Toward an Improved Understanding of Work Motivation Profiles

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Abstract

The present research proposes an improved understanding of work motivation by identifying employees' motivational profiles while taking into account the dual global and specific nature of work motivation proposed by self-determination theory (SDT). To document the construct validity of these latent profiles, we relied on the circumplex model of employees' wellbeing to investigate whether they differed in terms of burnout, work satisfaction, and work addiction. Results from analyses conducted among a sample of 955 employees revealed five distinct profiles characterized by differing levels of global and specific forms of motivation: Intrinsically Motivated, Poorly Motivated, Driven, Conflicted, and Self-Determined. Lower levels of burnout and work satisfaction were associated with profiles characterized by higher global levels of self-determination and more autonomous forms of motivation, matching theoretical expectations. Interestingly, work addiction was highest in the Driven profile and lowest in the Self-Determined profile, suggesting that autonomous forms of motivation are not always able to buffer the adverse effects of controlled forms of motivation. Our results also suggest that the specific qualities of work motivations are just as important as the global levels of self-determination in the identification of work motivation profiles.

Keywords: Work motivation; profiles; Self-Determination Theory (SDT); work addiction; burnout; work satisfaction; latent profile analysis (LPA); bifactor exploratory structural equation modeling (bifactor-ESEM).

Work motivation has been extensively studied within the field of organizational psychology (Kanfer, Frese, & Johnson, 2017). Motivation can generally be described as a complex multidimensional determinant of direction and persistence in goal-directed behavior (Pinder, 1998). Among the many motivational theories that have been developed over the decades (Kanfer et al., 2017), self-determination theory (SDT; Ryan & Deci, 2017) is one of the most well-articulated conceptual frameworks to guide the study of human motivation, particularly when applied to work settings (Deci, Olafsen, & Ryan, 2017; Gagné & Deci, 2005). SDT underscores the importance of engaging in work activities for self-determined reasons, driven by pleasure, interest, and personal importance relative to more extrinsically-driven motives, involving guilt and pressure (Ryan & Deci, 2017). Research conducted in the work area has generally supported these assertions in showing that work motivation can be manifested in a variety of ways, each presenting well-differentiated relations with work-related outcomes (Deci et al., 2017; Gagné & Deci, 2005).

Unfortunately, previous studies have generally considered the role of these various types of work motivation in isolation rather than considering the fact that each individual worker can be driven by a motivation configuration encompassing more than one type of motive (e.g., Vallerand, 1997). Clearly, being able to identify the most commonly occurring of those motivation profiles, and their implications, is likely to be helpful for managers and practitioners seeking to design interventions that better reflect the unique needs of each of these profiles of workers. Although research has, in the past decade, started to investigate the nature of these motivation profiles, these studies have generally failed to take into account the underlying dual nature of work motivation ratings. More precisely, recent research conducted within SDT has shown that motivation ratings were best represented by an operationalization allowing for a disaggregation of employees' global level of self-determination across all types of work motives, from the unique quality of each specific work motive over and above that global level (Howard, Gagné, Morin, & Forest, 2018; Litalien et al., 2017; Ryan & Deci, 2017).

The present study seeks to address these issues by identifying different profiles of workers characterized by distinct configurations of work motivations while taking into account the dual global/specific nature of work motivation. In addition, we document the implications of these work motivation profiles in relation to employees' levels of burnout, work satisfaction, and work addiction.

Work Motivations

According to SDT (Ryan & Deci, 2017), motivation can occur for a variety of reasons (usually referred to as behavioral regulations within SDT), assumed to be qualitatively distinct from one another and yet organized along a continuum of self-determination. At the most self-determined extreme of this continuum is *intrinsic motivation*. Intrinsically motivated workers engage in work activities perceived as inherently enjoyable and satisfying. Next, *identified regulation* occurs when working is perceived as personally important, valuable, and aligned with one's own personal values. Then, *introjected regulation* refers to a drive to work that results from internal pressures (e.g., avoiding guilt, maintaining self-worth). In contrast, *external regulation* occurs when work is mainly driven by external pressures. When specifically focusing on work motivation, Gagné et al. (2015) proposed to distinguish two subtypes of external regulation, assumed to occupy the same position on the SDT continuum. First, *external-social regulation* refers to work that is driven by social pressures, such as to obtain the approval of others or to avoid their criticism. Second, *external-material regulation* refers to work that is driven by material drivers, such as to achieve monetary gains or job security. Finally, located at the other extreme of the continuum, *amotivation* refers to a complete lack of desire, drive, motive, or felt pressure to engage in work-related activities. Intrinsic motivation and identified regulation are typically referred to as *autonomous* forms of motivation because they mainly involve autonomously-driven personal choices. In contrast, introjected regulation and external regulation are typically referred to as *controlled* forms of motivation because they involve internally- or externally-driven pressures to work that are unrelated to one's personal desires.

Various approaches have been used to verify the SDT continuum hypothesis, ranging from attempts to estimate a one-factor structure of work motivation representing this continuum, to multidimensional approaches seeking to assess whether associations between behavioral regulations would match the hypothetical continuum structure (e.g., Chemolli & Gagné, 2014; Guay, Morin, Litalien, Valois, & Vallerand, 2015; Howard, Gagné, & Bureau, 2017; Sheldon, Osin, Gordeeva, Suchkov, & Sychev, 2017; Wang, Morin, Ryan, & Liu, 2016). Unfortunately, both approaches present important limitations. Indeed, the one-dimensional perspective fails to account for the unique quality of each specific form of behavioral regulation. In contrast, the multidimensional perspective is unable to directly estimate the overall self-determination continuum (Ryan & Deci, 2017).

Recently, a third approach has been proposed, allowing for the estimation of employees' global levels of self-determined work motivation together with a concurrent estimate of the unique quality of each specific type of behavioral regulation left unexplained by this global factor (Howard et al., 2018; Litalien et al., 2017). Research adopting this new bifactor exploratory structural equation modeling (bifactor-ESEM; Morin, Arens, & Marsh, 2016) method have shown that, whereas global levels of self-determination displayed the strongest associations with outcomes, the specific factors also contributed to these outcomes beyond the global factor (Howard et al., 2018; Litalien et al., 2017).

Over and above the consideration of how best to account for the dual global and specific nature of work motivation, SDT also posits that these motivations should lead to distinct affective, cognitive, and behavioral outcomes. Previous studies have generally supported this assertion in showing that more autonomous forms of motivation tended to be positively related to work performance, psychological wellbeing, job satisfaction, commitment, and intentions to remain, while opposite or null relations were generally found with more controlled forms of motivation (Deci et al., 2017; Gagné & Deci, 2005; Ryan & Deci, 2017). Although these studies shed light on the unique importance of each type of work motive, they failed to consider that people generally endorse multiple behavioral regulations simultaneously (Vallerand, 1997). Thus, workers might work hard because they enjoy their job (i.e., intrinsic motivation) *and* because they want to achieve a promotion (i.e., external-material regulation). Likewise, by considering behavioral regulations in isolation, these studies are also unable to isolate the effects stemming from employees' global levels of self-determination versus the unique quality of each specific type of behavioral regulation. To address both limitations, the current person-centered study seeks to identify work motivation profiles defined based on the joint consideration of global levels of self-determined work motivation and specific levels of each behavioral regulation.

Work Motivation Profiles

Variable-centered approaches examine average relations between variables, assuming that all members of the sample are drawn from a single population so that results can be expected to generalize to all members of that population. Person-centered approaches relax this assumption by identifying subpopulations, or profiles, of workers characterized by distinct behavioral regulation configurations (Morin, 2016). For instance, a person-centered approach might identify a profile of workers that are mainly driven by autonomous reasons, whereas another profile could be driven by a combination of identified and introjected regulations. Person-centered approaches thus make it possible to identify different types of workers approaching work differently while jointly considering global and specific levels of motivation across a variety of behavioral regulations. This approach is thus directly aligned with SDT's assertion that workers are rarely driven by a single form of regulation, but rather by a more complex configuration of work motives (Vallerand, 1997). Person-centered approaches are able to explicitly test this assumption (Morin, Morizot, Boudrias, & Madore, 2011) while providing results that are naturally suited to the design of managerial interventions tailored at different types of employees (Morin & Marsh, 2015).

In the work area, a few person-centered studies have sought to identify the nature of the most commonly occurring work motivation profiles. Among those, some studies have focused on global autonomous and controlled motivation dimensions (e.g., Van den Berghe et al., 2014; Van den Broeck et al., 2013), whereas others have relied on a more comprehensive coverage of behavioral regulations (Gillet, Becker, et al., 2017; Gillet et al., 2018; Graves et al., 2015; Howard et al., 2016; Jansen in de Wal et al., 2014; Moran, Diefendorff, Kim, & Liu, 2012). Despite these variations, across studies, results seem to converge on employees' profiles characterized by: (i) *Autonomous*: high autonomous motivation coupled with low levels of controlled motivation and amotivation; (ii) *Motivated*: high autonomous and controlled motivations coupled with low amotivation, (iii) *Controlled*: low autonomous motivation, coupled with high controlled motivation and amotivation, and (iv) *Unmotivated*: low (to moderate) autonomous motivation, controlled motivation, and amotivation. Beyond these generic conclusions, some results have also revealed profiles presenting differentiated levels of introjected and external regulation, thus supporting the need to rely on a finer-grained representation of work motivation (Gillet, Becker et al., 2017; Moran et al., 2012).

Unfortunately, none of these studies has relied on an operationalization of work motivation allowing for the simultaneous consideration of global levels of self-determination and specific types of behavioral regulations (Howard et al., 2018). As noted by Morin and Marsh (2015), ignoring the presence of co-existing global (i.e., global self-determination levels) and specific (i.e., the unique quality associated with each type of behavioral regulation beyond global self-determination levels) factors is likely to result in a lack of precision and theoretical clarity in the estimation of latent profiles. This observation has led Morin, Boudrias et al. (2016, 2017) to recommend anchoring person-centered investigations in a comprehensive examination of the multidimensional structure of the constructs of interest, in order to be able to estimate latent profiles using indicators allowing for an accurate representation of the global versus specific nature of these constructs. This is the approach taken in the present study. Despite the novelty of this approach, results from studies relying on a more traditional representation of behavioral regulations (e.g., Gillet et al., 2018; Howard et al., 2016) allow us to expect:

Hypothesis 1. Four to six distinct work motivation profiles will be identified.

Hypothesis 2. At least one of those profiles will be dominated by moderate-to-high global levels of self-determined work motivation and/or of specific forms of autonomous motivation, one will be dominated by low global levels of self-determined work motivation and/or of specific forms of controlled motivation or amotivation, one will display high global and specific levels of motivation across dimensions, and one will display low to moderate global and specific levels of motivation across dimensions.

Hypothesis 3. We also expect additional profiles to display differentiated configurations of motivation across specific dimensions (e.g., distinct levels of external versus introjected regulations).

Outcomes of Work Motivation Profiles: Burnout, Work Satisfaction, and Work Addiction

The demonstration that the latent profiles extracted in any given study present well-differentiated relations with theoretically relevant outcomes is critical to the establishment of the construct validity of a person-centered solution (e.g., Marsh et al., 2009; Meyer & Morin, 2016; Muthén, 2003). In practical terms, the ability to demonstrate well-differentiated outcome associations is also a core component in the demonstration of the practical relevance of these profiles (e.g., Morin et al., 2011). Prior person-centered research on work motivation has established relations between a series of work outcomes and employees' motivational profiles. More precisely, and in accordance with SDT (Deci & Ryan, 2000; Ryan & Deci, 2017), these studies have shown that *Autonomous* profiles tended to result in more desirable work outcomes, whereas *Controlled* profiles tended to result in less desirable outcomes (e.g., Moran et al., 2012; Van den Broeck et al., 2013). Furthermore, additional studies also showed that profiles characterized by high levels of controlled motivation did not seem to result in problematic outcomes when these levels were accompanied by equally high levels of autonomous motivation (i.e., the *Motivated* profiles; Gillet et al., 2018; Howard et al., 2016), thus failing to support SDT's expectations regarding the undesirability of controlled forms of regulation (Ryan & Deci, 2017). In the present study, we relied on the circumplex model of subjective wellbeing at work (Bakker & Oerlemans, 2011) which, rather than treating well-being as a unitary construct, distinguishes among positive and negative forms of work-related wellbeing as a function of a pleasure/displeasure distinction and of a high/low activation distinction. Using this model allowed us to examine more precisely how employees' work motivation profiles are related to different aspects of wellbeing at work: (a) burnout (unpleasant, low activation); (b) work satisfaction (pleasant, low activation), and (c) work addiction (unpleasant, high activation).

Burnout. Burnout has been identified as one of the most detrimental wellbeing outcomes and is known to carry a heavy burden both for the employee and the organization (Maslach, Schaufeli, & Leiter, 2001). Across theoretical perspectives (Maslach, Jackson, & Leiter, 1997; Shirom & Melamed, 2006), burnout is typically defined as a psychological state resulting from work-related strain and characterized by a combination of emotional (e.g., emotional exhaustion), cognitive (e.g., feelings of disconnection from work and weariness), and behavioral (e.g., reduced efficacy and fatigue) manifestations. The circumplex model of well-being (Bakker & Oerlemans, 2011) characterizes burnout as a state of low activation and unpleasant affect.

Variable-centered research has generally corroborated the presence of negative associations between more autonomous forms of motivation and burnout components, as well as the positive associations between more controlled forms of motivation and burnout components (Fernet, Austin, & Vallerand, 2012; Fernet, Guay, & Senécal, 2004; Kuvaas, Buch, Weibel, Dysvik, & Nerstad, 2017). Likewise, emerging person-centered results tend to demonstrate lower levels of burnout to be associated with the *Autonomous* or *Motivated* profiles, and higher levels of burnout to be associated with the *Controlled* or *Unmotivated* profiles (Gillet et al., 2018; Howard et al., 2016). Interestingly, these results also support the previous assertion regarding the possible benefits of controlled forms of motivation when associated with matching levels of autonomous motivation. However, these previous studies failed to explicitly take into account the global levels of self-determined work motivation which have been shown, in previous variable-centered studies (Howard et al., 2018; Litalien et al., 2017), to represent a much stronger predictor of outcomes than the specific motivation factors reflecting the unique quality of employees' work motivation beyond their global level of self-determination. Consequently, the estimation of work motivation profiles defined using explicit and non-redundant estimates of employees' global and specific levels of work motivation is likely to lead to a more nuanced understanding of associations between these profiles and wellbeing outcomes (e.g., Morin, Boudrias et al., 2016, 2017).

