A Longitudinal Analysis of Motivation Profiles at Work

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Abstract

This paper examines the multidimensional nature of workplace motivation and the importance of a continuum structure in self-determination theory (SDT) through application of complementary variable- and person-centered approaches. This approach is taken to simultaneously model the complexity of motivation and highlight interactions between motivational factors. Additionally, this study represents an initial test of the temporal stability of work motivation profiles. A sample of 510 full-time employees were recruited from a range of occupations. Results support the central importance of a general factor representing self-determination as the most influential factor in an employee's motivation profile. However, smaller effects associated with the motivation subscales, especially identified regulation, were also noticed. Importantly, motivation profiles were found to be highly stable over the four-month duration of this study. Results lend support to the theoretical position that while general self-determination is an essential component of motivation, it alone does not fully describe an employee's motivation.

Keywords. Work Motivation; Self-Determination Theory; Continuum; Latent profiles; Bifactor-ESEM; Latent Transition Analyses.

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Motivation has long been acknowledged as a variable of central importance within the workplace context, as evidenced by the numerous theories devoted to its study (Kanfer, Frese, & Johnson, 2017). Not only is employee motivation linked to direction, intensity, and persistence of performance-based outcomes, but more recent developments have outlined its impact on employee well-being, development, and retention (Kanfer, Frese, & Johnson, 2017). However, too few studies have sought to identify commonly occurring configurations, or profiles, of work motivation among employees, and whether these configurations are stable or malleable. When one adopts a theoretical perspective according to which individuals can be motivated for a variety of different reasons occurring simultaneously, it becomes even more important to understand the effects associated with different motivation configurations. We examined these issues from the perspective of self-determination theory (Deci & Ryan, 1985) due to its comprehensive and well-supported multidimensional conceptualization of motivation.

Self-determination theory (SDT) depicts human motivation as being driven by distinct types of behavioral regulations reflecting psychological reasons underlying goal-directed behaviors (Deci & Ryan, 1985; Ryan & Deci, 2017). SDT further proposes that these various types of behavioral regulations, while retaining specificity, will be organized along a single overarching continuum of self-determination (Deci & Ryan, 1985; Howard, Gagné, & Bureau, 2017). SDT has received strong support from studies demonstrating the role of these behavioral regulations in the prediction of goal-directed behavior (e.g., Ryan & Deci, 2017). However, this support remains mainly focused on the isolated impact of each type of behavioral regulation. Given past work demonstrating that the effects of SDT motives may differ on the basis of the other motives experienced by employees (Deci, Koestner, & Ryan, 2001), this verification of the combined impact of behavioral regulations appears to be particularly important to our understanding of work motivation. Furthermore, although some research has looked at the combined impact of co-occurring behavioral regulations within distinct subpopulations, or profiles, of employees (see Howard, Gagné, Morin, & Van den Broeck, 2016), these *person-centered* studies have generally failed to account for the dual nature of motivation as proposed by SDT, which encompass both an underlying continuum of self-determination as well as co-existing subscales characterized by their own specificity and unique characteristics (Howard, Gagné, & Morin, 2020).

The current study was designed to contribute to this area of research in three related manners. First, this study adopts a person-centered perspective in order to identify subpopulations (i.e., profiles) of employees characterized by distinct motivational configurations, while also considering possible determinants and outcomes of these distinct configurations. Second, this study extends previous person-centered studies of work motivation profiles by incorporating a more refined representation of work motivation allowing us to jointly consider employees' global level of self-determination (reflecting the overarching self-determination continuum) together with the specific quality of their motivational orientation (Howard, Gagné, Morin, & Forest, 2018; Litalien et al., 2017). Third, the adoption of a longitudinal approach makes it possible to assess stability and change in motivational profiles over a time interval of four months.

The Motivation Continuum and Specific Motivational Qualities

Self-determination theory is built upon the premise that humans, across life contexts (work, education, etc.), experience a range of distinct motives (referred to as behavioral regulations) for engaging in goal-directed behaviors, and provides a typology of these motives which are assumed to follow an underlying continuum of self-determination (Deci & Ryan, 1985; Ryan & Deci, 2017; Sheldon, Osin, Gordeeva, Suchkov, & Sychev, 2017). At one extreme, intrinsic motivation reflects the desire to enact behaviors for the interest, excitement, and enjoyment of the behaviors themselves. Then, identified regulation refers to behaviors that are perceived as meaningful and aligned with personally held beliefs and values. Next, introjected regulation describes the pursuit of behaviors in order to attain feelings of pride and/or to avoid feelings of shame. Finally, external forms of regulation occur when the focus shifts from internally-driven reasons (e.g., interest, value, or pride) to externally-driven reasons. External-social regulation describes motivation driven by the desire to gain approval from others or to avoid criticisms (Gagné et al., 2015). External-material regulation is driven by more tangible reasons, including financial rewards or job retention.

While these different types of behavioral regulation have been well established, recent debate has arisen concerning the dimensionality of these motives, specifically how they can simultaneously exist as separate categories while also being considered points along a single-dimensional continuum (Chemolli & Gagné, 2014). Indeed, the logic of a continuum suggests that a one-dimensional representation could be sufficient to describe the motivational orientation of a majority of employees and calls into question the unique contribution of each specific type of behavioral regulation once accounting for the contribution of a global continuum structure. Determining whether motivation is best represented as a one- or multi-dimensional construct is of central importance to SDT, in addition to having implications for motivation theory more broadly.

Initial examination of this continuum structure was based on the observation of stronger correlations among theoretically closer types of behavioral regulations than among more distant ones (Chatzisarantis, Hagger, Biddle, Smith, & Wang, 2003; Ryan & Connell, 1989), ultimately suggesting that a predictable one-dimensional continuum might underlie human motivation. Additional evidence relating to predictive validity is evident in that autonomous forms of behavioral regulations tend to more strongly predict desirable outcomes (e.g., performance, wellbeing) and lower levels of undesirable outcomes (e.g., turnover, burnout). This linear progression of effect sizes associated with motivation types based on their continuum position has been supported in hundreds of studies (Ryan & Deci, 2017), with few exceptions (Gagné et al., 2015). However, Chemolli and Gagné (2014) recently applied Rasch analysis to directly test for the presence of a one-dimensional model of motivation in the work and education areas and failed to find evidence supporting the continuum hypothesis. Conversely, Guay, Morin, Litalien, Valois and Vallerand (2015) and Litalien, Guay and Morin (2015), based on more precise estimates derived through exploratory structural equation models (ESEM; Morin, Marsh, & Nagengast, 2013) supported the continuum of academic motivation more clearly than confirmatory factor analyses (CFA).

Howard et al. (2018) combined these two approaches (i.e., assessing an overarching dimension in a model including specific dimensions along with cross-loadings) via a bifactor-Exploratory Structural Equation Modeling (bifactor-ESEM; Morin, Arens, & Marsh, 2016) representation of work motivation. Howard et al. (2018) first demonstrated that it was possible to identify an overarching factor reflecting the global degree of self-determined work motivation that was aligned with the continuum hypothesis. The authors concluded that the general factor did indeed represent global levels of self-determined motivation, rather than global levels of motivation because, as hypothesized, the factor loadings on this general factor ranged from strongly positive (i.e. intrinsic motivation) to negative (amotivation items), with external regulation items presenting small positive loadings. If items from all subscales had loaded approximately equally on the general factor, then it might have been argued that this general factor rather reflected global levels of motivation in an undifferentiated manner. However, as the items associated with more self-determined subscales loaded more strongly and positively than items from less self-determined subscales, this was taken as strong evidence to indicate the self-determined nature of this general factor.

Second, they demonstrated that this global factor co-existed with equally viable specific factors reflecting the unique quality associated with each type of behavioral regulation over and above that global level of self-determination. These results thus supported the ambiguous proposition that motivation types followed a single overarching continuum structure while remaining meaningful in and of themselves (see Howard et al., 2020). Further supporting this assertion, these authors showed that whereas the global continuum factor was the strongest predictor of outcomes, the specific regulation factors still contributed to prediction over and above this global factor. These results have since been replicated once using the same measure as part of preliminary analyses reported by Gillet, Morin et al. (2018) and in a series of two studies conducted in the education area (Litalien et al., 2017).

The present study adopts this bifactor-ESEM representation of work motivation and combines it with a person-centered approach in order to identify employees' profiles differing from one another both in terms of the global degree of self-determination, but also in terms of specific behavioral regulations. This approach can identify motivation profiles in a way that more accurately reflects SDT's representation of work motivation.

A Person-Centered Perspective on Work Motivation

Unfortunately, these previous studies examining the dimensionality of motivation remain limited by their consideration of the various (global and specific) types of behavioral regulations as independent variables with additive effects, rather than considering the ways in which these behavioral regulations may be combined in distinct employee profiles, thereby more closely reflecting how work motivation is holistically experienced by distinct types of employees.

In a workplace, employees will rarely, if ever, report having a single reason for enacting behaviors, but instead have multiple reasons that may influence their decisions to various degrees. For example, one employee may decide to stay late to impress co-workers (external-social) and attract a financial reward through paid overtime (external-material), while still finding some degree of enjoyment in his or her work (intrinsic motivation). In contrast, another employee may arrive at the same decision based on a combined desire to push forward a project that he or she finds to be highly meaningful (identified regulation), while seeking to avoid guilt related to self-caused delays to the project timeline due to procrastination in the previous week (introjected regulation). Yet, over and above these specific orientations to work, both of these employees may tend to adopt a global orientation to this overtime work that feels to be essentially self-driven (e.g., finding intrinsic pleasure in the job or the project), or that feels to be essentially driven by external contingencies (e.g., the need for extra money or delays in project progression).

Person-centered analyses seek to model these combinations by identifying subpopulations of employees sharing a similar configuration of behavioral regulations, generally referred to as work motivation profiles. With the exception of studies relying on an artificial dichotomization of behavioral regulations into autonomous (intrinsic, identified) versus controlled (introjected, external) categories (e.g., Van den Broeck, Lens, De Witte, & Van Coillie, 2013), most person-centered studies conducted in the work area (i.e., Fernet et al., 2020; Gillet, Becker, Lafrenière, Huart, & Fouquereau, 2017; Gillet, Fouquereau, Vallerand, Abraham, & Colombat, 2018; Graves, Cullen, Lester, Ruderman, & Gentry, 2015; Howard et al., 2016; in de Wal, den Brok, Hooijer, Martens, & van den Beemt, 2014; Moran, Diefendorff, Kim, & Liu, 2012; Van den Berghe et al., 2014) have revealed profiles displaying matching (low, moderate, or high) levels of motivation, or following the continuum by displaying a smooth increase or decrease in motivation based on their continuum position (e.g., high intrinsic, moderate identified and introjected, and low external). Similar results have been reported in the education (Gillet, Morin, & Reeve, 2017) and sport (Wang, Morin, Ryan, & Liu, 2016) domains. These results suggest that there might be little value in considering specific forms of motivation over and above global levels of self-determined motivation, or at least make it hard to identify the relative contribution of the specific behavioral regulations.

