eight-profile solution. In Sample 2, the CAIC reached its lowest point for the four-profile solution, the BIC reached its lowest point for the fifth-profile solution, and the ABIC reached its lowest point for the eight-profile solution. Examination of the elbow plot was more informative, suggesting a plateau in the decrease of the value of the various information criteria occurring after the three-profile solution in Sample 1 and the four-profile solution in Sample 2.

Solutions including two, three, four, and five profiles were thus more specifically examined in both studies. This examination revealed that all of these solutions were statistically proper, and already showed a high level of similarity across samples in both studies. This apparent similarity thus already provides some support to the *configural* similarity of the model across samples in both studies. Moreover, this examination revealed that each new profile represented a meaningful addition (resulting in the addition of a qualitatively distinct profile) to the solution up to four profiles, whereas adding a fifth profile only resulted in the arbitrary division of an existing profile into smaller ones characterized by a very similar shape. Thus, a 4-profile solution was retained across all samples.

Table S8

Results from the Latent Profile Analysis Models (Study 2)

Model	LL	#fp	Scaling	AIC	CAIC	BIC	ABIC	Entropy	aLMR	BLRT
Sample 1										
1 Profile	-2418.494	6	1.015	4848.988	4881.887	4875.887	4856.837	Na	Na	Na
2 Profiles	-2385.733	13	1.001	4797.466	4868.746	4855.746	4814.471	.959	.002	< .001
3 Profiles	-2359.292	20	1.046	4758.583	4868.245	4848.245	4784.745	.560	.026	< .001
4 Profiles	-2338.548	27	1.019	4731.097	4879.140	4852.140	4766.415	.645	.049	< .001
5 Profiles	-2323.663	34	.921	4715.327	4901.753	4867.753	4759.803	.699	.017	< .001
6 Profiles	-2310.596	41	1.071	4703.192	4928.000	4887.000	4756.825	.726	.186	< .001
7 Profiles	-2302.190	48	.932	4700.381	4963.570	4915.570	4763.170	.751	.779	.667
8 Profiles	-2293.121	55	1.030	4696.242	4997.813	4942.813	4768.188	.804	.286	.063
Sample 2										
1 Profile	-961.516	6	1.034	1935.032	1961.088	1956.088	1937.068	Na	Na	Na
2 Profiles	-948.500	13	1.025	1923.000	1981.622	1968.622	1927.413	.467	.058	.109
3 Profiles	-924.957	20	.954	1889.914	1980.102	1960.102	1896.702	.988	.111	.044
4 Profiles	-911.416	27	.973	1876.832	1998.585	1971.585	1885.995	.697	.050	.023
5 Profiles	-895.989	34	.934	1859.978	2013.287	1979.287	1871.518	.731	.043	< .001
6 Profiles	-886.613	41	.919	1855.226	2040.111	1999.111	1869.141	.764	.064	.047
7 Profiles	-880.885	48	.921	1857.770	2074.221	2026.221	1874.061	.775	.392	.333
8 Profiles	-866.525	55	.918	1843.051	2091.067	2036.067	1861.718	.813	.570	.286

Note. LL: Model LogLikelihood; #fp: Number of free parameters; Scaling: Scaling factor associated with MLR loglikelihood 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; BLRT: Bootstrap Likelihood Ratio Test.

Table S9

Results from the Latent Profile Analysis Models (Study 3)

Model	LL	#fp	Scaling	AIC	CAIC	BIC	ABIC	Entropy	aLMR	BLRT
Sample 1										
1 Profile	-833.699	8	.961	1683.397	1707.641	1690.320	1682.320	Na	Na	Na
2 Profiles	-772.815	17	.936	1579.631	1631.148	1594.342	1577.342	.970	< .001	< .001
3 Profiles	-722.495	26	.977	1496.989	1575.781	1519.489	1493.489	.957	< .001	< .001
4 Profiles	-694.106	35	.911	1458.213	1564.278	1488.501	1453.501	.968	.007	< .001
5 Profiles	-669.288	44	1.071	1426.575	1559.915	1464.652	1420.652	.911	.450	< .001
6 Profiles	-644.025	53	.894	1394.050	1554.663	1439.914	1386.914	.936	.014	< .001
7 Profiles	-621.606	62	.897	1367.212	1555.099	1420.865	1358.865	.950	.011	< .001
8 Profiles	-610.525	71	.890	1363.049	1578.210	1424.490	1353.490	.918	.102	< .001
Sample 2										
1 Profile	-1801.777	8	.968	3619.554	3658.621	3650.621	3625.241	Na	Na	Na
2 Profiles	-1715.499	17	1.129	3464.997	3548.014	3531.014	3477.081	.644	.005	< .001
3 Profiles	-1666.380	26	1.059	3384.761	3511.727	3485.727	3403.242	.723	.002	< .001
4 Profiles	-1629.491	35	.954	3328.982	3499.898	3464.898	3353.860	.781	.010	< .001
5 Profiles	-1602.319	44	.982	3292.638	3507.504	3463.504	3323.914	.824	.078	< .001
6 Profiles	-1583.956	53	.988	3273.912	3532.728	3479.728	3311.586	.840	.077	< .001
7 Profiles	-1568.514	62	.960	3261.028	3563.794	3501.794	3305.099	.813	.384	.090
8 Profiles	-1555.031	71	.998	3252.062	3598.778	3527.778	3302.531	.826	< .001	.147