Work Satisfaction. Work satisfaction is also considered as a more positive component of employee's psychological wellbeing at work (Ryan & Deci, 2001) characterized by a combination of low activation and pleasant affect (Bakker & Oerlemans, 2011). In addition, work satisfaction has received a lot of scientific attention in the organizational literature as a simple, yet highly informative, source of information on employees' functioning (Faragher, Cass, & Cooper, 2005; Judge, Thoresen, Bono, & Patton, 2001). Research focusing on associations between work satisfaction and motivation has generally led to conclusions opposite to those associated with burnout. Indeed, variable-centered results have generally shown that work satisfaction tends to be positively associated with more autonomous forms of motivation, while being unrelated or negatively related to more controlled forms of motivation and to amotivation (Gagné et al., 2010; Gillet, Gagné, Sauvagère, & Fouquereau, 2013; Houlfort, Philippe, Vallerand, & Ménard, 2013). Person-centered studies essentially mirror these findings, showing that *Autonomous* and *Motivated* profiles tend to present higher levels of work satisfaction than *Controlled* and *Unmotivated* profiles (Gillet et al., 2018; Howard et al., 2016). However, similar to burnout, these previous person-centered studies (Gillet et al., 2018; Howard et al., 2016) failed to rely on a proper disaggregation of global and specific levels of work motivation. This suggests that associations with work satisfaction reported in these previous studies might reflect a confusing mixture of variance attributable to these global and specific components.

Work Addition. Work addiction (or workaholism) is a distinct type of wellbeing outcome reflecting an extreme and unhealthy type of intensive work involvement (Porter, 1996) that can be characterized by the combination of high activation and unpleasant affect (Bakker & Oerlemans, 2011), but is often neglected in person-centered research involving wellbeing outcomes (e.g., Gillet et al., 2018). As such, work addiction reflects a motivational process gone awry and having reached extreme levels (Andreassen & Pallesen, 2016).

Several theoretical perspectives have been developed to conceptualize work addiction. On the one hand, the organizational perspective focuses on workaholism, typically defined as an uncontrollable need to work excessively, coupled with the compulsion to maintain this extreme level of work involvement (Schaufeli, Bakker, van der Heijden, & Prins, 2009). On the other hand, a more clinical perspective relies on the well-established behavioral addiction components of Griffiths' (2005) model, arguing that work addiction is made up of seven components: salience (when working comes to dominate thinking), tolerance (increased amounts of working is required to support one's addiction), mood modification (excessive working comes to modify and improve one's mood), withdrawal (unpleasant feelings are experienced when one is unable to work), conflict (excessive working compromises social relationships and other activities), relapse (tendency to revert to extreme working tendencies when attempts are made to reduce one's work involvement) and health concerns (extreme working causes health-related problems). Despite theoretical differences between these approaches, empirical studies generally evidence a substantial overlap between measures of workaholism and work addiction (Andreassen, Griffiths, Hetland, & Pallesen, 2012), leading to an integrative theoretical acknowledgment that both essentially refer to the same underlying construct (Andreassen, Schaufeli, & Pallesen, 2018). In the present study, the clinical perspective of Griffiths (2005) on work addiction seemed to be more aligned to our decision to focus on work-related wellbeing components (in the form of the circumplex model of subjective wellbeing) as outcomes of work motivation profiles.

Although it is difficult to provide realistic prevalence rates as a result of several methodological shortcomings of research focusing on work addiction (Andreassen, 2014), estimates generally fall between 5% and 25% (Andreassen et al., 2014; Andreassen, Griffiths, Sinha, Hetland, & Pallesen, 2016; Orosz, Dombi, Andreassen, Griffiths, & Demetrovics, 2016; Sussman, Lisha, & Griffiths, 2011). The importance of considering work addiction as a relevant outcome of motivation profiles is underscored by previous research which has shown work addiction to be associated with a wide range of adverse consequences, including psychiatric difficulties (Andreassen et al., 2016), poorer work performance (Falco et al., 2013), work-family conflict (Gillet, Morin, Sandrin, & Houle, 2018), and poor physical and mental health (Clark, Michel, Zhdanova, Pui, & Baltes, 2016). Unfortunately, studies have paid less attention to the motivational underpinnings of work addiction (Tóth-Király, Bőthe, & Orosz, 2018). This is surprising given that motivation is known to represent a key driver of other forms of addictive behaviors (e.g., gaming, alcohol use, problematic pornography use; e.g., Ballabio et al., 2017; Bányai et al., 2019; Király et al., 2015; Kuntsche, 2007; Stark et al., 2017).

The few variable-centered studies having focused on the association between work addiction and motivation have generally shown that work addiction seemed to be mainly driven by controlled forms of motivation (e.g., introjected or external regulation), suggesting that addicted workers may be characterized by feelings of self-worth that are contingent on their ability to achieve high standards of performance and be driven by guilt and pressure (van Beek, Hu, Schaufeli, Taris, & Schreurs, 2012; van Beek, Taris, & Schaufeli, 2011). To the best of our knowledge, no person-centered study has yet considered the way distinct work motivation configurations might lead to greater, or lower, levels of work addiction. Previous variable-centered results lead us to expect higher levels of work addiction to be observed among *Controlled* profiles given the positive associations between work addiction and controlled forms of motivation reported by van Beek et al. (2011, 2012). Some person-centered studies conducted in the educational context (e.g., Gillet, Morin, & Reeve, 2017) have also showed that autonomous motivation might be able to buffer the negative effect of controlled motivation as long as they have matching levels. It is thus possible for employees to report high levels of work addiction only in the presence of purely controlled (but not autonomous) work motives for working. This proposition, however, is difficult to assess via variable-centered approaches as it would ideally require the incorporation of multiple interaction effects within the same model, whereas this type of research question naturally matches the capacities of person-centered approaches.

Overall, previous research results allow us to propose the following hypotheses:

Hypothesis 4. The more desirable profiles (i.e., characterized by moderate-to-high global levels of self-determined work motivation and/or of specific forms of autonomous motivation) will display higher levels of work satisfaction (H4a), and lower levels of burnout (H4b) and work addiction (H4c) compared to less desirable profiles (i.e., characterized by low global levels of self-determined work motivation and/or of specific forms of controlled motivation or amotivation) that were expected to display lower levels of work satisfaction, and higher levels of burnout and work addiction.

Research Question. Although we expect profiles characterized by high global and specific levels of motivation across dimensions (i.e., combining high specific levels of controlled motivation with matching specific levels of autonomous motivation) to display lower levels of burnout and higher levels of work satisfaction, we leave as an open research question whether these profiles will also display lower levels of work addiction when compared to less desirable ones.

Methods

Procedure and Participants

The present study was conducted per the Declaration of Helsinki and with the approval of the University Research Ethics Committee. The study was carried out with the adequate understanding and explicit consent of the participants. Questionnaires were filled out online in February-May 2018. Participants were recruited from mailing lists and groups from a variety of organizations, although information regarding organizational membership was not collected as part of our ethics protocol. Participants were informed about the general aim and the topic of the study. If they wished to participate, they had to check a box; otherwise, they were excluded from the study.

Participants were 955 Hungarian working adults (71.6% female), aged between 19 and 70 years (M = 37.3 years, SD = 11.6 years). These workers reported their highest level of education as primary (1.3%), secondary (34.5%) or higher (64.2%), and their place of residence as the capital city (40.8%), county capitals (19.2%), cities (25.8%), and villages (14.2%). In terms of work, 79.9% of the respondents had a full-time job, 15.9% had a part-time job, and 4.2% had occasional jobs. The majority of participants (57.3%) were white-collar employees, 15.3% blue-collar employees, and 27.4% managers. Almost one-third (32.9%) of the workers reported having worked for more than 20 years, 10.8% for 16-20 years, 9.4% for 11-15 years, 13% for 6-10 years, 10.7% for 4-5 years, 13.6% for 2-3 years, and 9.6% for less than 2 years. Finally, 31.6% reported having worked in their current position for 0-1 years, 22.2% for 2-3 years, 10.6% for 4-5 years, 12.4% for 6-10 years, 7.9% for 11-15 years, 4.6% for 16-20 years, and 10.8% for more than 20 years.

Measures

Translation. All measures not already available in Hungarian were adapted using a translation/back-translation procedure (Beaton, Bombardier, Guillemin, & Ferraz, 2000).

Work Motivation (Profile Indicator). The 19-item Multidimensional Work Motivation Scale (Gagné et al., 2015) was administered to assess six distinct work motivation facets: intrinsic motivation (e.g., "Because the work I do is interesting"; α = .92), identified regulation (e.g., "Because putting efforts in this job aligns with my personal values"; α = .80), introjected regulation (e.g., "Because otherwise I will feel ashamed of myself"; α = .68), material external regulation (e.g., "Because I risk losing my job if I don't put enough effort in it"; α = .69), social external regulation (e.g., "To get others' approval (e.g., supervisor, colleagues, family, clients …)"; α = .69), and amotivation (e.g., "I don't know why I'm doing this job, it's pointless work"; α = .86). Scale score reliability (α) for participants' global levels of self-determined work motivation was .84. Participants were asked to respond to each item on a seven-point scale (1 = not at all; 7 = completely) following to indicate "Why do you or would you put effort into your current job".

Work Addiction (Outcome). Work addiction was assessed with the Hungarian version (Orosz, Dombi, Andreassen, Griffiths, & Demetrovics, 2016) of the Bergen Work Addiction Scale (Andreassen, Griffiths, Hetland, & Pallesen, 2012). This scale assesses the core elements of work addiction (salience, tolerance, withdrawal, mood modification, relapse, and conflict) with seven items (e.g., "How often during the last year have you spent much more time working than initially intended?"; α = .77) matching the diagnostic criteria for addiction (Andreassen & Pallesen, 2016). Participants rated each item on a five-point scale (1 = never; 5 = always) while referring to the past 12 months.

Burnout (Outcome). The 14-item (global α = .93) Shirom-Melamed Burnout Measure (Hobfoll & Shirom, 2000; Shirom & Melamed, 2006) was used to measure burnout along three dimensions of physical fatigue (6 items, e.g., "I have no energy for going to work in the morning"; α = .90), emotional exhaustion (3 items, e.g., "I feel I am not capable of investing emotionally in coworkers and customers"; α = .79), and cognitive weariness (5 items, e.g., "I feel I'm not focused in my thinking"; α = 88). Participants were instructed to rate their feelings at work for the preceding 30 days using a seven-point scale (1 = never or almost never; 7 = always or almost always).

Work Satisfaction (Outcome). Participants' satisfaction at work was measured with the five-item (e.g., "I am satisfied with my work"; α = .87) Satisfaction with Life Scale (Diener, Emmons, Larsen, & Griffin, 1985; Martos, Sallay, Désfalvi, Szabó, & Ittzés, 2014) adapted to the work context by replacing the word "life" with the word "work" (Fouquereau & Rioux, 2002). Participants rated each item using a seven-point scale (1 = strongly disagree; 7 = strongly agree).

Analyses

Preliminary Measurement Models. All analyses were conducted in Mplus 8 (Muthén & Muthén, 2017). For work motivation, we first contrasted CFA, bifactor-CFA, ESEM, and bifactor-ESEM solutions to adequately capture the improved representation of work motivations advocated by Howard et al. (2018) and Litalien et al. (2017). In CFA, items were allowed to define their a priori factors, cross-loadings were not permitted, and correlations between the factors were freely estimated. In ESEM, the same set of factors were specified as in the CFA, but all cross-loadings were freely estimated and targeted to be as close to zero as possible via the confirmatory oblique target rotation procedure (Browne, 2001). In bifactor-CFA, items defined one G-factor and their a priori S-factor, cross-loadings were not allowed between the S-factors, and the factors were specified as orthogonal (i.e., not correlated, with all $r = 0$) as per typical bifactor specifications (Morin, Myers, & Lee, 2019; Reise, 2012). In bifactor-ESEM, factors were defined as in bifactor-CFA, but cross-loadings were freely estimated using orthogonal target rotation procedures (i.e., all factors were rotated to be uncorrelated with all $r = 0$). For burnout, a strategy was adopted similar to that described above in which we contrasted first-order and bifactor CFA and ESEM solutions to determine the optimal specification for the burnout measurement model. Because our goal was to achieve a global estimate of burnout while maintaining control over subscale specificity, we only used the burnout G-factor as profile outcome along with work satisfaction and work addiction as profile outcomes. Finally, work satisfaction and work addiction were modeled in a two-factor CFA model. Additional tests were also conducted to ascertain the distinctiveness of the factors by combing some of them.

Factor scores (standardized units with M = 0 and SD = 1) were derived from the most optimal measurement model to achieve partial control for measurement error present at the item level (Skrondal & Laake, 2001) and to retain the underlying bifactor structure of the motivation and burnout measures (Morin, Boudrias et al., 2016, 2017). For work motivation, the optimal measurement model from which the factor scores were extracted was a bifactor-ESEM solution encompassing one self-determination G-factor and six S-factors representing the unique qualities associated with each motivational regulation. For burnout, the optimal measurement model from which the factor scores were extracted was a bifactor-CFA solution, including a burnout G-factor and three S-factors representing physical, cognitive, and emotional exhaustion. Finally, work satisfaction and work addiction were best represented as a two-factor CFA solution. More information about these preliminary measurement models and tests of distinctiveness is provided in the online supplements. Correlations among all factor scores used in the present study are reported in Table 1.

Latent Profile Analysis (LPA). Alternative LPA solutions, including one to eight work motivation profiles, were estimated using Mplus' robust maximum-likelihood estimator (MLR) and allowing the means and variance of the profile indicators to be freely estimated across profiles (Diallo, Morin, & Lu, 2016; Peugh & Fan, 2013). In order to avoid converging on suboptimal solutions, these models were estimated using 5000 random start values, 1000 iterations, and retaining the 200 best solutions for final optimization (Hipp & Bauer, 2006).

In the selection of the optimal number of profiles, we considered the meaningfulness, the theoretical adequacy, and the statistical adequacy of the solutions (Morin, 2016). A variety of statistical indicators were also considered: the Akaike Information Criterion (AIC), the Bayesian Information Criterion (BIC), the Consistent AIC (CAIC), the Sample-Size-Adjusted BIC (SSABIC), the adjusted Lo-Mendell-Rubin (aLMR) likelihood ratio test, and the Bootstrap Likelihood Ratio Test (BLRT). A lower value on AIC, BIC, CAIC, and SSABIC suggests a better fitting solution. A non-significant p-value for aLMR and BLRT suggests the superiority of a model with one less profile. However, as the AIC, BIC, CAIC, and SSABIC often keep improving with the addition of more profiles, the graphical examination of "elbow plots" could facilitate the decision making where the point after which the slope flattens suggest that the optimal number of profiles have been reached. We also report the entropy. While this indicator is not used in class enumeration, it provides information about the precision of the classification with values ranging from 0 (lowest) to 1 (highest). Finally, outcome levels were contrasted across the profiles with a model-based approach (Lanza, Tan, & Bray, 2013) implemented using Mplus' auxiliary DCON function (Asparouhov & Muthén, 2014).

