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Motivation profiles at work: A self-determination theory approach

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ABSTRACT

Self-determination theory proposes that individuals experience distinct types of motivation to varying degrees. While it is well documented that these types of motivation differentially predict outcomes, very little attention has been paid to how they interact within individuals. The current study addresses the simultaneous occurrence of multiple motivation types within individual workers by adopting a person-centered approach on two samples of employees from different countries ($n = 723$ & 286). Four very similar motivation profiles were found across samples, representing balanced motivation, amotivated, autonomously regulated and highly motivated employees. In Sample 1, governmental employees presented a greater likelihood of membership in the least desirable amotivated profile. In Sample 2, autonomously and highly motivated profiles showed superior work performance and higher levels of wellbeing, while the amotivated profile fared the worst. The presence of external regulation in a profile appears unimportant when combined with autonomous forms of motivation, and detrimental to outcomes in the absence of autonomous forms of motivation. These results support the hypothesis that autonomous forms of motivation are far more important in promoting positive workplace outcomes than more controlling forms.

Motivation, generally defined as the energy, direction and persistence of behavior (Pinder, 1998), is an inherently complex concept as evidenced by the variety of approaches to its conceptualization and measurement. Self-determination theory (SDT; Deci & Ryan, 1985) offers a well-supported conceptualization which proposes that motivation is best represented by conceptually distinct, yet complementary, types of behavioral regulations experienced by individuals to varying degrees. While it is now well documented that these types of regulation differentially predict outcomes (e.g., Koestner & Losier, 2002), very little attention has been paid to how they interact within individuals. The current study addresses the simultaneous occurrence of multiple behavioral regulations within individual workers by adopting a person-centered approach to work motivation. While variable-centered analyses, which have dominated the field so far, have been extremely useful in their own right, the complexity of interactions between numerous types of motivation cannot easily be examined using traditional regression techniques, which become almost impossible to interpret when more than three interacting variables are simultaneously considered. No such limit exists when person-centered analyses are used to assess how configurations of motivation factors are organized within individuals.

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This shift to a person-centered strategy is more than just a shift in methods. It involves a fundamentally different way of thinking about motivation which may affect the design of interventions (Zyphur, 2009). When conceptualizing types of motivation as variables, we are not thinking about a whole person, but about one of the many components that make up a person's motivational profile. Resulting interventions are designed to increase one type of motivation (e.g., intrinsic) without taking into consideration how the intervention will impact the other types of motivation (e.g., extrinsic). Such an omission may well make interventions less effective. In contrast, the person-centered approach takes into account the interplay between a person's motives, and consequently may lead to interventions aiming to influence the person's whole motivational profile. This is likely to produce better tailored and cost efficient interventions for particular subpopulations of employees (Morin & Marsh, 2015). In practice, this approach would make SDT more compatible with how people in positions of authority, such as managers, actually think about the motivation of their employees (Morin, Morizot, Boudrias, & Madore, 2011; Zyphur, 2009).

As reviewed below, a few attempts have been made to conceptualize work motivation profiles. The present study, however, does so more comprehensively by: (a) including all types of regulation proposed by SDT (unlike Van den Broeck, Lens, De Witte, & Van Coillie, 2013), (b) using two large heterogeneous samples of workers from two countries (unlike Graves, Cullen, Lester, Ruderman, & Gentry, 2015) and, (c) utilizing the latest advances in latent profile analysis (unlike Moran, Diefendorff, Kim, & Liu, 2012 and Van den Broeck et al., 2013). As such it represents an incremental advancement in this area of research and potentially provides a more accurate representation of the types of profiles that are likely to be found in the work domain. Furthermore, it extends previous research by demonstrating how the relative frequency of the profiles differs across job categories (white collar, blue collar, governmental), and the relation between the profiles and a variety of outcomes, including in-role and extra-role performance, engagement, burnout, and job satisfaction.

1. Self-determination theory

SDT conceptualizes motivation as multiple distinguishable facets, each representing a different form of behavioral regulation, and assumed to follow a continuum of self-determination (Deci & Ryan, 1985; Gagné & Deci, 2005). At one extreme, intrinsic motivation occurs when an individual participates in an activity for the enjoyment inherent in the activity itself, while at the other extreme extrinsic motivation occurs when behaviors are enacted for an instrumental reason. SDT proposes that extrinsic motivation can be internalized to become autonomously regulated. Identified regulation, an internalized form of extrinsic motivation, occurs when an individual elects to act because the behavior or the outcome of the behavior is of personal significance. Identified regulation and intrinsic motivation, are autonomous forms of motivation, while the next two regulations are controlled forms of motivation. Introjected regulation, an internalized yet controlled form of extrinsic motivation, occurs when behaviors are undertaken in order to avoid negative self-feelings such as shame, or to attain positive self-feelings such as pride. External regulation, a non-internalized form of extrinsic motivation lying at the lower end of the continuum, occurs when behaviors are undertaken for externally derived rewards or punishments. The most current conceptualization of workplace motivation suggests that external regulation is best described through two components, external-social, and external-material (Gagné et al., 2015). External-social regulation is characterized by the desire to gain approval or respect from others, or to avoid criticism, whereas external-material regulation focuses on material rewards, and the avoidance of losing one's job.

Finally, amotivation is the absence of any desire to exert effort. Amotivation has been defined as a state in which individuals do not associate a behavior with subsequent outcomes, and as such, behaviors are executed for reasons unknown or not executed at all (Deci & Ryan, 1985). Accordingly, amotivated individuals are likely to feel detached from their actions, or may feel a lack of control over their present situation or behavior, and will therefore invest little time or energy towards such behaviors. This state was shown to be associated with a wide range of negative workplace outcomes including lower vitality, job satisfaction, affective commitment, adaptivity, proactivity, and job effort, as well as greater emotional exhaustion, burnout, and turnover intention (Gagné et al., 2015; Tremblay, Blanchard, Taylor, Pelletier, & Villeneuve, 2009). Thus, given that people are still enacting work behaviors despite their lack of motivation, and considering the notable negative consequences associated with amotivated behavior, it is our contention that amotivation is an important feature of the self-determination continuum to consider.

In addition to the empirical evidence demonstrating the negative influence of amotivation on performance and wellbeing, on a more theoretical point, a complete depiction of the continuum of motivation should not only include a variety of motives for engaging in specific behaviors (ranging from the intrinsic pleasure to external constraints) but also the complete lack of motive to engage in these behaviors (which forms the opposite pole of the self-determination continuum). This representation of the SDT continuum has been recently supported in the work area by a recent study by Howard, Gagné, Morin, and Forest (2016), in which it was found that amotivation is located along the same continuum as the behavioral regulations, with no evidence of discontinuity.

While there is ongoing debate concerning the presence of this continuum beyond a mere heuristic tool (Chemolli & Gagné, 2014), this research will examine whether the pattern of regulations expected from this continuum hypothesis is present in employee profiles. Specifically, support for the continuum hypothesis would be demonstrated if profiles follow a smooth increase/decrease in the level of the different regulations as a function of their position on the continuum. Alternatively, weak support would be found through the presence of profiles in which people experience similar levels of regulations assumed to be located at opposite poles of the continuum (e.g., intrinsic and external regulations; Grolnick & Ryan, 1987).

So far, substantial research has examined how these regulations relate to various antecedents and outcomes. Results generally demonstrate that intrinsic motivation and identified regulation yield more positive outcomes, such as productivity and retention, than introjected and external regulations (Gagné, 2014; Gagné & Deci, 2005), though some research has found differences in the effects of intrinsic versus identified regulation, and in the effects of introjected versus external regulation (Gagné et al., 2015; Koestner & Losier, 2002). This approach does not take into account the multidimensional nature of motivation, and the fact that workers may simultaneously endorse multiple reasons for doing their job. Moreover, this research does not shed light on how distinct motivational regulations interact in predicting outcomes. What happens when employees are motivated for both autonomous and controlled reasons, compared to employees who are only motivated for autonomous reasons? For instance, is it more important to have a high level of overall motivation or is the proportion of autonomous to controlled motivation more influential? How do amotivated employees compare to employees presenting controlled motivation? How combinations of specific regulations relate to key outcomes also remains unknown, and essentially unexplored because of the heavy reliance on variable-centered methods. Indeed, the complexity of interactions required to fully describe motivation (i.e., involving six interacting types of motivation) calls for the adoption of a person-centered approach. In response, the aims of this study are to establish which motivational profiles are most likely to emerge in the work domain and to examine predictors and outcomes of profile membership.

2. Motivational profiles

Few studies have applied a person-centered approach to motivation research across domains (education, sport, work, etc.). Most have used cluster analysis, a method which has been criticized (e.g., Meyer & Morin, 2016; Morin, Maïano, Nagengast, Marsh, Morizot & Janosz, 2011; Vermunt & Magidson, 2002) as being too sensitive to the clustering algorithm and measurement scales, as lacking clear guidelines for the selection of an optimal number of profiles, and as relying on rigid assumptions that do not always hold with real-life data (i.e., exact assignment of employees to a single profile, conditional independence, equality of the indicators' variances across clusters). Furthermore, cluster analytic studies have often relied on small samples of dubious generalizability (Boiché, Sarrazin, Grouzet, Pelletier, & Chanal, 2008; Gillet, Berjot, & Paty, 2009; Gillet, Berjot, Vallerand, Amoura, & Rosnet, 2012; Gillet, Vallerand, & Paty, 2013; Gillet, Vallerand, & Rosnet, 2009; McNeill & Wang, 2005).

