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On the temporal stability of self-determined work motivation profiles: A latent transition analysis

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Abstract

This study extends the research and theory on work motivation by examining temporal stability and change in employees' self-determined work motivation profiles and their differential relations to various predictors and outcomes. We gathered data at two time points over a 24-month period from a sample of 438 newly registered public health care nurses. Results of latent profile and latent transition analyses revealed four distinct profiles (strongly, moderately, self-determined, and poorly motivated), estimated from the position of global and specific behavioral regulations on the motivation continuum proposed by self-determination theory. These profiles were entirely stable at the within-sample level, although within-person changes in profile membership occurred for 30–40% of employees. Of particular interest, perceptions of job resources were consistently associated with greater likelihood of membership in the strongly and moderately motivated profiles. These profiles were also consistently associated with lower emotional exhaustion and intentions to leave the occupation and the organization and with higher in-role performance compared to the self-determined and poorly motivated profiles.

Keywords: work motivation, self-determination theory, job demands, job resources, latent profile analysis

A substantial body of research claims that the types of motivation that drive employees, or the various reasons for them to expend their efforts at work, play a major role in shaping their attitudes, behaviors, and well-being (Deci, Olafsen, & Ryan, 2017). Guided by self-determination theory (SDT; Deci & Ryan, 1985, 2000; Ryan & Deci, 2017), many studies support the idea that employees who invest in their work for motives that are more self-determined (pleasure, satisfaction, interest, or meaning) than less self-determined (internal or external pressures) are more committed to their organization (Gagné, Chemolli, Forest, & Koestner, 2008; Howard, Gagné, Morin, & Forest, 2018), perform their tasks better (Fernet, Trépanier, Austin, Gagné, & Forest, 2015), and enjoy better psychological health (Fernet, Austin, & Vallerand, 2012; Trépanier, Forest, Fernet, & Austin, 2015). While this framework is helpful for understanding how motivated efforts translate into benefits for both employees (e.g., growth, development, and well-being) and the organization (e.g., commitment, retention, and performance), the research is relatively silent about the complex interactions at play among the various types of behavioral regulation that may underpin goal-directed behaviors. This leaves certain questions unanswered, such as whether configurations of behavioral regulations change over time for specific employee profiles.

To address this issue, we draw on the theoretical and empirical literature to propose three main contributions to the research on work motivation. First, SDT (Deci & Ryan, 1985, 2000; Ryan & Deci, 2017) proposes that employees are governed by a combination of behavioral regulations situated along a single continuum of self-determination. However, the typical operationalization of this continuum, via the relative autonomy index (i.e., a sum-score of behavioral regulations weighted by their position on the continuum; Grolnick & Ryan, 1989), has been criticized (Chemolli & Gagné, 2014). Recently, Howard et al. (2018) showed that bifactor exploratory structural equation models (bifactor-ESEM; e.g., Morin, Arens, & Marsh, 2016) enable obtaining a clear, direct, and reliable assessment of employees' global levels of self-determination that reflects the theoretical SDT continuum (for a similar demonstration in the education field, see Litalien, Morin, Gagné, Vallerand, Losier, & Ryan, 2017). The present study is the first to adopt Howard et al.'s (2018) approach to examine the consistency (or variability) of motivation profiles over time.

Second, despite the acknowledgement that employees can be simultaneously driven by a combination of multiple reasons or motives (e.g., Howard, Gagné, Morin, & Van den Broeck, 2016), new perspectives are required to advance the understanding of the typical configurations that characterize work motivation, the organizational factors involved in their development, and the impacts on work-related outcomes. A person-centered approach could provide a more realistic, holistic, and dynamic view of work motivation focusing on types of employees rather than on potentially complex interactions among behavioral regulation types (Morin, Morizot, Boudrias & Madore, 2011). Importantly for the present study, this approach allows assessing longitudinal variations in employees' work motivation profiles.

Third, SDT proposes that the work environment plays a key role in shaping employee motivation (Deci et al., 2017; Gagné & Deci, 2005). Studies have convincingly demonstrated that work environment characteristics—more particularly supportive social aspects of the job, including leadership practices and support for autonomy— can help to foster self-determined motivation (Bono & Judge, 2003; Fernet et al., 2015; Wang & Gagné, 2013). Meanwhile, the constraining aspects of the work environment have received less attention. To improve this understanding, we draw on the job demands-resources (JD-R) model (Schaufeli & Bakker, 2004), which explicitly describes two distinct processes (motivational and energetic) that account for the associations between supportive (job resources) and constraining (job demands) aspects of the work environment and employee well-being and ill-being (Schaufeli & Bakker, 2004). However, and despite ample empirical support for the JD-R model (for a recent review, see Bakker & Demerouti, 2017), some recent studies have called into question the independence of these motivational and energetic processes. For example, research has shown that both the presence of job demands and the lack of job resources shared associations with the presence of less self-determined regulations, whereas the converse was found for more self-determined regulations (Fernet et al., 2015; Fernet, Trépanier, Austin, Levesque-Côté, 2016; Trépanier et al., 2015). The present study seeks to shed some light on this unresolved issue (Bakker & Demerouti, 2017) by examining employees' multidimensional work motivation profiles.

Theory and Hypotheses

Self-Determination Theory (SDT) and the Motivation Continuum

SDT (Deci & Ryan, 1985, 2000; Ryan & Deci, 2017) offers a multidimensional perspective on work motivation. The central idea is that people engage in activities for reasons that are more or less self-

determined, called behavioral regulations. These regulations wield considerable influence on psychological functioning and well-being (Ryan & Deci, 2017). On the job, behavioral regulations correspond to the different reasons for employees to spend their efforts. SDT distinguishes five main types of behavioral regulation: intrinsic motivation, identified, introjected and external regulation, and amotivation. Employees are driven by intrinsic motivation when they accomplish their job for the pleasure and satisfaction they derive from it. Identified regulation occurs when employees want to achieve goals that align with their personal values. They are governed by introjected regulation when they do their job to avoid anxiety, shame or guilt, or to bolster feelings of self-worth—all forms of internal pressures. External regulation occurs when work is carried out to avoid undesirable outcomes, or to obtain social or tangible rewards—all forms of external pressures. Finally, amotivation refers to a complete lack of volition to act. Employees are amotivated when they perceive that their actions are not aligned with the outcomes, or feel unable to achieve their goals (Deci & Ryan, 1985). Growing empirical evidence supports that these behavioral regulations operate in diverse life spheres, including work (Deci et al., 2017; Gagné & Deci, 2005).

According to SDT, these different regulations are situated along a single overarching continuum of self-determination, ranging from purely intrinsic to purely extrinsic types of regulations and finally to amotivation (e.g., Ryan & Deci, 2017; Sheldon, Osin, Gordeeva, Suchkov, & Sychev, 2017). Recently, Howard et al. (2018) and Litalien et al. (2017) proposed bifactor-ESEM as a way to obtain a reliable, direct, and meaningful assessment of global levels of self-determined motivation according to the theoretical SDT continuum (for a recent application of this approach, see also Gillet, Morin, Huart et al., 2018). More specifically, B-ESEM allows identifying a well-defined global factor that directly reflects the self-determination continuum. This global factor, reflecting participants' global levels of self-determined motivation, is defined by all the motivation items across the subscales. It is characterized by factor loadings ranging from strongly positive for intrinsic motivation items, moderately positive for identified regulation items, weakly positive for introjected regulation items, negligible or small and negative for external regulation items, to moderately negative for amotivation items. More importantly, this approach allows identifying the specific factors reflecting the variance that is uniquely attributable to each behavioral regulation type over and above that explained by the global factor, i.e., once participants global levels of self-determination are taken out from it. This allows capturing both the global effects of self-determination levels, and the residual effects that are uniquely associated with each subscale (e.g., the pursuit of pure pleasure for the intrinsic scale).

Previous studies have generally shown that higher global levels of self-determination or more self-determined behavioral regulations (i.e., intrinsic motivation and identified regulation) tend to be associated with more adaptive attitudes, including affective commitment to the organization (e.g., Gagné et al., 2008; Fernet, Trépanier, Demers, & Austin, 2017; Howard et al., 2018) and to the occupation (e.g., Fernet et al., 2017), and with more adaptive behaviors, including in-role performance (Fernet et al., 2015; Trépanier et al., 2015). On the other hand, they are negatively associated with psychological strain outcomes, including emotional exhaustion (Fernet et al., 2012; 2015). In contrast, behavioral regulations located at the opposite end of the continuum (introjected regulation, external regulation, and amotivation) tend to be positively related to intentions to leave the organization (e.g., Fernet et al., 2017; Gagné et al., 2015) and the occupation (e.g., Fernet et al., 2015; 2017) as well as emotional exhaustion (e.g., Fernet et al., 2015), but negatively associated with affective commitment to the organization (Gagné et al., 2015), affective commitment to the occupation (Fernet et al., 2017), and in-role performance (Fernet et al., 2015; Trépanier et al., 2015). Although these findings shed light on the associations between specific regulations and multidimensional indicators of job functioning, most of these studies used a variable-centered approach, which fails to account for the possibility that these relation might differ across employees with distinct motivation profiles.

A Person-Centered Approach to Work Motivation

The person-centered approach has been proposed as better suited to account for the differential impact of diverse motivation profiles on functioning (e.g., Howard et al., 2016; Gillet, Morin, & Reeves, 2018). Person-centered analyses seek to identify subpopulations, or profiles, of employees who differ in the intensity (quantity: more or less) and configuration (quality: intrinsic, identified, introjected, external, amotivated) of their behavioral regulations. Arguably, these profiles would provide a more holistic portrait of work motivation via a more nuanced consideration that ventures beyond the specific or relative impact of the different behavioral regulations.