Morin and Marsh (2015) refer to the types of profiles identified in these studies as presenting *level* differences (i.e., profiles differing from one another in a purely quantitative manner – in the present situation, profiles that could be entirely subsumed as differing on a single indicator of employees' global levels of self-determination). They note that such profiles provide evidence against the need for a person-centered approach, which should ideally result in the identification of at least a subset of profiles presenting *shape* differences (i.e., characterized by qualitatively distinct configurations – in the present situation configuration showing deviations from the continuum). However, they also noted that whenever global constructs (such as a global factor reflecting the level of self-determined motivation) co-exist with specific dimensions (such as specific factors reflecting the quality of motivation) assessed from the same indicators, then the failure to control for this global tendency may erroneously lead to the inflation of *level* differences in profile analyses. Morin, Boudrias et al. (2016, 2017) more recently noted that, in these situations, profiles could advantageously be estimated from factor scores taken from a bifactor model.

We adopt the approach advocated by Morin, Boudrias et al. (2016, 2017) in order to estimate work motivation profiles differentiated from one another on the basis of employees' global level of self-determination, as well as on their more specific behavioral regulation quality. Going back to the examples provided at the beginning of this section, the first individual could display high levels of overall self-determination coupled with high levels of external-social, external-material, and intrinsic motivations. The second employee could also be characterized by a high general self-determination, but also report high levels of introjected and identified regulations. In this case, although both employees would present an equally high levels of self-determined motivation, the shape of their motivation profiles would differ in important ways and be likely to have different implications. In contrast, the specific profiles described at the beginning of this section could also be anchored in much lower global levels of self-determinations, while presenting the same elevations in specific behavioral regulations described above. Once again, the resulting profiles are likely to have distinct implications. In all of these scenarios, these shape-related differences would support the need to account for both the global level of self-determination and for the specific forms of behavioral regulations in the estimation of the profiles. In contrast, identifying profiles differing only at the level of the global self-determination factor would support a one-dimensional representation of the motivation continuum but not the value of differentiating among specific types of behavioral regulations. Similarly, observing profiles differing only at the levels of the specific types of behavioral regulations but showing similar global levels of self-determination would support the value of differentiating among specific types of behavioral regulations, but not their organization along a single overarching dimension. As such, by studying motivation profiles based upon bifactor measurement models, this study will help to uncover the differentiated role of specific types of regulations above and beyond that of employees' global level of self-determination (Chemolli & Gagné, 2014; Howard et al., 2020; Sheldon et al., 2017).

A Longitudinal Perspective on the Stability of Work Motivation Profiles

In addition to adopting a more refined (i.e., global/specific) representation of work motivation, the present study also extends previous research on work motivation profiles by adopting a longitudinal perspective. In doing so, the current study examines stability and change in motivation profiles occurring at the within-person (i.e., whether specific individuals remain associated with same profiles over time) and within-sample (i.e., whether the profiles themselves remain unchanged over time) levels (Gillet, Morin et al., 2017; Kam et al., 2016). These verifications are important given that the ability to develop organizational interventions aiming to hire, promote, or differentially manage workers on the basis of their specific work motivation profiles requires the demonstration that the nature of the profiles themselves remain unchanged over time, and that work motivation profiles reflect relatively stable inter-individual differences in the absence of systematic change, intervention, or events (Kam, Morin, Meyer, & Topolnytsky, 2016; Meyer & Morin, 2016).

Although individual levels of motivation may change over time, evidence of some degree of within-person stability should alleviate concerns that motivation profiles may not endure over time and could be too responsive to day-to-day fluctuations to be worth considering as a guide for practice. For example, if employees could move from a high-motivation profile to a languishing profile characterized by very low levels of motivation over the span of a few days or months in an unpredictable manner (within-person instability), this would make it impossible for managers to use this information in any useful way. Likewise, if the nature (shape) of the identified motivation profiles was to change randomly over time (within-sample instability), such profiles would only have a very limited utility for practical purposes. In contrast, observing that motivation profiles remain stable over time in a specific sample, and that individual membership into these profiles also present some degree of stability at the individual level, would make it possible to use this information for purposes of targeted interventions aiming to improve workplace motivation, or even to differentially manage employees presenting distinct motivation profiles. Naturally, some evidence of within-person instability, showing that change in profile membership is possible, can also help to refine our expectations regarding the degree of resistance to expect in intervention contexts.

Initial evidence supporting both the within-sample (i.e., identification of the same profile structure) and within-person (i.e., stability of individual membership in specific profiles) stability of motivation profiles has recently been demonstrated in the educational domain over a period of two months (Gillet, Morin et al., 2017). Furthermore, a study by Fernet et al., (2020) demonstrated that while profiles were relatively stable within-sample over 24-month period, approximately 30-40% of employees changed motivational profile during this timeframe. This raises questions concerning whether employees are inherently more likely to transition between profiles when compared to students in an educational context, or whether the observed difference is a function of the substantially different timeframes (i.e. 2 vs 24 months). As such, replication in the work context over a moderate period of time is still required. The current study seeks to address this issue by focusing on employees assessed twice over a four-month period.

Construct Validation of Work Motivation Profiles

Once the generalizability or stability of a person-centered solution has been established, it becomes important to establish the construct validity of the identified profiles via the demonstration that the profiles present well-differentiated and meaningful relations with a series of theoretically-relevant predictors and outcomes (e.g., Morin, 2016). The general model of work motivation based on SDT (Gagné & Deci, 2005) includes predictors such as managerial behaviors and job design factors, as well as outcomes such as performance and turnover. Desirable forms of leadership (e.g., transformational), managerial support, motivational job design factors, and compensation systems that do not focus unduly on individual bonuses are assumed to foster need satisfaction and autonomous work motivation, which themselves should foster performance, well-being and retention. Previous person-centered studies of work motivation support to these propositions.

In terms of predictors, Graves et al. (2015) demonstrated that higher levels of supervisor support were related to membership in more autonomously motivated profiles, and that employees with positions higher in an organization's hierarchy presented a higher probability of belonging to more autonomously-driven profiles. Moran et al. (2012) showed that the satisfaction of employees' basic needs for autonomy, competence, and relatedness was positively related to membership into more autonomously-driven profiles. Finally, Howard et al. (2016) noted that white collar employees were more likely to be members of profiles characterized by autonomous forms of motivation than blue collar employees. They also suggested that differences between white- and blue-collar employees in terms of job design characteristics, such as the greater level of job autonomy associated with white collar positions, could partly explain their results. The current study was designed to further investigate this proposition by assessing the relations between a variety of job characteristic, described in the Job Characteristics Model (JCM; Morgeson & Humphrey, 2006), and profile membership. These characteristics include task significance, task variety, task identity, job autonomy, and feedback inherent in the job itself. Results from Howard et al. (2016) lead us to expect these characteristics be associated with membership into the profiles characterized by higher levels of autonomous types of regulations, as well as by higher levels on the global factor representing employees' overall degree of self-determination. Previous variable-centered results also generally support this expectation (e.g., Gagné, Senecal, & Koestner, 1997; Millette & Gagné, 2008). Furthermore, it is possible that poorly designed workplaces (i.e. low levels of autonomy & feedback) lead to increasingly poor motivation over time (a deterioration effect), or alternatively that well designed jobs allow for increasing quality of motivation, for example through ongoing job crafting.

Given recent debates concerning the effectiveness of certain extrinsic forms of motivation (i.e., external-material regulation) on performance (Cerasoli, Nicklin, & Ford, 2014; Gagné & Forest, 2008; Gerhart & Fang, 2015), the current study included three subscales related to perceived work performance (task proficiency, adaptivity, and proactivity; Griffin, Neal, & Parker, 2007) to assess whether the profiles would contribute to the prediction of personal beliefs about performance, and more specifically, examine how profiles with higher levels of external-material regulation will differ from the others. Specifically, research has indicated that while external regulation may have a negative influence on performance when considered in isolation (Gagné et al., 2015; Vasconcellos et al., 2019), additional evidence suggest that external and introjected regulations may actually be beneficial to some outcomes when accompanied by autonomous forms of motivation (Howard et al, 2016), or at least not as detrimental (Cerasoli et al., 2014; Gillet, Fouquereau et al., 2018). This more desirable effect of controlled forms of regulation has been theorized to be the result of the initial behavioral drive provided by more controlled forms of regulations, in conjunction with the longer terms benefits emerging from the more autonomous motives. As such, we expected that profiles characterized by stronger autonomous relative to controlled forms of motivation will relate more strongly to adaptive and proactive work performance perceptions (Gagné et al., 2015). In addition, we also included a measure of turnover intention as one of the most significant and costly workplace occurrences and is a commonly studied outcome of work motivation (Hom, Lee, Shaw, & Hausknecht, 2017). Based on previous research, we expect the most desirable outcome levels to be associated with profiles presenting higher levels of autonomous motivations or higher levels of global self-determination, and the least desirable outcomes to be associated with profiles presenting higher levels of controlled motivations or lower levels of global self-determination (e.g., Gagné et al., 2015; Howard et al., 2016). Finally, profiles characterized by high levels of self-determination and external regulation are expected to present higher levels of perceived performance and lower levels of turnover intentions. In summary, this study seeks to identify shape-differentiated employee motivation profiles by adopting an approach allowing for an accurate disaggregation of global level of self-determination from the specific quality of behavioral regulation. More precisely, this approach makes it possible to examine the added-value of the specific quality of behavioral regulations (intrinsic, identified, etc.), after accounting for the effects of global levels of self-determined motivation.

Hypotheses

While latent profile analysis is inherently exploratory, we note several hypothesis indicating the results we expect to observe. Results from studies relying on a more traditional representation of behavioral regulations (e.g., Gillet, Becker et al., 2017, Gillet, Fouquereau et al., 2018; Graves et al., 2015; Howard et al., 2016; in de Wal et al., 2014; Moran et al., 2012; Van den Berghe et al., 2014) allow us to expect the identification of at least three profiles representing primarily differing degree of self-determination. These expected profiles are in accordance with the "level" effects generally identified in these previous studies.

Additionally, we also expect additional profiles characterized by clearer shape differences involving the various regulation factors. These shape differences will represent the unique characteristics associated with regulation types above and beyond the degree of self-determination.

H1a: We expect three or more profiles primarily representing differing levels of self-determination.

H1b: We expect one or more profiles representing additional effects associated with regulation types.