Motivational profiling has also largely been limited by the dichotomization of motivation into the broad categories of autonomous and controlled regulations. This dichotomization is a commonly used practice that simplifies the profiles and makes them easier to estimate, but that also reduces the richness of potential findings and may hide potentially important configurations. Nonetheless, among studies using this dichotomization in the educational domain, the observed profiles of academic motivation have been relatively well replicated, and generally revealed profiles characterized by high autonomous/low controlled motivation (HA/LC), high autonomous/high controlled motivation (HA/HC), low autonomous/high controlled motivation (LA/HC), and low autonomous/low controlled motivation (LA/LC; Hayenga & Corpus, 2010; Liu, Wang, Tan, Koh, & Ee, 2009; Ratelle, Guay, Vallerand, Larose, & Senécal, 2007; Vansteenkiste, Sierens, Soenens, Luyck, & Lens, 2009). Results from the sport domain often replicate these profiles with slight variations (e.g. HA/HC, Moderate Autonomy/LC, HA/MC, MA/HC; Gillet, Vallerand, & Rosnet, 2009; Gillet et al., 2013).

Given the heavy reliance on financial compensation in the work domain, motivational profiles are likely to differ from those identified in the educational and sport domains, especially when focusing on a more comprehensive coverage of all types of regulations. This particularity of the work domain makes it important to look at external and introjected regulations as separate constructs. To our knowledge, only three studies have examined motivational profiles at work (Graves et al., 2015; Moran, Diefendorff, Kim, & Liu, 2012; Van den Broeck et al., 2013). Van den Broeck et al. (2013) applied cluster analysis to three samples of employees, collapsing the regulations into a controlled-autonomous dichotomy, leading to the identification of the same set of four profiles identified in the education and sport area. In contrast, Moran et al. (2012) applied cluster analysis to the full range of behavioral regulations. Through this more complete representation, these authors identified five clusters, most of which differed from those identified in the education and sport domain: one presenting moderate levels of motivation across regulation types, one presenting high levels of motivation across regulation types (corresponding to the HA/HC profile), one representing low levels of autonomy (low levels of identified and intrinsic motivation) and moderate levels on the other forms of regulation, one presenting a more self-determined profile (high on introjected, identified and intrinsic motivation), and one presenting moderate levels on most regulations except for a low level of introjection. Finally, Graves et al. (2015) identified six latent profiles in a small sample of managers. These profiles presented similar configurations of motivation (i.e., highest on intrinsic and identified regulation, followed by introjected, and lowest on external regulation) but different overall levels, so that one was higher on autonomous than controlled forms of motivation, while another was low on all forms of regulations. However, this study relied on a relatively small sample of managers, and provided insufficient information regarding model specification to allow other researchers to replicate their results or to objectively assess the adequacy of the analyses.

This relative lack of research in the work domain, the dichotomization of regulations into controlled or autonomous categories, and the reliance on cluster analyses performed on small samples clearly represent significant limitations of research in this area. In contrast, the present study applied latent profile analyses (LPA) to the full range of behavioral regulations as they occur in a work context using large heterogeneous samples of employees from two countries (Canada and Belgium) in order to derive a common set of work motivation profiles. Employees completed the recently validated Multidimensional Work Motivation Scale (Gagné et al., 2015), which has been shown to have several advantageous features (e.g., improved psychometric properties, greater content coverage in terms of motivation types) compared to traditional measures of work motivation (e.g., Gagné et al., 2010).

In contrast to cluster analyses, LPA is a far more flexible model-based approach to classification (Muthén, 2002). Being model-based, LPA allows for the estimation of alternative models in which the restrictive assumptions of cluster analyses can be relaxed. Importantly, LPA aims to find the smallest number of profiles that can describe associations among a set of continuous variables, relying on a formal set of objective criteria to guide the identification of the optimal number of latent profiles in the data. These profiles are called latent because they are prototypical in nature, which means that rather than forcing each employee to correspond to a single profile, all participants are allocated a probability of membership in all profiles based on their degree of similarity with each prototypical latent profile.

Due to the scarcity of research on motivational profiles in the work domain, especially of studies considering the full array of motivation types, it is difficult to specify hypotheses about the nature and number of expected profiles. Given that previous research has typically found four to six profiles, it was expected that a relatively small number of profiles (4–6) would be identified, and would represent not only different levels of overall motivation, but also different shapes, reflecting distinct combinations of regulation types. Based on previous research, it was also anticipated that a profile dominated by autonomous forms of regulation, a profile dominated by controlled forms of regulation, and at least one profile containing both autonomous and controlled forms of regulation would be identified. While the emergence of different profiles remains possible, in particular across the two samples considered here, the current study aimed to introduce a broad typology of meaningful profiles common to most workplaces. However, latent profile analyses suffer from the same limitations as variable-centered analyses in terms of generalizability and in providing a meaningful representation of the data (i.e., construct validity). In particular it has been previously argued that the only way to really support a substantive interpretation of latent profiles is to embark on a process of construct validation to demonstrate that the identified profiles either meaningfully relate to covariates (predictors, or outcomes), or can reliably be replicated across samples (Marsh, Lüdtke, Trautwein, & Morin, 2009; Morin, Morizot, Boudrias & Madore, 2011; Muthén, 2003). To address this issue, we tested whether the identified set of profiles generalized across two Western countries. Furthermore, we assessed the extent to which these profiles were related to a series of predictors and outcomes to which we now turn our attention.

3. Predictors of motivation profiles

To date little research has examined determinants of employees' motivation profiles. Among this limited research, Moran et al. (2012) showed that membership into more autonomously motivated profiles could be predicted by greater levels of satisfaction of the needs for competence, autonomy, and relatedness, while Graves et al. (2015) showed that members of the more autonomously motivated profiles tended to occupy hierarchically higher positions and to report receiving higher levels of supervisor support. These results are consistent with SDT, which proposes that the satisfaction of these needs and exposure to work-related context that support their satisfaction, are key determinants of autonomous motivation (Deci & Ryan, 1985; Gagné & Deci, 2005). As such, it is also to be expected that job categories allowing for greater levels of need satisfaction may result in a greater proportion of employees corresponding to predominantly autonomously-driven profiles (i.e., higher in intrinsic motivation and identified regulation). In particular, research shows that workplace characteristics that influence need satisfaction, such as job design, participative leadership, and organic (vs. bureaucratic) structures, tend to be associated with significantly higher levels of autonomous motivation (De Cooman, Stynen, Van den Broeck, Sels, & De Witte, 2013; Gillet, Gagné, Sauvagère, & Fouquereau, 2012). By this reasoning, it was expected that manufacturing and other blue-collar industries often characterized by less skill variety, autonomy, more directive leadership, and hourly wages, would be less likely to satisfy these needs. For this reason, we expected motivational profiles characterized by lower levels of autonomous motivation and higher levels of controlled motivation to be more frequent among employees working in these sectors. In contrast, white-collar employees from the technology sector should be more likely to experience task variety and participative leadership, which would likely facilitate need satisfaction (Blais, Brière, Lachance, Riddle, & Vallerand, 1993; Gagné, Senécal, & Koestner, 1997; Gagné et al., 2010). Thus, we expected motivational profiles characterized by higher levels of autonomous motivation and lower levels of controlled motivation to be more frequent among these employees. Finally, white-collar governmental employees should be more likely to experience highly bureaucratic job structures, which may stifle motivation, making it more likely for these employees to correspond to profiles characterized by lower levels of both autonomous and controlled motivation. This study incorporated blue-collar manufacturing, white-collar technological, and white-collar governmental job categories as predictors of profile membership to test these hypotheses.

4. Consequences of motivation profiles

Past research has found that profiles characterized by high levels of autonomous motivation seem to yield better performance outcomes. However, it is less clear how controlled types of motivation relate to performance. So far, most research conducted regarding the outcomes of motivational profiles have been conducted in the educational area. This research has shown that the HA/LC profile tends to be associated with higher levels of academic achievement, as well as lower levels of procrastination, openness to cheating, and school dropout than the HA/HC profile (Hayenga & Corpus, 2010; Ratelle et al., 2007; Vansteenkiste et al., 2009). In contrast, the LA/LC and LA/HC profiles both yielded lower levels of academic achievement and higher levels of procrastination, but did not differ from one another, indicating that the presence of controlled motivation had negligible effects on performance (Vansteenkiste et al., 2009). However, additional results suggested that controlled motivation may actually detract from optimal performance, measured by grade point average and self-perceived skill acquisition, even when autonomous motivation is also present (Hayenga & Corpus, 2010; Liu et al., 2009). It thus appears that profile composition, or the ratio of autonomous to controlled motivation, may represent a stronger predictor of performance outcomes than the simple overall “quantity” of motivation that characterizes a specific profile.