Note. LL: Model LogLikelihood; #fp: Number of free parameters; Scaling: Scaling factor associated with MLR loglikelihood 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; BLRT: Bootstrap Likelihood Ratio Test.

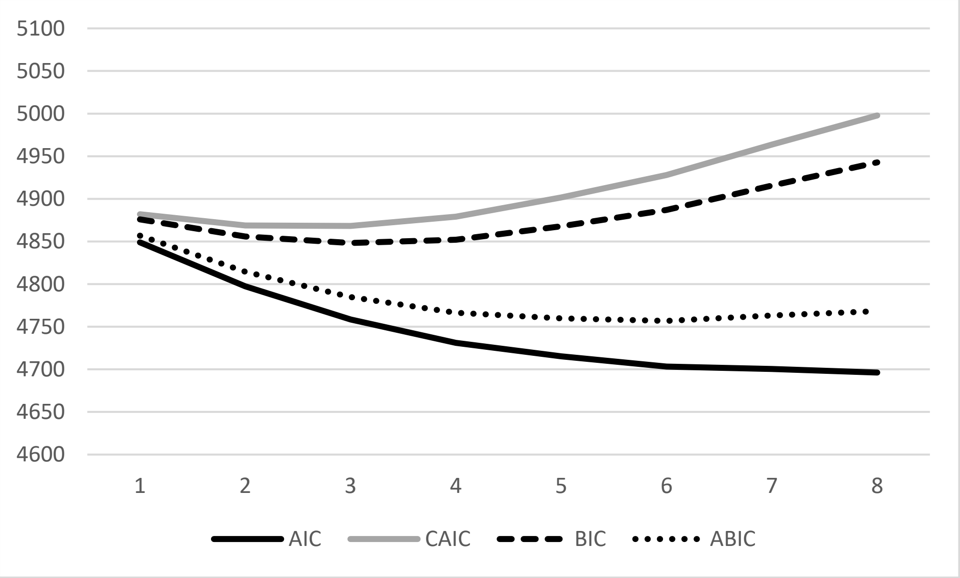

Figure S1
Elbow Plot of the Value of the Information Criteria for Solutions Including Different Numbers of Latent Profiles (Study 2, Sample 1)