This study also seeks to assess the degree of within-sample and within-person stability in work motivation profiles identified over a four-month period of stable employment. The two previous studies examining profile stability were conducted over two-month (in an education setting; Gillet, Morin et al., 2017) and 24-month periods (Fernet et al., 2020). In the present study, we used a four-month time interval to replicate and expand on initial education focused evidence (Gillet, Morin et al., 2017), while remaining sensitive to more immediate effects than those considered by Fernet et al., (2020). Based on previous findings, we expect the within-sample stability to be very high, leading to the identification of similar profiles across time. Additionally, considering the sample as a whole is not undergoing any large systematic changes or interventions, we also expect to observe relatively high levels of within-person stability, with relatively few people transitioning between profiles over time.

H2a: Highly similar profiles will be identified at both measurement points.

H2b: Relatively few participants will transition between profiles over time.

Finally, the current study assesses the construct validity of these profiles by considering their relations with the predictors of job design characteristics, and outcomes of self-reported performance and turnover intentions. Based on previous studies of motivation profiles, we propose the following hypotheses.

H3: Job design characteristics (job autonomy, feedback, task significance, task variety, & task identity) are expected to increase the probability of individuals belonging to more self-determined profiles, as well as any additional profile characterized by very high levels of intrinsic and identified regulation.

H4: Profiles characterized by a greater degree of self-determination, or high levels of intrinsic and identified motivation, will be associated with higher perceived performance and lower turnover intention.

Methods

Participants and Procedures

This study relies on a sample of employees receiving a regular ongoing salary from heterogeneous workplaces and industries (e.g., information technology, administration, healthcare, sales, etc.) across the United States. Participants were recruited through Amazon's Mechanical Turk (Mturk; Buhrmester, Kwang, & Gosling, 2011) as part of a larger ongoing project involving a series of online self-report Qualtrics surveys, in which a small financial incentive was offered for participation. While concerns have been expressed over the suitability of data originating from online survey platforms, recent research evidence indicates that these concerns may have been exaggerated (Cheung, Burns, Sinclair, & Sliter, 2017; Goodman, Cryder, & Cheema, 2013; Walter, Seibert, Goering, & O'Boyle, 2019). However, in line with recommendations provided in these recent studies regarding ways to maximize the value of data collected within only survey platforms, we implemented several quality checks throughout the data collection. Given the employment context of the study, participants reporting less than 25 hours of paid employment per week were excluded from the survey as part of the Mturk sampling process.

This study relies on a sample of 510 participants (50.2% males, M_{age} = 36.75, SD_{age} = 10.93) who completed the Time 1 survey, and a second identical survey four months later, provided identifying data allowing them to be matched across time points, and who passed a series of quality checks. Thus, attention checks were included in the questionnaire which automatically excluded participants answering any of the three instructed-response items incorrectly (Gummer, Roßmann, & Silber, 2018; n = 164). Furthermore, participants who completed the entire questionnaire in under eight minutes were deemed to have provided poor quality data and were therefore removed (n = 40). This exclusion criteria was established based upon pre-administration trials of the questionnaire by the researchers in which it was observed that 8-10 minutes was a conservative estimate of the minimum time required to answer the 193 mandatory questions (approx. 2.5 seconds per item; Ward & Meade, 2018). Participants had been working for their organizations for an average of 6.16 years (SD = 5.90) and were primarily non-managers (56.3%), but also included 28% line supervisors or team managers, 12.9% mid-level managers, and 2.8% senior managers or executives. The average salary of participants was USD $42,200 (SD = $27,283), and they worked an average of 39.75 (SD = 7.53) work hours each week.

Measures

Motivation. Motivation was measured using the Multidimensional Work Motivation Scale (MWMS; Gagné et al., 2015). When completing this instrument, participants answer statements following the stem “Why do you or would you put efforts into your current job?” using a 1 (not at all) to 7 (completely) Likert-type response scale. This scale assessed five types of motivation, including external regulation – material (3 items; α_{time1} = .65; α_{time2} = .72; e.g. “Because others will reward me financially only if I put enough effort in my job”), external regulation – social (3 items; α_{time1} = .77; α_{time2} = .77; e.g. “To get others’ approval”), introjected regulation (4 items; α_{time1} = .76; α_{time2} = .79; e.g. “Because I have to prove to myself that I can”), identified regulation (3 items; α_{time1} = .86; α_{time2} = .91; e.g. “Because putting efforts in this job has personal significance to me”), and intrinsic motivation (3 items; α_{time1} = .93; α_{time2} = .94; e.g. “Because the work I do is interesting”).

Work design. Participants completed the Work Design Questionnaire (Morgeson & Humphrey, 2006). The subscales measuring work scheduling autonomy (3 items; e.g., “The job allows me to make my own decisions about how to schedule my work”), decision making autonomy (3 items; e.g., “The job gives me a chance to use my personal initiative or judgment in carrying out the work”), and work methods autonomy (3 items; e.g., “The job allows me to make decisions about what methods I use to complete my work”) were very highly correlated (r_{mean} = .907). Given the high correlations and the fact that these slight variations of autonomy were not theoretically pertinent in the current study, these subscales were combined into a single job autonomy scale (α_{time1} = .94; α_{time2} = .95). Additional subscales included task variety (4 items; α_{time1} = .92; α_{time2} =.93; e.g., “The job requires the performance of a wide range of tasks”), task significance, (4 items; α_{time1} = .89; α_{time2} =.90; e.g., “The results of my work are likely to significantly affect the lives of other people”), task identity (4 items; α_{time1} =

.87; α_{time2} = .87; e.g., “The job involves completing a piece of work that has an obvious beginning and end”), and feedback (3 items; α_{time1} = .84; α_{time2} = .85; e.g., “The job itself provides me with information about my performance.”). All items were rated on a 5-point response scale (1- strongly disagree to 5- strongly agree).

Turnover intentions. Participants completed four items assessing their intention to stay in their current organization (α_{time1} = .78; α_{time2} = .80; e.g., “How likely is it that you will leave this organization of your own choice during the next year?”; Meyer, Allen, & Smith, 1993). All items were measured on a 5-point Likert-type scale (1- not at all likely to 5- very likely).

Performance. Participants completed a self-reported measure of performance (Griffin, Neal, & Parker, 2007) assessing task proficiency (3 items; α_{time1} = .82; α_{time2} = .79; e.g., “Carried out the core parts of your job well”), proactivity (3 items; α_{time1} = .86; α_{time2} = .87; e.g., “Made changes to the way your core tasks are done”), and adaptivity (3 items; α_{time1} = .77; α_{time2} =.75; e.g., “Adapted well to changes in core tasks”). All items were rated on a 5-point Likert-type response scale (1- very little to 5- a great deal).

Analyses

Model Estimation. All analyses were realized with the robust maximum likelihood estimator (MLR) and the Mplus 7.3 (Muthén & Muthén, 2015) statistical package. Full information maximum likelihood estimation (FIML; Enders, 2010) was used to deal with missing responses on specific questionnaire items (*M* = .1%). Preliminary measurement models were first estimated at both time points to identify the optimal model for further analyses and to verify its measurement invariance across time points. LPAs were then conducted separately at each time point. Both optimal time-specific solutions were then combined into a single longitudinal LPA, which was used to systematically assess the degree of similarity of these solutions across time points. A latent transition analysis (LTA) was then estimated to assess the within-person stability in profile membership across time points. Finally, predictors and outcomes were incorporated into this final LTA.

Preliminary Analyses. CFA, bifactor-CFA, ESEM, and bifactor-ESEM representations of responses to the MWMS measure were estimated separately at each time point following the sequence used by Howard et al. (2018) and Morin et al.’s (Morin, Arens, & Marsh, 2016; Morin, Boudrias et al., 2016, 2017) recommendations. In CFA, each item was only allowed to load on the factor it was assumed to measure with no cross-loadings permitted. This model included five correlated factors representing external-material regulation, external-social regulation, introjected regulation, identified regulation, and intrinsic motivation. In ESEM, the same set of five factors was represented using a confirmatory oblique target rotation (Asparouhov & Muthén, 2009; Browne, 2001). Target rotation is a confirmatory form of rotation which makes it possible to freely estimate cross-loadings while relying on an a priori specification of the main loadings and constraining cross-loadings to be as close to zero as possible. In bifactor-CFA, all items defined one G-factor reflecting the global level of self-determination as described by Howard et al. (2018) and Litalien et al. (2017), as well as five S-factors corresponding to specific levels of external-material regulation, external-social regulation, introjected regulation, identified regulation, and intrinsic motivation. No cross-loading was allowed between the S-factors, and all factors were set to be orthogonal according to bifactor assumptions (Morin, Arens, & Marsh, 2016; Reise, 2012). Finally, bifactor-ESEM estimated the same set of G- and S-factors as the bifactor-CFA solution, while allowing for the free estimation of all cross-loadings using an orthogonal bifactor target rotation (Morin, Arens, & Marsh, 2016; Reise, Moore, & Maydeu-Olivares, 2011).

Based on the final retained measurement model, we then proceeded to tests of measurement invariance across time points (Millsap, 2011): (a) configural invariance, (b) weak invariance (loadings), (c) strong invariance (loadings, intercepts), (d) strict invariance (loadings, intercepts, uniquenesses), (e) invariance of the latent variances-covariances (loadings, intercepts, uniquenesses, variances-covariances), and (f) latent means invariance (loadings, intercepts, uniquenesses, variances-covariances, latent means). A priori correlated uniquenesses between matching indicators of the factors utilized at the different time-points were included in these longitudinal models to avoid inflated stability estimates (Marsh, 2007).

All LPAs were conducted using factor scores saved from the optimal preliminary models. Factor scores provide a way to achieve a partial control for the measurement errors present at the item level (Estabrook & Neale, 2013; Skrondal & Laake, 2001) and to retain the underlying structure (e.g., bifactor structure, measurement invariance) of each measure (for additional details, see Morin, Boudrias et al., 2016, 2017; Morin, Meyer, Creusier, & Biétry, 2016). To ensure the comparability of measurement across time waves, all factors scores were saved from longitudinally invariant measurement models in standardized units (M = 0 and SD = 1; Millsap, 2011). These preliminary analyses are fully reported in the online supplements.

Latent Profile and Latent Transition Analyses. LPA including 1 to 8 profiles were first estimated based on a single time point (Morin & Wang, 2016). These analyses relied on the estimation of profile-specific means and variances of the motivation factor scores (Morin, Maïano, et al., 2011; Peugh & Fan, 2013) using 7000 random sets of start values (the 200 best were retained for final optimization) and 200 iterations (Hipp & Bauer, 2006).