However, in the work domain, researchers have theorized that some levels of introjected and external regulation may prove beneficial in predicting positive outcomes (Boiché et al., 2008; Moran et al., 2012; Van den Broeck et al., 2013). A meta-analysis also found that while intrinsic motivation was more strongly related to the quality of the work completed, external regulation was more strongly associated with the quantity of work completed (Cerasoli, Nicklin, & Ford, 2014). Likewise, work pressure, theorized to foster external regulation, was positively related to the quantity of work effort and engagement (De Cooman et al., 2013; Van den Broeck, De Cuyper, De Witte, & Vansteenkiste, 2010). The one profile study in the work domain that has examined performance showed that the HA/LC and HA/HC profiles yielded comparable levels of self-reported in-role performance, and higher levels than those observed in the LA/HC and LA/LC profiles (Moran et al., 2012).

As suggested above, the quality and quantity of performance may be promoted through different motivational profiles (Cerasoli et al., 2014). Similarly, required (in-role) and discretionary (extra-role) performance may also be differentially affected by motivational profiles (Gagné et al., 2015). For instance, we might expect that profiles characterized by high levels of autonomous types of motivation would yield greater levels of in-role and extra-role performance, while profiles presenting high levels of controlled types of motivation would only yield greater levels of in-role performance. The question is whether controlled types of motivation will stifle extra-role performance, as has been suggested in some variable-centered research (Battistelli, Galletta, Portoghese, & Vandenberghe, 2013).

Past research also found that profiles characterized by high levels of autonomous motivation yield better wellbeing outcomes (Van den Broeck et al., 2013). In this situation, unlike what is observed in the prediction of performance, controlled motivation does not seem to have any advantage in promoting wellbeing — it even seems to decrease it. In the educational domain, the HA/LC profile was found to be associated with lower levels of school-related anxiety than the HA/HC profile, while the LA/LC and LA/HC profiles were associated with the highest levels of school anxiety (Vansteenkiste et al., 2009). In the work domain, Van den Broeck et al. (2013) and Graves et al. (2015) both found that HA/HC and HA/LC profiles reported the greatest (and equal) levels of job satisfaction. However, strain was lower in the HA/LC than in the HA/HC profile; followed by the LA/LC profile. Employees from the LA/HC profile reported the highest levels of work-related strain. The present study expands on these studies by the inclusion of work engagement (vigor, dedication, and absorption; Schaufeli & Bakker, 2003) and burnout (emotional exhaustion, cynicism, and personal inefficacy; Maslach, Schaufeli, & Leiter, 2001) as potential outcomes of employees' motivational profiles.

5. Method

5.1. Participants and procedure

This study incorporated two samples of data collected between 2008 and 2013. Sample 1 consisted of 723 Canadian employees recruited within three different industry sectors: 105 from the technological sector, 319 from the government sector and 299 from the manufacturing sector ($\text{Mean}_{\text{age}} = 44.30$; female = 15.8% [54.1% gender info missing]). The subsample of 105 white collar technology sector employees was previously used in the MMWS validation study (Gagné et al., 2015). These employees completed surveys containing the original English ($n = 178$) or French ($n = 545$) versions of the MWMS. Sample 2 consisted of 286 Belgian employees ($\text{Mean}_{\text{age}} = 41.66$ years; female = 57.7%; $\text{Mean}_{\text{Tenure}} = 9.39$ years) who completed Dutch versions of the outcome measures, in addition to the Dutch MWMS. In both countries, a variety of organizations were approached with the possibility to participate in this study of work motivation. These organizations were selected mainly through a process of convenience based on lead investigators' contacts and proximity. Employees from the organization who agreed to participate had the possibility to complete confidential surveys on an online platform or in paper format on their work premises. Participation was voluntary.

5.2. Measures

A variable specifying job category (e.g., blue collar manufacturing, white collar technology, white collar governmental) was available only for Sample 1 ($n = 723$) and was subsequently dummy-coded in two complementary variables to reflect white collar technology sector employees (1; $n = 105$) versus others (0) and governmental employees (1; $n = 319$) versus others (0).

The MWMS (Gagné et al., 2015) includes 19 items assessing six distinct motivation types. Each item is an answer to the question "Why do you or would you put effort into your current job?" along a 1 (not at all) to 7 (completely) point Likert scale. Sample items include, "I don't know why I'm doing this job, it's pointless work" (Amotivation; Cronbach's $\alpha = 0.74$ & 0.87 in Samples 1 and 2 respectively), "Because others will reward me financially only if I put enough effort in my job (e.g., employer, supervisor…)" (External regulation material; $\alpha = 0.60$ & 0.70), "To get others' approval (e.g., supervisor, colleagues, family, clients…)" (External regulation social; $\alpha = 0.78$ & 0.76), "Because otherwise I will feel ashamed of myself" (Introjected regulation; $\alpha =$ 0.69 & 0.71), "Because putting efforts in this job aligns with my personal values" (Identified regulation; $\alpha = 0.78$ & 0.67), and "Because the work I do is interesting" (Intrinsic motivation; $\alpha = 0.90$ & 0.88). Validation evidence for the MWMS has demonstrated a good fit for a six-factor structure, equivalence of the underlying measurement model across the English, French and Dutch linguistic versions used in the present study, acceptable scale score reliability (α from 0.70 to 0.90 for all subscales), and supported the convergent and discriminant validity of scales (Gagné et al., 2015).

The outcomes variables were available only in Sample 2. In-role performance was measured by seven self-reported items taken from Abramis (1994). Items were rated on a 1 (really bad) to 5 (really good) Likert scale with each item based on the question stem of, "In the last (seven days/week you worked), how well were you…" Items included, "doing your best work," and "showing initiative in your work" ($\alpha = 0.85$). Extra-role performance was measured by 9 items from Morrison (1994), with each item rated 1 (totally disagree) to 5 (totally agree) along a Likert scale ($\alpha = 0.81$; e.g., "I help in the training of new colleagues" and "I take active part in meetings of the organization"). Job satisfaction was measured through 14 items taken from De Witte, Hooge, Vandoorne, and Glorieux (2001). Items were rated on a 5-point scale (1, totally dissatisfied to 5, totally satisfied) in response to questions such as, "How satisfied are you in general with your work?" ($\alpha = 0.89$). Engagement was measured using 15 items from the Utrech Work Engagement Scale (UWES, Schaufeli & Bakker, 2003) on a 1 (very rarely) to 6 (always) Likert scale. Subscales for vigor (5 items, e.g., "When I get up in the morning, I feel like going to work"), dedication (5 items, e.g., "I am enthusiastic about my job"), absorption (5 items, e.g., "When I am working, I forget everything else around me") were combined into an overall measure of work engagement for the sake of parsimony ($\alpha = 0.95$). Finally, burnout was measured on a 6-point scale using the Schaufeli and van Dierendonck (1993) adaptation of the Maslach Burnout Inventory. Two subscales of emotional exhaustion (5 items; e.g., "working all day is a heavy burden for me") and cynicism (4 items; e.g., "I doubt the usefulness of my work") were included and combined in the current analyses ($\alpha = 0.93$), and scored from 1 (very rarely) to 6 (always).

6. Analyses

6.1. Preliminary measurement models

Preliminary measurement models were estimated in both samples using the robust maximum likelihood estimator (MLR) available in Mplus 7.3 (Muthén & Muthén, 1998-2015), in conjunction with Full Information Maximum Likelihood (FIML) estimation to deal with the very low level of missing data present in this data set (0% to 2.8% per item; M = 1.1%). In each sample, we contrasted a classical confirmatory factor analytic (CFA) model, in which each of the six MWMS factors was defined on the basis of it's a priori items, with no cross-loading allowed between items and non-target factors, with an exploratory structural equation modeling (ESEM; Asparouhov & Muthén, 2009; Morin, Marsh, & Nagengast, 2013), which was defined in the same manner as the CFA model while allowing for the free estimation of cross-loadings between items and non-target factors. These ESEM models were specified using a confirmatory approach using target rotation (Asparouhov & Muthén, 2009), which allows for the pre-specification of target loadings in a confirmatory manner, while cross-loadings are targeted to be as close to zero as possible. Recent studies conducted on motivational data show the advantages of using an ESEM measurement model (Guay, Morin, Litalien, Valois, & Vallerand, 2015; Litalien, Guay, & Morin, 2015) in terms of obtaining reduced estimates of factor correlations more in line with theoretical expectations. This decision is also based on the results from simulation studies (Asparouhov & Muthén, 2009; Sass & Schmitt, 2010; Schmitt & Sass, 2011) and studies of simulated data (Marsh, Lüdtke, Nagengast, Morin, & Von Davier, 2013; Morin, Arens, & Marsh, 2015) showing that forcing cross-loadings (even as small as 0.100, Marsh et al., 2013) present in the population model to be exactly zero (as in CFA) forces these cross-loadings to be absorbed through an inflation of the factor correlations. In contrast, these same studies show that the free estimation of cross-loadings, even when none are present in the population model, still provides unbiased estimates of the factor correlations (also see Asparouhov, Muthén, & Morin, 2015; Morin, Arens & Marsh, 2015). Thus, Asparouhov et al. (2015, p. 1564) note that:

> "*Overall, these studies clearly show that the inclusion of cross-loadings is neither logically flawed nor logically incorrect but rather empirically supported by statistical research. Going back to the flawed argument that cross-loadings "taint" the nature of the constructs, these results rather show that it is the exclusion of these cross-loadings that modifies the meaning of the constructs.*"

Given the known oversensitivity of the chi-square test of exact fit (χ^2) to sample size and minor model misspecifications (e.g., Marsh, Hau, & Grayson, 2005), we relied on goodness-of-fit indices to describe the fit of these models (Hu & Bentler, 1999): (a) the comparative fit index (CFI), (b) the root mean square error of approximation (RMSEA) and its 90% confidence interval (CI); and (c) the standardized root mean square residual (SRMR). Values >0.90 and 0.95 for the CFI respectively indicate adequate and excellent model fit, while values smaller than 0.08 or 0.06 for the RMSEA and SRMR respectively support acceptable and excellent model fit. In both samples, these results revealed the clear superiority of the ESEM measurement model [(Sample 1: $\chi^2 = 124.575$, df = 72, $p < 0.001$; CFI = 0.986; RMSEA = 0.032; CI = 0.022 to 0.041; SRMR = 0.016); (Sample 2: $\chi^2 = 161.020$, df = 72, $p < 0.001$; CFI = 0.955; RMSEA = 0.066; CI = 0.052 to 0.079; SRMR = 0.020)], when compared to the CFA model [(Sample 1: $\chi^2 = 421.443$, df = 137, $p < 0.001$; CFI = 0.924; RMSEA = 0.054; CI = 0.048 to 0.059; SRMR = 0.058); (Sample 2: $\chi^2 = 401.719$, df = 137, $p < 0.001$ CFI = 0.866; RMSEA = 0.082; CI = 0.073 to 0.092; SRMR = 0.070)]. This conclusion was supported by an assessment of the parameter estimates obtained from both models, which revealed generally well-defined factors, and reduced factor correlations in the ESEM [(Sample 1: $|r| = 0.015$ to 0.761; $M_{|r|} = 0.281$); (Sample 2: $|r| = 0.026$ to 0.446; $M_{|r|} = 0.234$)], when compared to CFA model [(Sample 1: $|r| = 0.057$ to 0.836; $M_{|r|} = 0.366$); (Sample 2: $|r| = 0.021$ to 0.844; $M_{|r|} = 0.401$)].

LPA were conducted using factor scores (specified to have a mean of 0 and a standard deviation of 1) from the retained ESEM measurement models (e.g., Kam, Morin, Meyer, & Topolnytsky, 2016; Morin & Marsh, 2015). In comparison with scale scores, factor scores have the advantage of providing a partial control for measurement errors by giving more weight to items presenting lower levels of measurement errors (Kam et al., 2016; Morin & Marsh, 2015; Skrondal & Laake, 2001). Correlations and estimates of scale score reliability for all variables (including these factor scores) used in the present study are reported in Table 1.

Table 1
Correlations and scale score reliability (α) estimates for the variables used in the present study.

	1	2	3	4	5	6	7	8	9	10	11
1. Amotivation	–	0.137*	0.190*	−0.200*	−0.396*	−0.401*					
2. Ext-material	0.107	–	0.465*	0.324*	0.191*	0.137*					
3. Ext-social	0.79*	0.304*	–	0.297*	0.015	−0.095*					
4. Introjected	−0.039	0.200*	0.218*	–	0.357*	0.246*					
5. Identified	−0.133	0.108	0.345*	0.441*	–	0.761*					
6. Intrinsic	−0.361*	0.209*	−0.026	0.399*	0.446*	–					
7. In-role performance	−0.161*	−0.084	−0.029	0.222*	0.247*	0.252*	–				
8. Extra-role performance	−0.054	−0.133*	−0.059	0.207*	0.247*	0.264*	0.329*	–			
9. Engagement	−0.453*	0.035	−0.142*	0.265*	0.374*	0.660*	0.345*	0.359*	–		
10. Burnout	0.426*	0.029	−0.175*	−0.185*	−0.287*	−0.456*	−0.292*	−0.165*	−0.438*	–	
11. Job satisfaction	−0.506*	0.021	−0.175*	0.240*	0.331*	0.612*	0.234*	0.220*	0.646*	−0.500*	
α (Sample 1)	0.741	0.781	0.600	0.692	0.775	0.898					
α (Sample 2)	0.886	0.695	0.761	0.711	0.671	0.882	0.846	0.810	0.946	0.927	0.885

Note: Sample 1 is above diagonal. Sample 2 is below diagonal. External-M = external-material regulation; External-S = external-social regulation. Scores are all factor scores from preliminary models with a mean of 0 and standard deviation of 1.
* $p < 0.05$.

6.2. Latent profile analyses

Based on our expectation that 4 to 6 latent profiles would be identified, models including 1 to 8 profiles were estimated in each sample using the robust Maximum Likelihood (MLR) estimator available in Mplus. The means and variances of the six motivation factors were freely estimated in all profiles (Morin, Maïano, Nagengast, Marsh, Morizot & Janosz, 2011; Peugh & Fan, 2013), using 7000 random sets of start values, 300 iterations for each random start, and the 200 best solutions retained for final stage optimization (Hipp & Bauer, 2006). All models converged on well replicated solutions.

In order to determine the optimal number of profiles in each sample, it is important to consider the substantive meaning and theoretical conformity of the profiles (Marsh et al., 2009; Muthén, 2003), the statistical adequacy of the solution, and a variety of statistical indicators. Among these statistical indicators, we report the Akaike Information Criterion (AIC), the Bayesian Information Criterion (BIC), the Consistent AIC (CAIC), the sample-adjusted BIC (ABIC), the adjusted version of the Lo, Mendell, and Rubin likelihood ratio test (LMR), and the Bootstrap Likelihood Ratio Test (BLRT). The entropy was also examined, and indicates the precision with which the cases are classified into the profiles (on a 0 to 1 scale). However, the entropy should not be used in itself to determine the optimal number of profiles (Lubke & Muthén, 2007; Peugh & Fan, 2012, 2013, 2015; Tein, Coxe, & Cham, 2013).

Extensive simulation research has looked at the performance of these various indicators to help in selecting the optimal number of latent profiles in the data in the context of latent profile analyses and other forms of person-centered mixture models. Overall, these studies converge in supporting the efficacy of the CAIC, the BIC, the ABIC, and the BLRT in choosing the model which best recovers the sample's true parameters (e.g., Henson, Reise, & Kim, 2007; McLachlan & Peel, 2000; Morgan, 2015; Nylund, Asparouhov, & Muthén, 2007; Peugh & Fan, 2012, 2013, 2015; Tein et al., 2013; Tofighi & Enders, 2008; Tolvanen, 2007; Yang, 2006). In particular, a recent simulation study (Diallo, Morin, & Lu, 2016) suggest that the BIC and CAIC should be privileged under conditions of high entropy (e.g., ≥0.800), whereas the ABIC and BLRT appear to perform better in conditions of low entropy (e.g., ≤0.500). In contrast, the bulk of current research evidence suggests that, like the entropy, the AIC and LMR/ALMR should not be used in the class enumeration process (e.g., Diallo et al., 2016; Henson et al., 2007; Nylund et al., 2007; Peugh & Fan, 2013; Tofighi & Enders, 2007; Yang, 2006). In the current study, these indicators are thus simply reported to ensure a thorough disclosure of results, but will not be used to select the optimal number of profiles. A lower value on the AIC, CAIC, BIC and ABIC suggests a better-fitting model. Both the LMR and BLRT compare a k-profile model with a k-1-profile model. A significant p value indicates that the k-1-profile model should be rejected in favor of a k-profile model. However, since these tests are all variations of tests of statistical significance, the class enumeration procedure can still be heavily influenced by sample size (Marsh et al., 2009). That is these indicators frequently keep on improving with the addition of latent profiles to the model without reaching a minimum. In these cases, information criteria should be graphically presented through "elbow plots" illustrating the gains associated with additional profiles (Morin & Marsh, 2015; Morin, Maïano, Nagengast, Marsh, Morizot & Janosz, 2011; Petras & Masyn, 2010). In these plots, the point after which the slope flattens suggests the optimal number of profiles that should be examined, together with adjacent solutions including one more and one less profile, for theoretical conformity and statistical adequacy.

6.3. Latent profile analyses with predictors and outcomes

Starting from the final LPA solution retained for Sample 1, we then proceeded to tests of the relations between the two dummy variables created to reflect job categories and the probability of membership into the profiles. These two variables were included to the final model through a multinomial logistic regression. In multinomial logistic regressions, each predictor has k-1 (with k being the number of profiles) complementary effects for each possible pairwise comparison of profiles. The

Table 2
Class enumeration.