Results

Work Motivation Profiles

Fit indices associated with the different profile solutions are reported in Table 2 and graphically depicted in Figure S1. The aLMR supported either the 3- or the 5-profile solution, while the BLRT failed to converge on any specific solution. The AIC and SSABIC continuously decreased with the addition of further profiles, but their decrease reached the first plateau around 5 profiles. Finally, the CAIC and BIC reached their lowest value at the 5-profile solution. On this basis, solutions including 4 to 6 profiles were examined more carefully. This inspection revealed that all solutions were proper statistically and that increasing the number of profiles resulted in the addition of theoretically meaningful, distinct, and interpretable profiles up to the 5-profile solution. Conversely, the addition of a sixth profile simply led to the arbitrary division of one profile into two smaller ones with similar shapes, thus failing to provide any additional theoretical contribution. The five-profile solution was thus retained for interpretation and further analyses, supporting *Hypothesis 1*. This solution is graphically illustrated in Figure 1 (exact parameter estimates and confidence intervals are reported in Table S9 of the online supplements). It is interesting to note that the entropy (i.e., .678) and classification probabilities of participants into their most likely profile (ranging from .735 to .953) were indicative of a satisfactory level of classification accuracy for this 5-profile solution.

Profile 1 was characterized by average levels of global self-determination coupled with moderately high specific levels of intrinsic motivation, average specific levels of identified, introjected, and external-social regulations, as well as low specific levels of amotivation. This *Intrinsically Motivated* profile characterized 14.7% of the workers. Profile 2 was characterized by slightly lower than average global levels self-determination and specific levels of identified regulation, higher than average specific levels of amotivation, and average specific levels on the other regulations. This *Poorly Motivated* profile was the largest, corresponding to 44.4% of the workers. Profile 3 was characterized by high levels of global self-determination, high specific levels of identified, introjected and external-material regulations, average specific levels of external-social regulation and amotivation, and slightly lower than average specific levels of intrinsic motivation. This *Driven* profile was the smallest, corresponding to 2.4% of the workers. Profile 4 was characterized by slightly lower than average levels of global self-determination and specific levels of intrinsic motivation, slightly higher than average specific levels of identified regulation and amotivation, and average specific levels on all other regulations. This *Conflicted* profile corresponded to 26.7% of the workers. Finally, Profile 5 was characterized by high levels of global self-determination, slightly higher than average specific levels of identified regulation, lower than average specific levels of amotivation, and average specific levels on the other regulations. This *Self-Determined* profile corresponded to 11.8% of the workers. The identification of the *Poorly Motivated, Driven, and Self-Determined* profiles match *Hypothesis 2,* whereas the identification of the *Intrinsically Motivated* and the *Conflicted* profile supported *Hypothesis 3*.

Outcomes of Work Motivation Profiles

Levels of work addiction, work satisfaction, and burnout were compared across the five profiles. The results from these comparisons are reported in Table 3 (more detailed profile comparisons are presented in Table S10 of the online supplements). Many of these comparisons were statistically significant and in the expected direction, thus lending support for the construct validity of the profiles and to *Hypothesis 4*. Burnout was lowest in the *Driven* and *Self-Determined* profiles, which did not differ from one another, followed by the *Intrinsically Motivated* profile, then by the *Poorly Motivated* profile, and finally by the *Conflicted* profile. Work satisfaction was highest in the *Driven* and *Self-Determined* profiles, which did not differ from one another, followed by the *Intrinsically Motivated* profile, then by the *Poorly Motivated* profile, and finally by the *Conflicted* profile. Finally, work addiction was lower in the *Self-Determined* and *Intrinsically Motivated* profiles, which did not statistically differ from one another, than in the *Conflicted* and the *Driven* profiles, which also did not differ from one another. Although levels of work addiction could not be differentiated between the *Poorly Motivated* profile, the *Driven* profile, and the *Intrinsically Motivated* profiles, these levels remained statistically lower in the *Poorly Motivated* profile than in the *Self-Determined* profile and statistically higher in the *Poorly Motivated* profile than in the *Conflicted* profile.

Discussion

The first purpose of this study was to identify work motivation profiles while relying on a proper disaggregation of workers' global levels of self-determined work motivation from the unique quality associated with each behavioral regulation beyond this global level (Howard et al., 2018; Litalien et al., 2017; Ryan & Deci, 2017). This approach also allowed us to simultaneously consider both of these components (global and specific), thus addressing the limitations of previous studies that failed to take into account this dual multidimensional nature of work motivation.

Characteristics of Work Motivation Profiles

Our results revealed five profiles that best represented the motivation configurations observed among the current sample of workers, thus supporting Hypothesis 1. Three of these profiles match Hypothesis 2. Thus, a *Self-Determined* profile was found to be characterized by high global levels of self-determination, coupled with moderately high specific levels of identified regulation, moderately low specific levels of amotivation, and average levels on the other specific regulation. This profile corresponds to the *Autonomous* profiles identified in previous studies (e.g., Gillet, Becker et al., 2017). Likewise, we also identified a more extreme *Driven* profile, characterized by high global levels of self-determination coupled with high specific levels of identified, introjected and external-material regulations, and average to low specific levels of external-social regulation, amotivation and intrinsic motivation. This profile matches the *Motivated* profile identified in previous studies (e.g., Howard et al., 2016). Finally, we identified a *Poorly Motivated* profile, characterized by slightly lower than average global levels of self-determination, coupled by average levels on most other specific types of behavioral regulations, and high specific levels of amotivation. This profile presents important similarities with the *Unmotivated* profiles often identified in previous studies (e.g., Gillet et al., 2018). The *Poorly Motivated* profile was the largest, 44.4% of workers belong to this profile, suggesting that almost half of our sample was not well motivated to put more effort into work. Conversely, the *Driven* profile was the smallest, implying that only 2.4% of workers seems to be driven to work by a strong combination of self-determined, autonomous (i.e., personal choice), and controlled (e.g., internal or external pressures) motives.

Supporting Hypothesis 3, we also identified two additional profiles displaying a more precise configuration than what previous studies had been able to identify using a more classical operationalization of work motivation. The first of those profiles presented an *Intrinsically Motivated* configuration that was clearly dominated by high specific levels of intrinsic motivation and higher than average specific levels of identified regulation. In contrast, this profile only presented average global levels of self-determination and low levels on the remaining specific types of behavioral regulations. This profile is particularly interesting in displaying an almost pure intrinsic drive, not matched by more global levels of self-determination or specific levels of identified regulation, thus supporting the value of adopting a finer-grained representation of work motivation.

Likewise, the remaining *Conflicted* profile presented a configuration that was dominated by high specific levels of identified regulation and amotivation, coupled with average to low levels on the remaining regulations. This profile is particularly interesting as it characterized almost one-third of the present sample who seem to find work personally important, and yet not very stimulating. This could possibly be explained by the fact that many jobs are multifaceted, requiring workers to engage in a variety of tasks. For instance, a mechanic might feel that being able to efficiently repair a car is important, but dislikes having to deal with administrative issues, such as ordering car parts. Likewise, a nurse might feel a strong sense of personal dedication to helping patients, but not the clerical part of the nursing job.

Taken together, the identification of these five profiles shows the added value of relying on a finer-grained representation of work motivation that incorporates both a global self-determination factor and the specific qualities of behavioral regulations, while also supporting the generalizability of at least some core types of profiles across methodological approaches. Importantly, global levels of self-determination appeared to play a critical role (i.e., being the core defining characteristic and the motivation dimension presenting the highest level) in the definition of two out of the five profiles (i.e., *Self-Determined* and *Driven*). Likewise, the unique quality of the behavioral regulations appeared central to the definition of at least two other profiles (i.e., *Intrinsically Motivated*, and *Conflicted*).

These results have clear implications for SDT and extend upon the previous results reported by Gillet et al. (2018) and Howard et al. (2016) in this regard by showing that it is possible to simultaneously take into account the global levels of self-determination together with the specific qualities of participants' behavioral regulations in the estimation of work motivation profiles. Importantly, our results show that both aspects (global and specific) seem to play an equally important role in the definition of distinct subsets of work motivation profiles and contribute to our understanding of how work motivations combine within employees. For instance, the reliance on a more traditional approach within which work motivation would have been simply defined as a series of interrelated dimensions without a common core (i.e., global self-determination levels) might have resulted in the estimation of profiles (such as those reported by Howard et al., 2016 and Gillet et al., 2018) within which it would have been difficult, if not impossible, to clearly identify the effects attributable to both components. In contrast, our approach has facilitated the separation of employees' global sense of volition from the unique qualities of their specific behavioral regulations, revealing some profiles mainly driven by this global level of self-determination across all components, and others primarily driven by a more specific type of work motivation. Still, future studies are needed to test the generalizability and replicability of these profile solutions.

Associations between Work Motivation Profiles and Outcomes

This study also extends scientific knowledge on the outcomes of workers' motivational profiles by relying on the circumplex model of subjective wellbeing at work (Bakker & Oerlemans, 2011) that provides a comprehensive coverage of positive and negative indicators of employee wellbeing. When we first consider burnout and work satisfaction, our results generally met Hypothesis 4 in showing the least desirable outcomes (high levels of burnout and low levels of work satisfaction) to be associated with the *Conflicted* profile, immediately followed by the *Poorly Motivated* one. These results are consistent with previous results showing the undesirable consequences of a lack of motivation (Cresswell & Eklund, 2005; Howard et al., 2016; Lonsdale, Hodge, & Rose, 2009). When workers lack motivation, they do not really know why they should put more effort into their work and do not have the desire to carry out work-related tasks. Nevertheless, amotivated workers still complete mandatory tasks, but are more likely to see their personal resources become depleted by it. In contrast, profiles characterized by high specific levels of intrinsic motivation (i.e., *Intrinsically Motivated* profile) or high global levels of self-determination (i.e., *Driven* and *Self-Determined* profiles) presented the most desirable outcomes (low levels of burnout and high levels of work satisfaction). This result is in accordance with those from previous studies and SDT in general, showing the desirability of more self-determined forms of motivation (e.g., Fernet, Chanal, & Guay, 2017; Gagné & Deci, 2005; Howard et al., 2016; Ryan & Deci, 2017).

A key finding pertains to our Research Question regarding the associations between profile membership and work addiction. Even though previous variable-centered studies have suggested that controlled forms of motivation might contribute to work addiction (Sandrin & Gillet, 2018; van Beek et al., 2011; Van den Broeck et al., 2011), the present study uncovered a more nuanced pattern of associations between motivation and work addiction. Indeed, work addiction was the lowest in the *Self-Determined* and *Intrinsically Motivated* profiles, suggesting that self-determined and intrinsically motivated workers tend to demonstrate low addiction to work because they more volitionally engage in it. Conversely, workers in the *Conflicted* profile reported higher levels of work addiction, possibly because they face conflicting motives related to various parts of their work seen as being either personally important or not at all worth expending energy. These co-existing and conflicting motives might orient workers toward a more rigid and compulsive approach to work.

Surprisingly, however, work addiction was the highest in the *Driven* profile, which was characterized by high levels of self-determination (similar to those observed in the *Self-Determined* profile) coupled with high level of more controlled forms of motivation. Thus, this profile also seems to face conflicting motives linked to the enjoyment of many aspects of their work, coupled with a feeling of self-imposed or externally-driven obligation to meet work demands. This finding is in line with prior variable-centered studies reporting that controlled forms of motivation predicted work addiction (Sandrin & Gillet, 2018; van Beek et al., 2011; Van den Broeck et al., 2011). However, as an important implication for SDT and the circumplex model, whereas previous variable- and person-centered results have generally supported the idea that autonomous forms of motivation are unequivocally positive and even able to curb the undesirable effects of controlled forms of work motivation (e.g., Gillet et al., 2017; Howard et al., 2016), the present results suggest that this is not the case as far as work addiction is considered. Indeed, in this context, exposure to a conflicting combination of autonomous and controlled forms of motivation (i.e., a *Driven* profile) or autonomous forms of motivation and amotivation (*Conflicted*) appeared to carry important risks in terms of work addiction. Thus, in these contexts, autonomous forms of motivation appear unable to buffer workers against the adverse effects of controlled forms of motivations or amotivation.

More generally, an overview of these outcome-related findings reveals important information about the nature of work motivation. Thus, the *Self-Determined* profile appeared to be the most desirable from an outcome perspective, followed by the *Intrinsically Motivated* profile. The remaining three profiles appeared to be less desirable for different reasons. For instance, the *Poorly Motivated* profile appeared to be less desirable because of the higher levels of burnout and the lower levels of work satisfaction associated with it. Conversely, the *Conflicted* profile seemed to be less desirable because of its higher levels of work addiction and burnout, and of its low levels of work satisfaction. This profile thus appears to carry risk in terms of subjective wellbeing at work. Finally, the *Driven* profile did present benefits in terms of high work satisfaction and low burnout, but these benefits were mitigated by the high levels of work addiction associated with this profile. Thus, contrasting the *Self-Determined* and *Driven* profiles, it appears that both seem to characterize workers who enjoy working. However, this comparison also suggests that there are limits to displaying a fully *Driven* approach to work characterized by both autonomous and controlled forms of motivation.

Practical Implications

As for practical implications for managers and organizations wishing to foster workers' autonomous motivation, our results suggest that belonging to the *Conflicted* profile is associated with lower work satisfaction as well as higher burnout and work addiction. To counter amotivation, managers should strive to provide workers with either internal (e.g., providing meaning for the job) or even external (e.g., offering additional monetary compensation) incentives. These incentives might help workers to transition into at least a *Poorly Motivated* profile, which is associated with less detrimental outcomes. However, one should not put too much emphasis on external factors as these might only provide a short-term motivational enhancement and might impede the development of more adaptive motivational forms. Importantly, for workers at risk for work addiction, emphasis on external incentives should be kept to a minimum.