Selecting the number of profiles to retain at each time point relied on the consideration of the statistical suitability of solutions as well as their theoretical meaningfulness and conformity (Marsh, Lüdtke, Trautwein, & Morin, 2009; Morin, 2016; Muthén, 2003). In addition, statistical indicators which have been demonstrated to be helpful in guiding that selection (e.g., Diallo, Morin, & Lu, 2016, 2017; Nylund, Asparouhov, & Muthén, 2007; Peugh & Fan, 2013; Tein, Coxe, & Cham, 2013; Tofighi & Enders, 2008). First, a lower value on the consistent Akaïke Information Criterion (CAIC), the Bayesian Information Criterion (BIC), and the sample-size adjusted BIC (ABIC) indicate a greater degree of fit to the data. Second, a significant p value on the Bootstrap Likelihood Ratio Test (BLRT) indicates that the model can be retained when compared to the model including one fewer profile. However, because these indicators share a sample size dependency (Marsh et al., 2009), they sometimes fail to converge on an optimal solution. In this situation, a graphical display can be examined to locate a plateau which can be used to pinpoint the solution (Morin, Maïano et al., 2011). The entropy, ranging from 0 to 1, will also be reported to summarize the classification accuracy of each solution.

The similarity of the time-specific LPA solutions was then examined through longitudinal tests of similarity for LPA solutions (Morin, Meyer et al., 2016; Morin & Litalien, 2017). This sequence of tests is conditional on the identification of a similar number of profiles across time points, referred to as *configural* similarity. Moving from this initial model of *configural* similarity, the second step of this sequence tests the *structural* similarity of the solution (i.e., whether the profiles maintained the same shape). The third step focuses on the *dispersion* similarity of the solution (i.e., whether within-profile variability remains similar), while the fourth step assesses the *distributional* similarity of the solution (i.e., whether the size of the profiles remains unchanged). At each stage of this sequence, Morin, Meyer et al. (2016) note that profile similarity is supported by the observation of a decrease on the value of two out of the three recommended information criteria (i.e. CAIC, BIC, ABIC).

A latent transition analysis (LTA; Collins & Lanza, 2010) model was then estimated (using the manual auxiliary 3-step approach described in Asparouhov & Muthén, 2014 and Morin & Litalien, 2017) from the most similar model from these preceding steps to assess within-person stability and change in profile membership. This LTA solution was then used to investigate the extent to which relations between predictors and profiles (*predictive similarity*) and between profiles and outcomes (*explanatory similarity*) remained stable over time.

Predictors and Outcomes. We first conducted multinomial logistic regressions to assess the relations between predictors and profile membership. In these analyses, the predictors were used to predict the profiles at both time points. Four alternative models were contrasted. First, we estimated a null effects model in which the relations between the predictors and profile membership were constrained to be exactly zero at both time points. Second, relations between predictors and the profiles were estimated freely at both time points, and the relations between these variables and the profiles estimated at Time 2 were also freely estimated within each of the profiles estimated at Time 1. This model tests the effects of the predictors to specific profile-to-profile transitions occurring across tome points. A third model allowed all predictions to be freely estimated across time points but constrained them to be equal across Time 1 profiles. This model thus allows the predictors to have a different effect on profile membership over time, without allowing them to predict specific profile transitions. Finally, the last model was one in which the relations between predictors and profiles were constrained to equality over time (i.e., *predictive* similarity). Lastly, outcomes were integrated into the LTA. In a first model, relations between profiles and outcomes were allowed to differ across time, and a second model was used to assess the *explanatory* similarity of the solution by constraining these associations to be equal across time points. Mean-level differences across profiles were tested using the Mplus MODEL CONSTRAINT command which relies on the multivariate delta method (Kam et al, 2016; Raykov & Marcoulides, 2004).

Results

Preliminary Measurement Models

Table 1 presents the goodness-of-fit indices of the alternative preliminary measurement models estimated separately at both time points for the MWMS measure. Both the CFA and bifactor-CFA models failed to achieve acceptable fit at both time points according to most indices. In contrast, both ESEM and bifactor-ESEM were able to achieve excellent, and comparable, fit at both time points according to all indices. A detailed comparison of these alternative models is reported in the online supplements and led us to retain the B-ESEM solution due to (a) excellent model fit, (b) well defined general and specific factors, and (c) theoretical meaningfulness and conformity (see Howard et al., 2018; Litalien et al., 2017). Correlations between all study variables at each timepoint are presented in Table 2.

Latent Profile Solutions

The results from the time-specific LPA are reported in Table S10 of the online supplements. The ABIC continuously improved with the inclusion of additional profiles without reaching a minimum. The CAIC and BIC respectively supported the 2- and 4-profile solution at Time 1, and the 4- and 4/5-profiles solution at Time 2 (the BIC was almost identical for solutions including 4 and 5 profiles at Time 2). Examination of the graphical displays reported in Figure S1 of the online supplements revealed a flattening in the decrease of the ABIC around 4/5 profiles at Time 1, and no clear inflexion point at Time 2. We thus carefully examined solutions including 3 to 6 profiles at both time points. These solutions were all proper statistically and highly similar over time. Moving from a 3-profile solution to a 4-profile solution resulted in the addition of meaningfully different profiles to the solution across time points, whereas moving from a 4- to 5- or 6-profile solution simply resulted in the arbitrary division of one profile into similar, but much smaller, (e.g., 1.36%) profiles. For these reasons, we retained the 4-profile solution at both time points.

A longitudinal LPA model of *configural* similarity including 4-profiles at each time point was thus estimated. The fit indices from all longitudinal models are reported in Table 3, and support the *structural*, *dispersion*, and *distributional* similarity of profiles across time points as each of these constraints decreased the value of the information criteria. The model of *distributional* similarity was retained for interpretation and is presented graphically in Figure 1 (see Table S11 of the online supplements for exact parameter estimates). As shown in Table S12, this model has a high classification accuracy, varying from 85.4% to 91.5% at Time 1, and from 86.3% to 90.0% at Time 2.

Profile 1 represented participants presenting high levels of global self-determination, coupled with moderately high levels of intrinsic motivation, and average or slightly under average levels of external-material, external-social, introjected, and identified regulations. This *Highly Self-Determined* profile represented 22.3% of the sample at both time points. Members of Profile 2 were characterized by average levels of global self-determination and introjected regulation, slightly below average levels of external-material, external-social, and intrinsic regulations, and above average levels of identified regulation. This *Identified* profile represented 28.9% of the sample across time points. Members of Profile 3 were predominantly characterized by extremely low levels of global self-determination, but average or slightly below average levels on the other regulations. This *Low Self-Determined* profile represented 15.7% of the sample across time points. Finally, Profile 4 represented participants with moderately high levels of external-material, external-social, and introjected regulations, average levels of identified regulation and intrinsic motivation, and slightly above average levels of global self-determination. This *Externally Regulated* profile represented 33% of the sample across time points.

In order to test the consistency of the results obtained in the current sample relative to samples used in prior LPA studies conducted in the work area, analyses were replicated using factors scores from a first order ESEM solution (in which global versus specific levels of motivation where not disaggregated). The results from these alternative models are reported in Tables S11, 12, and13 of the online supplements. This comparative 4-profile solution is reported in Figure S2 of the online supplements where it is contrasted with results from Howard et al. (2016). Figure S2 makes two things obvious. First, these results are very similar to those obtained by Howard et al. (2016) irrespective of the fact that these authors also incorporated a measure of amotivation. Thus, when applying the same operationalization, profiles of workplace motivation are extremely consistent across studies. These profiles mainly follow the expected self-determination continuum. This observation is aligned with Morin, Boudrias et al.'s (2016, 2017) observation that when a global construct is expected to underlie ratings obtained across multiple indicators, relying on bifactor factor scores helps to extract profiles that can differ from one another both in terms of this global construct (here the global level of self-determination), but also based on their specific levels of behavioral regulations. For instance, two of the profiles identified in the present study (Figure 1) differ mainly on the basis of presenting high (*Highly Self-Determined*) or low (*Low Self-Determined*) global levels of self-determination. In contrast, two additional profiles are both characterized by average global levels of self-determination but differ from one another in the experience of a more *Identified*, or *Externally Regulated* type of behavioral regulation.

Latent Transitions

A LTA solution was estimated from this final LPA of distributional similarity. Table 4 presents transition probabilities associated with this LTA. These results showed a high degree of membership stability in each profile over time, with stability rates ranging from 97.4% to 100%. Given the high level of profile stability, transitions were relatively rare, suggesting that membership in motivation profiles in the context of stable employment are highly stable. Still, employees initially characterized by a *Highly Self-Determined* profile (Profile 1), when they transitioned to another profile at Time 2, only did so toward the *Identified* profile (Profile 2: 0.8%). Likewise, among employees initially corresponding to the *Identified* profile (Profile 2), 2.6% transitioned toward the *Highly Self-Determined* profile (Profile 1).

Predictors

Predictors were included to the previously established LTA solution. As shown in Table 3, the model of *predictive* similarity resulted in the lowest information criteria values, indicating that relations between the predictors and profile membership did not change over time. Results are reported in Table 5.

When examining the five dimensions of work design, autonomy and task significance displayed the strongest and most similar results with increases in either of these factors being associated with a greater likelihood of belonging to the *Highly* S*elf-Determined* relative to the *Identified* (OR = 2.67 & 2.35 for autonomy and task significance respectively), *Low Self-Determined* (OR = 4.15 & 3.65), and *Externally Regulated* (OR = 1.99 & 2.33) profiles, as well as into the *Identified* profile compared to the *Low Self-Determined* one (OR = 1.58 & 1.56). Both also predicted a lower likelihood of membership in the *Low Self-Determined* profile compared to the *Externally Regulated* one (OR = .48 & .44). Although task variety and task identification showed no statistically significant relation with the likelihood of membership into the various profiles, feedback predicted a lower likelihood of membership into the *Low Self-Determined* profile relative to the *Externally Regulated* one (OR = .62). Finally, no predictors differentially predicted the likelihood of membership in the *Identified* profile relative to the *Externally Regulated* one.

Outcomes

Outcomes were included to the model. As presented in Table 3, the information criteria were lowest in the model of *explanatory* similarity, which was thus retained for interpretation. The within-profile means (and 95% confidence intervals) of each outcome are reported in Table 6. The results revealed differentiation between all profiles. As expected, the *Highly Self-Determined* profile was the most strongly associated with desirable workplace outcomes, being associated with the highest levels of self-reported task proficiency, proactivity, and adaptivity, as well as with the lowest levels of turnover intentions. Likewise, the *Low Self-Determined* profile displayed the least desirable levels of work outcomes, being associated with the highest levels of turnover intention, as well as the lowest levels of perceived task proficiency, proactivity, and adaptivity. In the remaining profiles, outcome levels systematically fell between these two extremes. These two profiles were undistinguishable in terms of perceived proactivity and adaptivity, suggesting that profile-specific levels of global self-determination was the main driver of associations with these outcomes. However, levels of perceived task proficiency and turnover intention were respectively higher and lower in the *Identified* profile than in the *Externally Regulated* profile, despite the fact that levels of global self-determination were slightly lower in the *Identified* profile.