	Log likelihood	#fp	scaling	AIC	CAIC	BIC	ABIC	Entropy	LMR	BLRT
Sample 1 ($n = 723$)										
1 Profile	−5746.162	12	1.163	11,516.324	11,583.325	11,571.325	11,533.222	Na	Na	Na
2 Profiles	−5054.193	25	1.020	10,158.385	10,297.971	10,272.971	10,193.588	0.816	<0.001	<0.001
3 Profiles	−4808.461	38	1.135	9692.922	9905.092	9867.092	9746.431	0.840	0.002	<0.001
4 Profiles	−4611.800	51	1.196	9325.600	9610.354	9559.354	9397.414	0.861	0.086	<0.001
5 Profiles	−4491.730	64	1.118	9111.461	9468.799	9404.799	9201.581	0.851	0.018	<0.001
6 Profiles	−4384.863	77	1.093	8923.726	9353.648	9276.648	9032.151	0.867	<0.001	<0.001
7 Profiles	−4291.002	90	1.044	8762.005	9264.512	9174.512	8888.735	0.861	0.002	<0.001
8 Profiles	−4226.600	103	1.099	8659.200	9234.291	9131.291	8804.236	0.853	0.162	<0.001
Sample 2 ($n = 286$)										
1 Profile	−2281.653	12	2.0090	4587.305	4643.177	4631.177	4593.124	Na	Na	Na
2 Profiles	−1714.199	25	0.9661	3478.397	3594.797	3569.797	3490.520	0.930	<0.001	<0.001
3 Profiles	−1589.459	38	0.9764	3254.917	3431.845	3393.845	3273.344	0.897	<0.001	<0.001
4 Profiles	−1473.405	51	1.1226	3048.810	3286.266	3235.266	3073.540	0.886	0.023	<0.001
5 Profiles	−1416.272	64	1.0316	2960.545	3258.528	3194.528	2991.579	0.890	0.012	<0.001
6 Profiles	−1380.270	77	1.0258	2914.539	3273.051	3196.051	2951.877	0.906	0.033	<0.001
7 Profiles	−1347.972	90	1.0299	2875.944	3294.983	3204.983	2919.585	0.917	0.232	<0.001
8 Profiles	−1315.187	103	1.0627	2836.373	3315.940	3212.940	2886.319	0.911	0.227	<0.001

Note: #fp = number of free parameters; AIC = Akaike information criterion; CAIC = constant AIC; BIC = Bayesian information criterion; ABIC = sample size adjusted BIC; LMR = p value associated with the adjusted Lo–Mendell–Rubin likelihood ratio test; BLRT = p value associated with the bootstrap likelihood ratio test.

regression coefficients reflect the increase, for each unit increase in the predictor (with dummy variables this reflects the difference between the job category coded 1 and the remaining job categories), that can be expected in the log-odds of the outcome (i.e., the probability of membership in one profile versus another). For simplicity, we report odds ratios (OR), reflecting the change in likelihood of membership in a target profile versus a comparison profile associated with the target job category. For example, an OR of 3 suggests that employees from the target job category are three-times more likely than others to be member of the target profile (versus the comparison profile).

Then, starting from the final LPA solution retained for Sample 2, we tested the relations between profile membership and the multiple outcome variables available in this sample (performance, extra-role behaviors, job satisfaction, engagement, and burnout), through the direct inclusion of these outcomes in the model as additional profile indicators (Morin & Wang, 2016). The MODEL CONSTRAINT command of Mplus was used to systematically test mean-level differences across all specific pairs of profiles (using the multivariate delta method: e.g., Raykov & Marcoulides, 2004).

7. Results

The fit indices for the alternative solutions estimated separately in both samples are reported in Table 2. For both samples, the CAIC, BIC, ABIC, and BLRT kept on improving with the addition of latent profiles. However, we also note that the entropy values are quite high (≥0.800) for all of the estimated models in both samples. Following Diallo et al.'s (2016) recommendations, this suggests that the decision of how many profiles to retain should mainly focus on the BIC and CAIC. Because these indicators failed to reach a minimum, we relied on a graphical representation of these information criteria (Morin & Marsh, 2015; Morin, Maïano, Nagengast, Marsh, Morizot & Janosz, 2011; Petras & Masyn, 2010). These plots are reported in Fig. 1, and show that the decreases in values of most information criteria reached a plateau around 4 profiles in both Samples 1 and 2. Examination of the 4-profile

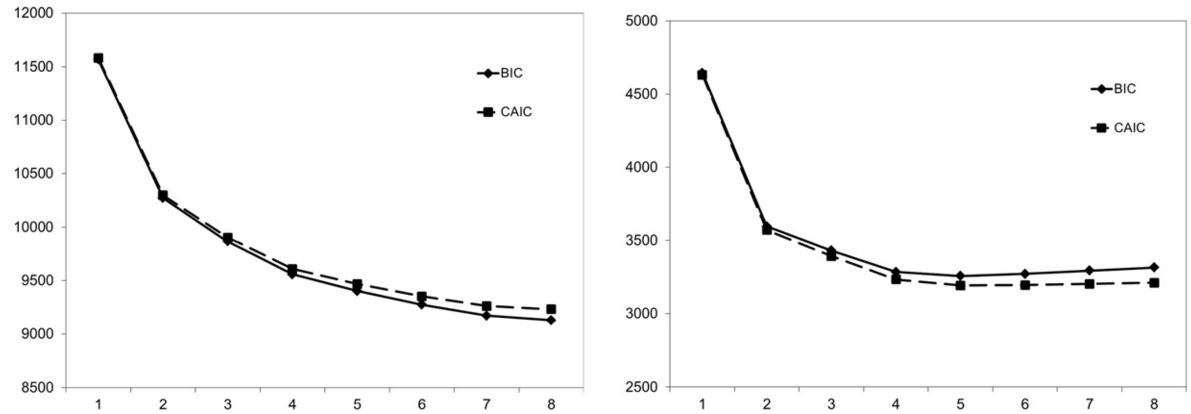

Fig. 1. Elbow plot for the information criteria in Samples 1 (left) and 2 (right).

Table 3
Posterior classification probabilities for the most likely latent profile membership (row) by latent profile (column).

	Amotivated (P.1)	Moderately autonomous (P.2)	Highly motivated (P.3)	Balanced (P.4)
Sample 1				
Amotivated (P.1)	0.902	0.001	0.001	0.096
Moderately autonomous (P.2)	0.003	0.976	0.014	0.007
Highly motivated (P.3)	0.000	0.008	0.938	0.054
Balanced (P.4)	0.041	0.010	0.032	0.917
Sample 2				
Amotivated (P.1)	0.942	0.004	0.000	0.054
Moderately autonomous (P.2)	0.000	0.925	0.034	0.041
Highly motivated (P.3)	0.000	0.031	0.941	0.028
Balanced (P.4)	0.007	0.023	0.021	0.949

Note. P: profile.

solutions and of the adjacent 3- and 5-profile solutions showed that all solutions were fully proper statistically in both samples. This examination also revealed that adding a fourth profile always resulted in the addition of a well-defined qualitatively distinct and theoretically meaningful profile to the solution, whereas adding a fifth profile resulted in the arbitrary division of one of the existing profile into smaller profiles differing only quantitatively from one another. As this additional small profile did not add anything meaningful in theoretical terms (i.e., it has the same meaning as already present profiles), the more parsimonious 4-profile solution was thus retained for each sample, in line with the conclusion suggested by the statistical indicators. This solution provides a reasonable level of classification accuracy, with an entropy value of 0.861 in Sample 1 and 0.886 in Sample 2. Classification probabilities are presented in Table 3. These results clearly demonstrate the high level of classification accuracy of these solutions, with average posterior probabilities of class membership in the dominant profile varying from 0.887 to 0.950 in Sample 1 and from 0.923 to 0.980 in Sample 2, with low cross-probabilities (varying from ≤0.001 to 0.073 in Sample 1 and from <0.001 to 0.042 in Sample 2).