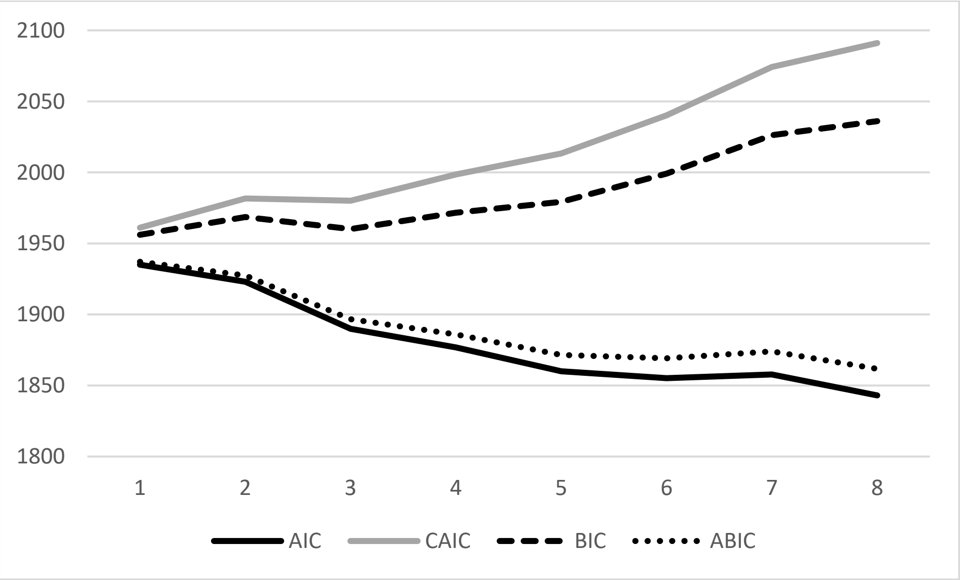

Figure S2
Elbow Plot of the Value of the Information Criteria for Solutions Including Different Numbers of Latent Profiles (Study 2, Sample 2)

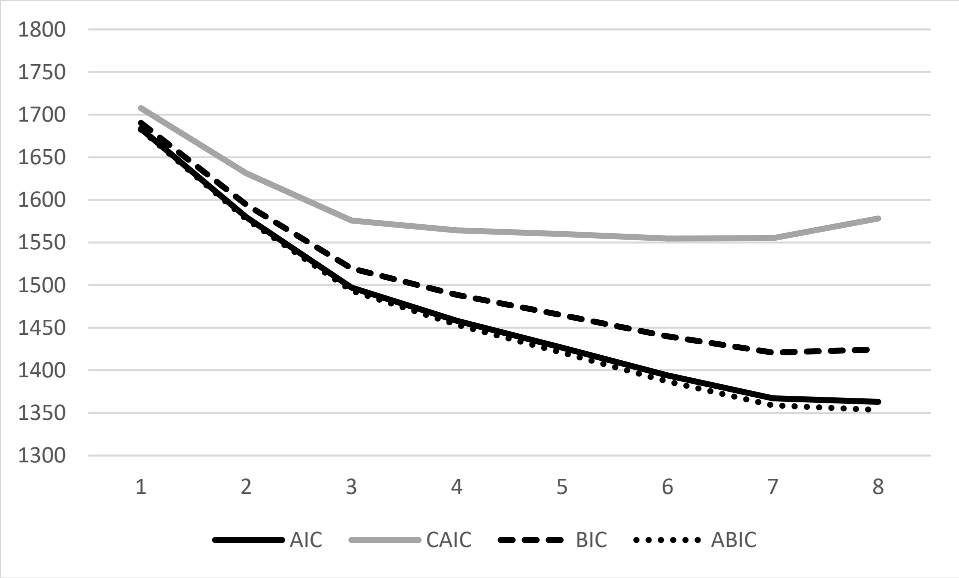

Figure S3
Elbow Plot of the Value of the Information Criteria for Solutions Including Different Numbers of Latent Profiles (Study 3, Sample 1)

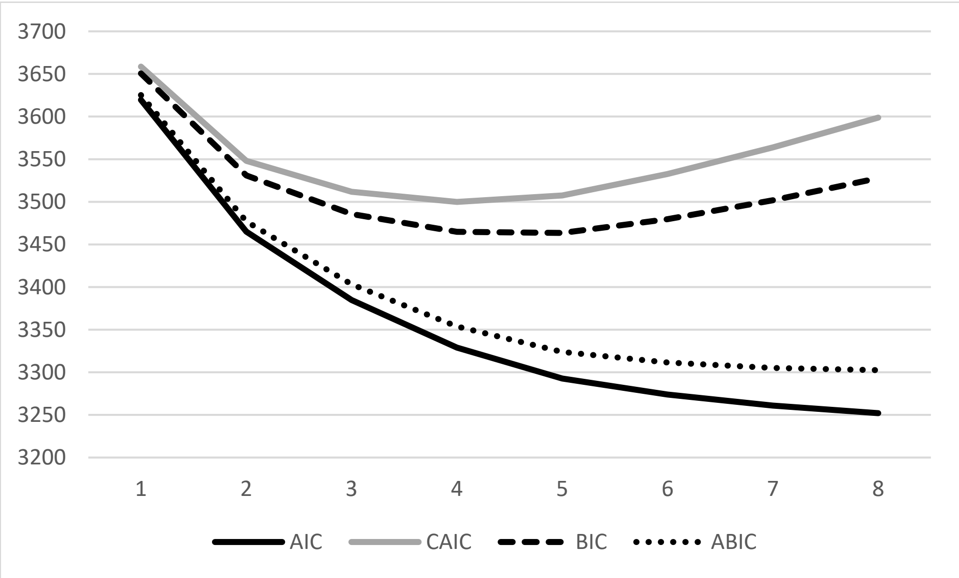

Figure S4
Elbow Plot of the Value of the Information Criteria for Solutions Including Different Numbers of Latent Profiles (Study 3, Sample 2)