Discussion

Relying on a recent operationalization of work motivation (Howard et al., 2018; Litalien et al., 2017), we sought to identify naturally occurring work motivation profiles of employees, while relying on a proper disaggregation of employees' ratings of their global level of self-determined motivation (reflecting the SDT continuum as confirmed by the relative size of item loadings on the general factor, which followed their theoretical position on the continuum), from more specific ratings of the quality of their behavioral regulation. Previous studies, failing to take into account this global/specific nature of work motivation, have led to the identification of level-differentiated motivation profiles matching the hypothesized continuum of motivation (Graves et al., 2015; Howard et al., 2016; Moran et al., 2012). Interestingly, when estimated using a similar approach, the profiles estimated here perfectly matched those reported by Howard et al. (2016). In contrast, when taking this global/specific multidimensionality into account, profiles were found to differ primarily in terms of the global level of self-determined motivation. However, these profiles also revealed additional, albeit less central, differences in the specific quality of employees' behavioral regulation configuration, indicating the potential additional role played by specific behavioral regulations in predicting outcomes.

Motivational Profiles, Work Design Factors, and Outcomes

The results first revealed that, as expected (Hypothesis 1a), employees' global level of self-determination (the G-factor) was the most important component for at least two of the profiles. Thus, whereas the *Highly Self-Determined* profile was primarily characterized by a high level of self-determination, the *Low Self-Determined* profile was characterized by a very low level of self-determination. Still, the results also illustrate that the definition of the last two profiles, both characterized by an average level of global self-determination, was anchored in the specific quality of the remaining behavioral regulations, thus providing some support for hypothesis 1b. This indicates that individual regulations continue to contribute to employee's motivation profiles beyond general self-determination, albeit more weakly.

This study also considered the role of motivational work design factors in the prediction of profile membership. The results first showed that the work design factors of autonomy and task significance, and to a lesser extent feedback, predicted a higher likelihood of membership into more self-determined profiles compared to less self-determined ones. These results partially support hypothesis 3 indicating that motivating work design factors are associated with membership into profiles characterized by higher global levels of self-determination or by more autonomous behavioral regulations. In doing so, these results partly explain the differences reported by Howard and colleagues (Howard et al., 2016) across samples of blue- and white-collar employees. In contrast, neither task identification, nor task variety, proved to be associated with profile membership. However, these specific results could also be explained by our simultaneous consideration of a broad range of work design factors in a multivariate analysis in which the effects of each factor are estimated over what it shares with the other factors.

Finally, it was interesting to note that none of the predictors considered in this study were able to differentially predict membership into the *Identified* relative to the *Externally Regulated* profiles, calling into question the meaningfulness of this distinction. Implication of these results suggest that the impact of work design might be more pronounced on global levels of self-determination than on specific behavioral regulations. This is a novel finding given that previous work examining bifactor structures of motivation have typically not explored predictors of these global and specific factors (Howard et al., 2018; Litalien et al., 2017). Thus, whereas these previous studies have supported the predictive validity of these factors in relation to various outcome variables, the examination of their nomological network had yet to consider their predictors. As such, current results contribute to the construct validation of this bifactor representation of work motivation through the incorporation of predictors. However, clearly, further work on predictors, and outcomes, of general and specific factors of motivation is still required to further document their complete nomological network, and more specifically to determine what factors may be responsible for membership in either the *Identified* or *Externally Regulated* profiles. This question becomes more important when considering that the distinctive nature of the *Identified* relative to the *Externally Regulated* profile was more clearly established when outcomes were considered.

When the profiles were examined with respect to outcomes, the results also provided clear and unambiguous support for hypothesis 4, that is the key role of self-determination as ascribed by SDT. As expected, these results showed that the most desirable outcome levels (higher levels of self-reported task proficiency, proactivity, and adaptivity, and lower levels of turnover intentions) were associated with the *Highly Self-Determined* profile, that the least desirable levels were associated with the *Low Self-Determined* profile, and that moderate levels were associated with the *Identified* and *Externally Regulated* profiles. However, while self-determination was clearly the strongest driving force of outcome associations, these results also supported the distinct nature of the *Identified* and *Externally Regulated* profiles, showing the first to be associated with higher levels of task proficiency and lower levels of turnover intentions. This indicates that specific behavioral regulations, particularly identified regulation, may uniquely contribute to our understanding of work motivation. Previous studies have similarly concluded that, for some outcomes at least, specific regulation factors also play a role, albeit weaker than that of global levels of self-determination (Howard et al., 2018; Litalien et al., 2017). It remains to be seen how practically important these unique regulation qualities are in comparison to overall self-determination.

Taken together, these profiles and the associations with predictors and outcomes clearly indicate the central importance of employees' global levels of self-determination. However, the fact that the external and identified profiles were distinguished within the sample, and the slight differences observed between these profiles in terms of outcome prediction, indicate that the unique characteristics of behavioral regulations do indeed play a role, although less marked than that of the global factor. Implications for the continuum of self-determination (Howard et al., 2017, 2018; Litalien et al., 2018) are therefore nuanced as results support both the centrality of a continuum structure (an ostensibly one-dimensional construct) as well as the unique characteristics associated with each type of regulation (indicative of a multi-dimensional construct; see Howard et al., 2020). While results demonstrating the unique characteristics of the specific regulations factors were somewhat limited in the current study, these results still serve as a "proof of concept" and suggest a clear need for further research to consider a broader range of predictors and outcomes more likely to be related to specific behavioral regulations (such as psychological empowerment, continuance commitment, creativity, and workplace deviance; e.g., Cerasoli et al., 2014; Van den Broeck et al., 2016).

Profile Stability

A final objective was to assess the within-sample and within-person stability of the motivation profiles over a four-month period. In terms of within-sample stability, results indicated that the number (configural similarity), nature (structural similarity), degree of inter-individual variations within each profile (dispersion similarity), sizes (distributional similarity), relations with predictors (predictive similarity) and relations with outcomes (explanatory similarity) remained unchanged over time in the current sample, supporting hypothesis 2a. Finding this degree of within-sample stability is a substantial step forward in the person-centered approach to motivation research as it supports the idea that profiles can be reliably identified and are unlikely to shift over the span of several months in the absence of systematic change, intervention, or events. Given that participants were not asked about any notable or ongoing changes influencing them throughout this period, it would be interesting to further examine how robust this finding is to changes in participants' personal and contextual characteristics, and to identify under which circumstances workplace or personal events could affect the stability of these motivation profiles. This stability is an essential characteristic of the person-centered approach as it suggests that the profiles are meaningful, rather than providing an ephemeral snapshot of a metaphorical shifting of sand. As it stands, this study is among the first to examine the within-sample stability of SDT motivation profiles (Fernet et al., 2020; Gillet, Morin et al., 2017). Our ability to replicate the profiles identified by Howard et al. (2016) when relying on first-order ESEM factor scores also supports the idea that motivation profiles tap into stable underlying mechanisms.

With regard to hypothesis 2b and within-person profile stability, employees' membership into specific profiles was unlikely to change over time, indicating that, contrary to a previous study conducted over a 24 months period (Fernet et al., 2020) membership in work motivation profiles is very stable over the span of several months. None of the *Low Self-Determined* or *Externally Regulated* employees transitioned to a different profile four months later, and only .8% to 2.6% of the *Highly Self-Determined* or *Identified* employees did so (those who did transitioned between these two profiles). It would be easy to interpret these results as evidence suggesting that profiles dominated by external forms of regulations or low levels of motivation are more stable than the more autonomously-driven or motivated profiles. We urge caution in this regard given the limited number of profile transitions identified here, which strongly indicate stability. Although these transitions suggest that change is possible, possibly due to idiosyncratic modifications in the specific reality of individual participants, the rarity of these transitions makes it hard to identify systematic patterns. For practical purposes, these results show that, in the absence of any systematic modification in employees' individual, professional, or organizational contexts, individual motivation profiles reflect stable inter-individual differences which may be used to guide managerial decisions and interventions.

Although high levels of within-person profile stability were also reported in an education context by Gillet, Morin et al. (2017), these authors reported more frequent changes in profile membership over a shorter time period of two months (with an average rate of stability in profile membership of 70.15%). It is likely that this difference in rates of stability could simply reflect the distinct nature of the samples: Gillet, Morin et al. (2017) focused on the academic motivation of first-year undergraduate university students during their first semester, while we relied on employees with an average of 6.16 years of organizational tenure. This interpretation is reinforced by results from Kam et al. (2016) who reported rates of stability similar to those observed here in their study of organizational commitment profiles (a construct intimately related to motivation: Meyer, Becker, & Vandenberghe, 2004) conducted among employees followed over a period of eight months in a context of organizational changes.

Limitations and Future Directions

This study presents limitations that need to be kept in mind. First, data was only available at two time points, precluding the reliance on growth mixture models. Such models would have allowed us to more precisely analyze continuity and change over time. In addition, this study relied on a relatively short time interval of four months. Despite the fact that our results showed that individual changes in profile membership was possible over this time period, it remains highly likely that levels of both within-sample and within-profile stability would decrease over longer time periods, particularly for samples of employees exposed to important organizational, professional, and personal changes. As such, future research should consider the current study as a starting point to more extensive examinations of profile stability over more measurement points, and more turbulent, time intervals. In particular, conducting similar research while focusing on samples of organizational newcomers, or samples of employees who undergo career changes or promotions, is likely to be very informative.

Second, no measure of amotivation was included. While the appropriateness of considering amotivation to be part of work motivation has been previously debated (Chatzisarantis et al., 2003; Howard et al., 2017), this omission complicated our ability to compare the present results to those obtained by Howard et al. (2016, 2018). Fortunately, results from our bifactor-ESEM measurement models essentially replicated those obtained by Howard et al. (2018; also see Gillet, Morin et al., 2018), and profile estimates from first-order ESEM factor scores replicated those reported by Howard et al. (2016: see Figure S2 of the online supplements). However, it would be interesting for future studies to more extensively assess the role of amotivation in the identification of employees' work motivation profiles.

Third, all measures were self-reported, and therefore vulnerable to social desirability and subjectivity. Although common method biases are unlikely to play a role in person-centered results (for a more extensive discussion of this issue, see Meyer & Morin, 2016), it would still be important for future research to incorporate more objective measures of performance outcomes (e.g., supervisor's report, official turnover or medical leave reports) or work context predictors (e.g., observational data, group-based aggregates, supervisors' reports).