The retained 4-profile solutions are represented in Fig. 2 for Sample 1, and Fig. 3 for Sample 2 (with exact numerical results reported in Table 4). These figures make it rapidly obvious that the profile structure is remarkably similar across samples, providing clear support to the generalizability of the profiles. For both samples, Profile 1 characterized *amotivated* employees (corresponding to 27.6% of the employees in Sample 1 and 13.1% in Sample 2) presenting very high levels of amotivation and average to low levels on all other motivation factors. For this profile, it is noteworthy that levels of motivation decrease as a direct function of their relative degree of self-determination as proposed by SDT. Profile 2 (11.5% in Sample 1; 27.8% in Sample 2) characterizes employees presenting very low levels of social and material forms of external regulations, low levels of amotivation and introjection, and average or slightly above average levels of identified regulation and intrinsic motivation. This *moderately autonomous* profile thus also appears to follow the continuum structure of self-regulation proposed by SDT in that it presents a single dominant regulation type with levels of other regulations tapering off as they become more theoretically distant. Profile 3 characterizes *highly motivated* employees (25.6% in Sample 1; 22% in Sample 2) presenting a relatively low level of amotivation and moderate to high levels on the other types of regulations which increase as a direct function of their relative degree of self-regulation according to SDT. This profile clearly presents the highest levels on the more autonomous forms of motivation (identified regulation and intrinsic motivation) out of all profiles identified in both samples. This *highly autonomous* profile thus also appears

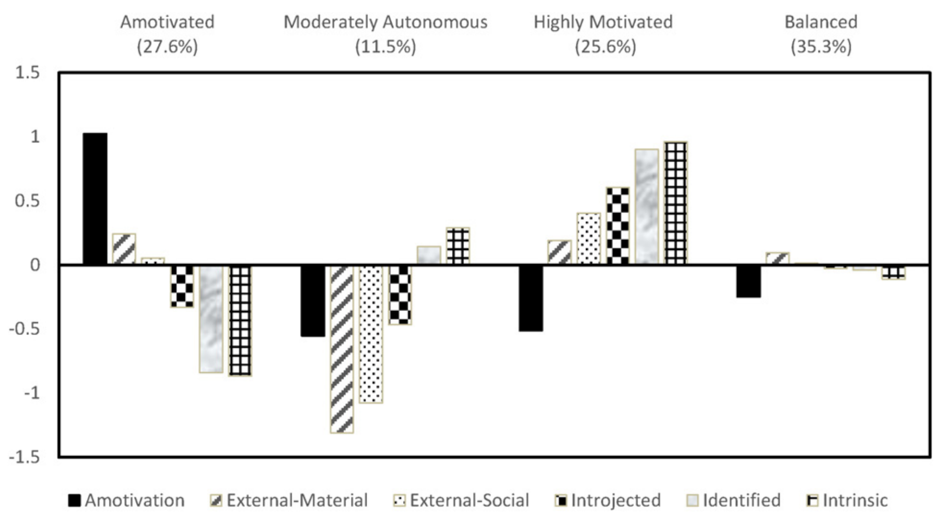

Fig. 2. Sample 1 profiles ($n = 723$). *Note*. Indicators are estimated from factor scores with a mean of 0 and a standard deviation of 1.

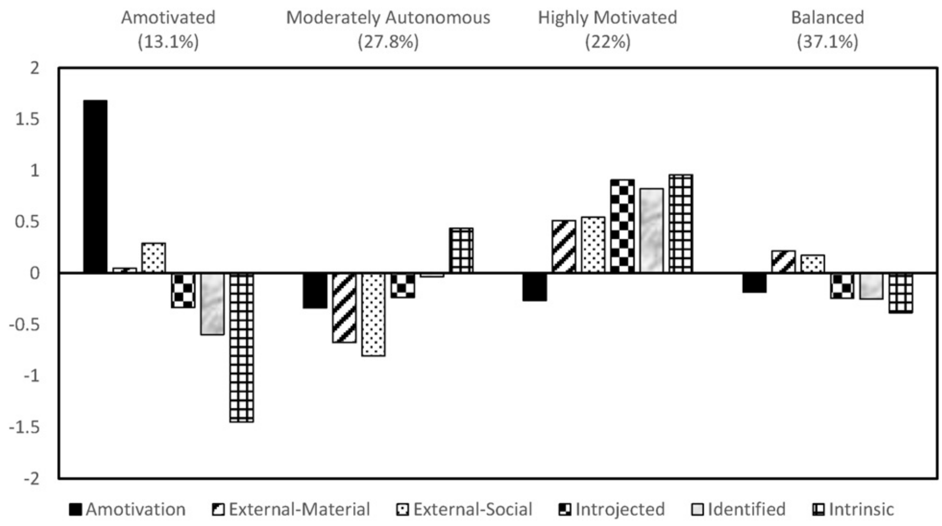

Fig. 3. Sample 2 profiles ($n = 286$). *Note*. Indicators are estimated from factor scores with a mean of 0 and a standard deviation of 1.

to follow the continuum structure of self-regulation proposed by SDT. Finally, Profile 4 characterizes employees presenting average levels of all regulations although the results obtained in Sample 2 suggest that this profile may also show a tendency to have slightly above average levels of external regulation, and slightly below average levels of autonomous forms of regulation. This profile, which also follows the self-regulation continuum proposed by SDT, thus appears to describe employees with *balanced* motivation (35.3% in Sample 1; 37.1% in Sample 2).

7.1. Predictors of profile membership

Results from the multinominal logistic regression examining relations between job category and profile membership in Sample 1 are reported in Table 5. Given that both dummy predictors were simultaneously considered, the blue-collar employees were used as the comparison group, with the effects of the first dummy predictor representing differences between white-collar technology sector employees and all other employees, and the second representing differences between white-collar governmental employees and all other employees. These results show that white-collar technology employees presented a lower likelihood of membership in the *moderately autonomously motivated* profile (Profile 2) than in all other profiles when compared to employees from other job categories. In contrast, white-collar governmental employees presented a greater likelihood of membership into the least desirable *amotivated* profile (Profile 1) than in all other profiles when compared to all other employees. These employees were also less likely to be in the *moderately autonomously motivated* (Profile 2) or *highly motivated* (Profile 3) profiles than in the *balanced* profile (Profile 4).

Table 4
Mean levels of motivation in the retained latent profile models.

	Amotivated (P.1)		Moderately autonomous (P.2)		Highly motivated (P.3)		Balanced (P.4)	
	Mean	Variance	Mean	Variance	Mean	Variance	Mean	Variance
Sample 1								
Amotivation	1.025	1.169	−0.554	0.019	−0.515	0.019	−0.249	0.080
External-M	0.053	0.841	−1.075	0.112	0.403	0.632	0.015	0.581
External-S	0.242	0.786	−1.308	0.006	0.192	0.889	0.095	0.63
Introjected	−0.331	0.764	−0.467	0.761	0.605	0.489	−0.027	0.532
Identified	−0.840	1.005	0.143	0.498	0.901	0.119	−0.041	0.222
Intrinsic	−0.867	1.009	0.288	0.54	0.961	0.126	−0.11	0.250
Sample 2								
Amotivation	1.679	4.131	−0.338	0.002	−0.264	0.002	−0.183	0.004
External-M	−0.050	1.152	−0.675	0.193	0.514	0.461	0.218	0.608
External-S	0.292	0.624	−0.805	0.260	0.548	0.824	0.175	0.608
Introjected	−0.335	1.301	−0.236	0.510	0.909	0.183	−0.243	0.504
Identified	−0.597	1.352	−0.034	0.611	0.823	0.276	−0.251	0.399
Intrinsic	−1.450	0.974	0.437	0.267	0.961	0.091	−0.384	0.424

Note. P: profile; External-M = external-material regulation; External-S = external-social regulation; indicators are estimated from factor scores with mean of 0 and a standard deviation of 1.

Table 5
Results from multinominal logistic regression evaluating relations between job type and latent profile membership (Sample 1).

Job category	Profile 1 vs. 2		Profile 1 vs. 3		Profile 1 vs. 4	
	Coefficient (SE)	OR	Coefficient (SE)	OR	Coefficient (SE)	OR
White collar	1.118 (0.413)**	3.059**	−0.320 (0.429)	0.726	0.235 (0.397)	1.265
Government	1.544 (0.397)**	4.683**	1.557 (0.303)**	4.745**	0.803 (0.363)*	2.232*
	Profile 2 vs. 3		Profile 2 vs. 4		Profile 3 vs. 4	
	Coefficient (SE)	OR	Coefficient (SE)	OR	Coefficient (SE)	OR
White collar	−1.438 (0.485)**	0.237**	−0.883 (0.407)*	0.413*	0.555 (0.444)	1.742
Government	0.014 (0.351)	1.014	−0.740 (0.351)*	0.477*	−0.754 (0.267)**	0.470**

Note. OR = odds ratio; SE = standard error of the coefficient.
* $p < 0.05$.
** $p < 0.01$.

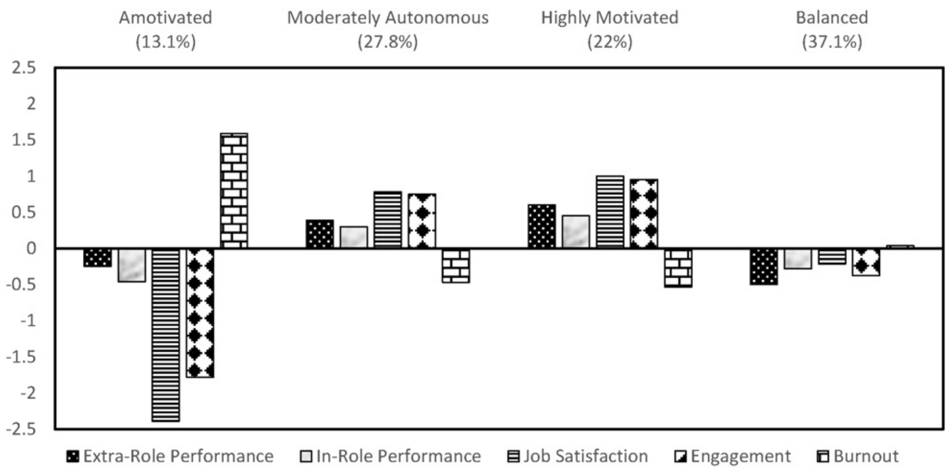

Fig. 4. Outcomes associated with profile membership. *Note.* Indicators are estimated from factor scores with a mean of 0 and a standard deviation of 1.