Ultimately, the most optimal work environment should nurture and mobilize autonomous types of motivation by providing rationale and stimulation via goal framing (Vansteenkiste, Lens, & Deci, 2006). This suggestion is supported by our findings showing that the *Intrinsically Motivated* and *Self-Determined* profiles were associated with the most desirable outcomes. Goal framing might help workers understand why it is personally important for them to engage in an activity that they might otherwise find uninteresting. Managers could also focus on demonstrating a need-supportive behavior that includes elements of autonomy-support, involvement, and structure (Reeve & Halusic, 2009), reflecting on the three basic psychological needs of their workers. In an educational setting, Jang, Reeve, and Halusic (2016) demonstrated that students reported higher levels of positive outcomes (e.g., conceptual learning) and perceived their teacher as more need-supportive when their teacher took their perspective and adjusted the lesson plan to the students. Using this method, managers might find it a fruitful avenue to adjust the work conditions to their workers, which might lead to higher autonomous motivation and more positive outcomes. Overall, need-supportive behaviors are likely to facilitate the development of autonomous motivations (Olafsen, Deci, & Halvari, 2018) as well as indirectly decrease burnout and work addiction.

Limitations and Future Directions

The present study contributed to the more in-depth understanding of the joint effects of global and specific components of work motivation. Still, future studies are needed to more thoroughly test this representation via the incorporation of additional outcomes, including objectively measured ones (e.g., turnover, performance). Importantly, although our choice of outcomes was guided by the circumplex model of subjective wellbeing at work (Bakker & Oerlemans, 2011), this model encompasses a fourth type of well-being indicator, characterized by a high level of activation and pleasant affect (e.g., engagement), which was not considered in the present studies. Likewise, future studies would also benefit from the consideration of possible determinants of profile membership, such as job demands and resources (Bakker & Demerouti, 2007). As SDT posits that the satisfaction and frustration of basic psychological needs are cardinal for self-determined motivation to emerge (Vansteenkiste & Ryan, 2013), it might be worthwhile to investigate the differential effect of global need fulfillment and its specific factors on work motivations (e.g., Sánchez-Oliva et al., 2017; Tóth-Király, Bőthe, Orosz, & Rigó, 2019). Given recent advancements in person-centered studies of basic psychological needs satisfaction (Gillet et al., 2019; Tóth-Király, Bőthe, Orosz, & Rigó, 2018), it might be interesting to more formally verify associations between need fulfillment profiles and work motivation profiles.

Another limitation comes from the cross-sectional nature of this study, which precludes inferences of causality or directionality. Likewise, even though the treatment of outcomes was based on theory, we cannot rule out reciprocal influences, reverse causality, or spurious associations. For this reason, longitudinal studies should be conducted to test the directionality of the associations as well as the temporal stability of the profiles. More specifically, it would be interesting to examine the within-sample and within-person stability of the profiles. It might be informative if such longitudinal studies were conducted among newcomers or workers who are in the process of change within an organization. Self-reported questionnaires were used; thus, biases (e.g., social desirability or self-selection) should be taken into account when interpreting the results. To address this limitation, ratings from other data sources (e.g., colleagues or supervisors) could be obtained. In addition, although the present study relied on a careful management of our online questionnaire and equally careful data management, screening and cleaning procedures, it would seem important for future questionnaire-based studies to incorporate attention checks to systematically control for careless responding (e.g., Huang, Curran, Keeney, Poposki, & DeShon, 2012).

Finally, we relied on a sample of Hungarian workers who were recruited from different organizations. These workers had different work-related characteristics; for instance, the majority were white-collar workers so that blue-collar workers were comparatively underrepresented. In addition, more than half of the respondents only worked in their current position for 0-3 years, and we were able to recruit a smaller proportion of workers who reported having worked in their position for a longer period of time. Naturally, these characteristics of the sample limit the generalizability of our findings to other groups. Replications thus should be made with the inclusion of workers from different cultures, age groups, languages, professions, or work environments. In particular, some of our participants were not full-time employees. To assess the likely impact of this element, we calculated the proportion of full-time and non-fulltime employees belonging to each profile. Three out of the five profiles (Intrinsic, Poorly Motivated, and Conflicted) include 75-80% of full-time employees and 20-25% of non-fulltime employees. The proportions are different in the other two profiles (Driven and Self-Determined), where 97-100% of the group members are full-time employees, and 0-3% are the non-fulltime employees. Whereas we believe that the presence of non-fulltime employees did not confound our findings because they did not belong to one single profile, it is still interesting to note that non-fulltime employees belonged to profiles where the global levels of self-determination were average or low, and not into the most motivated profiles. Future research should more carefully consider the likely impact of employee characteristics on motivation profiles.

Conclusions

In sum, five work motivation profiles were identified in a sample of employees. The identification of these profiles showed that the global and specific qualities of work motivations are equally important in understanding how work motivations combine within employees. Further, these profiles were found to be differently associated with indicators of subjective wellbeing at work, showing that belonging to profiles characterized by high global levels of self-determination or high specific levels of intrinsic motivation is mostly associated with positive outcomes when these motivations are not coupled with matching levels of controlled forms of motivation.

References

Andreassen, C.S. (2014). Workaholism: An overview and current status of the research. *Journal of Behavioral Addictions*, *3*, 1-11.

Andreassen, C.S., Griffiths, M.D., Hetland, J., & Pallesen, S. (2012). Development of a work addiction scale. *Scandinavian Journal of Psychology*, *53*, 265-272.

Andreassen, C.S., Griffiths, M.D., Hetland, J., Kravina, L., Jensen, F., & Pallesen, S. (2014). The prevalence of workaholism: a survey study in a nationally representative sample of Norwegian employees. *PLoS One*, *9*, e102446.

Andreassen, C.S., Griffiths, M.D., Sinha, R., Hetland, J., & Pallesen, S. (2016). The relationships between workaholism and symptoms of psychiatric disorders: a large-scale cross-sectional study. *PLoS One*, *11*, e0152978.

Andreassen, C.S., & Pallesen, S. (2016). Workaholism: An addiction to work. In *Neuropathology of drug addictions and substance misuse* (pp. 972-983). Academic Press.

Andreassen, C.S., Schaufeli, W. B., & Pallesen, S. (2018). Myths about "The myths about work addiction" Commentary on: Ten myths about work addiction (Griffiths et al., 2018). *Journal of Behavioral Addictions*, *7*, 858-862.

Asparouhov, T., & Muthén, B.O. (2014). Auxiliary variables in mixture modeling: Three-step approaches using Mplus. *Structural Equation Modeling, 21*, 1–13.

Bakker, A.B., & Demerouti, E. (2007). The job demands-resources model: State of the art. *Journal of Managerial Psychology*, *22*, 309-328.

Bakker, A.B., & Oerlemans, W.G.M. (2011). Subjective well-being at work in organizations. In K. Cameron, & G. Spreitzer (Eds.), *Handbook of positive organizational scholarship* (pp. 178–189). Oxford: Oxford University Press.

Ballabio, M., Griffiths, M.D., Urbán, R., Quartiroli, A., Demetrovics, Z., & Király, O. (2017). Do gaming motives mediate between psychiatric symptoms and problematic gaming? An empirical survey study. *Addiction Research & Theory*, *25*, 397-408.

Bányai, F., Griffiths, M.D., Demetrovics, Z., & Király, O. (2019). The mediating effect of motivations between psychiatric distress and gaming disorder among esport gamers and recreational gamers. *Comprehensive Psychiatry*, *94*. Early view doi: 10.1016/j.comppsych.2019.152117

Beaton, D.E., Bombardier, C., Guillemin, F., & Ferraz, M.B. (2000). Guidelines for the process of cross-cultural adaptation of self-report measures. *Spine*, *25*, 3186-3191.

Browne, M. (2001). An overview of analytic rotation in exploratory factor analysis. *Multivariate Behavioral Research*, *36*, 111-150.

Chemolli, E., & Gagné, M. (2014). Evidence against the continuum structure underlying motivation measures derived from self-determination theory. *Psychological Assessment*, *26*, 575-585.

Clark, M.A., Michel, J.S., Zhdanova, L., Pui, S.Y., & Baltes, B.B. (2016). All work and no play? A meta-analytic examination of the correlates and outcomes of workaholism. *Journal of Management*, *42*, 1836-1873.

Cresswell, S.L., & Eklund, R.C. (2005). Motivation and burnout in professional rugby players. *Research Quarterly for Exercise and Sport*, *76*, 370-376.

Deci, E.L., & Ryan, R.M. (2000). The" what" and" why" of goal pursuits: Human needs and the self-determination of behavior. *Psychological Inquiry*, *11*, 227-268.

Deci, E.L., Olafsen, A.H., & Ryan, R.M. (2017). Self-determination theory in work organizations: The state of a science. *Annual Review of Organizational Psychology & Organizational Behavior*, *4*, 19-43.

Diallo, T.M.O, Morin, A.J.S. & Lu, H. (2016). Impact of misspecifications of the latent variance-covariance and residual matrices on the class enumeration accuracy of growth mixture models. *Structural Equation Modeling*, *23*, 507-531.

Diener, E.D., Emmons, R.A., Larsen, R.J., & Griffin, S. (1985). The satisfaction with life scale. *Journal of Personality Assessment*, *49*, 71-75.

Falco, A., Girardi, D., Kravina, L., Trifiletti, E., Bartolucci, G.B., Capozza, D., & Nicola, A. (2013). The mediating role of psychophysic strain in the relationship between workaholism, job performance, and sickness absence: A longitudinal study. *Journal of Occupational and Environmental Medicine*, *55*, 1255-1261.

Faragher, E.B., Cass, M., & Cooper, C.L. (2005). The relationship between job satisfaction and health: a meta-analysis. *Occupational and Environmental Medicine*, *62*, 105-112.

Fernet, C., Austin, S., & Vallerand, R.J. (2012). The effects of work motivation on employee exhaustion and commitment: An extension of the JD-R model. *Work & Stress*, *26*, 213-229.

Fernet, C., Chanal, J., & Guay, F. (2017). What fuels the fire: job-or task-specific motivation (or both)? On the hierarchical and multidimensional nature of teacher motivation in relation to job burnout. *Work & Stress*, *31*, 145-163.

Fernet, C., Guay, F., & Senécal, C. (2004). Adjusting to job demands: The role of work self-determination and job control in predicting burnout. *Journal of Vocational Behavior*, *65*, 39-56.

Fouquereau, E., & Rioux, L. (2002). Élaboration de l'Échelle de satisfaction de vie professionnelle (ÉSVP) en langue française: Une démarche exploratoire. *Canadian Journal of Behavioural Science/Revue canadienne des sciences du comportement*, *34*, 210-215.

Gagné, M., & Deci, E.L. (2005). Self-determination theory and work motivation. *Journal of Organizational Behavior*, *26*, 331-362.

Gagné, M., Forest, J., Gilbert, M.H, Aubé, C., Morin, E., & Malorni, A. (2010). The Motivation at Work Scale: Validation in two languages. *Educational & Psychological Measurement*, *70*, 628-646.

Gagné, M., Forest, J., Vansteenkiste, M., Crevier-Braud, L., Van den Broeck, A., Aspeli, A.K., ... & Halvari, H. (2015). The Multidimensional Work Motivation Scale: Validation evidence in seven languages and nine countries. *European Journal of Work & Organizational Psychology*, *24*, 178-196.

Gillet, N., Becker, C., Lafrenière, M.A., Huart, I., & Fouquereau, E. (2017). Organizational support, job resources, soldiers' motivational profiles, work engagement, and affect. *Military Psychology*, *29*, 418-433.

Gillet, N., Fouquereau, E., Vallerand, R.J., Abraham, J., & Colombat, P. (2018). The role of workers' motivational profiles in affective and organizational factors. *Journal of Happiness Studies*, *19*, 1151-1174.

Gillet, N., Gagné, M., Sauvagère, S., & Fouquereau, E. (2013). The role of supervisor autonomy support, organizational support, and autonomous and controlled motivation in predicting employees' satisfaction and turnover intentions. *European Journal of Work and Organizational Psychology*, *22*, 450-460.

Gillet, N., Morin, A.J.S., Huyghebaert, T., Alibran, E., Barrault, S., & Vanhove, C. (2019). Students' Need Satisfaction Profiles: Similarity and Change over the Course of a University Semester. *Applied Psychology*. Early view doi: 10.1111/apps.12227

Gillet, N., Morin, A.J.S., & Reeve, J. (2017). Stability, change, and implications of students' motivation profiles: A latent transition analysis. *Contemporary Educational Psychology*, *51*, 222-239.

Gillet, N., Morin, A.J.S., Sandrin, E., & Houle, S.A. (2018). Investigating the combined effects of workaholism and work engagement: A substantive-methodological synergy of variable-centered and person-centered methodologies. *Journal of Vocational Behavior*, *109*, 54-77.

Graves, L.M., Cullen, K.L., Lester, H.F., Ruderman, M.N., & Gentry, W.A. (2015). Managerial motivational profiles: Composition, antecedents, and consequences. *Journal of Vocational Behavior*, *87*, 32-42.

Griffiths, M.D. (2005). A ‘components’ model of addiction within a biopsychosocial framework. *Journal of Substance Use*, *10*, 191-197.

Guay, F., Morin, A.J.S., Litalien, D., Valois, P., & Vallerand, R.J. (2015). Application of exploratory structural equation modeling to evaluate the academic motivation scale. *Journal of Experimental Education*, *83*, 51-82.

Hipp, J.R., & Bauer, D.J. (2006). Local solutions in the estimation of growth mixture models. *Psychological Methods*, *11*, 36-53.

Hobfoll, S.E., & Shirom, A. (2000). Conservation of resources theory: Applications to stress and management in the workplace. In R.T. Golembiewski (Ed.), *Handbook of organization behavior* (2nd Rev. ed., pp. 57– 81). New York: Dekker.

Houlfort, N., Philippe, F.L., Vallerand, R.J., & Ménard, J. (2013). On passion and heavy work investment: personal and organizational outcomes. *Journal of Managerial Psychology*, *29*, 25-45.

Howard, J.L., Gagné, M., & Bureau, J.S. (2017). Testing a continuum structure of self-determined motivation: A meta-analysis. *Psychological Bulletin*, *143*, 1346-1377.

Howard, J.L., Gagné, M., Morin, A.J.S., & Forest, J. (2018). Using bifactor exploratory structural equation modeling to test for a continuum structure of motivation. *Journal of Management*, *44*, 2638-2664.

Howard, J., Gagné, M., Morin, A.J.S., & Van den Broeck, A. (2016). Motivation profiles at work: A self-determination theory approach. *Journal of Vocational Behavior*, *95*, 74-89.

Huang, J.L., Curran, P.G., Keeney, J., Poposki, E.M., & DeShon, R.P. (2012). Detecting and deterring insufficient effort responding to surveys. *Journal of Business and Psychology, 27,* 99-114.

Jang, H., Reeve, J., & Halusic, M. (2016). A new autonomy-supportive way of teaching that increases conceptual learning. *The Journal of Experimental Education*, *84*, 686-701.