Additionally, the data used in the present study was collected through the Amazon Mechanical Turk online survey platform. While recent research evidence supports the validity of this type of data collection, showing that it generally leads to conclusion matching those from other forms of data collection (Buhrmester et al., 2011; Cheung et al., 2017; Goodman et al., 2013), we acknowledge that replication of these results through alternate forms of data collection and within new independent samples would improve the generalizability of our results.

Finally, the current sample included employees from a wide range of industries and occupations. While useful in describing work motivation broadly and maximizing generalizability, it remains possible for results to differ as a function of employees' occupation, work environments, or type of industry (e.g., Howard et al., 2016). Future research would thus do well to consider the boundary condition across which the current results can be considered to be generalizable.

Implications for Theory, Research, and Practice

SDT (Deci & Ryan, 1985; Ryan & Deci, 2017) has always advocated a theoretically ambiguous proposition that employees' motivation would be characterized by a combination of meaningfully distinct types of behavioral regulations, and yet that these behavioral regulations would be organized along a single underlying continuum (Howard et al., 2020). Recent research has shown that it was possible for SDT to "have its cake and eat it too" (Howard et al., 2018; Litalien et al., 2017; Sheldon et al., 2017), showing that a global level of self-determination reflecting the SDT continuum was able to co-exist with behavioral regulations retaining a meaningful level of specificity and explanatory power. The current study adds to this body of research by supporting the dual nature of worker motivation suggested in previous variable-centered analyses (Howard et al., 2018; Litalien et al., 2017).

This study also demonstrates that it is possible to identify employee profiles that simultaneously consider the global level of self-determination alongside the unique quality of the specific types of behavioral regulation over and above that global level. Modeling profiles in this manner allows researchers to avoid conflating the degree of self-determination with regulation-specific characteristics. In doing so, this approach makes it possible to more clearly identify global levels of self-determination as the crucial component underlying relations with predictors and outcomes, while also making it possible to more clearly assess the added-value of each specific regulation factor.

From a research perspective, this study reinforces the need for SDT researchers to incorporate similar methods as part of their routine set of statistical analyses. Beyond motivation, previous research has also shown the suitability of the bifactor-ESEM framework to provide a more accurate representation of multiple constructs known to be closely related to work motivation, such as need satisfaction and frustration (Sánchez-Oliva et al., 2017; Tóth-Király, Morin, Bőthe, Orosz, & Rigó, 2018), psychological health and well-being (Morin, Boudrias et al., 2016, 2017), and workplace commitment (Perreira et al., 2018). The present study demonstrates the importance of incorporating this perspective into the initial stages of any study relying on these constructs. Failing to do so risks improper disaggregation of the effects attributed to the global construct known to underlie employees' ratings across multiple dimensions, from the specificity associated with each dimension. This was demonstrated in this study by our identification of employee profiles differing from one another both in the level, and specificity, of their motivation.

Finally, the current study also has a few important practical implications. For instance, by contributing to the mounting evidence that motivation profiles and their associations with predictors and outcomes can be reliably identified both across studies, and across time points within a specific study, the present study suggest that it might be viable to start to devise organizational interventions aiming to promote the emergence of specific types of profiles, target employees matching specific motivation profiles for developmental purposes, and more generally to use motivation profiles as a guide for managerial practice and intervention. For example, given the demonstrated impact of autonomy and task significance in the likelihood of belonging to the *Highly Self-Determined* profile, the current results suggest these two work design characteristics may be ideal targets for interventions (e.g., job redesign, onboarding socialization practices) aiming to improve motivation. In particular, given the observation of strong levels of within-person profile stability, induction and socialization processes designed to clearly articulate and foster the autonomy inherent in, and significance of, the new job for organizational newcomers might be a particularly fruitful method to ensure ongoing motivation. Additionally, managers, supervisors, and mentors may benefit from training in this area in order to be able to emphasize these motivating elements.

References

Asparouhov, T., & Muthén, B. O. (2009). Exploratory structural equation modeling. *Structural Equation Modeling, 16,* 397–438.

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

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

Buhrmester, M., Kwang, T., & Gosling, S.D. (2011). Amazon's Mechanical Turk: A new source of inexpensive, yet high-quality, data? *Perspectives on Psychological Science, 6,* 3-5.

Cerasoli, C.P., Nicklin, J.M., & Ford, M.T. (2014). Intrinsic motivation and extrinsic incentives jointly predict performance: A 40-year meta-analysis. *Psychological Bulletin, 140*, 980-1008.

Chatzisarantis, N.L., Hagger, M.S., Biddle, S.J., Smith, B., & Wang, J.C.K. (2003). A meta-analysis of perceived locus of causality in exercise, sport, and physical education contexts. *Journal of Sport and Exercise Psychology, 25*, 284-306.

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

Cheung, J. H., Burns, D. K., Sinclair, R. R., & Sliter, M. (2017). Amazon Mechanical Turk in organizational psychology: An evaluation and practical recommendations. *Journal of Business and Psychology, 32*, 347-361.

Collins, L.M., & Lanza, S.T. (2010). *Latent class and latent transition analysis: With applications in the social, behavioral, and health sciences*. New York, NY: Wiley.

Deci, E. L., Koestner, R., & Ryan, R. M. (2001). Extrinsic rewards and intrinsic motivation in education: Reconsidered once again. *Review of Educational Research, 71*(1), 1-27.

Deci, E.L., & Ryan, R.M. (1985). *Intrinsic motivation and self-determination in human* *behavior*. New York: Plenum.

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.

Diallo, T.M.O., Morin, A.J.S, & Lu, H. (2017). The impact of total and partial inclusion or exclusion of active and inactive time-invariant covariates in growth mixture. *Psychological Methods*, *22*, 166-190.

Enders, C.K. (2010). *Applied missing data analysis*. New York, NY: Guilford.

Estabrook, R., & Neale, M. (2013). A comparison of factor score estimation methods in the presence of missing data: Reliability and an application to nicotine dependence. *Multivariate Behavioral Research*, *48*, 1-27

Fernet, C., Litalien, D., Morin, A.J., Austin, S., Gagné, M., Lavoie-Tremblay, M., & Forest, J. (2020). On the temporal stability of self-determined work motivation profiles: a latent transition analysis. *European Journal of Work and Organizational Psychology*, *29*(1), 49-63.

Gagné, M., & Deci, E.L. (2005). Self-determination theory and work motivation. *Journal of Organizational Behavior*, *26*(4), 331-362.

Gagné, M., & Forest, J. (2008). The study of compensation systems through the lens of self-determination theory: Reconciling 35 years of debate. *Canadian Psychology*, *49*, 225-232.

Gagné, M., Forest, J., Vansteenkiste, M., Crevier-Braud, L., Van den Broeck, A., Aspeli, A., ... & 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.

Gagné, M., Senecal, C.B., & Koestner, R. (1997). Proximal job characteristics, feelings of empowerment, and intrinsic motivation: A multidimensional model. *Journal of Applied Social Psychology*, *27*, 1222-1240.

Gerhart, B., & Fang, M. (2015). Pay, intrinsic motivation, extrinsic motivation, performance, and creativity in the workplace: Revisiting long-held beliefs. *Annual Review of Organizational Psychology and Organizational Behavior, 2*, 489-521.

Gillet, N., Becker, C., Lafrenière, M.-A., Huart, I., & Fouquereau, E. (2017). Organizational support, job resources, soldier's 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., Morin, A.J.S., Huart, I., Odry, D., Chevalier, É., Coillot, H., & Fouquereau, E. (2018). Self-determination trajectories during police officers' vocational training program: A growth mixture analysis. *Journal of Vocational Behavior*, *109*, 27-43.

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.

Goodman, J. K., Cryder, C. E., & Cheema, A. (2013). Data collection in a flat world: The strengths and weaknesses of mechanical Turk samples. *Journal of Behavioral Becision Making*, *26*, 213-224.

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.

Griffin, M.A., Neal, A., & Parker, S.K. (2007). A new model of work role performance: Positive behavior in uncertain and interdependent contexts. *Academy of Management Journal*, *50*(2), 327-347.

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. *The Journal of Experimental Education*, *83*(1), 51-82.

Gummer, T., Roßmann, J., & Silber, H. (2018). Using Instructed Response Items as Attention Checks in Web Surveys. *Sociological Methods & Research*, 0049124118769083.

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

Hom, P.W., Lee, T.W., Shaw, J.D., & Hausknecht, J.P. (2017). One hundred years of employee turnover theory and research. *Journal of Applied Psychology*, *102*, 530-545.

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. (2020). Putting the pieces together: Reviewing the structural conceptualization of motivation within SDT. *Motivation & Emotion*. https://doi.org/10.1007/s11031-020-09838-2

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*(7), 2638-2664

Howard, J.L, 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.

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

Kam, C., Morin, A.J.S., Meyer, J.P., & Topolnytsky, L. (2016). Are commitment profiles stable and predictable? A latent transition analysis. *Journal of Management*, *42*, 1462-1490.

Kanfer, R., Frese, M., & Johnson, R.E. (2017). Motivation related to work: A century of progress. *Journal of Applied Psychology*, *102*(3), 338-355.

Litalien, D., Guay, F., & Morin, A.J.S. (2015). Motivation for PhD studies: Scale development and validation. *Learning and Individual Differences*, *41*, 1-13.

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. (2007). Application of confirmatory factor analysis and structural equation modeling in sport/exercise psychology. In G. Tenenbaum & R. C. Eklund (Eds.), *Handbook of sport psychology* (3rd ed., pp. 774 –798). Hoboken, NJ: Wiley.

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.

Meyer, J.P., Allen, N.J., & Smith, C. (1993). Commitment to organizations and occupations: Extension and test of a three-component conceptualization. *Journal of Applied Psychology*, *78*, 538-551.

Meyer, J.P., Becker, T.E., & Vandenberghe, C. (2004). Employee commitment and motivation: A conceptual analysis and integrative model. *Journal of Applied Psychology*, *89*, 991-1007.

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.

Millette, V., & Gagné, M. (2008). Designing volunteers' tasks to maximize motivation, satisfaction and performance. *Motivation and Emotion*, *32*, 11-22.

Millsap, R. (2011). *Statistical approaches to measurement invariance*. New York: Taylor & Francis.

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

Morgeson, F.P., & Humphrey, S.E. (2006). The Work Design Questionnaire (WDQ): Developing and validating a comprehensive measure for assessing job design and the nature of work. *Journal of Applied Psychology, 91,* 1321–1339.

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, UK: Edward Elgar.