7.2. Outcomes of profile membership

Outcomes variables were added to the final 4-profile solution retained for Sample 2. Mean levels of each outcome across the four profiles are graphically depicted in Fig. 4, while the exact mean levels of the outcomes and the statistical significance for each pairwise comparison of outcome levels across profiles are reported in Table 6. Most of these comparisons are statistically significant, with only a few exceptions, supporting the predictive validity of the extracted latent profiles. Starting with performance, the results show that levels of both in-role and extra-role performance are highest in both the *highly motivated* profile (Profile 3) and the *moderately autonomous* profile (Profile 2), and lowest among both the *amotivated* (Profile 1) and *balanced* (Profile 4) profiles, which could not be distinguished from one another. Levels of job satisfaction and engagement significantly differed in a similar manner across profiles, being highest among the *highly motivated* profile (Profile 3) and the moderately autonomous profile (Profile 2), followed by the *balanced* profile (Profile 4), and lowest among the *amotivated* profile (Profile 1). Finally, levels of burnout were highest in the *balanced* profile (Profile 4), followed by the *amotivated* profile (Profile 1), and then by both the *highly motivated* (Profile 3) and *moderately autonomous* (Profile 2) profiles, which could not be distinguished from one another.[1]

8. Discussion

This study aimed to extend motivation theory and research through the identification of profiles of employees based on the simultaneous consideration of the six forms of behavioral regulation assumed to form the underlying continuum of self-determination proposed by SDT (Deci & Ryan, 1985). The current study provides an incremental contribution to the literature, finding four motivation profiles in the work domain that replicated across two reasonably large and heterogeneous samples of employees from two different countries. Prior research has generally been plagued by the reliance on small samples, the use of cluster analyses, and the arbitrary dichotomization of behavioral regulations into two broad categories of autonomous and controlled

[1] Upon request from a reviewer, all analyses were replicated while controlling for gender. These additional models converged on results substantively identical to those reported here. Additional details are available upon request from the corresponding author.

Table 6
Outcome means and pairwise comparisons between profiles (Sample 2).

	Standardized profile means				Profile comparisons						Summary of comparisons
	Amotivated (P.1)	Moderately autonomous (P.2)	Highly motivated (P.3)	Balanced (P.4)	1 vs 2	1 vs 3	1 vs 4	2 vs 3	2 vs 4	3 vs 4	
In-role performance	−0.408	0.267	0.400	−0.249	−0.675**	−0.808**	−0.159	−0.133	0.516**	0.650**	1 = 4 < 2 = 3
Extra-role performance	−0.202	0.319	0.496	−0.408	−0.521**	−0.697**	0.206	−0.177	0.727**	0.904**	1 = 4 < 2 = 3
Job satisfaction	−1.544	0.505	0.646	−0.138	−2.049**	−2.190**	−1.406**	−0.140	0.643**	0.784**	1 < 4 < 2 = 3
Engagement	−1.283	0.538	0.684	−0.271	−1.821**	−1.967**	−1.012**	−0.146	0.809**	0.955**	1 < 4 < 2 = 3
Burnout	1.257	−0.372	−0.423	0.030	1.629**	1.681**	−1.228**	0.051	−0.401**	−0.453**	2 = 3 < 4 < 1

Note. Indicators are estimated from factor scores with a mean of 0 and a standard deviation of 1.
* $p < 0.05$.
** $p < 0.01$.

regulations (Graves et al., 2015; Moran et al., 2012; Van den Broeck et al., 2013). In contrast, this study relied on two large samples of employees from Canada and Belgium from across multiple industries and job categories. Additionally, unlike much of the past person-centered research, the current study used state of the art analyses to not only identify an optimal number of profiles, but also to include antecedents and outcome variables in a statistically more advanced and rigorous manner than previously possible. A final key contribution of this study lies in the demonstration of the value of considering the whole range of behavioral regulations in the estimation of motivation profiles, as opposed to dichotomizing motivation into autonomous and controlled composite variables. In particular, the nature of the profiles observed in the present study, which generalized across samples, supported the underlying continuum structure of motivation proposed by SDT (Deci & Ryan, 1985). In sum, the comprehensive sampling and analyses employed in the current research lend support to the robustness and reliability of the detected profiles.

In line with prior research conducted in the education, sport, and work domains, our results revealed four latent profiles, which were replicated across the two samples. Particularly important is the observation that these profiles revealed qualitative and quantitative differences in employees' experiences of work motivation. These profiles showed that not only do employees experience varying *amounts* of overall motivation or self-determination, they also tend to experience different *types* of motivation. Additionally, our results revealed that the relative likelihood of membership into these profiles differed as a function of job type, and that it was associated with a variety of work-related performance and wellbeing outcomes. Meyer, Morin, and Vandenberghe (2015) recently noted that the value of person-centered analyses in the work domain depends not only on their ability to identify subgroups of employees differing from one another meaningfully on a set of variables, but also on the ability to demonstrate that these subgroups emerge regularly across samples, can be predicted in a meaningful manner, and are relevant to the prediction of work outcomes. As they met all of these criteria, our results can be considered highly meaningful.

As anticipated, we found a profile containing predominantly autonomous forms of regulation, a balanced profile containing roughly equal levels of all regulations, and at least one profile containing both autonomous and controlled forms of regulation. External regulation seemed to stand on its own in these profiles, whereas introjected regulation seemed to cluster more closely with autonomous forms of regulation, showing the importance of considering regulations at this level instead of aggregating them into global controlled and autonomous variables. For instance, the *highly motivated* profile was characterized by high levels of intrinsic motivation, identified regulation, and introjected regulation, and slightly above average levels of external regulation. Looking at the positive performance and wellbeing outcomes associated with this profile, it appears to be one of the most desirable profiles. Our results further revealed that white-collar technology sector employees are somewhat more disposed to correspond to this profile compared to the *moderately autonomous* profile. However, these white-collar workers were equally as likely to correspond to the amotivated and balanced profiles as to the highly motivated profile. This suggests that job characteristics known to be more prevalent in the white-collar technology sector, such as the more frequent use of participative management, enriched job designs and task variety, and even profit-sharing schemes, may result in situations where employees either have their basic psychological needs met and therefore experience autonomous forms of motivation (Blais et al., 1993; Gagné & Forest, 2008; Gagné et al., 1997, 2010), or alternatively experience amotivation or external pressure to perform — a kind of polarizing effect in which these practices either work well or fail badly.

The *moderately autonomous profile* was characterized by low levels of external and introjected regulations, and above average levels of identified regulation and intrinsic motivation. This profile is similar to the *highly motivated* profile in its shape, but not in the overall level of motivation. This profile also presented above average levels of performance and wellbeing, performing as well as the highly motivated profile. This indicates that while the overall quantity of motivation may play some role in influencing work outcomes, the shape of the profile appears to have more important outcome implications. Specifically, as long as a profile is dominated by autonomous rather than controlled forms of regulation, individuals will display above average levels of performance and wellbeing. This finding suggests that increasing all motivation types may not improve performance or wellbeing. Rather, it appears more important to increase identified regulation and intrinsic motivation, while ensuring that they remain higher than external regulation.

The moderately autonomous profile becomes even more interesting when compared to the *balanced* profile, given that both are characterized by similar *amounts* of overall motivation. However, while the *moderately autonomous* profile is dominated by autonomous motivation, the *balanced* profile is generally average across all regulations. Such a comparison allows for a clear examination of the relative importance of shape effects while holding reasonably constant the overall quantity of motivation. The results showed that the *moderately autonomous* profile was far more desirable than the *balanced* profile, which was associated with significantly lower levels on all indicators of performance and wellbeing. Thus, motivation profiles dominated by an emphasis on meaning and interest appear to lead to higher performance and wellbeing, compared to the balanced or amotivated profiles, regardless of overall amount of motivation. These results comparing the *highly autonomous* and *moderately autonomous* profiles, as well as the *moderately autonomous* and *balanced* profiles, are important. Indeed, these comparisons suggest that, far from being an effective motivator (Cerasoli et al., 2014; Gerhart & Fang, 2015), an emphasis on social and material rewards may have a negative impact on performance when it is not accompanied by a comparable emphasis on meaning, interest and pleasure (Gagné & Deci, 2005). Worse, this negative impact may be accompanied by an equally negative impact on wellbeing, making it doubly difficult for these employees to increase their performance in the long term (e.g., Ryan, Deci, & Grolnick, 1995). Interestingly, the previously discussed results regarding the fact that the moderately autonomous and highly motivated profiles are associated with similarly desirable outcomes suggest that high levels of autonomous regulations appear to protect employees from the effects of high levels of more controlled forms of regulations.