Section 4

Additional Results

Table S10

Associations between Profile Membership and the Correlated Outcome Variables (Study 2, Sample 2)

	Profile 1: *M* [CI]	Profile 2: *M* [CI]	Profile 3: *M* [CI]	Profile 4: *M* [CI]	Significant Differences
Perceived health	-.345 [-1.041; .351]	.612 [.355; .869]	.587 [.558; .616]	-.470 [-.650; -.290]	1 = 4 < 2 = 3
Perceived stress	-.502 [-1.019; .015]	-.465 [-.681; -.249]	.258 [-.032; .548]	.408 [.230; .586]	1 = 2 < 3 = 4
Work performance	6.395 [5.017; 7.772]	6.975 [6.481; 7.469]	7.091 [4.196; 9.986]	7.886 [7.647; 8.125]	1 = 2 < 4; 1 = 2 = 3

Note: M: Mean; CI: 95% Confidence Interval; indicators of perceived health and stress are estimated from factor scores with a mean of 0 and a standard deviation of 1; Profile 1: *Low Global and Specific Workaholism*; Profile 2: *Average Global and Specific Workaholism*; Profile 3: *Low Global and Average Specific Workaholism*; and Profile 4: *High Global and Average Specific Workaholism*.

Table S11

Associations between Profile Membership and the Correlated Outcome Variables (Study 3)

	Profile 1: *M* [CI]	Profile 2: *M* [CI]	Profile 3: *M* [CI]	Significant Between-Profile Differences (Both Samples)	
Presenteeism	.109 [-.073, .290]	1.017 [.740, 1.294]	-.470 [-.587, -.354]	2 > 1 > 3	
Work-family conflicts	.254 [.128, .380]	1.285 [1.165, 1.406]	-.701 [-.816, -.586]	2 > 1 > 3	
Emotional exhaustion	.270 [.120, .420]	1.110 [.968, 1.252]	-.656 [-.814, -.498]	2 > 1 > 3	
Job satisfaction	2.897 [2.781, 3.012]	2.483 [2.331, 2.635]	3.171 [3.089, 3.253]	3 > 1 > 2	
Work performance	7.852 [7.609, 8.094]	6.676 [6.166, 7.186]	8.476 [8.271, 8.682]	3 > 1 > 2	
	Profile 4: *M* [CI]	Profile 4: *M* [CI]	Significant Between-Profile Differences Involving Profile 4		Significant Between-Sample Differences (Profile 4)
	Sample 1: Nurses	Sample 2: Educators	Sample 1: Nurses	Sample 2: Educators	
Presenteeism	-.862 [-.990, -.734]	.022 [-.196, .239]	2 > 1 > 3 > 4	2 > 1 = 4 > 3	Sample 2 > Sample 1
Work-family conflicts	-1.337 [-1.514, -1.159]	.450 [.244, .656]	2 > 1 > 3 > 4	2 > 1 = 4 > 3	Sample 2 > Sample 1
Emotional exhaustion	-1.177 [-.1583, -.771]	.103 [-.092, .297]	2 > 1 > 3 > 4	2 > 1 = 4 > 3	Sample 2 > Sample 1
Job satisfaction	3.152 [2.968, 3.336]	3.026 [2.908, 3.144]	4 > 1 > 2; 4 = 3	3 > 1 = 4 > 2	Sample 1 = Sample 2
Work performance	9.205[8.782, 9.629]	8.205 [7.966, 8.443]	4 > 3 > 1 > 2	1 = 4; 3 = 4; 4 > 2	Sample 1 > Sample 2

Note: M: Mean; CI: 95% Confidence interval; indicators of presenteeism, work-family conflicts, and emotional exhaustion are estimated from factor scores with a mean of 0 and a standard deviation of 1; Profile 1: *Average Global and Specific Workaholism*; Profile 2: *High Global and Average Specific Workaholism*; Profile 3: *Low Global and Average Specific Workaholism*; Profile 4 (Nurses): *Low Global Workaholism/High Specific Workaholism and Psychological Detachment;* and Profile 4 (Educators): *Average Global Workaholism/Low Specific Workaholism and Psychological Detachment*.