Morin, A.J.S., Arens, A., & 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., & Desrumaux, P. (2016). Further reflections on disentangling 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., & Litalien, D. (2017). Webnote: Longitudinal tests of profile similarity and latent transition analyses. Substantive Methodological Synergy Research Lab: smslabstats.weebly.com/webnotes.html

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

Morin, A.J.S, Marsh, H.W, & Nagengast, B. (2013). Exploratory structural equation modeling: an introduction. In G.R. Hancock & R.O. Mueller (Eds), *Structural Equation Modeling: A Second Course*, 2nd edition (pp. 395– 436). Greenwich, CT: IAP.

Morin, A.J.S., Maïano, C., Nagengast, B., Marsh, H.W., Morizot, J., & Janosz, M. (2011). Growth mixture modeling of adolescents trajectories of anxiety across adolescence: The impact of untested invariance assumptions. *Structural Equation Modeling, 18*, 613–648.

Morin, A.J.S., Meyer, J.P., Creusier, J., & Biétry, F. (2016). Multiple-group analysis of similarity in latent profile solutions. *Organizational Research Methods*, *19*, 231-254.

Morin, A.J.S., & Wang, J.C.K. (2016). A gentle introduction to mixture modeling using physical fitness performance data. In N. Ntoumanis & N. Myers (Eds.), *An introduction to intermediate and advanced statistical analyses for sport and exercise scientists* (pp. 183-210). London, UK: 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. (2015). Mplus. *The comprehensive modelling program for applied researchers: user's guide, 5.*

Nylund, K., Asparouhov, T., & Muthén, B. (2007). Deciding on the number of classes in latent class analysis and growth mixture modeling. *Structural Equation Modeling*, *14*, 535-569.

Perreira, T.A., Morin, A.J.S., Hebert, M., Gillet, N., Houle, S., & Berta, W. (2018). The short form of the workplace affective commitment multidimensional questionnaire (WACMQ-S): A bifactor-ESEM approach among healthcare professionals. *Journal of Vocational Behavior, 106*, 62-83.

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

Raykov, T., & Marcoulides, G.A. (2004). Using the delta method for approximate interval estimation of parameter functions in SEM. *Structural Equation Modeling*, *11*, 621-637.

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

Reise, S. P., Moore, T. M., & Maydeu-Olivares, A. (2011). Targeted bifactor rotations and assessing the impact of model violations on the parameters of unidimensional and bifactor models. *Educational and Psychological Measurement*, *71*, 684–711.

Ryan, R.M., & Connell, J.P. (1989). Perceived locus of causality and internalization: examining reasons for acting in two domains. *Journal of Personality and Social Psychology*, *57*, 749-761.

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

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.

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 and Social Psychology Bulletin*, *43*, 1215-1238.

Skrondal, A., & Laake, P. (2001). Regression among factor scores. *Psychometrika*, *66*, 563–576.

Tein, J.-Y., Coxe, S., & Cham, H. (2013). Statistical power to detect the correct number of classes in latent profile analysis. *Structural Equation Modeling*, *20*, 640-657.

Tofighi, D., & Enders, C. (2008). Identifying the correct number of classes in growth mixture models. In G. R. Hancock, & K. M. Samuelsen (Eds.), *Advances in latent variable mixture models* (pp. 317-341). Charlotte, NC: Information Age.

Tóth-Király, I., Morin, A.J.S., Bőthe, B., Orosz, G., & Rigó, A. (2018). Investigating the multidimensionality of need fulfillment: A bifactor exploratory structural equation modeling representation. *Structural Equation Modeling*, *25*, 267-286.

Vasconcellos, D., Parker, P. D., Hilland, T., Cinelli, R., Owen, K. B., Kapsal, N., ... & Lonsdale, C. (2019). Self-determination theory applied to physical education: A systematic review and meta-analysis. Advanced Online Publication. *Journal of Educational Psychology*.

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 & Exercise*, *15*, 407-417.

Van den Broeck, A., Ferris, D., Chang, C., & Rosen, C. (2016). A review of self-determination theory's basic psychological needs at work. *Journal of Management*, *42*, 1195-1229.

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. *Journal of Vocational Behavior*, *82*, 69-78.

Walter, S. L., Seibert, S. E., Goering, D., & O'Boyle, E. H. (2019). A tale of two sample sources: Do results from online panel data and conventional data converge?. *Journal of Business and Psychology*, *34*, 425-452.

Wang, J.C.K., Morin, A.J.S., Ryan, R.M., & Liu, W.C. (2016). Students' motivational profiles in the physical education context. *Journal of Sport & Exercise Psychology*, *38*, 612-630.

Ward, M. K., & Meade, A. W. (2018). Applying social psychology to prevent careless responding during online surveys. *Applied Psychology*, *67*(2), 231-263.

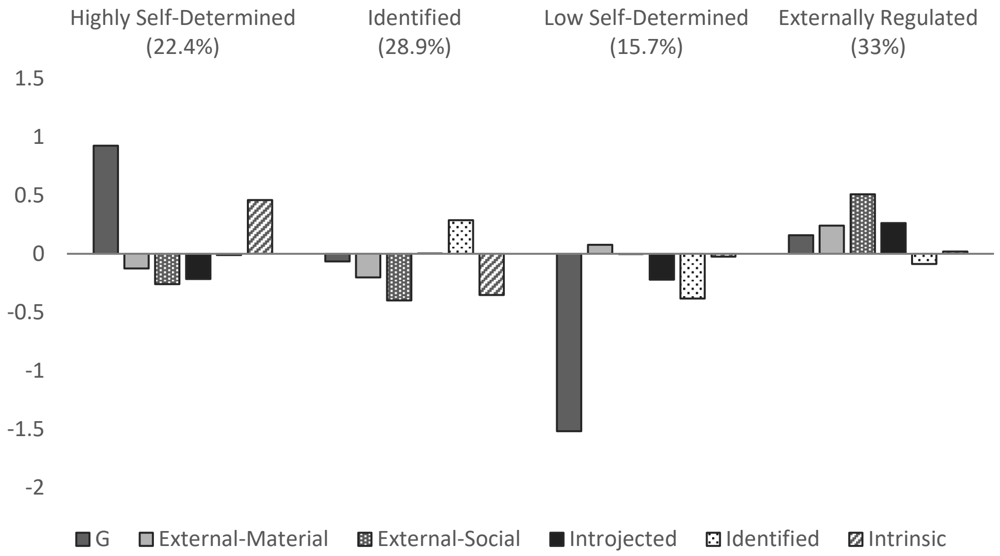

Figure 1

Final Set of Motivation Profiles (Estimated from bifactor ESEM Factor Scores) Identified in the Present Study at Both Time Points (Distributional Similarity).

Note: Profile indicators are estimated from factor scores with a mean of 0 and standard deviation of 1. G = general self-determined motivation.

Table 1

Fit Statistics of the Motivation Measurement Models

	χ^2	df	CFI	TLI	RMSEA	90% CI	$\Delta\chi^2$	Δdf	ΔCFI	ΔTLI	ΔRMSEA
Time 1											
CFA	634.912*	94	.843	.800	.106	.098; .114	---	---	---	---	---
Bifactor-CFA	386.510*	88	.913	.882	.082	.073; .090	---	---	---	---	---
ESEM	101.313*	50	.985	.964	.045	.032; .057	---	---	---	---	---
Bifactor-ESEM	75.972*	39	.989	.967	.043	.028; .057	---	---	---	---	---
Time 2											
CFA	650.298*	94	.863	.825	.108	.100; .116	---	---	---	---	---
Bifactor-CFA	441.216*	88	.913	.881	.089	.081; .097	---	---	---	---	---
ESEM	78.194*	50	.993	.983	.033	.018; .047	---	---	---	---	---
Bifactor-ESEM	52.939*	39	.997	.989	.026	.000; .043	---	---	---	---	---
Longitudinal Invariance											
Configural Invariance	337.522*	282	.994	.989	.020	.010; .027	---	---	---	---	---
Weak Invariance	400.868*	342	.994	.991	.018	.009; .025	63.457	60	.000	+.002	-.002
Strong Invariance	408.570*	352	.994	.991	.018	.008; .025	6.945	10	.000	.000	.000
Strict Invariance	475.585*	368	.988	.984	.024	.017; .030	252.227*	16	-.006	-.007	+.006
Latent Var.-Covar. Invariance	514.339*	389	.986	.982	.025	.019; .031	34.570	21	-.002	-.002	+.001
Latent Means Invariance	538.991*	395	.984	.980	.027	.021; .032	3.756	6	-.002	-.002	+.002

Note. * $p < .01$; CFA: confirmatory factor analyses; 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; Δ: Change in fit from the previous model in the sequence; $\Delta\chi^2$: scaled chi-square difference tests.

Table 2

Variable Correlations at Time 1 (Under the Diagonal), Time 2 (Above the Diagonal), and Across Time (Next Page)

Correlations	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18	19
1. Global		0	0	0	0	0	.408**	.392**	.512**	.347**	.490**	-.388**	.439**	.492**	.546**	.096*	.122**	.099*	.116**
2. Ext. Mat.	0		0	0	0	0	-.090*	-.083	-.067	.011	.017	-.070	-.013	-.092*	-.032	-.025	-.134**	-.168**	-.066
3. Ext. Soc.	0	0		0	0	0	-.051	-.123**	-.105*	-.112*	-.088*	.013	-.119**	-.061	-.076	.017	-.048	-.187**	-.011
4. Introjected	0	0	0		0	0	-.053	-.049	.061	-.071	-.062	.111*	-.027	-0.04	-.031	-.054	.093*	.014	.014
5. Identified	0	0	0	0		0	.014	.038	.082	.057	.100*	-.050	.227**	.033	.112*	-.009	.036	.156**	.023
6. Intrinsic	0	0	0	0	0		.243**	.167**	.208**	.060	.224**	-.317**	-.110*	.196**	.099*	.170**	-.079	.040	.137**
7. Autonomy	.417**	-.067	-.111*	-.054	-.018	.211**		.481**	.334**	.529**	.491**	-.392**	.287**	.502**	.481**	.044	-.020	.084	.250**
8. T. Variety	.345**	-.063	-.059	-.112*	.021	.258**	.373**		.420**	.263**	.449**	-.325**	.349**	.413**	.439**	-.004	.028	.098*	.161**
9. T. Significance	.462**	-.058	-.106*	-.087*	.024	.213**	.299**	.317**		.349**	.563**	-.357**	.248**	.390**	.387**	.153**	.039	.107*	.103*
10. T. Identity	.245**	.094*	-.148**	-.090*	.077	.037	.472**	.076	.266**		.505**	-.355**	.409**	.272**	.435**	.036	-.047	.069	.050
11. Feedback	.470**	.071	-.099*	-.115**	.052	.150**	.470**	.415**	.538**	.458**		-.437**	.347**	.387**	.477**	.090*	-.051	.074	.108*
12. Turn. Int.	-.406**	-.015	.039	.130**	-.038	-.319**	-.423**	-.268**	-.311**	-.359**	-.417**		-.269**	-.224**	-.304**	-.174**	.002	-.062	-.079
13. Proficiency	.430**	-.004	-.102*	.009	.139**	-.129**	.296**	.328**	.271**	.373**	.386**	-.268**		.314**	.656**	.032	.160**	.133**	.022
14. Proactivity	.466**	-.071	-.075	-.072	-.004	.153**	.444**	.331**	.358**	.168**	.378**	-.169**	.321**		.740**	.082	-.005	-.001	.247**
15. Adaptivity	.519**	-.009	-.115**	-.104*	.023	.077	.416**	.411**	.386**	.342**	.489**	-.275**	.642**	.713**		.015	.074	0.05	.158**
16. Salary	.141**	-.019	.033	-.072	-.036	.154**	.130**	.024	.146**	.066	.103*	-.211**	.009	-.009	-.026		-.168**	.162**	.215**
17. Gender	.118**	-.186**	-.057	.084	.086	-.120**	-.037	.017	.047	.004	-.053	-.040	.103*	-.011	.053	-.168**		.085	-.049
18. Age	.160**	-.135**	-.165**	-.015	.158**	.046	.091*	.077	.142**	.065	.055	-.142**	.145**	.070	.089*	.162**	.085		.132**
19. Manag. Level	.154**	-.050	.035	.015	-.041	.150**	.232**	.134**	.068	-.026	.120**	-.151**	.005	.260**	.140**	.215**	-.049	.132**	