Only a handful of studies have applied person-centered analyses to identify naturally occurring profiles of work motivation (e.g., Gillet, Fouquereau, Vallerand, Abraham, & Colombat, 2018; Graves, Cullen, Lester, Ruderman, & Gentry, 2015; Howard et al., 2016; Moran, Diefendorff, Kim, & Liu, 2012; Van den Broeck, Lens, De Witte, & Van Coillie, 2013). Despite some variability, notably in the number of identified profiles (4 to 6), distinct associations were found between the profiles and job functioning indicators. Whereas these studies provide valuable insights into natural motivation configurations, some gaps remain in our understanding of how these profiles evolve, along with their predictors and potential outcomes. For instance, most of the identified profiles either displayed matching levels of motivation (low, moderate, or high), or they followed the continuum hypothesis by displaying smooth increases or decreases in the behavioral regulations as a function of their position on the continuum (e.g., high intrinsic, moderate identified and introjected, and low external).

Morin and Marsh (2015) point out that profiles identified in these studies present *level* differences (i.e., profiles differing quantitatively). They take this as evidence against the added value of a person-centered approach, which, ideally, should reveal at least some profiles that present *shape* differences (i.e., qualitatively distinct configurations). However, they also noted that whenever global constructs (e.g., a global factor reflecting the quantity of self-determination) co-exist with specific dimensions (e.g., specific factors reflecting the quality of motivation) that are assessed with the same indicators, the failure to control for this global tendency may lead to erroneously inflated *level* differences. Expanding on this proposal Morin, Boudrias et al. (2016, 2017) recommend that person-centered analyses should be systematically preceded by a comprehensive examination of the psychometric multidimensionality of the profile indicators, and should be estimated based on factor scores from these preliminary measurement models. In particular, they demonstrated that bifactor-ESEM factor scores enabled identifying profiles that differed in terms of both global and specific factors. This is the approach we adopted in the present study, which aims to assess longitudinal variations in employees' work motivation profiles.

Stability and Change in Motivation Profiles

Motivation has been theoretically conceptualized as a dynamic process, in the sense that employees develop, adapt, and modify their behavioral regulations as they interact with the work environment. For decades, SDT-based research has evidenced that employees' behavioral regulations vary as a function of work environment characteristics (Deci et al., 2017; Gagné & Deci, 2005). Unfortunately, the bulk of prior research has used designs that preclude considering how employees' behavioral regulations develop on the job and how this development differs across employee subgroups.

It is worth mentioning that the statistical analysis methods (e.g., correlations, regressions, cross-lagged analyses) used in previous longitudinal studies (e.g., Fernet et al., 2012; Olafsen et al., 2018) failed to consider the possible existence of distinct employee subpopulations, or profiles, which may show distinct variations in longitudinal stability and change. Despite their interest, these studies focus on the rank-order stability of behavioral regulations considered on their own, rather than providing direct estimates of the consistency of profile structures within a specific sample over time, within specific individuals over time, or in association with other variables (Kam, Morin, Meyer, & Topolnytsky, 2016; Morin, Meyer, Creusier & Biétry, 2015). In this study, we used a person-centered latent transition analysis (LTA; Collins & Lanza, 2010) to address this limitation.

Still, it is important to note that some degree of stability in motivation profiles is to be expected. Arguably, the ability to develop organizational strategies to recruit or differentially support employees based on their work motivation profiles would require the profiles to remain largely unchanged over time without intervention and to show relatively stable inter-individual differences (Kam et al., 2016; Meyer & Morin, 2016). Although individual levels of motivation may change over time, evidence of some degree of stability in motivation profiles should alleviate doubts that the profiles are too transient and affected by daily variations in working conditions to have any practical value. Despite recent support for both the within-sample and within-person stability of students' motivation profiles over a two-month period (Gillet et al., 2018), such evidence is lacking in the work area.

Predictors of Motivation Profiles

According to SDT, environmental conditions in the workplace that support the satisfaction of employees' basic needs for autonomy, competence, and relatedness are likely to foster more autonomous types of behavioral regulation (Deci & Ryan, 2000; Gagné & Deci, 2005), thereby increasing employees' global and specific levels of self-determination. In contrast, task-related pressures and constraints, which tend to frustrate basic needs, should generate more controlled behavioral regulations, and even

amotivation, hence lowering global self-determination. Despite the fact that these theoretical propositions have recently received meta-analytic support (Van den Broeck, Ferris, Chang, & Rosen, 2016), current knowledge remains limited regarding our understanding of how, and which, work characteristics come to impact employee motivation, leading Van den Broeck et al. (2016) to recommend a better integration between SDT and other dominant organizational theories.

To gain a clearer understanding of how work environment factors influence employee motivation, we draw on the JD-R model (Bakker & Demerouti, 2017; Schaufeli & Bakker, 2004), according to which job demands and resources actively shape employee functioning. Job demands refer to "physical, psychological, social, or organizational aspects of the job that require sustained physical and/or psychological (i.e., cognitive or emotional) effort and are therefore associated with certain physiological and/or psychological costs" (Schaufeli & Bakker, 2004: 296). Examples are role-related problems (e.g., role conflict, ambiguity, and overload) as well as emotional (e.g., dealing with people problems), cognitive (e.g., solving complex tasks), and physical demands (e.g., moving heavy objects). In contrast, job resources refer to "physical, psychological, social, or organizational aspects of the job that […] are functional in achieving work goals" (Schaufeli & Bakker, 2004: 296). They may differ in nature (cognitive, emotional, and physical). Examples include social support, job control, and recognition, all of which enrich the work experience and facilitate personal and professional growth (Bakker & Demerouti, 2007; Schaufeli & Bakker, 2004).

The JD-R model posits two psychological processes that explain job strain (e.g., emotional exhaustion, psychological distress, psychosomatic complaints) and motivational outcomes (e.g., engagement, commitment, turnover intentions, performance). First, there is an energetic process, whereby job demands drain employees' mental and physical energy and lead to strain reactions and ill-being (Bakker & Demerouti, 2007; Schaufeli & Bakker, 2004). Second, there is a motivational process, whereby job resources promote employee motivation and adaptive outcomes, such as work engagement and organizational commitment (Bakker, Demerouti, de Boer, & Schaufeli, 2003; Boyd, Bakker, Pignata, Winefield, Gillespie, & Stough, 2011). The motivational process is based on the premise that not only are job resources instrumental for achieving work goals, they also foster employee growth and development (Schaufeli & Bakker, 2004). Despite the considerable empirical support for the JD-R model (see Bakker and Demerouti, 2017), there is growing empirical evidence that job resources are involved in both the energetic and motivational processes, and that this involvement occurs via distinct forms of behavioral regulation (Fernet et al., 2012, 2015, 2016). This suggests that, just like an exposure to excessive job demands, an exposure to a lack of job resources can be detrimental for employee functioning because it would prevent them from enjoying feelings of volition, freedom, and self-endorsed choices and actions (deCharms, 1968).

In support of this proposal, some studies (Fernet et al., 2015, 2016; Trépanier et al., 2015) have found the more self-determined types of behavioral regulation (intrinsic motivation and identified regulation) to be negatively associated with job demands and positively associated with job resources. In contrast, the behavioral regulations located at the other end of the continuum (introjected and external regulation, and amotivation) tend to be positively associated with job demands and negatively associated with job resources. In addition, these studies suggest that job demands and resources are distinctively related to job strain (emotional exhaustion, psychological distress, and psychosomatic complaints) and motivation (job engagement, commitment or performance) outcomes via their effect on the quality of the behavioral regulations (more or less self-determined). Based on the theory and the available empirical evidence, the following hypotheses are proposed:

Hypothesis 1a: Perceptions of job demands increase employees' likelihood of membership into the least adaptive motivation profiles (characterized by lower global levels self-determination, or dominated by higher levels of amotivation and/or introjected and external regulation).

Hypothesis 1b: Perceptions of job resources increase employees' likelihood of membership into the more adaptive motivation profiles (characterized by moderate-to-high global levels of self-determination, or dominated by higher levels of intrinsic motivation and identified regulation).

Attitudinal, Affective, and Behavioral Outcomes of Motivation Profiles

We also examine the relevance of the self-determination profiles by assessing their associations with attitudinal (turnover intentions), affective (emotional exhaustion), and behavioral (in-role performance) outcomes. In the nursing profession, turnover places a high toll on health care systems, along with substantial costs (e.g., recruitment, replacement, training) for already overtaxed institutions. Moreover,

turnover rates tend to spike at career start (e.g., Kovner, Brewer, Fatehi, & Jun, 2014; O'Brien-Pallas, Murphy, & Shamian 2008). During this period, nurses regularly cope with overwhelming problems, both professional (e.g., excess workload; Chiu, Chung, Wu, & Ho, 2009) and personal (e.g., burnout; Laschinger & Fida, 2014), which may then hinder the quality of care that they provide (e.g., performance; Lavoie-Tremblay, Fernet, Lavigne, & Austin, 2016). It is therefore important to find ways to retain committed, healthy, and effective employees at this challenging time. In the absence of objective turnover data, we consider one of the most strongly established predictors: turnover intentions (Hayes et al., 2012; Lee, Carswell, & Allen, 2000; Tett & Meyer, 1993; Meyer, Stanley, Herscovitch, & Topolnytsky, 2002). Turnover intentions generally refer to a conscious and deliberate willingness to leave the organization or the occupation (Tett & Meyer, 1993). Each of these targets (organization, occupation) is likely to be closely related to employees' levels of self-determined work motivation (Fernet et al., 2017). Of particular interest, Graves et al. (2015) found that intentions to leave the organization were higher for employees in the *very low internal profile* (characterized by average to very low behavioral regulations) compared to more adaptive motivation profiles (*self-determined*, *high internal*, and *moderately high* behavioral regulations).