Jansen in de Wal, J., den Brok, P.J., Hooijer, J.G., Martens, R.L., & van den Beemt, A. (2014). Teachers' engagement in professional learning: Exploring motivational profiles. *Learning and Individual Differences*, *36*, 27-36.

Judge, T.A., Thoresen, C.J., Bono, J.E., & Patton, G.K. (2001). The job satisfaction-job performance relationship: A qualitative and quantitative review. *Psychological Bulletin*, *127*, 376-407.

Kanfer, R., Frese, M., & Johnson, R.E. (2017). Motivation related to work: A century of progress. *Journal of Applied Psychology*, *102*, 338-355.

Király, O., Urbán, R., Griffiths, M.D., Ágoston, C., Nagygyörgy, K., Kökönyei, G., & Demetrovics, Z. (2015). The mediating effect of gaming motivation between psychiatric symptoms and problematic online gaming: An online survey. *Journal of Medical Internet Research*, *17*, e88.

Kuntsche, E.N. (2007). *Tell me… why do you drink? A study of drinking motives in adolescence*. Lausanne (CH): SFA ISPA Press.

Kuvaas, B., Buch, R., Weibel, A., Dysvik, A., & Nerstad, C.G. (2017). Do intrinsic and extrinsic motivation relate differently to employee outcomes? *Journal of Economic Psychology*, *61*, 244-258.

Lanza, S.T., Tan, X., & Bray, B.C. (2013). Latent class analysis with distal outcomes: A flexible model-based approach. *Structural Equation Modeling, 20,* 1–26.

Litalien, D., Morin, A.J.S., Gagné, M., Vallerand, R.J., Losier, G.F., & Ryan, R.M. (2017). Evidence of a continuum structure of academic self-determination: A two-study test using a bifactor-ESEM representation of academic motivation. *Contemporary Educational Psychology*, *51*, 67-82.

Lonsdale, C., Hodge, K., & Rose, E. (2009). Athlete burnout in elite sport: A self-determination perspective. *Journal of Sports Sciences*, *27*, 785-795.

Marsh, H.W., Lüdtke, O., Trautwein, U., & Morin, A.J.S. (2009). Classical latent profile analysis of academic self-concept dimensions: Synergy of person-and variable-centered approaches to theoretical models of self-concept. *Structural Equation Modeling*, *16*, 191-225.

Martos, T., Sallay, V., Désfalvi, J., Szabó, T., & Ittzés, A. (2014). Az Élettel való Elégedettség Skála magyar változatának (SWLS-H) pszichometriai jellemzői [Psychometric characteristics of the Hungarian version of the Satisfaction with Life Scale (SWLS-H)]. *Mentálhigiéné és Pszichoszomatika*, *15*, 289-303.

Maslach, C., Jackson, S.E., & Leiter, M.P. (1997). Maslach Burnout Inventory: Third edition. In C. P. Zalaquett & R. J. Wood (Eds.), *Evaluating stress* (p. 191–218). Scarecrow Education.

Maslach, C., Schaufeli, W., & Leiter, M. (2001). Job burnout. *Annual Review of Psychology*, *52*, 397-422.

Meyer, J.P., & Morin, A.J.S. (2016). A person-centered approach to commitment research: Theory, research, and methodology. *Journal of Organizational Behavior, 37*, 584-612.

Moran, M., Diefendorff, J., Kim, T., & Liu, Z. (2012). A profile approach to self-determination theory motivations at work. *Journal of Vocational Behavior, 81*, 354-363.

Morin, A.J.S. (2016). Person-centered research strategies in commitment research. In J.P. Meyer (Ed.), *The handbook of employee commitment* (pp. 490-508). Cheltenham: Edward Elgar.

Morin, A. J.S., Arens, A. K., & Marsh, H. W. (2016). A bifactor exploratory structural equation modeling framework for the identification of distinct sources of construct-relevant psychometric multidimensionality. *Structural Equation Modeling, 23*, 116-139.

Morin, A.J.S., Boudrias, J.-S., Marsh, H.W., Madore, I., & Desrumeaux, P. (2016). Further reflections on disentengling shape and level effects in person-centered analyses: An illustration exploring the dimensionality of psychological health. *Structural Equation Modeling, 23*, 438-454.

Morin, A.J.S., Boudrias, J.S., Marsh, H.W., McInerney, D.M., Dagenais-Desmarais, V., Madore, I., & Litalien, D. (2017). Complementary variable-and person-centered approaches to the dimensionality of psychometric constructs: Application to psychological wellbeing at work. *Journal of Business and Psychology*, *32*, 395-419.

Morin, A.J.S., & Marsh, H. W. (2015). Disentangling shape from level effects in person-centered analyses: An illustration based on university teachers' multidimensional profiles of effectiveness. *Structural Equation Modeling*, *22*, 39-59.

Morin, A.J.S., Morizot, J., Boudrias, J.S., & Madore, I. (2011). A multifoci person-centered perspective on workplace affective commitment: A latent profile/factor mixture analysis. *Organizational Research Methods*, *14*, 58-90.

Morin, A.J.S., Myers, N.D., & Lee, S. (2019). Modern factor analytic techniques: Bifactor models, exploratory structural equation modeling (ESEM) and bifactor-ESEM. In G. Tenenbaum & R. C. Eklund (Eds.), *Handbook of sport psychology* (4th ed.). New York, NY: Wiley.

Muthén, B.O. (2003). Statistical and substantive checking in growth mixture modeling: Comment on Bauer and Curran (2003). *Psychological Methods, 8*, 369-377.

Muthén, L.K., & Muthén, B.O. (2017). Mplus user guide. Los Angeles, CA: Muthén & Muthén.

Olafsen, A.H., Deci, E.L., & Halvari, H. (2018). Basic psychological needs and work motivation: A longitudinal test of directionality. *Motivation and Emotion*, *42,* 178-189.

Orosz, G., Dombi, E., Andreassen, C.S., Griffiths, M.D., & Demetrovics, Z. (2016). Analyzing models of work addiction: Single factor and bi-factor models of the Bergen Work Addiction Scale. *International Journal of Mental Health and Addiction*, *14*, 662-671.

Pinder, C.C. (1998). *Motivation in work organizations*. NJ: Upper Saddle River.

Peugh, J. & Fan, X. (2013). Modeling unobserved heterogeneity using latent profile analysis: A Monte Carlo simulation. *Structural Equation Modeling, 20*, 616-639.

Porter, G. (1996). Organizational impact of workaholism: Suggestions for researching the negative outcomes of excessive work. *Journal of Occupational Health Psychology, 1,* 70-84.

Reeve, J., & Halusic, M. (2009). How K-12 teachers can put self-determination theory principles into practice. *Theory and Research in Education*, *7*, 145-154.

Reise, S.P. (2012). The rediscovery of bifactor measurement models. *Multivariate Behavioral Research*, *47*, 667-696.

Ryan, R.M., & Deci, E.L. (2001). On happiness and human potentials: A review of research on hedonic and eudaimonic well-being. *Annual Review of Psychology, 52*, 141-166.

Ryan, R.M., & Deci, E.L. (2017). *Self-determination theory. Basic psychological needs in motivation, development, and wellness*. New York, NY: Guildford Press.

Sánchez-Oliva, D., Morin, A.J.S., Teixeira, P.J., Carraça, E.V., Palmeira, A.L., & Silva, M.N. (2017). A bifactor exploratory structural equation modeling representation of the structure of the basic psychological needs at work scale. *Journal of Vocational Behavior, 98*, 173-187.

Sandrin, E., & Gillet, N. (2018). Déterminants et conséquences du workaholisme chez des salariés français. *Psychologie Française, 63,* 1-9.

Schaufeli, W.B., Bakker, A.B., Van der Heijden, F.M., & Prins, J.T. (2009). Workaholism, burnout and well-being among junior doctors. *Work & Stress, 23*, 155-172.

Sheldon, K.M., Osin, E.N., Gordeeva, T.O., Suchkov, D.D., & Sychev, O.A. (2017). Evaluating the dimensionality of self-determination theory's relative autonomy continuum. *Personality & Social Psychology Bulletin*, *43*, 1215-1238.

Shirom, A., & Melamed, S. (2006). A comparison of the construct validity of two burnout measures in

two groups of professionals. *International Journal of Stress Management*, *13*, 176-200.
Skrondal, A., & Laake, P. (2001). Regression among factor scores. *Psychometrika*, *66*, 563-575.
Stark, R., Kruse, O., Snagowski, J., Brand, M., Walter, B., Klucken, T., & Wehrum-Osinsky, S. (2017). Predictors for (problematic) use of Internet sexually explicit material: Role of trait sexual motivation and implicit approach tendencies towards sexually explicit material. *Sexual Addiction & Compulsivity*, f*24*, 180-202.
Sussman, S., Lisha, N., & Griffiths, M. (2011). Prevalence of the addictions: a problem of the majority or the minority?. *Evaluation & The Health Professions, 34,* 3-56.
Tóth-Király, I., Bőthe, B., & Orosz, G. (2018). Seeing the forest through different trees: A social psychological perspective of work addiction: Commentary on: Ten myths about work addiction (Griffiths et al., 2018). *Journal of Behavioral Addictions*, *7,* 875-879.
Tóth-Király, I., Bőthe, B., Orosz, G., & Rigó, A. (2018). On the importance of balanced need fulfillment: A person-centered perspective. *Journal of Happiness Studies*, 1-22. Early view doi: 10.1007/s10902-018-0066-0
Tóth-Király, I., Bőthe, B., Orosz, G., & Rigó, A. (2019). A new look on the representation and criterion validity of need fulfillment: Application of the Bifactor exploratory structural equation modeling framework. *Journal of Happiness Studies, 20,* 1609-1626.
Vallerand, R.J. (1997). Toward a hierarchical model of intrinsic and extrinsic motivation. *Advances in Experimental Social Psychology, 29,* 271-360.
van Beek, I., Hu, Q., Schaufeli, W.B., Taris, T.W., & Schreurs, B.H. (2012). For fun, love, or money: What drives workaholic, engaged, and burned-out employees at work? *Applied Psychology, 61,* 30-55.
van Beek, I., Taris, T.W., & Schaufeli, W.B. (2011). Workaholic and work engaged employees: Dead ringers or worlds apart?. *Journal of Occupational Health Psychology*, *16*, 468-482.
Van den Berghe, L., Soenens, B., Aelterman, N., Cardon, G., Tallir, I. B., & Haerens, L. (2014). Within-person profiles of teachers' motivation to teach: Associations with need satisfaction at work, need-supportive teaching, and burnout. *Psychology of Sport and Exercise*, *15*, 407-417.
Van den Broeck, A., Lens, W., De Witte, H., & Van Coillie, H. (2013). Unraveling the importance of the quantity and the quality of workers’ motivation for well-being: A person-centered perspective. *Journal of Vocational Behavior*, *82*, 69-78.
Van den Broeck, A., Schreurs, B., De Witte, H., Vansteenkiste, M., Germeys, F., & Schaufeli, W. (2011). Understanding workaholics' motivations: A self-determination perspective. *Applied Psychology*, *60*, 600-621.
Vansteenkiste, M., Lens, W., & Deci, E.L. (2006). Intrinsic versus extrinsic goal contents in self-determination theory: Another look at the quality of academic motivation. *Educational Psychologist*, *41*, 19-31.
Vansteenkiste, M., & Ryan, R.M. (2013). On psychological growth and vulnerability: basic psychological need satisfaction and need frustration as a unifying principle. *Journal of Psychotherapy Integration*, *23*, 263-280.
Wang, J.C., Morin, A.J.S., Ryan, R.M., & Liu, W.C. (2016). Students’ motivational profiles in the physical education context. *Journal of Sport and Exercise Psychology*, *38*, 612-630.

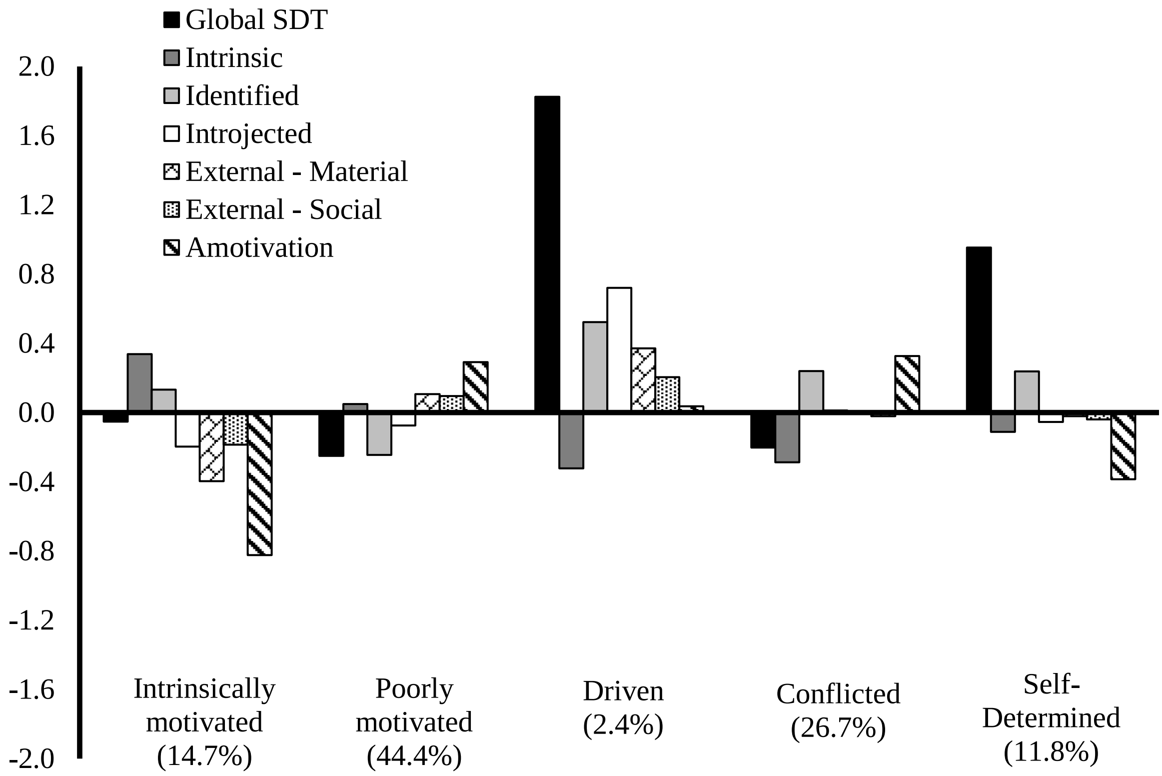

Figure 1. *The Final 5-Profile Solution*

Note. Indicators were estimated from factor scores saved from preliminary measurement models with a mean of 0 and a standard deviation of 1; SDT: Self-determined motivation.