Finally, the amotivated profile characterizes employees for whom work is neither motivated by meaning, guilt, enjoyment, or rewards but are rather mainly *amotivated*, suggesting they may possibly feel “trapped” in their position due to high perceived sacrifices associated with leaving (i.e., continuance commitment; Morin, Meyer, McInerney, Marsh, & Ganotice, 2015). In line with our expectations, white collar governmental employees, who tend to be exposed to more rigid bureaucratic structures, presented a significantly greater likelihood of membership into this profile (De Cooman et al., 2013; Gillet et al., 2013), followed by membership in the *balanced* profile, strongly suggesting that characteristics of this job are highly detrimental to autonomous motivation. Also in line with our expectations, employees from this *amotivated* profile presented the lowest levels of wellbeing out of all profiles, and levels of performance that were undistinguishable from those observed in the *balanced* profile. This profile appeared to be the least desirable.

It is interesting to note that the amotivated and highly motivated profiles both follow the expected continuum structure so closely that it could be argued that for these profiles a single factor representing global self-determined motivation (e.g., Howard et al., 2016) could be sufficient to describe these employees satisfactorily. Alternately, for the moderately autonomous and balanced profiles where the profiles do not follow the continuum structure as perfectly, it appears necessary to take into account qualitative distinctions between the various motivation subscales in order to obtain a complete picture of employees' work motivation.

In regards to previous person-centered research on work motivation, the current results provide an incremental contribution to the literature by replicating, in part, the profiles found by Graves et al. (2015), and expanding greatly on the cluster analytic results of Van den Broeck et al. (2013) and Moran et al. (2012). All of these studies succeeded in identifying the most extreme profiles, including a highly motivated profile characterized by above average levels of all types of motivation, and an amotivated profile characterized by below average levels on most types of motivation. The *moderately autonomous* profile identified in the current study also largely replicates the self-determined profile found by Graves et al. (2015) in a sample of managers. The *balanced* profile, which shows a slight tendency towards an external focus, is a more novel finding of the current study. Not only has this profile allowed for a highly insightful comparison between two profiles characterized by similar global amounts of motivation but different shapes, but it suggests that some employees draw motivation from multiple sources equally but do not seem to thrive in their workplace as a result of it.

Finally, the current study provides evidence of generalizability of the reported profiles. Like with variable-centered research, the confidence with which person-centered results can be used to guide practice depends on replicability and the convergence of results obtained from a variety of samples. Through multiple samples and studies, it becomes possible to identify a set of core profiles which are commonly occurring in most work contexts, and more peripheral profiles which may arise due to specific workplace circumstances or in specific subgroups of employees (Solinger, Van Olffen, Roe, & Hofmans, 2013). The current study offers a set of four core profiles which, interestingly, replicate some of the profiles found by Graves et al. (2015). This suggests that the subset of replicated profiles are more likely to reflect core profiles of employee motivation, whereas the additional profiles reported by Graves et al. may be more peripheral, arising specifically in manager sub-populations.

In sum, our results incrementally add to previous research by examining work motivation profiles in the most rigorous manner available to date (i.e., through the incorporation of all regulation types into state-of-the-art LPA) with reasonably large and heterogeneous samples of employees from two countries. Additionally we provide initial evidence which demonstrates that profile membership varies as a function of job category with white-collar technology sector employees less likely to be in the moderately autonomously motivated profile, while government employees are more likely to be amotivated in their work. Lastly our results show that profile membership has meaningful implications for a wide range of work outcomes with profile characterized by predominantly autonomous forms of motivation being associated with more positive performance and wellbeing outcomes.

8.1. Limitations and directions for future research

Though the current study presents several advantages over previous research, it also presents notable limitations. As with all cross-sectional research it is impossible to reach clear conclusions regarding the directionality of the associations between the observed motivational profiles and the so-called outcome variables on the basis of a single study. The possibility thus remains that the observed associations follow reversed or even reciprocal relations as performance and wellbeing may themselves act as predictor of employee motivation profiles. However, lending confidence to the current interpretations, prior longitudinal research has supported the idea of directional relationships through which motivation levels predict later levels of performance and wellbeing (e.g., Baker, 2003; Dysvik & Kuvaas, 2013). Still, future research is needed to clarify this issue, and particularly to investigate possible reciprocal relations among these constructs (e.g., Morin et al., 2016). Longitudinal studies will also be needed to examine the development and temporal stability of motivation profiles. It would be most useful to know how, and under which conditions, the different profiles found in the present study develop and evolve over time, considering both organizational newcomers (Bauer & Erdogan, 2014) as well as employees at later career stages (Gould & Hawkins, 1978). Like the present study, future person-centered research should also strive to favor LPA over more traditional cluster analyses for reasons covered comprehensively elsewhere (Meyer & Morin, 2016; Morin, Maïano, Nagengast, Marsh, Morizot & Janosz, 2011; Vermunt & Magidson, 2002). In particular, LPA tends to rely on far less stringent assumptions, which can be relaxed as needed, relative to cluster analyses, as well as a lower level of reactivity to measurement scales and clustering algorithm. Furthermore, LPA allows for the direct incorporation of covariates into the model, without the need to rely on suboptimal two-step strategies. Finally, research would also benefit from devoting attention to the effects of specific modifiable organizational design factors, such as organizational structure, job design, leadership style, and compensation systems, on membership into specific motivational profiles. While our results suggest a clear relation between job categories and membership into specific profiles, a finer grained analysis of the mechanisms involved in these relations would have important practical relevance to the design of specific interventions to improve employee motivation. In this regard, it would be particularly useful to know how organizational changes, such as job design changes and compensation system changes, are able to predict changes in profile membership that would affect transitions from one profile to another.

8.2. Practical implications

In person-centered research, evidence for generalizability is built from an accumulation of studies, from which it becomes possible to identify a core set of profiles emerging with regularity, together with more peripheral profiles emerging irregularly under specific conditions (Solinger et al., 2013). The fact that the profiles identified in this study are in line with theoretical expectations and emerged consistently across two independent samples of employees recruited in two countries supports their generalizability. Though additional research is needed, we can suggest that organizations can use these four profiles to think about how employees falling into these profiles can be best managed. For example, knowing that the *balanced* profile has lower than average performance, probably because of a lack of meaning and enjoyment, organizations could try to provide meaning (e.g., through task significance; Grant, 2008) and stimulation (e.g., through job redesign; Hackman & Oldham, 1975) to employees. Specifically, employers may find that while a job has inherent meaningfulness and intrinsically enjoyable factors, employee motivation, and therefore performance, remains below expectations. Results from this study indicate that this may occur when external motivators are equally influential as more autonomous factors (such as is the case in the *balanced* profile). In these conditions, reducing the external focus and promoting more autonomously-driven reasons could be enough to nudge employees away from the *balanced* profile, with its largely below average outcomes, and into the *moderately autonomous* profile. Such a small adjustment could lead to employees being driven predominately by autonomous factors and subsequently performing more successfully and experiencing greater wellbeing. As such, knowing that autonomous motivation is relatively more important than external regulations in promoting performance and wellbeing, organizations may wish to focus more on meaning and enjoyment than on rewards and punishments.

The drawback of the variable-centered approach is that it often leads to thinking about an intervention that will improve a variable (e.g., intrinsic motivation) without taking into consideration what it may do to other forms of motivation (e.g., introjection). Conversely, the person-centered approach allows managers to consider employees as whole entities, rather than focusing narrowly on isolated individual characteristics. This approach recognizes the complexity of human motivation and behavior, and as such may provide a more complete and integrated description of this reality.

Our results could also prove particularly useful in informing the long-standing debate on the impact of incentives on work motivation. Gerhart and Fang (2015, also see Cerasoli et al., 2014) recently argued that controlled types of motivation may yield positive outcomes and that these motivation types could be promoted through the use of monetary incentives. Results of the current study suggest a relatively weak association between external material regulation and performance, and offer no support for the proposition that external rewards are successful in increasing performance when accompanied by autonomous forms of motivation. Similar conclusions have been put forward in previous person-centered research by Van den Broeck et al. (2013) and Moran et al. (2012), who also found more positive outcomes associated with more autonomously driven profiles than profiles driven by controlled regulations even when accounting for differing levels of global motivation.

In regard to the outcomes considered in this study, it is clear that organizations should attempt to promote profiles characterized by relatively higher levels of autonomous than external forms of regulations, through meaning making and the stimulation of people's interests for the work they do. It seems that as long as organizations can achieve this, they do not need to focus so much on promoting external regulation through material and social rewards or punishments. Our results thus indicate that it is not worth promoting controlled forms of motivation in addition to promoting autonomous forms of motivation, as has been argued by Gerhart and Fang (2015). Furthermore, the outcomes associated with the externally regulated profile suggest that there is an important risk associated with focusing on the promotion of external forms of regulations. As such, it appears that organizations would benefit more from a focus on nurturing more autonomous forms of motivation through increases in job meaningfulness, interest, and autonomy, than from a focus on social and material rewards.

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