As a core component of burnout, emotional exhaustion is an affective strain reaction resulting from lengthy exposure to job stressors (Maslach, Schaufeli, & Leiter, 2001). Research has shown that nurses report high exhaustion at the start of their career (Cho, Laschinger, & Wong, 2006). For instance, in a longitudinal study, high burnout (including emotional exhaustion) during the first three years of practice was shown to be associated with concurrent intentions to leave the profession (Rudman & Gustavsson, 2011). The SDT research has also produced abundant evidence for a relation between emotional exhaustion and self-determined work motivation (e.g., Fernet, Chanal, & Guay, 2017). Of particular interest, Howard et al. (2016) found higher levels of burnout in employees who belonged to *balanced* (average regulations, for all types) or *amotivated* profiles compared to *highly motivated* and *moderately autonomous* profiles.

Finally, in-role performance refers to actions and behaviors intended to accomplish core job tasks (Motowidlo, 2003). As the first years in a profession can be particularly challenging for some nurses, they may either perform lower or perceive their performance as lower (Lavoie-Tremblay et al., 2016). Although the relation between in-role performance and employees' self-determined motivation has been largely ignored, some studies obtained a negative relation between less self-determined regulations and in-role performance and a positive relation between more self-determined regulations and in-role performance (Fernet et al., 2015; Trépanier et al., 2015). Howard et al. (2016) found higher in-role performance in more adaptive profiles (*highly motivated* and *moderately autonomous*) compared to less adaptive profiles (*amotivated* and *balanced*). We therefore propose that:

Hypothesis 2: The more adaptive self-determination profiles (characterized by moderate-to-high global levels of self-determination, or dominated by higher levels of intrinsic motivation and identified regulation) are negatively associated with intentions to leave the occupation (H2a) and the organization (H2b) and with emotional exhaustion (H2c), and positively associated with in-role performance (H2d).

Method

Procedure and Participants

This study was conducted over a 24-month period. Data were collected at two time points (October 2014 and October 2016) from newly registered French Canadian nurses with three years or less of experience. All participants worked in the public health care sector in the province of Québec, Canada and were members of the Québec professional nursing association. Potential participants were contacted via a letter sent to their home explaining the study purpose and providing a link to an online questionnaire. They were invited by email to respond to an identical questionnaire 23 months later. It was emphasized that their responses would remain anonymous and that participation was voluntary.

The sample included 438 nurses (87.8% women) with an average age of 25.9 years (*SD* = 6.3) and average work experience of 1.3 years (*SD* = 0.5). The majority (76.3%) held a permanent position, and fewer than half (43.5%) worked full time. A total of 438 nurses participated at T1 and 235 at T2 (46.3% attrition rate). Additional analyses (MANOVA) showed no significant differences in any of the variables (i.e., motivation, demands, resources, and outcomes) or demographic characteristics (i.e., age, sex, tenure, employment status, and work schedule) between participants assessed at both measurement times (T1 and

T2) versus T1 only (main effect; F [16, 285] = 0.913, p = .555; Wilk's Λ = .951). Details on missing data are provided in the online supplements. This sample was fairly representative of the demographics of novice nurse members in Québec's professional nursing association (e.g., 43% full time; 87% women; mean age 27.8 years).

Measures

All measures were administered in French. Measures not previously validated in French (job demands and resources) were adapted using a classical translation back-translation procedure (Brislin, 1980; Vallerand, 1989) involving independent bilingual translators. Except for the control variables, which were assessed at T1 only, all variables were assessed at both time points. Items from all adapted measures are reported in the first section of the online supplements.

Work Motivation. The Multidimensional Work Motivation Scale (Gagné et al., 2015) was used to assess behavioral regulations. Participants rated their key reasons for investing efforts in their job on a seven-point scale ranging from 1 (*not at all for this reason*) to 7 (*exactly for this reason*). This instrument assessed amotivation (3 items; e.g., "I do little because I don't think this work is worth putting effort into"; α = .723 at T1 and .787 at T2), external regulation (3 items; e.g., "To get others' approval"; α = .757 at T1 and .787 at T2), introjected regulation (4 items; e.g., "Because otherwise, I would be ashamed of myself"; α = .651 at T1 and .676 at T2), identified regulation (3 items; e.g., "Because putting efforts in this job has personal significance to me"; α = .679 at T1 and .655 at T2), and intrinsic motivation (3 items; e.g., "Because I have fun doing my job"; α = .884 at T1 and .901 at T2).

Job Demands and Resources. We used an adapted version of the DISC 2.0 questionnaire (van de Ven, Vlerick, & De Jonge, 2008) containing six subscales to assess cognitive, emotional, and physical job demands and resources. Sample job demand items are, "My job requires high concentration and precision" (cognitive; four items; α = .827 at T1 and at .848 T2), "I have to do a lot of emotionally draining work" (emotional; four items; α = .785 at T1 and .793 at T2), and "I have to perform a lot of physically strenuous tasks to do my job" (physical; four items; α = .877 at T1 and .885 at T2). Sample items for job resources are, "I get information from others (e.g., colleagues, supervisors) to solve complex tasks" (cognitive; four items; α = .715 at T1 and .698 at T2), "I get emotional support from others (e.g., patients, colleagues, supervisors) when a tough situation occurs at work" (emotional; four items; α = .883 at T1 and .911 at T2), and "I can take a break when my work becomes too physically strenuous" (physical; four items; α = .764 at T1 and .762 at T2). Participants indicated on a five-point scale ranging from 1 (*never*) to 5 (*almost always*) the frequency with which they experienced these situations. Previous studies support the scale's reliability and validity (e.g., Fernet et al., 2015).

Emotional Exhaustion. We assessed emotional exhaustion with the Maslach Burnout Inventory – General Survey (MBI-GS; Schaufeli, Leiter, Maslach, & Jackson, 1996). This dimension is generally considered to be the primary component of burnout (Maslach et al., 2001). The subscale contains five items, such as, "I feel emotionally drained by my work" (α = .930 at T1 and .936 at T2). All items were rated on a seven-point scale ranging from 0 (*never*) to 6 (*daily*). The scale's factor structure, scale score reliability, and validity have been confirmed by Schaufeli et al. (1996) as well as extensive international research (Schutte, Toppinen, Kalimo, & Schaufeli, 2000).

In-Role Performance. We assessed in-role performance with a four-item self-report scale adapted from Williams and Anderson (1991). Participants rated their work performance on a scale from 1 (*do not agree at all*) to 7 (*very strongly agree*). A sample item is, "I complete my assigned duties adequately" (α = .917 at T1 and .943 at T2). Previous studies support the reliability and validity of this version (e.g., Fernet et al., 2015; Trépanier et al., 2015).

Turnover Intentions. We assessed employees' intentions to leave the occupation and the organization with six items (3 items for each target) adapted from O'Driscoll and Beehr (1994): "I'm thinking about leaving the nursing profession" (α = .916 at T1 and .920 at T2) and "I'm thinking about leaving my current health care facility" (α = .922 at T1 and .915 at T2). Items were scored on a seven-point scale ranging from 1 (*strongly disagree*) to 7 (*strongly agree*). Previous studies support the reliability and validity of this version (e.g., Fernet et al., 2015).

Analyses

Preliminary Analyses

We performed a series of preliminary analyses, as detailed in the online supplements. We began by verifying the adequacy of the measurement models underlying the responses to our various instruments, and their longitudinal measurement invariance across time points (Millsap, 2011). Measurement models

for the motivation variables were estimated with bifactor exploratory structural equation modeling (bifactor-ESEM; Morin, Arens, & Marsh, 2016; Morin, Arens, Tran, & Caci, 2016). This choice is based on recent studies suggesting that bifactor-ESEM measurement models are well-suited for representing measures of work (Howard et al., 2018), sport (Gunnel & Gaudreau, 2015) and academic (Litalien et al., 2017) motivation according to SDT (Deci & Ryan, 1985, 2000; Ryan & Deci, 2000). Indeed, their results suggested that bifactor-ESEM allows a precise estimate of the global continuum of self-determination, which, as proposed by SDT, underlies all motivation ratings (i.e., the global "quantity" of self-determination), along with direct estimates of the specificities remaining for each of the motivation facets addressed in the instrument (i.e., the "quality" of human motivation). For the predictors and outcomes measures, we used a confirmatory factor analytic (CFA) model that included four first-order factors for the outcomes (emotional exhaustion, in-role performance, intention to leave the organization, and intention to leave the profession), and two higher-order factors for the predictors (demands and resources), each of which were estimated from three first-order factors each (cognitive, physical, and emotional demands and resources). The interested reader can refer to the supplementary material for a detailed presentation of these models, the demonstration of their longitudinal invariance, and for the correlation estimates.

We used factor scores (standardized units; $M = 0$, $SD = 1$) rather than scale scores to estimate the profiles and their relations with the predictors and outcomes. By giving less weight to the items that are subject to higher levels of measurement error, factor scores provide some control for measurement error (Skrondal & Laake, 2001). To ensure comparability across the two time points, we extracted these scores from longitudinally invariant measurement models (Millsap, 2011). For a more extensive discussion of the advantages of using factor scores in the estimation of latent profile analyses, see Morin, Boudrias et al. (2016, 2017) and Morin, Meyer et al. (2016).