Note: * $p < .05$; ** $p < .01$; Variables are factor scores with a standard deviation of 1 and a grand mean of 0, and bifactor measurement models (such as those used for the motivation measure) are orthogonal in nature, leading to uncorrelated factors.

Table 2 (continued)

Time 1	Time 2														
	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15
1. Global	**.758****	0	0	0	0	0	.338**	.343**	.440**	.280**	.424**	-.372**	.442**	.442**	.521**
2. Ext. Mat.	0	**.695****	0	0	0	0	-.131**	-.080	-.112*	.029	-.023	-.020	-.012	-.100*	-.043
3. Ext. Soc.	0	0	**.794****	0	0	0	-.064	-.067	-.086	-.071	-.072	-.008	-.133**	-.095*	-.095*
4. Introjected	0	0	0	**.714****	0	0	-.040	-.103*	-.019	-.057	-.076	.103*	.006	-.021	-.041
5. Identified	0	0	0	0	**.734****	0	-.055	-.033	-.060	-.016	.027	.033	.133**	-.067	.007
6. Intrinsic	0	0	0	0	0	**.756****	.247**	.222**	.212**	.107*	.227**	-.289**	-.081	.211**	.120**
7. Autonomy	.406**	-.065	-.106*	-.064	.034	.153**	**.791****	.338**	.268**	.457**	.421**	-.376**	.311**	.440**	.442**
8. T. Variety	.307**	-.093*	-.133**	-.050	.027	.174**	.346**	**.705****	.279**	.161**	.302**	-.252**	.284**	.310**	.365**
9. T. Significance	.414**	-.065	-.126**	-.024	.082	.190**	.257**	.296**	**.773****	.274**	.462**	-.340**	.232**	.323**	.339**
10. T. Identity	.247**	.032	-.164**	-.109*	.117**	-.028	.285**	.080	.186**	**.701****	.336**	-.313**	.376**	.155**	.328**
11. Feedback	.432**	.065	-.117**	-.095*	.110*	.135**	.337**	.408**	.479**	.389**	**.720****	-.396**	.358**	.360**	.458**
12. Turn. Int.	-.322**	-.019	.053	.121**	-.056	-.278**	-.347**	-.286**	-.263**	-.327**	-.388**	**.806****	-.279**	-.187**	-.271**
13. Proficiency	.370**	.020	-.077	-.015	.207**	-.137**	.211**	.305**	.208**	.320**	.289**	-.257**	**.789****	.177**	.490**
14. Proactivity	.415**	-.081	-.066	-.047	.041	.110*	.380**	.325**	.337**	.196**	.310**	-.170**	.252**	**.724****	.583**
15. Adaptivity	.489**	-.012	-.106*	-.057	.094*	.038	.384**	.422**	.347**	.356**	.426**	-.307**	.538**	.510**	**.757****
16. Salary	.096*	-.025	.017	-.054	-.009	.170**	.044	-.004	.153**	.036	.090*	-.174**	.032	.082	.015
17. Gender	.122**	-.134**	-.048	.093*	.036	-.079	-.020	.028	.039	-.047	-.051	.002	.160**	-.005	.074
18. Age	.099*	-.168**	-.187**	.014	.156**	.040	.084	.098*	.107*	.069	.074	-.062	.133**	-.001	.050
19. Manag. Level	.116**	-.066	-.011	.014	.023	.137**	.250**	.161**	.103*	.050	.108*	-.079	.022	.247**	.158**

Note: * $p < .05$; ** $p < .01$; Variables are factor scores with a standard deviation of 1 and a grand mean of 0, and bifactor measurement models (such as those used for the motivation measure) are orthogonal in nature, leading to uncorrelated factors.

Table 3

Fit statistics of Latent Profile and Latent Transition Analyses

Model	LL	#fp	Scaling	CAIC	BIC	ABIC	Entropy
Final Latent Profile Analyses							
Time 1	-3728.16	51	1.141	7825.281	7774.281	7612.400	.647
Time 2	-3695.43	51	1.142	7759.807	7708.807	7546.926	.686
Longitudinal Latent Profile Analyses							
Configural Similarity	-7423.59	102	1.142	15585.088	15483.088	15159.326	.666
Structural Similarity	-7440.89	78	1.335	15446.062	15368.062	15120.479	.634
Dispersion Similarity	-7449.27	54	1.656	15289.200	15235.200	15063.796	.620
Distributional Similarity	-7449.67	51	1.752	15268.302	15217.302	15055.420	.618
Latent Transition Analysis	-893.53	15	.400	1895.579	1880.579	1832.967	.932
Predictive Similarity: Predictors							
Null Effects	-975.295	15	.333	2059.107	2044.107	1996.495	.932
Profile-Specific Free Relations with Predictors	-846.168	105	.255	2451.948	2346.948	2013.664	.940
Free Relations with Predictors	-865.522	45	.521	2056.592	2011.592	1868.756	.929
Predictive Similarity	-877.028	30	.698	1971.089	1941.089	1845.864	.936
Explanatory Similarity							
Free Relations with Outcomes	-6310.737	46	1.351	12954.258	12908.258	12762.247	.713
Explanatory Similarity	-6317.506	30	1.610	12852.044	12822.044	12726.819	.708

Note. LL: Model Log Likelihood; #fp: Number of free parameters; Scaling: scaling factor associated with MLR log likelihood estimates; CAIC: Constant Akaïke Information Criteria; BIC: Bayesian Information Criteria; ABIC: Sample-Size adjusted BIC.

Table 4

Transition Probabilities for the Final Latent Transition Model

Time 1	Transition Probabilities to Time 2 profiles			
	Profile 1	Profile 2	Profile 3	Profile 4
Profile 1	.992	.008	0	0
Profile 2	.026	.974	0	0
Profile 3	0	0	1.00	0
Profile 4	0	0	0	1.00

Note. Profile 1: *Highly Self-Determined*. Profile 2: *Identified*. Profile 3: *Low Self-Determined*. Profile 4: *Externally Regulated*.

Table 5

Results from Multinomial Logistic Regression for Predictor Variables on Profile Membership.

	Profile 1 vs. Profile 2		Profile 1 vs. Profile 3		Profile 1 vs. Profile 4		Profile 2 vs. Profile 3		Profile 2 vs. Profile 4		Profile 3 vs. Profile 4	
	Coef. (SE)	OR	Coef. (SE)	OR	Coef. (SE)	OR	Coef. (SE)	OR	Coef. (SE)	OR	Coef. (SE)	OR
Autonomy	.982 (.237)**	2.670	1.422 (.263)**	4.145	.690 (.233)**	1.994	.455 (.200)*	1.576	-.271 (.168)	.763	-.738 (.180)**	.478
T. Variety	.007 (.193)	1.007	.336 (.183)	1.399	.300 (.164)	1.350	.325 (.173)	1.384	.288 (.163)	1.334	-.038 (.140)	.963
T. Significance	.856 (.219)**	2.354	1.294 (.236)**	3.647	.846 (.191)**	2.330	.444 (.199)*	1.559	-.003 (.162)	.997	-.453 (.172)**	.636
T. Identification	-.014 (.221)	.986	.137 (.228)	1.147	.242 (.197)	1.274	.139 (.191)	1.149	.245 (.175)	1.278	.102 (.169)	1.107
Feedback	.280 (.282)	1.323	.483 (.285)	1.621	.006 (.258)	1.006	.203 (.215	1.225	-.274 (.192)	.760	-.478 (.185)*	.620

Note: * *p* < .05, ** *p* < .01; SE: Standard Error of the coefficient; OR: Odds Ratio; The coefficients and OR reflects the effects of the predictor on the likelihood of membership into the first listed profile relative to the second listed profile; Predictors are estimated from factor scores with a mean of 0 and a standard deviation of 1; Profile 1: *Highly Self-Determined*. Profile 2: *Identified*. Profile 3: *Low Self-Determined*. Profile 4: *Externally Regulated.*

Table 6

Mean Outcome Levels [and Confidence Intervals] as a Function of Profile Membership

Outcomes	Profile 1	Profile 2	Profile 3	Profile 4	Summary of Significant Differences
Turnover Intentions	-.618 [-.741; -.495]	.266 [.036; .469]	.675 [.470; .879]	-.096 [-.241; .048]	1<4<2<3
Perceived Proficiency	.600 [.488; .712]	.288 [.143; .434]	-1.059 [-1.345; -.773]	-.150 [-.098; .193]	3<4<2<1
Perceived Proactivity	.799 [.663; .935]	-.089 [-.313; .135]	-1.148 [-1.433; -.864]	.048 [-.208; .110]	3<4=2<1
Perceived Adaptivity	.847 [.718; .976]	.058 [-.155; .271]	-1.270 [-1.545; -.994]	-.049 [-.339; .039]	3<4=2<1

Note. Outcomes are estimated with factors scores with a mean of 0 and standard deviation of 1. Profile 1: *Highly Self-Determined*. Profile 2: *Identified*. Profile 3: *Low Self-Determined*. Profile 4*: Externally Regulated*.

Data and Supplemental Materials

Data and supplemental materials are available via Open Science Framework and can be accessed through the following link:

https://osf.io/mf6np/?view_only=3827becec7ee4f609eca93e6b2dc8402