Table 1
Correlations between the variables of the study

	1	2	3	4	5	6	7	8	9	10	11	12
1. Global self-determination (G)	—											
2. Intrinsic regulation (S)	.000	—										
3. Identified regulation (S)	.000	.000	—									
4. Introjected regulation (S)	.000	.000	.000	—								
5. External regulation –Material (S)	.000	.000	.000	.000	—							
6. External regulation – Social (S)	.000	.000	.000	.000	.000	—						
7. Amotivation (S)	.000	.000	.000	.000	.000	.000	—					
8. Burnout: Global (G)	-.483**	-.267**	-.116**	.065*	.074*	.101**	.291**	—				
9. Burnout: Physical (S) [1]	.176**	.007	.100**	.110**	.057	.068*	-.086**	.000	—			
10. Burnout: Cognitive (S)	.286**	.187**	-.042	.058	.046	.099**	-.107**	.000	.000	—		
11. Burnout: Emotional (S)	-.047	.064	-.090**	-.025	-.001	.107**	.010	.000	.000	.000	—	
12. Work satisfaction	.579**	.328**	.104**	.010	-.020	-.010	-.293**	-.796**	.160**	.547**	.082*	—
13. Work addiction	-.002	-.097**	.011	.148**	.162**	.120**	.089**	.469**	.532**	.094**	-.104**	-.226**

Note. * $p < .05$; ** $p < .01$; G: Orthogonal global factor score saved from a preliminary bifactor measurement model; S: Orthogonal specific factor saved from a preliminary bifactor measurement model.

[1] When considering the correlations involving the burnout S-factors, it is important to keep in mind that these burnout indicators are factor scores saved from a bifactor measurement model resulting in a disaggregation of employees' global burnout levels from their specific levels of physical fatigue, emotional exhaustion, and cognitive weariness. The disaggregation of global versus specific variance components afforded by the reliance on a bifactor model changes the meaning of the S-factors. Whereas in a typical CFA model, cognitive weariness scores would simply reflect cognitive weariness, in a bifactor model this S-factor reflects what is unique to cognitive weariness items beyond what is already explained by the G-factor. In applied terms, these can be taken to reflect imbalance in specific levels of cognitive weariness in relation to global burnout levels, i.e. levels of weariness that are independent from burnout and thus, potentially, healthier. The nature of the (positive) correlations between work satisfaction and these S-factors seems to match this interpretation. In other words, these correlations suggest that the global burnout factor seems to have absorbed all of the "undesirable" aspects of burnout shared across the physical, cognitive, and emotional dimensions, leaving the S-factors to represent "pure" forms of fatigue, emotional drain, and weariness that are perhaps more normative (e.g., characterizing hard-working employees reporting a more pleasant and satisfying form of fatigue at the end the work day).

Table 2

Fit Statistics for Latent Profile Analyses

Model	LL	fp	Scaling	AIC	CAIC	BIC	SSABIC	Entropy	aLMR	BLRT
1 Profile	-8105.127	14	1.020	16238.254	16320.318	16306.318	16261.855	NA	NA	NA
2 Profiles	-8025.250	29	1.078	16108.499	16278.489	16249.489	16157.386	.381	.001	< .001
3 Profiles	-7950.271	44	1.088	15988.542	16246.457	16202.457	16062.715	.515	.007	< .001
4 Profiles	-7878.000	59	1.171	15874.001	16219.842	16160.842	15973.460	.616	.188	< .001
5 Profiles	-7815.021	74	1.063	15778.042	16211.808	16137.808	15902.787	.678	.041	< .001
6 Profiles	-7770.782	89	1.149	15719.565	16241.257	16152.257	15869.597	.725	.431	< .001
7 Profiles	-7736.676	104	1.080	15681.353	16290.971	16186.971	15856.671	.749	.063	< .001
8 Profiles	-7695.648	119	0.995	15629.297	16326.840	16207.840	15829.901	.765	.087	< .001

Note. LL: loglikelihood; fp: number of free parameters; AIC: Akaike Information Criterion; CAIC: constant AIC; BIC: Bayesian Information Criterion; SSABIC: Sample-Size Adjusted BIC; aLMR: p-value associated with the adjusted Lo-Mendell-Rubin likelihood ratio test; BLRT: Bootstrap Likelihood Ratio Test; NA: Not Applicable.

Table 3

Outcome Means and Pairwise Comparisons between the Five Profiles

Outcome	Intrinsically Motivated Mean [95% CI]	Poorly Motivated Mean [95% CI]	Driven Mean [95% CI]	Conflicted Mean [95% CI]	Self-Determined Mean [95% CI]	Differences between profiles
Burnout	-.477 [-.599, -.355]	.134 [.060, .208]	-.821 [-1.117, -.525]	.471 [.365, .577]	-.765 [-.892, -.638]	3 = 5 < 1 < 2 < 4
Work Satisfaction	.507 [.382, .632]	-.128 [-.202, -.054]	.943 [.645, 1.241]	-.671 [-.779, -.563]	.857 [.728, .986]	4 < 2 < 1 < 5 = 3
Work Addiction	-.111 [-.246, .024]	-.001 [-.077, .075]	.334 [-.003, .671]	.213 [.111, .315]	-.223 [-.370, -.076]	1 = 5 < 4 = 3; 5 < 2 < 4; 1 = 2; 2 = 3

Note. CI: confidence interval.

Online Supplements for:

Toward an Improved Understanding of Work Motivation Profiles

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

Appendix 1
Preliminary Measurement Models

Preliminary analyses were carried out to (1) examine the psychometric properties of the measures; (2) determine the optimal measurement structure for the measures of work motivation and burnout; (3) assess the discriminant validity of all constructs; and (4) derive factor scores from these measurement models that served as a basis for the estimation of the main analyses.

Model Estimation

Preliminary analyses were conducted with Mplus 8 (Muthén & Muthén, 2017) and models were estimated with the robust weighted least square mean- and variance-adjusted (WLSMV) which has been shown to be superior to maximum-likelihood-based estimators for ordinal indicators (such as Likert ratings), especially when participants' ratings follow asymmetric response thresholds (Finney & DiStefano, 2013; Morin, Myers, & Lee, 2019). Given the known oversensitivity of the chi-square test (χ^2) to sample size and minor misspecifications (Marsh, Hau, & Grayson, 2005), the adequacy of the alternative measurement models was assessed using sample size independent indices: the comparative fit index (CFI), the Tucker-Lewis Index (TLI), and the root mean square error of approximation (RMSEA) with its 90% confidence interval. CFI and TLI were deemed to suggest an adequate or excellent level of fit when their values were higher than .90 and .95, respectively. Conversely RMSEA was deemed to suggest acceptable and excellent level of fit when it had a value smaller than .08 and .06, respectively. Finally, for all models, we also report model-based composite reliability indices calculated as McDonald's (1970) omega (ω) coefficient from the standardized parameter estimates.

Work Motivation

With respect to work motivations, the decision to rely on the bifactor exploratory structural equation modeling (bifactor-ESEM; Morin, Arens, & Marsh, 2016; Morin, Arens, Tran, & Caci, 2016) framework is based on recent evidence showing that the structure of measures of academic (Litalien et al., 2018) and work (Howard, Gagné, Morin, & Forest, 2018) motivation anchored in self-determination theory (SDT; Ryan & Deci, 2017) was best represented using this analytical framework. In bifactor-ESEM, the bifactor component allows one to estimate a global (G-) factor reflecting workers' global levels of self-determination across all types of behavioral regulations, while also taking into account the unique motivational qualities associated with each subscale and not explained by the G-factor as part of the series of orthogonal specific (S-) factors. The ESEM component allows for the free estimation of all cross-loadings between items and all factors. This free estimation has been shown in recent statistical research to result in more accurate depiction of the latent constructs underpinning each factors when even very small (i.e., .100) cross-loadings are present in the population model, and yet to remain unbiased when no cross-loadings are present in the population model (for a review, see Asparouhov, Muthén, & Morin, 2015). In addition, prior SDT motivation studies have also supported the value of ESEM-based measurement models (Guay, Morin, Litalien, Valois, & Vallerand, 2015; Tóth-Király et al., 2017).

In the present study, in order to ascertain the superiority of the a priori bifactor-ESEM model, we contrasted of four alternative solutions, as recommended by suggested by Morin and colleagues (Morin, Arens, et al., 2016; Morin, Boudrias et al., 2016, 2017; Morin et al., 2019): A first-order CFA solution, a bifactor-CFA solution, a first-order ESEM solution, and a bifactor-ESEM solution. In the first-order CFA solution, items were specified as associated with their a priori factors, all cross-loadings were constrained to zero, and factors were allowed to correlate freely with one another. In the first-order ESEM solutions, the factors were specified the same way as in the CFA, but all cross-loadings between items and S-factors were freely estimated and targeted to be as close to zero as possible through the application of a confirmatory approach involving the use of an oblique target rotation (Browne, 2001). In bifactor-CFA, items were associated with one G-factor and their a priori S-factor, cross-loadings were set to zero between the S-factors, and all factors were specified as orthogonal (i.e., not allowed to correlate) as per typical bifactor specifications (Morin et al., 2019). In bifactor-ESEM, factors were defined as in bifactor-CFA, but all cross-loadings were freely estimated and targeted to be close to zero as possible via the use of an orthogonal target rotation.

The need to contrast all four alternative solutions is anchored in empirical evidence showing that each of these alternative solutions is able to absorb unmodelled sources of multidimensionality, thus potentially hiding model misfit that could negatively impact the results (Morin, Arens, et al., 2016; Murray & Johnson, 2013). Thus, an unmodelled G-factor may lead to inflated factor correlations in

CFA, or inflated cross-loadings in ESEM. Similarly, unmodelled cross-loadings tend to produce inflated factor correlations in CFA, or inflated G-factor loadings in bifactor-CFA. Therefore, when interpreting the results and contrasting the models, we followed a sequential strategy proposed by Morin and colleagues (Morin, Boudrias et al., 2016, 2017; Morin et al., 2019). This strategy starts by the comparison of the first-order CFA and ESEM solutions. This comparison supports the ESEM solution when (1) the factors are equally well-defined in both solutions and (2) the estimates of factor correlations are reduced in ESEM relative to CFA (Morin, Boudrias et al., 2016, 2017; Morin et al., 2019). The retained first-order solution then needs to be contrasted with its bifactor counterpart. In this second comparison, the bifactor solution is supported when it results in (1) a well-defined G-factor (matching the continuum structure of motivation: Howard et al., 2018; Litalien et al., 2018), and (2) at least some well-defined S-factors (Morin, Boudrias et al., 2016, 2017; Morin et al., 2019).

Burnout

Recent studies have also shown that incorporating a bifactor (Mészáros, Ádám, Szabó, Szigeti, & Urbán, 2014), ESEM (Trépanier, Fernet, Austin, & Ménard, 2015), or both (Doherty, Mallett, Leiter, & McFadden, 2019; Isoard-Gautheur et al., 2018) components helped to achieve a clearer and more adequate presentation of burnout. Therefore, we adopted a strategy similar to that described above in order to determine the optimal specification for the burnout measurement model.

Work Satisfaction and Work Addiction

Given the need to contrast alternative specification for the work motivation and burnout measures, initial tests of measurement structure for the remaining outcome measures (work satisfaction and work addiction) were first conducted in a separate two-factor CFA model, before combining all three retained solution into a single model used for tests of discriminant validity.

Discriminant Validity

To ascertain the empirically distinct nature of each constructs assessed in the present study, we contrasted a global measurement model (M1) underpinning all constructs (build based on the results from the previous stages) with alternative models in which the constructs were combined in a pairwise manner: (M2) work satisfaction ratings were combined with work addiction ratings into a single latent factor; (M3) work satisfaction ratings were combined into a single factor with global levels of self-determination (motivation G-factor); (M4) work satisfaction ratings were combined into a single factor with global levels of burnout (burnout G-factor); (M5) work addiction ratings were combined into a single factor with global levels of self-determination (motivation G-factor); (M6) work addiction ratings were combined into a single factor with global levels of burnout (burnout G-factor); (M7) global levels of self-determination (motivation G-factor) where combined with global levels of burnout (burnout G-factor) into a single G-factor.

Results

Work Motivation

Model fit information for all measurement models is reported in Table S1. For the work motivation measure, standardized parameter estimates from the first-order CFA and ESEM solutions are reported in Tables S2. These results first show that the ESEM solution outperformed the CFA solution in terms of model fit (ΔCFI = +.040, ΔTLI = +.038, ΔRMSEA = -.037). This ESEM solution also resulted in well-defined intrinsic (ω = .939), identified (ω = .823), external-material (ω = .741), external-social (ω = .666) and amotivation (ω = .903) factors (λ = .357 to .976, M_λ = .732). Conversely, the introjection factor (ω = .613) appeared to be mainly defined by two items (λ_{14} = .863, λ_{19} = .533), while two other items displayed lower target loadings (λ_2 = .064, λ_8 = .179), but higher cross-loadings on the external-social (λ_2 = .584, λ_8 = .404) and, to a smaller extent, identified (λ_2 = .246, λ_8 = .253) factors. These cross-loading suggest that these items may better tap into workers' overall self-determination rather than into their specific levels of introjected regulation. The presence of multiple statistically significant cross-loadings also suggests a presence of a self-determination G-factor. Finally, examination of the factor correlations, reported in Table S3, reveal that these correlations were meaningfully reduced in ESEM (r = .003 to .671, M_r = .268) when compared to CFA (r = .029 to .751, r = .386), thus further supporting the value of the ESEM solution.

The ESEM solution was thus retained, and contrasted with its bifactor counterpart. This solution resulted again in an improved level of fit to the data (ΔCFI = +.005, ΔTLI = +.008, ΔRMSEA = -.012). Parameter estimates for this bifactor-ESEM solution are reported in Table S4 and revealed a reliable (ω = .909) self-determination G-factor well-defined by factor loadings matching the SDT continuum from intrinsic (λ = .678 to .844, M_λ = .777), identified (λ = .517 to .585, M_λ = .550), introjected (λ = .083 to .593, M_λ = .392), external-material (λ = -.035 to .094, M_λ = .045), external-social (λ = .051 to .168, M_λ = .112), and amotivation (λ = -.491 to -.608, M_λ = -.548) items. Likewise, the identified (λ = .464 to .641, M_λ = .563; ω = .752), external-material (λ = .614 to .707, M_λ = .654; ω = .727), external-social (λ = .480 to .804, M_λ = .595; ω = .717), and amotivation (λ = .586 to .710, M_λ = .661; ω = .855) S-factors were also generally well-defined, whereas the intrinsic (λ = .418 to .492, M_λ = .447; ω = .797) and introjected (λ = .464 to .641, M_λ = .490; ω = .757) seemed to retain less specificity once the variance explained by the G-factor was taken into account. Still, the fact that some of the S-factors retained less specificity does not mean that they are not meaningful, particularly when modelled using an approach that explicitly controls for both measurement error and associations with the global motivation construct, such as the approach taken in the present study. Altogether, these results support the value of the bifactor-ESEM solution for the work motivation measure.