Latent Profile Analysis (LPA) and Latent Transition Analysis (LTA)

We conducted the analyses using Mplus 7.4 (Muthén & Muthén, 2015), with the robust maximum likelihood estimator (MLR). At both time points, we used 3,000 random sets of start values, and 100 iterations to estimate the LPA models, and we retained the 100 best solutions for final stage optimization (Hipp & Bauer, 2006). Because of the strategy used to generate the factor scores, there were no missing data in these models. This strategy has the advantage of maximizing the sample size for the analysis (N = 438), which is important given that LPA/LTA are large sample strategies.

At both measurement times, 1 to 8 latent profiles solutions were estimated based on the six motivation factors (including the global self-determination factor) as profile indicators. Means and variances for these indicators were free to vary across profiles (Diallo, Morin & Lu, 2016; Morin, Maïano et al., 2011; Peugh & Fan, 2013). The online supplements present detailed information on the model comparison procedures used to select the optimal LPA at each time point.

Once the best profile solution was identified at both measurement times, we verified the extent to which the two LPA profile solutions were similar by including them in a single LPA longitudinal model. Kam et al. (2016) call these tests of *within-sample stability*, and they are used to determine whether the same number of profiles presenting a similar arrangement can be identified at each time measurement. Accordingly, we used a systematic tests of longitudinal profile similarity, as suggested by Morin and Litalien (2017), which is an optimization of the tests of profile similarity across multiple groups proposed by Morin, Meyer et al. (2016). First, we examined whether the LPA solutions at each measurement time contained the same number of profiles. We then integrated them into a single longitudinal LPA model (i.e., *configural* similarity), without other equality constraints. This model of configural similarity served as a baseline for comparison with subsequent models to which constraints were added sequentially. Second, we tested for *structural* similarity by constraining the means of the indicators (i.e., the six motivation factors) within each profile to be equal across measurement times. This step is used to verify whether the shape of the profiles is similar or stable over time. If it is the case, we then test the *dispersion* similarity of the profiles by constraining the variances of the profile indicators to be equal across measurement times. This third step is used to verify whether the within-profile variability remains similar across measurement times. Fourth, from the most similar model in the prior sequence, we tested the *distributional* similarity of the profiles by including equality constraints on class probabilities across measurement times. This determines whether the prevalence of the profiles is similar over time. Each model was compared to the previous (less restrictive) one using the aforementioned information criteria. According to Morin, Meyer et al. (2016), the hypothesis of profile similarity is supported when the values

for at least two indices out of the Consistent Akaïke Information Criterion (CAIC), the Bayesian Information Criterion (BIC), and the sample-size Adjusted BIC (ABIC) are lower for the model containing more equality constraints.

The most similar model from the previous sequence was then converted to an LTA (Collins & Lanza, 2010), in order to investigate what Kam et al. (2016) refer to as *within-person stability* in profile membership: whether individual employees correspond to the same profile over time, as well as the nature of observed profile transitions. This sequence was then extended to tests of *predictive* and *explanatory* similarity to investigate whether the associations between the profiles and, respectively, their predictors and outcomes remain the same across time points. Following Morin and Litalien's (2017) recommendations, all LTA were estimated using the manual auxiliary 3-step approach (Asparouhov & Muthén, 2014). Generic details of the method implementation are provided by Asparouhov and Muthén (2014) and Morin and Litalien (2017), and their application in this study is detailed in the online supplements.

Predictors and Outcomes of Profile Membership. To test the associations between the time-specific predictor measures (job demands and resources) and the likelihood of profile membership, we conducted multinomial logistic regressions. In a first model, these associations were freely estimated at both measurement times and the predictions of profile membership at T2 were free to vary across T1 profiles, which allowed exploring relations between predictors and specific profile-to-profile transitions. In a second model, the associations between predictors and profile membership were still freely estimated across measurement times, but constrained to equality across profiles. Finally, to test for the *predictive* similarity of the profiles, we constrained these logistic regression coefficients to be equal across measurement times.

The outcomes (emotional exhaustion, in-role performance, intentions to leave the occupation and organization) were integrated into the LTA solution and first allowed to differ across profiles and time points. We then tested the *explanatory* similarity of the profiles by constraining the means of the outcomes to be equal across measurement times, while still being allowed to differ across profiles. The Mplus' MODEL CONSTRAINT function was used to examine the statistical significance of the mean differences between each pair of profiles, based on the multivariate delta method (Kam et al, 2016; Raykov & Marcoulides, 2004).

Results

Profile Selection and Interpretation

The procedures used to select the optimal number of profiles at each time point are detailed in the online supplements. These procedures supported and converged on a 4-profile solution at each time points, supporting the *configural* similarity of the solution. To verify the extent to which these 4-profile LPA solutions were similar across measurement times, they were first integrated into a longitudinal LPA model of *configural* similarity. The profile similarity results are presented in Table 1. Compared to this initial model, the second model resulted in lower values for all the information criteria (CAIC, BIC, and ABIC), thereby supporting the *structural similarity* of this 4-profile solution across time points. Similarly, the next two models also resulted in lower values for these criteria, sequentially supporting the *dispersion* and the *distributional* similarities of the profiles across measurement times. Overall, these results suggest that the number, structure, dispersion (i.e., within profile variability), and size of the profiles are similar across measurement times. The last model of *distributional similarity* was selected for interpretation, as illustrated in Figure 1 (see Table S4 of the online supplements for within-profile means).

In the interpretation of these profiles, it is important to keep in mind that whereas scores on the global self-determination factor reflect participants' global levels of self-determined work motivation across all types of behavioral regulation, the specific factors reflect the unique variance associated with each behavioral regulation that is unexplained by this global factor (and should therefore not be interpreted directly, unlike a more typical first-order score). Profile 1 was the least differentiated. It described employees with average levels on most specific motivation factors (identified, introjected and external regulation, and amotivation). This profile also showed a moderately high level of global self-determination but moderately low specific levels of intrinsic motivation. This profile was labeled *Moderately Motivated* and characterized 39.5% of the employees.

Profile 2, described employees with particularly low scores of global self-determination and moderately high specific scores of amotivation. Members of this profile also presented slightly above average specific scores on introjected and external regulation, average specific scores on intrinsic

motivation, and slightly below average specific scores on identified regulation. This *Poorly Motivated* profile characterized 36.6% of the employees. Profile 3 showed a seemingly opposite pattern, describing employees with moderately high specific levels of intrinsic motivation, slightly above average global levels of global self-determination and specific levels of identified regulation, and low specific levels on introjected and external regulation, and amotivation. This *Self-Determined* profile described 18.4% of the employees presenting above average levels of global self-determination coupled by specific levels of behavioral regulations that matched their relative position on the SDT continuum of motivation (i.e., relatively high intrinsic motivation and identified regulation, and low levels of introjected and external regulation and amotivation).

Finally, Profile 4 described employees with a very high level of global self-determination combined with high specific levels of identified, introjected, and external regulation. This profile was also characterized by moderately high specific levels of amotivation, and average specific levels of intrinsic motivation. The size of this *Strongly Motivated* profile, characterized by average to high scores on most motivation types, was relatively small (5.5%).

Latent Transitions

As mentioned above, we converted the distributional similarity model to an LTA using the manual auxiliary 3-step approach (Asparouhov & Muthén, 2014; Morin & Litalien, 2017). Table 2 presents the transition probabilities resulting from these LTA model. Consistent with the nature of our sample of organizational newcomers, these results show a moderate level of within-person stability in profile membership, indicating that between 30% and 40% of employees will change profile over time.

More precisely, membership into the first two profiles is moderately stable over time. Thus, 69.7% of employees corresponding to profile 1 (*Moderately Motivated*) and 69.6% of employees corresponding to profile 2 (*Poorly Motivated*) at T1 remain in the same profile at T2. Corresponding stability rates are lower for profiles 3 (*Self-Determined*: 57.6%) and 4 (*Strongly Motivated*: 60.9%). When employees in the *Strongly Motivated* profile (4) at T1 transition to another profile at T2, these transitions involve all of the other profiles at a similar level: 9.5% transition to the *Moderately Motivated* profile (1), 15.9% transition to the *Poorly Motivated* profile (2) and 13.7% transition to the *Self-Determined* profile (3). In contrast, none of the employees who were initially in the *Self-Determined* profile (3) transition to the *Poorly Motivated* profile (2), suggesting that, at least from a transitional perspective, the *Self-Determined* profile might be more desirable than the more undifferentiated *Strongly Motivated* profile. For *Self-Determined* employees, the dominant transition is to the *Moderately Motivated* profile (1: 28.5%), followed by the *Strongly Motivated* Profile (4: 13.9%). Almost none of the employees who were initially in the *Moderately Motivated* (1: .9%) or *Poorly Motivated* (2: 0%) profiles transition to the *Strongly Motivated* profile (4). However, 10.6% of the *Moderately Motivated* (1) employees and 16.1% of the *Poorly Motivated* (2) employees transition to the *Self-Determined* profile (3) at T2. Finally, 18.8% of the *Moderately Motivated* (1) employees transition to the *Poorly Motivated* Profile (2) at T2, whereas a similar proportion (14.2%) of those initially in the *Poorly Motivated* profile (2) transition to the *Moderately Motivated* profile (2) at T2.

Predictors of Profile Membership (Predictive Similarity)

Next, predictors (job resources and demands) were added to the *distribution similarity* model. This model showed the lowest values on all information criteria, supporting the *predictive similarity* of the profiles (see Table 1). This result suggests that the relations between predictors and profiles are similar across time points, and that the predictors do not directly contribute to the prediction of specific profile-to-profile transitions. These results are reported in Table 3[1]. Only perceptions of job resources predict the likelihood of membership in the various motivation profiles, with no significant effects of job demands when resources are taken into account. Employees who perceived higher job resources presented a higher likelihood of membership into the *Strongly Motivated* profile (4) relative to all other profiles, and into the *Moderately Motivated* profile (1) relative to the *Poorly Motivated* one (2). These results do not support Hypothesis 1a, which posits that perceptions of job demands should increase the likelihood of membership into the least adaptive profiles. However, they are consistent with H1b, which proposes that perceptions

[1] Additional tests were also conducted to assess the possible role of demographic characteristics (i.e., age, sex, tenure, employment status, and work schedule) in profile predictions. These tests, reported in Table S5 of the online supplements, were consistent with a lack of effects of these additional predictors on the likelihood of profile membership (i.e., a null effects model resulted in the lowest value on all indicators).

of job resources should increase the likelihood of membership in the more adaptive profiles.

Outcomes of Profile Membership (Explanatory Similarity)

As with the predictors, we added outcomes to the final retained model (i.e., the *distribution similarity* model). The *explanatory similarity* of the profiles was also supported, as the model in which the relations between profiles and outcomes were constrained to equality across measurement times resulted in lower values on all information criteria than the model in which these relations were freely estimated (see Table 1). These results thus suggest that the relations between profiles and outcomes are similar across measurement times. The means of the outcomes within each profile are reported in Table 4 and illustrated in Figure 2 and are highly consistent across outcomes.

Emotional exhaustion and intentions to leave the organization and the occupation were higher in profile 2 (*Poorly Motivated*), followed by profile 3 (*Self-Determined*), and the lowest in profiles 1 (*Moderately Motivated*) and 4 (*Strongly Motivated*), which were practically indistinguishable. In support of Hypotheses H2a, H2b, and H2c, these results show that the more adaptive profiles were associated with lower levels of intentions to leave the occupation and the organization as well as emotional exhaustion. Levels of in-role performance followed a similar, yet reversed pattern, being the highest in profile 4 (*Strongly Motivated*), followed by profile 1 (*Moderately Motivated*), and lowest in profiles 2 (*Poorly Motivated*) and 3 (*Self-Determined*), which were almost indistinguishable. In support of H2d, these results show that the more adaptive profiles are positively associated with employees' levels of in-role performance.

These results show the worst outcomes are associated with the *Poorly Motivated* profile (2), providing support for the SDT proposition that less self-determined types of regulation should be associated with less desirable outcomes. This should be particularly the case when global levels of self-determination are low. In contrast, the most desirable profile, from an outcome perspective, was the *Strongly Motivated* profile (4). However, when undesirable outcomes are considered (intentions to leave, emotional exhaustion), this profile was impossible to distinguish from the *Moderately Motivated (*1) profile, suggesting that global levels of self-determination could be the key driver of outcomes. More precisely it suggests that a minimal threshold of global level of self-determination appears necessary to prevent or limit certain undesirable outcomes, but that the positive effects of exceeding that threshold might be limited to more positive outcomes (such as performance). This threshold was not reached for the *Self-Determined* (3) profile, which was the second least desirable profile. Although this result seems unexpected from an SDT perspective, the present study used factor scores obtained from bifactor measurement models. Bifactor models extract a global factor that represents the total quantity of self-determination, which, based on SDT, is arguably the key determinant of psychosocial adaptation and performance, when properly disaggregated from the specificity remaining at the subscale level (Howard et al., 2018). The fact that profile 3 (*Self-Determined*) presents slightly higher than average levels of intrinsic motivation and identified regulation should be interpreted while keeping in mind that these indicators reflect the intrinsic motivation and identified regulation ratings, but not explained by global levels of self-determination, and thus something that reflects a purer sense of pleasure and identification, respectively.

Discussion

This study aimed to enrich our understanding of how work motivation profiles develop over time. Accordingly, we identified four motivation profiles (Moderately, Poorly, Self-determined, and Strongly Motivated) in a sample of newly registered nurses. Furthermore, the basic structure of these profiles remained unchanged over a 24-month period. One noteworthy finding was that the employees' perceptions of job resources predicted their profile membership, whereas their perceptions of job demands were only minimally related to profile membership. In addition, these motivation profiles presented associations with a series of attitudinal (intentions to leave the organization and occupation), affective (emotional exhaustion), and behavioral (in-role performance) outcomes that generally matched our theoretical expectations and supported the practical usefulness of adopting a person-centered perspective to examine work motivation. These findings have several important theoretical and managerial implications.

Theoretical Contributions

Distinct and Stable Motivation Profiles. Our central contribution lies in the identification of distinct and stable motivation profiles at work. According to Howard et al.'s (2018) recommendation for how to best represent work motivation, we identified employee profiles that differed in terms of not only the

global quantity of self-determined work motivation, but also the specific features (quality) of behavioral regulations. These four profiles align well with those reported in the literature (Gillet, Fouquereau et al., 2018; Graves et al., 2015; Howard et al., 2016). They reveal that employees' global level of self-determination (the G-factor) was by far the most important component in the definition of three of the profiles, which were characterized by a strong, a moderate, or low global level of self-determined motivation. However, an additional profile was identified, with only average levels of global self-determination, and which was clearly anchored in the specific quality of the behavioral regulations that were unexplained by the global levels of self-determination (i.e., the self-determined profile, which can thus be taken to reflect a simple quest for pure pleasure or a fuller, internalized sense of achievement). As we can only speculate on the contributions of the specific factors, it would be informative for future studies to delve further into the phenomenology of each regulation type (Litalien et al., 2017).

Our results also provide new insights into the temporal consistency and dynamic nature of work motivation. Although the start of a career wields considerable influence over employees' subsequent attitudes and motivation (Kammeyer-Mueller & Wanberg, 2003), our results showed that the nature and structure of the profiles themselves remained essentially unchanged over a 24-month period (i.e., within-sample stability) in a sample of nurses with three years or less of experience. This suggests that, even during the turbulence of career initiation, when employees are still establishing early profiles of work motivation, the basic configurations of behavioral regulations that underlie these profiles remain relatively stable. This supports the notion that these profiles capture some core intrapsychic mechanisms. This represents an important step forward in the motivation research, as it supports the idea that identifiable work motivation profiles are unlikely to shift over time in the absence of meaningful changes that impact employee motivation. It also supports the possibility of devising intervention strategies based on person-centered results without having to worry that motivation profiles are too volatile and affected by daily fluctuations to be informative. To date, this study is the first to examine the within-sample stability of SDT profiles in the work context, although similar profile stability has been identified in the education field (Gillet et al., 2018).

Despite this encouraging level of within-sample stability in terms of prototypical profiles at work, we also noted some variability in profile membership for individual employees. Our results thus supported the dynamic nature of individual levels of work motivation by showing more limited levels of within-person stability. In other words, although the profiles were generally stable, 30–40% of the employees migrated from one profile to another over time. Interestingly, whereas our results showed that the strongly motivated profile was the most desirable from an outcomes perspective, the self-determined profile was the most desirable from a transitional perspective. That is, no employee who initially belonged to this profile migrated "down" to the poorly motivated profile, which was associated with the least desirable outcomes. Still, this self-determined profile posed a challenge for SDT, as it was not found to be systematically associated with levels of functioning that were comparable, or as desirable, as those observed for the strongly motivated profile. Given that these profiles were identified based on a proper disaggregation of global (quantity of self-determined work motivation) versus specific (quality of the behavioral regulations) behavioral regulations, these unexpected results suggest that in order to achieve optimal functioning, the purer sense of pleasure and identification that characterizes this profile needs to be accompanied by higher levels of global self-determination. However, it is worth noting that in nursing, as in other occupations, certain tasks can be less pleasurable or valued (e.g., paperwork) and therefore would require some forms of internal or external pressure to perform them. This could explain why the self-determined profile was associated with lower in-role performance compared to the strongly and moderately motivated profiles. Further studies are needed to clarify the role of specific types of behavioral regulation once employees' global level of self-determination is taken into account (e.g., Howard et al., 2018). Nevertheless, our identification of prototypical motivation profiles early in the career provides the conceptual and empirical bases on which to build a more solid understanding of how employee motivation is shaped and developed. It would be informative to extend these results by investigating how the observed motivation profiles evolve over the course of a career, and how they emerge during the transition to the job.

The Role of Job Demands and Resources. Consistent with the view that the work environment entails conditions that direct and energize employee behaviors (Gagné & Deci, 2005), our results shed new light on which factors can predict motivation profiles. We found that employees with positive perceptions of job resources were more likely to correspond to the more adaptive motivation profiles

(strongly motivated and, to a lesser extent, moderately motivated). Whereas the motivational benefits of job resources have been abundantly demonstrated (e.g., Bakker & Demerouti, 2017), our results provide empirical support for these benefits in terms of behavioral regulation profiles. These findings enrich and refine those from previous studies (Fernet et al., 2012; Fernet et al., 2015; Trépanier et al., 2015), which found job resources to be associated mainly with self-determined types of regulation (intrinsic motivation and identified regulation). Job resources appear to facilitate the development of adaptive motivation profiles even in the presence of introjected and external regulation or amotivation, insofar as employees are driven by high global levels of self-determination. These findings provide support for the premise that behavioral regulations stem from the relationship that employees have with their job.