Burnout

As shown in Table S1, the three-factor CFA solution resulted in an excellent level of fit to the data according to the CFI and TLI, and in a marginal level of model fit according to the RMSEA. Contrasting with this solution, the ESEM alternative resulted in a decrease in model fit (ΔCFI = -.002, ΔTLI = -.022, ΔRMSEA = +.023). The results from these two solutions are reported in Table S5 and reveal factors that are equally well-defined in CFA (physical: λ = .745 to .892, M_λ = .812, ω = .921; cognitive: λ = .665 to .867, M_λ = .799, ω = .900; emotional: λ = .748 to .810, M_λ = .782, ω = .825) and ESEM (physical: λ = .491 to .997, M_λ = .754, ω = .914; cognitive: λ = .701 to .926, M_λ = .784, ω = .899; emotional: λ = .707 to .785, M_λ = .733, ω = .803). Factor correlation from these two models are reported in Table S6 and reveal that the ESEM solution (r = .658 to .796, M_r = .716) did not result in substantially decreased correlations compared to the CFA solution (r = .570 to .747, M_r = .654). For these reasons (i.e., reduced model fit and similar factor correlations) the CFA solution was preferred over the ESEM solution. This CFA solution was then compared to its bifactor counterpart, reported in Table S7. Interestingly, the bifactor-CFA solution resulted in an increased in model fit relative to the CFA solution (ΔCFI = +.009, ΔTLI = +.006, ΔRMSEA = -.006). In this bifactor model, the global burnout factor was well-defined and reliable (λ = .552 to .840, M_λ = .691, ω = .952). The emotional (λ = .512 to .535, M_λ = .520, ω = .677), physical (λ = .010 to .627, M_λ = .318, ω = .669) and cognitive (λ = .334 to .474, M_λ = .397, ω = .692) burnout S-factors also retained a moderate amount of specificity over and above the G-factor. It is also interesting to note that the definition of the bifactor CFA factors was highly similar to those of the bifactor ESEM solution (global: λ = .481 to .856, M_λ = .681, ω = .955; physical: λ = .034 to .654, M_λ = .350, ω = .728; cognitive: λ = .300 to .586, M_λ = .417, ω = .736; emotional: λ = .502 to .577, M_λ = .532, ω = .696), which resulted in negligible cross-loadings ($|\lambda|$ = .003 to .174, $M_{|\lambda|}$ = .071), reinforcing our decision to retain the more parsimonious bifactor CFA.

Work Satisfaction, Work Addiction and the Global Measurement Model

The remaining model (work satisfaction and work addiction) resulted in a generally acceptable level of fit to the data. The parameter estimates from this model are reported in Table S8 and reveal well-defined factors representing work satisfaction (λ = .646 to .907, M_λ = .792; ω = .897) and work addiction (λ = .467 to .787, M_λ = .611; ω = .810) that proved to be relatively independent from one another (r = -.120, p < .01). Finally, the global model underpinning all measurement components (M1: bifactor-ESEM work motivation, bifactor-CFA burnout, and-two factor CFA for work satisfaction and work addiction) also resulted in a fully acceptable level of fit to the data, and was used to generate factor scores for the main analyses. Because our goal was to achieve a global estimate of burnout while maintaining control over the subscale specificities, we only used the burnout G-factor as profile outcome along with work satisfaction and work addiction as profile outcomes.

Discriminant Validity

As shown in Table S1, when compared to the a priori global solution including all constructs (M1), all of the alternative solutions in which pairs of latent constructs were combined in a pairwise manner resulted in a substantial decrease in model fit, thus supporting the discriminant validity of our a priori factor solution.

References

Asparouhov, T., Muthén, B., & Morin, A.J.S. (2015). Bayesian Structural equation modeling with cross-loadings and residual covariances. *Journal of Management*, *41*, 1561-1577.

Browne, M. (2001) An overview of analytic rotation in exploratory factor analysis. *Multivariate*

Behavioral Research, 36, 111-150.
Doherty, A., Mallett, J., Leiter, M., & Mc Fadden, P. (2019). Measuring burnout in social work: factorial validity of the Maslach Burnout Inventory-Human Services Survey. *European Journal of Psychological Assessment*, 1-22. Early view doi: 10.1027/1015-5759/a000568
Finney, S.J., & DiStefano, C. (2013). Non-normal and categorical data in structural equation modeling. In G.R. Hancock, & R.O. Mueller (Eds.). *Structural equation modeling: A second course* (pp. 439-492). (2nd ed.). Charlotte, NC: Information Age.
Guay, F., Morin, A.J.S., Litalien, D., Valois, P., & Vallerand, R.J. (2015). Application of exploratory structural equation modeling to evaluate the academic motivation scale. *Journal of Experimental Education, 83*, 51-82.
Howard, J.L., Gagné, M., Morin, A.J.S., & Forest, J. (2018). Using bifactor exploratory structural equation modeling to test for a continuum structure of motivation. *Journal of Management, 44*, 2638-2664.
Isoard-Gautheur, S., Martinent, G., Guillet-Descas, E., Trouilloud, D., Cece, V., & Mette, A. (2018). Development and evaluation of the psychometric properties of a new measure of athlete burnout: The Athlete Burnout Scale. *International Journal of Stress Management, 25*, 108-123.
Litalien, D., Morin, A.J.S., Gagné, M., Vallerand, R.J., Losier, G.F., & Ryan, R.M. (2017). Evidence of a continuum structure of academic self-determination: A two-study test using a bifactor-ESEM representation of academic motivation. *Contemporary Educational Psychology*, *51*, 67-82.
Marsh, H.W., Hau, K.-T., & Grayson, D. (2005). Goodness of fit evaluation. In A. Maydeu-Olivares & J. McArdle (Eds.), *Contemporary Psychometrics* (pp. 275-340). Mahwah, NJ: Erlbaum.
McDonald, R.P. (1970). Theoretical foundations of principal factor analysis, canonical factor analysis, and alpha factor analysis. *British Journal of Mathematical & Statistical Psychology*, *23*, 1-21.
Mészáros, V., Ádám, S., Szabó, M., Szigeti, R., & Urbán, R. (2014). The Bifactor Model of the Maslach Burnout Inventory–Human Services Survey (MBI-HSS)—An Alternative Measurement Model of Burnout. *Stress and Health*, *30*, 82-88.
Morin, A.J.S., Arens, A.K., & Marsh, H.W. (2016). A bifactor exploratory structural equation modeling framework for the identification of distinct sources of construct-relevant psychometric multidimensionality. *Structural Equation Modeling, 23*, 116-139.
Morin, A.J.S., Arens, K., Tran, A., & Caci, H. (2016). Exploring sources of construct-relevant multidimensionality in psychiatric measurement: A tutorial and illustration using the Composite Scale of Morningness. *International Journal of Methods in Psychiatric Research*, *25*, 277-288.
Morin, A.J.S., Boudrias, J.-S., Marsh, H.W., Madore, I., & Desrumeaux, P. (2016). Further reflections on disentengling shape and level effects in person-centered analyses: An illustration exploring the dimensionality of psychological health. *Structural Equation Modeling*, *23*, 438-454.
Morin, A.J.S., Boudrias, J.-S., Marsh, H.W., McInerney, D.M., Dagenais-Desmarais, V., Madore, I., & Litalien, D. (2017). Complementary variable- and person-centered approaches to the dimensionality of psychometric constructs: Application to psychological wellbeing at work. *Journal of Business and Psychology, 32*, 395-419.
Morin, A.J.S., Myers, N.D., & Lee, S. (2019). Modern factor analytic techniques: Bifactor models, exploratory structural equation modeling (ESEM) and bifactor-ESEM. In G. Tenenbaum & R. C. Eklund (Eds.), *Handbook of sport psychology* (4th ed.). New York, NY: Wiley.
Murray, A.L., & Johnson, W. (2013). The limitations of model fit in comparing the bi-factor versus higher-order models of human cognitive ability structure. *Intelligence, 41*, 407–422.
Muthén, L.K., & Muthén, B.O. (1998-2017). *Mplus user's guide (8th ed.)*. Los Angeles, CA: Author.
Ryan, R.M., & Deci, E.L. (2017). *Self-determination theory. Basic psychological needs in motivation, development, and wellness*. New York, NY: Guildford Press.
Tóth-Király, I., Orosz, G., Dombi, E., Jagodics, B., Farkas, D., & Amoura, C. (2017). Cross-cultural comparative examination of the Academic Motivation Scale using exploratory structural equation modeling. *Personality and Individual Differences, 106*, 130-135.
Trépanier, S. G., Fernet, C., Austin, S., & Ménard, J. (2015). Revisiting the interplay between burnout and work engagement: An Exploratory Structural Equation Modeling (ESEM) approach. *Burnout Research*, *2*, 51-59.

Table S1

Goodness-of-Fit Statistics for the Estimated Preliminary Measurement Models

	χ^2	df	CFI	TLI	RMSEA (90% CI)
Work Motivation					
Five-factor CFA	1550.124*	137	.949	.936	.104 (.099, .109)
Five-factor ESEM	378.232*	72	.989	.974	.067 (.060, .073)
Bifactor CFA	3715.028*	133	.871	.834	.168 (.163, .173)
Bifactor ESEM	232.394*	59	.994	.982	.055 (.048, .063)
Burnout					
Three-factor CFA	593.884*	74	.963	.954	.103 (.096, .111)
Three-factor ESEM	595.059*	52	.961	.932	.126 (.117, .135)
Bifactor CFA	452.273*	63	.972	.960	.097 (.089, .106)
Bifactor ESEM	175.727*	41	.990	.978	.071 (.060, .082)
Work Satisfaction and Work Addiction	599.661*	53	.941	.926	.106 (.098, .114)
Tests of Discriminant Validity					
M1. All constructs estimated separately	3658.485*	844	.936	.925	.059 (.057, .061)
M2. Work satisfaction and work addiction combined	5636.272*	847	.892	.874	.077 (.075, .079)
M3. Work satisfaction and global self-determination combined	3897.903*	847	.931	.919	.061 (.059, .063)
M4. Work satisfaction and global burnout combined	20487.807*	847	.556	.482	.156 (.154, .158)
M5. Work addiction and global self-determination combined	5585.846*	847	.893	.875	.077 (.075, .078)
M6. Work addiction and global burnout combined	4607.389*	847	.915	.901	.068 (.066, .070)
M7. Global self-determination and global burnout combined	14145.898*	858	.700	.654	.127 (.126, .129)

Note. * $p < .05$; ** $p < .01$; CFA: Confirmatory factor analysis; ESEM: Exploratory structural equation modeling; 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 of the RMSEA.

Table S2

Standardized Parameter Estimates from the Six-Factor CFA and ESEM Solutions for the Work Motivation Scale

	CFA		ESEM						
	Factor (λ)	δ	Intrinsic (λ)	Identified (λ)	Introjected (λ)	External - Material (λ)	External - Social (λ)	Amotivation (λ)	δ
Intrinsic motivation									
Item 3	.837**	.299	**.723****	.089**	-.047*	-.023	.010	-.078**	.315
Item 9	.945**	.107	**.976****	-.017	-.002	-.040**	.027	.025	.086
Item 15	.965**	.068	**.962****	-.053**	.051**	.026	-.096**	-.056**	.058
ω	.941		.939						
Identified regulation									
Item 5	.822**	.325	.111**	**.571****	.064*	.018	.044	-.156**	.389
Item 11	.780**	.391	-.018	**.695****	.117**	.031	-.082**	-.117**	.376
Item 17	.847**	.283	.063*	**.841****	.147**	.054**	-.167**	.032	.193
ω	.857			.823					
Introjected regulation									
Item 2	.580**	.663	.032	.246**	**.064**	-.018	.584**	.080*	.502
Item 8	.693**	.520	.168**	.253**	**.179****	-.023	.404**	.016	.525
Item 14	.602**	.637	-.044*	-.012	**.863****	-.077**	.092*	-.034	.260
Item 19	.757**	.427	.082**	.329**	**.533****	.022	-.068*	-.042	.412
ω	.755				.613				
External regulation – Material									
Item 6	.628**	.605	.054	.086*	-.201**	**.676****	.086**	.116**	.539
Item 12	.741**	.451	-.051	.067*	-.089**	**.707****	.124**	-.109**	.479
Item 18	.671**	.550	-.048	-.038	.141**	**.686****	-.080**	-.020	.478
ω	.722					.741			
External regulation – Social									
Item 1	.629**	.604	-.027	.011	.029	.009	**.693****	-.158**	.481
Item 7	.786**	.382	.040	-.057	.172**	.213**	**.591****	-.001	.425
Item 13	.633**	.599	-.001	-.215**	.353**	.289**	**.357****	.152**	.444
ω	.726						.666		
Amotivation									
Item 4	.835**	.303	.059*	-.040	-.001	-.020	-.017	**.881****	.257
Item 10	.898**	.193	.014	-.033	-.028	.042	-.039	**.895****	.160
Item 16	.897**	.196	-.223**	.024	-.004	-.050	-.005	**.721****	.249
ω	.909							.903	

Note. * p < .05; ** p < .01; CFA: Confirmatory factor analysis; ESEM: Exploratory structural equation modeling; λ: Factor loading; δ: Item uniqueness; ω: model-based omega composite reliability based on McDonald (1970); Target factor loadings are in bold.

Table S3

Latent Factor Correlations from the First-order CFA (below the diagonal) and ESEM (above the diagonal) Solutions for the Work Motivation Scale

	Intrinsic	Identified	Introjected	External – Material	External – Social	Amotivation
Intrinsic motivation	—	.567**	.170**	-.056	.132**	-.671**
Identified regulation	.636**	—	.396**	-.010	.245**	-.544**
Introjected regulation	.427**	.751**	—	.346**	.289**	-.109**
External regulation – Material	-.070	.053	.321**	—	.322**	.164**
External regulation – Social	.054	.201**	.719**	.644**	—	-.003
Amotivation	-.734**	-.653**	-.375**	.120**	.029	—

Note. * p < .05; ** p < .01; CFA: Confirmatory factor analysis; ESEM: Exploratory structural equation modeling.