Our results also showed that when employees' perceptions of job resources were taken into consideration, perceptions of job demands were not associated with any of the identified profiles. This finding is surprising, given that SDT posits that job demands would be positively related to less self-determined types of regulation (Fernet et al., 2015; Trépanier et al., 2015). Considering the nature of self-determined motivation (overall *quantity* of self-determined motivation vs. specific *quality* of motivation facets) that characterized the profiles identified in the present study, these results suggest that once perceptions of job resources are taken into account, job demands have little additional impact on the deeply held motives that drive employees to invest in their job. This results needs to be interpreted while taking into account the correlations found in this study between these two work environment characteristics (r = -.540 at Time 1 and -.521 at Time 2). Despite being consistent with correlations reported by others (e.g., Trépanier et al., 2015), these correlations also suggest that a balancing act might be at play between job demands and resources. More precisely, these results suggest that it is a lack of alignment between available job resources and demands that drives motivation profiles so that having more resources than demands yields benefits, whereas having fewer caries risk. These results invite future researchers to reconsider the particularities and types of job demands, because independently of their nature (cognitive, emotional, or physical), they may reflect challenge (e.g., job responsibility and complexity) or hindrance stressors (e.g., role ambiguity, conflict, and overload) that would act differently on job functioning (Podsakoff, LePine, & LePine, 2007).

The Importance of Self-Determination Profiles from an Outcome Perspective. This study extends the knowledge of the potential effects of employees' motivation on their functioning at work. A key finding is that, compared to the self-determined and poorly motivated profiles, the strongly and moderately motivated profiles appeared to be consistently associated with more favorable outcomes. It is noteworthy that these two most desirable (strongly and moderately motivated) profiles differed from each other in terms of in-role performance, suggesting that the minimum threshold of global level of self-determination could be higher for this specific outcome. Thus, higher global levels of self-determination, as observed in the *strongly motivated profile* (which accounted for 5.5% of the participants in this sample), appeared to enable these strongly motivated employees to better align their efforts with formal task objectives. Our findings also provide further insights into how motivation regulations can limit or even prevent unfavorable outcomes. Although researchers have begun to recognize that motivation quality acts on burnout (Fernet et al., 2017), it is generally assumed that the autonomous (intrinsic motivation and identified regulation) and controlled (introjected and external regulation) forms of motivation are independent and mutually exclusive. Our findings challenge this assumption, suggesting that global levels of self-determination might be a key motivational driver of burnout (at least, the emotional exhaustion component of burnout). This is particularly relevant, because burnout has been demonstrated to be relatively stable over the course of a career (Bakker, Schaufeli, Sixma, Bosveld, & Van Dierendonck, 2000; Fernet, Gagné, & Austin, 2010; Toppinen-Tanner, Kalimo, & Mutanen, 2002). Finally, and consistent with the research on work attitudes, which points to the need to account for various work-related targets for those attitudes (Hayes et al., 2012; Morin, Meyer et al., 2015), our results identified motivation profiles that were associated with lower intentions to leave both the profession and the organization. This again raises the possibility that early identification of stable motivation profiles in a career could have a substantial and persistent impact on individual functioning within the organization.

Limitations and Future Directions

This study includes limitations that nevertheless open up promising research avenues. First, we made exclusive use of self-report measures, which run the risk of social desirability and self-evaluation bias. Future studies could include other data sources (e.g., peer perceptions of job demands and resources, supervisor's performance ratings) and consider other outcomes (e.g., actual turnover) to widen the scope

of the findings. Second, although identifying profiles over time provides a rich source of information, it does not allow determining causality. Despite support in the literature for some proposed associations (e.g., Fernet et al., 2012) and the longitudinal relations demonstrated in the present study, we cannot exclude the possibility of reciprocal or inverse relations. Thus, it is plausible that turnover intentions or emotional exhaustion could act on employee motivation (Dagenais-Desmarais, Leclerc, & Londei-Shortall, 2018), or that additional variables (e.g., personality, supervisor's leadership) may impact both. Future studies should apply experimental designs to more thoroughly examine the nature of the observed relations. Third, although we adopted a recognized theoretical perspective to determine the choice of predictors liable to act on profile membership, the analysis was based on a limited number of theoretical antecedents. Whereas the dynamic character of self-determined motivation during the first years of a career has been established, further studies are needed to enrich our understanding of the predictors involved in the shaping of these profiles. One promising research direction would be to examine socialization practices and other work design characteristics, the motivational potential of which has been studied extensively (see Parker, Morgeson, & Johns, 2017), but not necessarily longitudinally. Future studies would also do well to consider how motivation profiles emerge across the transition to the workplace. Fourth, although we focused on career start, we examined the consistency of the profiles at only two intervals (0 and 24 months) and in employees with varying length of experience, even though all had three years or less of employment. Future studies could address larger samples to extend the scope, recruit upcoming employees and follow them across the transition to employment, and consider distinct time periods and intervals. It would also be valuable to examine the consistency of motivation profiles at other career stages (e.g., nearing retirement) and during career transitions (e.g., internal job changers, organizational insiders). Fifth, in terms of generalizability, our results are based on a French Canadian sample of nurses, and should therefore be replicated in employees in other occupations, industries, and cultures. Lastly, although we used state-of-the-art procedures to handle missing data (e.g., Enders, 2010; Graham, 2009), the attrition rate observed between time points (46.3%) was high, which might have impacted some of the results, particularly those related to profile stability. Clearly, additional statistical research is needed to better understand the impact of missing time points on the estimation of complex mixture models such as LTA.

Managerial Implications

Notwithstanding the above limitations, our findings have significant implications for managers who seek to foster employee motivation and optimal functioning. Organizations would benefit by adopting, as part of their staff career development programs, methods to identify stable motivation profiles. In addition, they could adapt their socialization practices to promote more desirable motivation profiles. Our study demonstrates that it is possible to target, early on, the employees who are most likely to present an adaptive motivation profile as opposed to those who are at risk for persistent motivational deficits. Let us recall that over two thirds of the employees who belonged to the *poorly motivated profile* remained in this profile for the entire 24 months of the study. This supports the need to find ways to promote self-determination via internalization (such as efforts to increase identified regulation, whereby employees achieve a better match between their own values and professional goals and those of the organization for which they work). Armed with this understanding, organizations could implement socialization practices to help employees not only learn relevant job skills, but also internalize in a self-determined manner the values, skills, expected behaviors, and social knowledge they need to perform their job (Perrot & Campoy, 2009). Mentorship and preceptorship programs are examples of activities that could facilitate socialization. That said, and considering the stability we observed for some of the profiles, a strategy of small steps with gradual and progressive changes would be recommended as the most effective. In fact, it is highly unlikely that an employee belonging to the *poorly motivated profile* would vault from one day to the next to the *strongly motivated profile* if the organization simply sits on its hands and does nothing to help.

To facilitate adaptive motivation profiles in nurses, for example, policymakers could revisit the rules and regulations that govern the nursing profession. For instance, a recent systematic review of how governmental scope-of-practice regulations affect health care delivery by nurse practitioners suggests that more autonomous practices should be encouraged to improve the quality of primary care, along with increased user frequency and lower costs (Xue, Ye, Brewer, & Spetz, 2016). In addition, health care managers would benefit from rethinking elements of the environment, including the availability of job resources. Through their actions, managers have a substantial influence over employees' attitudes and perceptions (Bass & Riggio, 2006). Furthermore, they are often in a position to define and shape the

workplace reality (Smircich & Morgan, 1982). Managers who are good leaders can induce positive perceptions of job resources and create a work atmosphere that nurtures collaboration and information sharing. They can also be available to provide employees with information, clear up role and task ambiguities, and offer help and guidance as needed. Fernet et al. (2015) supported this line of reasoning by showing that transformational leadership practices that inspire employees to put the organization's needs before their own (Avolio, 1999) were associated with more self-determined regulations. Such practices may foster positive perceptions of job resources and limit perceptions of job demands.

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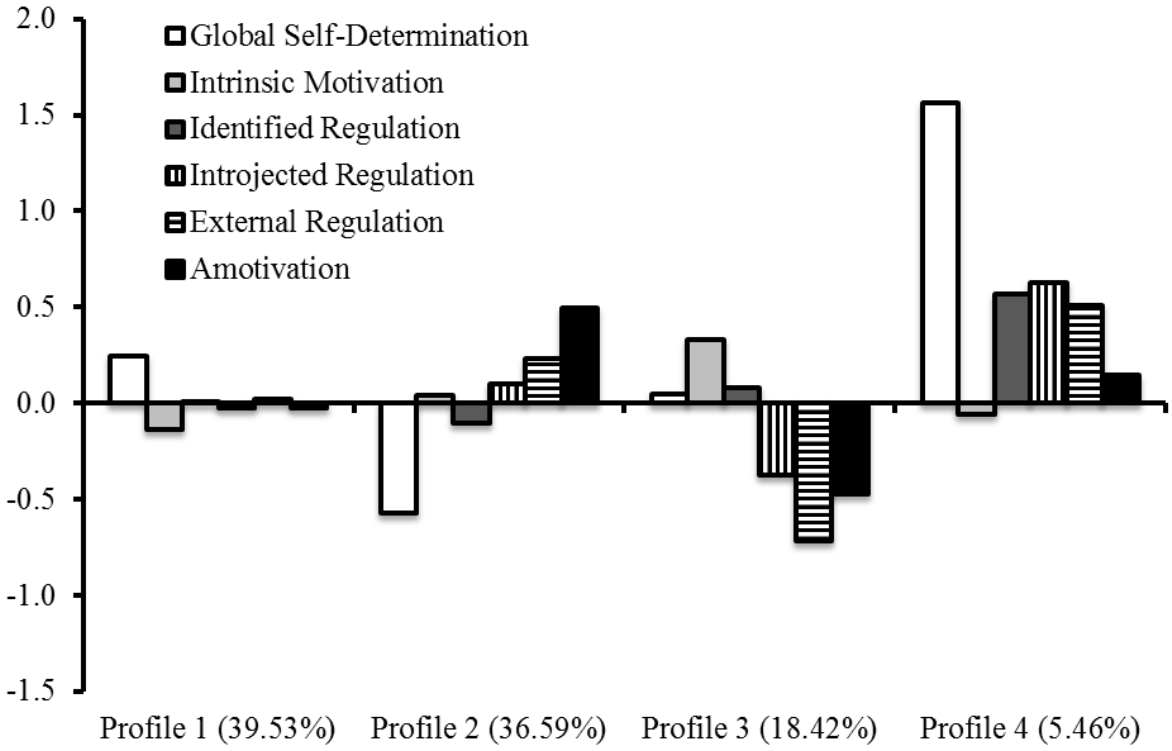

Figure 1. Final 4-Profile Solution Identified in this Study at Both Time Points.
Note. Profile indicators are factor scores with mean of 0 and a standard deviation of 1; Profile 1 = Moderately Motivated; Profile 2 = Poorly Motivated; Profile 3 = Self-Determined Motivated; Profile 4 = Strongly Motivated

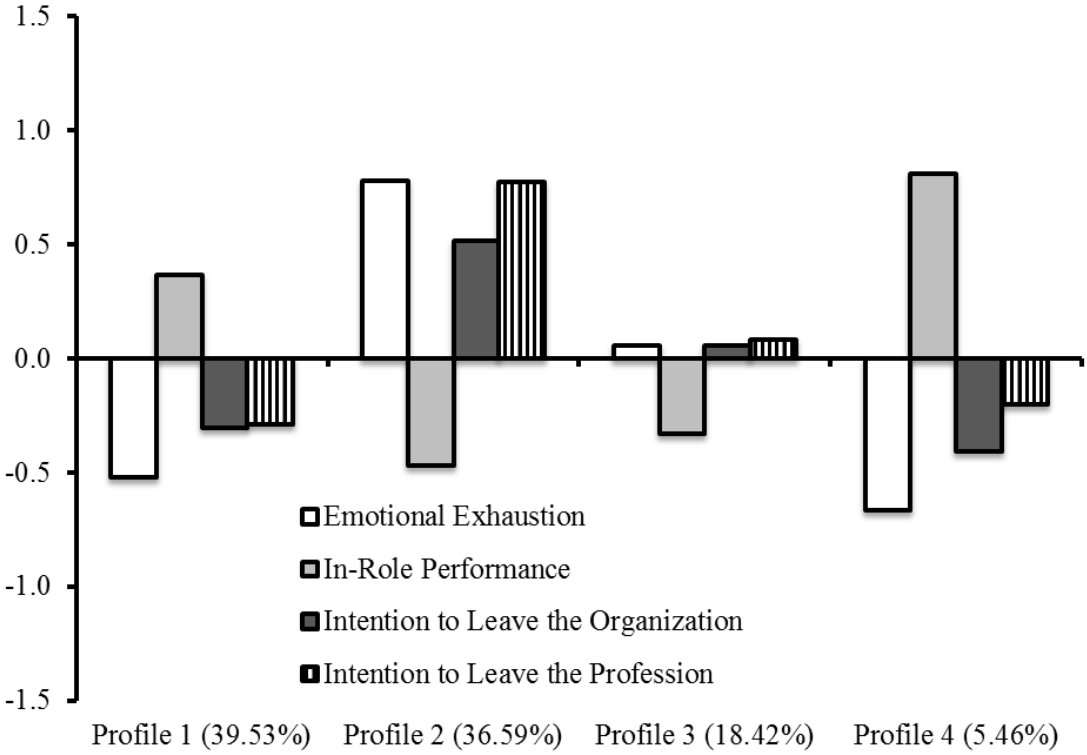

Figure 2. Outcome Levels across the Four Profiles at Both Time Points.
Note. Outcomes are factor scores with mean of 0 and a standard deviation of 1; Profile 1 = Moderately Motivated; Profile 2 = Poorly Motivated; Profile 3 = Self-Determined Motivated; Profile 4 = Strongly Motivated

Table 1
Results from the Latent Profile Analyses and Latent Transition Analyses

Model	LL	#fp	Scaling	CAIC	BIC	ABIC
Longitudinal Latent Profile Analyses						
Configural Similarity	-4254.424	102	1.0237	9232.393	9130.393	8806.691
Structural Similarity	-4271.621	78	1.0884	9096.54	9018.540	8771.004
Dispersion Similarity	-4295.114	54	1.3361	8973.281	8919.281	8747.909
Distributional Similarity	-4296.522	51	1.4767	8954.817	8903.817	8741.965
Predictive Similarity						
Profile-Specific Free Relations with Predictors	-713.974	51	.7863	1786.143	1735.143	1573.309
Free Relations with Predictors	-725.774	27	1.1223	1641.181	1614.181	1528.504
Equal Relations with Predictors	-728.561	21	1.0094	1604.614	1583.614	1516.976
Explanatory Similarity						
Free Relations with Outcomes	-4091.267	55	1.1689	8572.927	8517.927	8343.381
Equal Relations with Outcomes	-4094.271	39	1.3775	8465.367	8426.367	8302.597

Note. LL: Model LogLikelihood; #fp: Number of free parameters; Scaling = scaling factor associated with MLR loglikelihood estimates; CAIC: Consistant Akaïke Information Criteria; BIC: Bayesian Information Criteria; ABIC: Sample-Size adjusted BIC.

Table 2

Transitions Probabilities for the Final Latent Transition Analysis

	Transition Probabilities to Time 2 Profiles			
	Profile 1	Profile 2	Profile 3	Profile 4
Time 1				
Profile 1	.697	.188	.106	.009
Profile 2	.142	.696	.161	.000
Profile 3	.285	.000	.576	.139
Profile 4	.095	.159	.137	.609

Note. Profile 1 = Moderately Motivated; Profile 2 = Poorly Motivated; Profile 3 = Self-Determined Motivated; Profile 4 = Strongly Motivated

Table 3

Results from Multinomial Logistic Regressions for the Effects of the Predictors on Profile Membership

	Latent Profile 1 vs. 4		Latent Profile 2 vs. 4		Latent Profile 3 vs. 4	
	Coef. (SE)	OR	Coef. (SE)	OR	Coef. (SE)	OR
Demands	-.086 (.410)	.918	-.094 (.410)	.910	-.499 (.444)	.607
Resources	-.585 (.239)*	.557	-1.117 (.361)**	.327	-.846 (.378)*	.429
	Latent Profile 1 vs. 3		Latent Profile 2 vs. 3		Latent Profile 1 vs. 2	
	Coef. (SE)	OR	Coef. (SE)	OR	Coef. (SE)	
Demands	.413 (.248)	1.511	.405 (.235)	1.499	.008 (.168)	1.008
Resources	.261 (.220)	1.299	-.271 (.233)	.763	.532 (.180)**	1.703

Notes. **: $p < .01$; *: $p < .05$. SE: standard error of the coefficient; OR: Odds Ratio. The coefficients and OR reflects the effects of the predictors on the likelihood of membership into the first listed profile relative to the second listed profile; Predictors are factor scores with mean of 0 and a standard deviation of 1; Profile 1 = Moderately Motivated; Profile 2 = Poorly Motivated; Profile 3 = Self-determined Motivated; Profile 4 = Strongly Motivated

Table 4

Time-Invariant Associations between Profile Membership and the Outcomes

	Profile 1 M [CI]	Profile 2 M [CI]	Profile 3 M [CI]	Profile 4 M [CI]	Significant Differences ($p \leq .05$)
Emotional exhaustion	-.523 [-.680; -.366]	.777 [.610; .945]	.059 [-.181; .299]	-.664 [-.974; -.355]	2 > 3 > 1 = 4
In-role performance	.368 [.212; .523]	-.469 [-.644; -.294]	-.331 [-.546; -.116]	.808 [.634; .983]	4 > 1 > 2 = 3
Intention to leave the organization	-.302 [-.456; -.148]	.518 [.341; .696]	.056 [-.134; .245]	-.408 [-.603; -.212]	2 > 3 > 1 = 4
Intention to leave the occupation	-.289 [-.396; -.183]	.774 [.585; .963]	.084 [-.025; .194]	-.200 [-.456; .057]	2 > 3 > 1 = 4

Note**.** M: Mean; CI: 95% Confidence Interval; Outcomes are factor scores with mean of 0 and a standard deviation of 1; Profile 1 = Moderately Motivated; Profile 2 = Poorly Motivated; Profile 3 = Self-Determined; Profile 4 = Strongly Motivated.