Table S4

Standardized Parameter Estimates from the Bifactor ESEM Solution for the Work Motivation Scale

	SDT (λ)	Intrinsic (λ)	Identified (λ)	Introjected (λ)	External - Material (λ)	External - Social (λ)	Amotivation (λ)	δ
Intrinsic motivation								
Item 3	**.678****	**.418****	.073**	.050*	-.063**	-.069**	-.195**	.311
Item 9	**.809****	**.492****	.008	-.012	-.094**	.008	-.119**	.079
Item 15	**.844****	**.431****	-.008	-.041**	-.040*	-.079**	-.158**	.067
ω		.797						
Identified regulation								
Item 5	**.548****	.100**	**.464****	.184**	-.008	.058*	-.213**	.391
Item 11	**.517****	-.022	**.585****	.108*	-.023	.044	-.154**	.352
Item 17	**.585****	-.003	**.641****	.198**	.022	-.062*	-.071**	.198
ω			.752					
Introjected regulation								
Item 2	**.083**	.266	.100*	**.909****	.108**	.246**	-.052	.011
Item 8	**.400****	.080	.203**	**.363****	.037	.326**	-.049	.550
Item 14	**.493****	-.516**	.066	**.378***	.041	.241**	.140**	.265
Item 19	**.593****	-.254**	.279**	**.309***	.073**	.030	.011	.403
ω				.757				
External regulation – Material								
Item 6	**-.035**	.095**	.028	.032	**.614****	.232**	.108**	.546
Item 12	**.075****	-.005	.057*	.068**	**.642****	.287**	-.015	.492
Item 18	**.094****	-.205**	-.081**	.123*	**.707****	.081*	.104**	.411
ω					.727			
External regulation – Social								
Item 1	**.148****	.103*	.045	.352**	.085**	**.502****	-.131**	.565
Item 7	**.168****	-.005	.061**	.191**	.212**	**.804****	.050	.238
Item 13	**.051**	-.221**	-.123**	.235**	.356**	**.480****	.248**	.459
ω						.717		
Amotivation								
Item 4	**-.491****	-.066**	-.135**	-.009	.052*	.055*	**.688****	.258
Item 10	**-.544****	-.087**	-.134**	-.031	.107**	.054*	**.710****	.159
Item 16	**-.608****	-.172**	-.079**	.034	.031	.028	**.586****	.248
ω	.909						.855	

Note. * p < .05; ** p < .01; CFA: Confirmatory factor analysis; ESEM: Exploratory structural equation modeling; λ: Factor loading; δ: Item uniqueness; ω: model-based omega composite reliability based on McDonald (1970); Target factor loadings are in bold.

Table S5

Standardized Parameter Estimates for the First-Order CFA and ESEM Burnout Measurement Models

	CFA Physical (λ)	Cognitive (λ)	Emotional (λ)	δ	ESEM Physical (λ)	Cognitive (λ)	Emotional (λ)	δ
Physical								
Item 1	.750**			.438	**.997****	-.133**	-.152**	.310
Item 3	.745**			.446	**.719****	-.011	.064	.439
Item 5	.831**			.309	**.910****	.013	-.108**	.256
Item 8	.837**			.299	**.659****	.054	.192**	.316
Item 10	.892**			.205	**.748****	.097**	.093**	.224
Item 12	.814**			.337	**.491****	.211**	.175**	.383
ω	.921				.914			
Cognitive								
Item 2		.665**		.558	.038	**.767****	-.166**	.511
Item 6		.837**		.299	.178**	**.701****	-.037	.331
Item 9		.849**		.279	-.039	**.786****	.131**	.283
Item 11		.867**		.249	-.075*	**.926****	.027	.209
Item 13		.778**		.395	.035	**.739****	.013	.400
ω		.900				.899		
Emotional								
Item 4			.748**	.441	.121**	-.061	**.708****	.449
Item 7			.810**	.343	.011	.105**	**.707****	.383
Item 14			.787**	.380	.032	-.001	**.785****	.355
ω			.825				.803	

Note. * $p < .05$; ** $p < .01$; CFA: Confirmatory factor analysis; ESEM: Exploratory structural equation modeling; λ: Factor loading; δ: Item uniqueness; ω: model-based omega composite reliability based on McDonald (1970); Target factor loadings are in bold.

Table S6

Latent Factor Correlations from the First-order CFA (below the diagonal) and ESEM (above the diagonal) Solutions for the Burnout Scale

	Physical	Cognitive	Emotional
Physical	—	.747**	.570**
Cognitive	.796**	—	.656**
Emotional	.658**	.693**	—

Note. ** $p < .01$; CFA: Confirmatory factor analysis; ESEM: Exploratory structural equation modeling.

Table S7

Standardized Parameter Estimates for the Bifactor CFA and ESEM Burnout Measurement Models

	Bifactor CFA					Bifactor ESEM				
	Burnout (λ)	Physical (λ)	Cognitive (λ)	Emotional (λ)	δ	Burnout (λ)	Physical (λ)	Cognitive (λ)	Emotional (λ)	δ
Physical										
Item 1	.597**	.627**			.251	**.559****	**.654****	.069**	-.003	.256
Item 3	.662**	.360**			.432	**.609****	**.438****	.094**	.116**	.415
Item 5	.711**	.495**			.249	**.678****	**.531****	.094**	-.020	.249
Item 8	.816**	.145**			.313	**.841****	**.165****	-.140**	-.039	.245
Item 10	.840**	.268**			.222	**.856****	**.277****	-.058**	-.073**	.182
Item 12	.818**	.010			.331	**.831****	**.034**	-.069*	-.059*	.301
ω		.669					.728			
Cognitive										
Item 2	.555**		.430**		.507	**.481****	.172**	**.586****	.043	.394
Item 6	.751**		.334**		.325	**.681****	.174**	**.456****	.079**	.292
Item 9	.745**		.389**		.294	**.791****	-.129**	**.300****	.027	.267
Item 11	.746**		.474**		.219	**.789****	-.105**	**.397****	-.012	.208
Item 13	.684**		.357**		.404	**.693****	-.013	**.346****	.004	.400
ω			.692					.736		
Emotional										
Item 4	.552**			.535**	.408	**.518****	.098**	.058*	**.577****	.386
Item 7	.610**			.512**	.366	**.592****	-.010	.098**	**.518****	.371
Item 14	.592**			.513**	.387	**.621****	-.083**	-.037	**.502****	.355
ω	.952			.677		.955			.696	

Note. * p < .05; ** p < .01; CFA: Confirmatory factor analysis; ESEM: Exploratory structural equation modeling; λ: Factor loading; δ: Item uniqueness; ω: model-based omega composite reliability based on McDonald (1970); Target factor loadings are in bold.

Table S8

Standardized Parameter Estimates for the Work Satisfaction and Work Addiction Measurement Model

	Work satisfaction(λ)	Work addiction(λ)	δ
Work satisfaction			
WSAT1	.907		.177
WSAT2	.703		.506
WSAT3	.901		.188
WSAT4	.646		.583
WSAT5	.805		.352
Work addiction			
WADD1		.467	.782
WADD2		.501	.749
WADD3		.518	.732
WADD4		.664	.559
WADD5		.602	.637
WADD6		.787	.381
WADD7		.739	.454
ω	.897	.810	

Note. * $p < .05$; ** $p < .01$; λ: Factor loading; δ: Item uniqueness; ω: model-based omega composite reliability based on McDonald (1970); Target factor loadings are in bold.

Table S9

Exact Means of the Different Work Motivation Factors in the Final Retained 5-Profile Solution

	Profile 1	Profile 2	Profile 3	Profile 4	Profile 5
	Mean [95% CI]	Mean [95% CI]	Mean [95% CI]	Mean [95% CI]	Mean [95% CI]
Global SDT	-.053 [-.261, .155]	-.251 [-.382, -.121]	1.825 [1.739, 1.910]	-.202 [-.428, .024]	.953 [.781, 1.124]
Intrinsic	.338 [.113, .562]	.050 [-.040, .139]	-.323 [-.428, -.218]	-.287 [-.507, -.067]	-.112 [-.347, .124]
Identified	.133 [-.070, .337]	-.245 [-.362, -.129]	.523 [.409, .636]	.239 [.010, .467]	.237 [.010, .464]
Introjected	-.196 [-.393, .002]	-.075 [-.169, .020]	.720 [.530, .911]	.012 [-.170, .195]	-.054 [-.257, .150]
External – Material	-.396 [-.598, -.193]	.106 [.018, .194]	.371 [-.118, .859]	.006 [-.172, .184]	-.022 [-.240, .197]
External – Social	-.185 [-.410, .039]	.096 [.005, .186]	.204 [-.248, .657]	-.021 [-.208, .165]	-.039 [-.264, .185]
Amotivation	-.824 [-.905, -.743]	.291 [.168, .415]	.036 [-.044, .116]	.326 [.150, .501]	-.386 [-.485, -.287]
	Variance [95% CI]	Variance [95% CI]	Variance [95% CI]	Variance [95% CI]	Variance [95% CI]
Global SDT	.189 [.088, .289]	.567 [.413, .722]	.029 [.002, .056]	1.000 [.759, 1.240]	.146 [.093, .199]
Intrinsic	.718 [.539, .897]	.420 [.348, .493]	.045 [.021, .070]	1.050 [.694, 1.406]	.570 [.381, .758]
Identified	.904 [.617, 1.191]	.353 [.237, .469]	.049 [.006, .091]	.888 [.653, 1.124]	.422 [.267, .578]
Introjected	.657 [.506, .809]	.362 [.267, .457]	.179 [.081, .277]	.780 [.627, .933]	.661 [.504, .817]
External – Material	.616 [.478, .755]	.367 [.271, .463]	1.237 [.755, 1.720]	1.001 [.733, 1.269]	.905 [.615, 1.195]
External – Social	.838 [.627, 1.048]	.364 [.272, .456]	1.135 [.502, 1.769]	1.047 [.792, 1.301]	.757 [.503, 1.010]
Amotivation	.043 [.025, .060]	.431 [.319, .543]	.022 [.007, .037]	.815 [.564, 1.067]	.032 [.013, .050]

Note. SDT: Self-determined motivation; Factors were estimated from factor scores with a mean of 0 and a standard deviation of 1.; CI: confidence interval; Profile 1: Intrinsically Motivated; Profile 2: Poorly Motivated; Profile 3: Driven; Profile 4: Conflicted; Profile 5: Self-Determined.

Table S10

Comparisons of the Outcomes Between the Five Profiles

		Burnout				
	Mean	Differences between the outcome means (Δ)				
		Profile 1	Profile 2	Profile 3	Profile 4	Profile 5
Profile 1	-.477	0				
Profile 2	.134	.611	0			
Profile 3	-.821	-.344	-.955	0		
Profile 4	.471	.948	.337	1.292	0	
Profile 5	-.765	-.288	-.899	.056	-1.236	0
		Work satisfaction				
	Mean	Differences between the outcome means (Δ)				
		Profile 1	Profile 2	Profile 3	Profile 4	Profile 5
Profile 1	.507	0				
Profile 2	-.128	-.635	0			
Profile 3	.943	.436	1.071	0		
Profile 4	-.671	-1.178	-.543	-1.614	0	
Profile 5	.857	.350	.985	-.086	1.528	0
		Work addiction				
	Mean	Differences between the outcome means (Δ)				
		Profile 1	Profile 2	Profile 3	Profile 4	Profile 5
Profile 1	-.111	0				
Profile 2	-.001	.110	0			
Profile 3	.334	.445	.335	0		
Profile 4	.213	.324	.214	-.121	0	
Profile 5	-.223	-.112	-.222	-.557	-.436	0

Note. The differences were calculated based on the numerical order of the profiles (e.g., mean of Profile 2 subtracted from mean of Profile 1; mean of Profile 3 subtracted from mean of Profile 1; mean of Profile 4 subtracted from mean of Profile 1, etc.

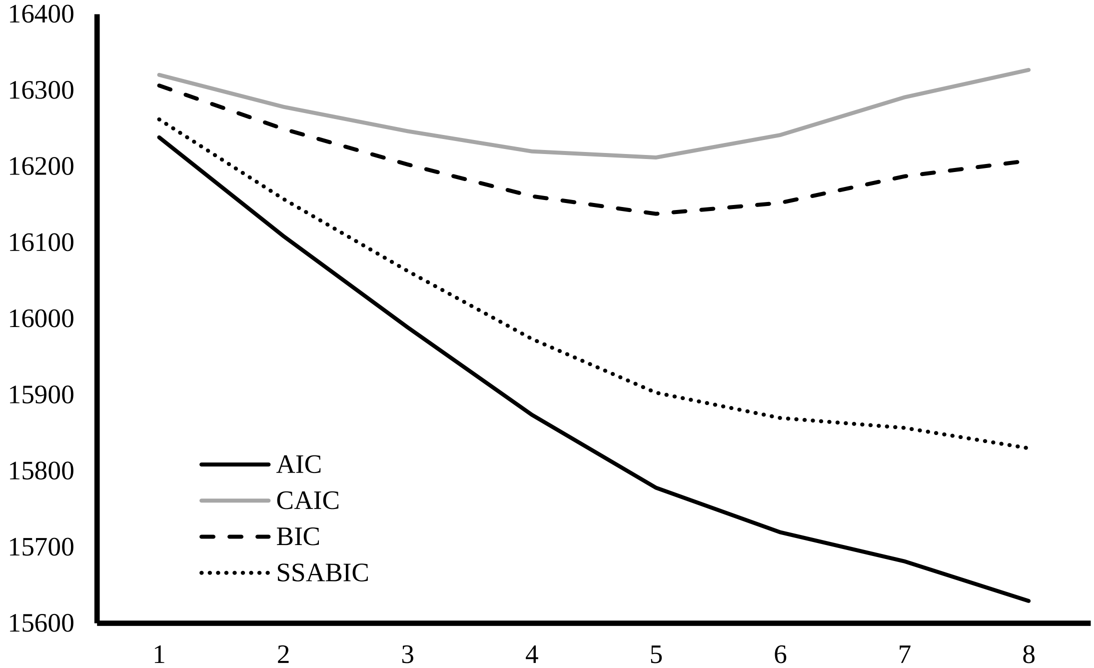

Figure S1. *Elbow Plot for the Information Criteria Used in Class Enumeration*

Note. AIC: Akaike Information Criterion; BIC: Bayesian Information Criterion; CAIC: Consistent AIC; SSABIC: Sample-Size-Adjusted BIC.