Online Supplemental Materials for:

On the temporal stability of self-determined work motivation profiles: A latent transition analysis

The Adapted Measures Used in the Study

Job Demands
My job requires high concentration and precision
I have to solve work-related problems within a limited time frame
I have to remember many things simultaneously
I have to do a lot of mentally taxing work
I have to deal with people (e.g., patients, colleagues, supervisors) who have unrealistic expectations
I have to control my emotions to complete my tasks within a limited time frame
I have to do a lot of emotionally draining work
I have to display emotions (e.g., towards patients, colleagues, supervisors) that are inconsistent with my actual feelings
I have to perform a lot of physically strenuous tasks to do my job
I have to bend and/or stretch a lot at work
I have to work in uncomfortable and/or impractical postures
I have to lift or move heavy persons and/or objects (more than 10 kg)

Job Resources
I feel respected by others at work (e.g., patients, colleagues, supervisors)
I get emotional support from others (e.g., patients, colleagues, supervisors) when a tough situation occurs at work
I can express my emotions after a tough situation occurs, without experiencing negative consequences (from supervisors, colleagues, patients)
Other people (e.g., patients, colleagues, supervisors) lend a listening ear when I face tough situations
I can plan my work so that physical tasks require no more physical exertion that I can manage
I have access to adequate technical equipment for accomplishing physically strenuous tasks
I can take a break when my work becomes too physically strenuous
I receive physical help from others (e.g., patients, colleagues, supervisors) to lift or move heavy persons and objects
I can take a mental break when tasks require a lot of attention
I can vary complex tasks with simple tasks
I get information from others (e.g., colleagues, supervisors) to solve complex tasks
I am able to use my knowledge and intellectual skills to solve complex tasks

In-Role Performance
I complete my assigned duties adequately
I fulfill the responsibilities that are specified in my job description
I perform the tasks that are expected of me
I meet the formal performance requirements of the job

Turnover Intentions
I'm thinking about leaving the nursing profession
I plan to look for a new job (in a field other than nursing) in the next 12 months
I intend to change my profession within the next three years
I'm thinking about leaving my current health care facility
I plan to look for a job in another health care facility
I intend to change my health care facility within the next three years

Note. For purposes of this article, we followed the translation-back-translation procedure described by Vallerand and Halliwell (1983) to retranslate the adapted French Canadian items used into English.

Preliminary Measurement Models

Preliminary measurement models were estimated using Mplus 7.31 (Muthén & Muthén, 2015). Due to the complexity of the measurement models underlying all constructs assessed in the present study, these preliminary analyses were conducted separately for the motivation variables and the covariates (predictors and outcomes). These models were first estimated separately for each time point (Time 1: n = 438; Time 2: n = 234). For the motivation measure, a bifactor exploratory structural equation model (B-ESEM; Morin, Arens, & Marsh, 2016; Morin, Arens, Tran, & Caci, 2016) including one global factor (G-factor: global self-determined motivation) and five specific orthogonal factors (S-factors: intrinsic motivation, identified regulation, introjected regulation, external regulation, and amotivation) was estimated following Howard, Gagné, Morin, and Forest's (2018) recommendations. For the covariates, a confirmatory factor analytic (CFA) model including four first-order factors for the outcomes (emotional exhaustion, in-role performance, intention to quit the organization, and intention to quit the profession), and two higher-order factors for the predictors (demands and resources) themselves estimated from 3 first-order factors each (cognitive, physical, and emotional demands and resources) was estimated. Longitudinal models were then estimated across both time points and included a total of 14 factors [(1 G-factor + 6 S-factors) x 2 time points] for the motivation measure, and 24 factors [(10 first-order factors +2 higher-order factors) x 2 time points] for the covariates. All factors were allowed to correlate across time-points. A priori correlated uniquenesses between matching indicators of the factors utilized at the different time-points were included in the longitudinal models, as well as in all of the covariates models between three pairs of items with parallel wording (Marsh, Abduljabbar et al., 2013; Marsh, Scalas, & Nagengast, 2010).

All of these measurement models were estimated with the robust weighted least square estimator (WLSMV). The choice to rely on WLSMV estimation is linked to the fact that this estimator is more suited to the ordered-categorical nature of the Likert scales used in the present study than traditional maximum likelihood (ML) estimation or robust alternatives (MLR) (Finney & DiStefano, 2013). Although ML/MLR is to some extent robust to non-normality, its assumptions of underlying continuity are harder to approximate when using ordinal rating scales, especially when responses categories follow asymmetric thresholds (as is the case in this study). In these conditions, WLSMV estimation has been found to outperform ML/MLR (Bandalos, 2014; Beauducel & Herzberg, 2006; Finney & DiStephano, 2013; Flora & Curran, 2004; Lubke & Muthén, 2004; Rhemtulla, Brosseau-Liard, & Savalei, 2012).

Longitudinal B-ESEM (motivation variables) and CFAs (predictors and outcomes) models were estimated using the data from all respondents who completed at least one measurement point (corresponding to N = 443) rather than a listwise deletion strategy focusing only on employees having answered both two time points (Enders, 2010; Graham, 2009). To account for missing responses, models were estimated based on the full available information, based on algorithms implemented in Mplus for WLSMV (Asparouhov & Muthén, 2010). This procedure has comparable efficacy to multiple imputation, while being more efficient (Enders, 2010; Jeličič, Phelps, & Lerner, 2009; Larsen, 2011), and allows missing data to be conditional on all observed and latent variables included in the model, which includes the constructs themselves at preceding time points in this study.

Before saving the factor scores for our main analyses, we verified that the measurement model operated in the same manner across time points, through sequential tests of measurement invariance (Millsap, 2011). For the motivation variables, we assessed (1) configural invariance, (2) weak invariance (loadings), (3) strong invariance (loadings and thresholds), (4) strict invariance (loadings, thresholds, and uniquenesses); (5) invariance of the latent variance-covariance matrix (loadings, thresholds, uniquenesses, and latent variances and covariances); (6) latent means invariance (loadings, thresholds, uniquenesses, latent variances and covariances, and latent means). For the covariates, because of the presence of higher-order factors representing demands and ressources, these tests had to be conducted in two steps (Morin, Moullec, Maïano, Layet, Just, & Ninot, 2011). First, the sequence was conducted on the first-order measurement structure, in models excluding the higher-order factors. An additional step (4b) was included to test the invariance of the correlated uniquenesses included between the three pairs of parallel-worded items. Second, the higher-order factors were added to the most invariant model from steps 1 to 4b from the first-order measurement invariance tests, and the sequence was repeated to test the invariance of the higher-order factors.

Given the known oversensitivity of the chi-square test of exact fit (χ^2) to sample size and minor model misspecifications (e.g., Marsh, Hau, & Grayson, 2005), we relied on sample-size independent

goodness-of-fit indices to describe the fit of the alternative models (Hu & Bentler, 1999): the comparative fit index (CFI), the Tucker-Lewis index (TLI), as well as the root mean square error of approximation (RMSEA) and its 90% confidence interval. Values greater than .90 for the CFI and TLI indicate adequate model fit, although values greater than .95 are preferable. Values smaller than .08 or .06 for the RMSEA respectively support acceptable and excellent model fit. Like the chi square, chi square difference tests present a known sensitivity to sample size and minor model misspecifications so that recent studies suggest complementing this information with changes in CFIs and RMSEAs (Chen, 2007; Cheung & Rensvold, 2002) in tests of measurement invariance. A ΔCFI of .010 or less and a ΔRMSEA of .015 or less between two subsequent models supports the invariance hypothesis.

The results from the B-ESEM and CFA models are reported in Table S1. These results support the a priori measurement models (at each time point, and longitudinally), as well as their complete measurement invariance across time points as none of the changed in goodness-of-fit indices exceeded the recommended cut-off scores (ΔCFI ≤ .010; ΔTLI ≤ .010; ΔRMSEA ≤ .015; and overlapping RMSEA confidence intervals). To ensure that the latent profiles estimated at each time point were based on fully comparable measures of motivation and could be related to fully equivalent covariates measures, the factor scores used in main analyses were saved from the models of complete measurement invariance (loadings, thresholds, uniquenesses, latent variance-covariance, correlated uniquenesses [CFA models only], and latent means). Although only strict measurement invariance is required to ensure that measurement of the constructs remains equivalent across time points for models based on factor scores (e.g., Millsap, 2011), there are advantages to saving factors scores from a model of complete measurement invariance for use in latent profile analyses. Indeed, saving factor scores based on a measurement model in which both the latent variances and the latent means are invariant (i.e., respectively constrained to take a value of 1 and 0 in all time points) provides scores on profile indicators that can be readily interpreted as deviation from the grand mean expressed in standard deviation units. The resulting correlations estimated between the factor scores saved from these final measurement models and used as the input for the main analyses are reported in Table S2.

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Table S1

Goodness-of-Fit Statistics of the Longitudinal Measurement Model and the Invariance Models of the Retained Solution

Description	χ^2 (*df*)	CFI	TLI	RMSEA	90% CI	MD $\Delta\chi^2$ (*df*)	ΔCFI	ΔTLI	ΔRMSEA
Motivation Measurement Models									
Time 1 (*N* = 438)	53.899(39)	.998	.994	.030	[.000, .047]	-	-	-	-
Time 2 (*N* = 234)	46.301(39)	.999	.996	.028	[.000, .056]	-	-	-	-
Configural Invariance	290.324*(282)	.999	.999	.008	[.000, .021]	-	-	-	-
Weak Invariance	372.297*(382)	.997	.996	.014	[.000, .023]	81.689(60)	-.002	-.003	.006
Strong Invariance	429.541*(401)	.997	.997	.013	[.000, .022]	60.414(59)	.000	.001	-.001
Strict Invariance	482.539*(417)	.994	.993	.014	[.000, .023]	55.110*(16)	-.003	-.004	.001
Latent Variance-Covariance Invariance	517.822*(438)	.993	.992	.020	[.012, .027]	36.371(21)	-.001	-.001	.006
Latent Means Invariance	540.066*(444)	.991	.990	.022	[.015, .028]	14.162(6)	-.002	-.002	.002
Covariates Measurement Models									
Time 1 (*N* = 438)	1885.162*(678)	.956	.952	.066	[.063, .070]	-	-	-	-
Time 2 (*N* = 234)	1559.502*(678)	.955	.951	.077	[.072, .082]	-	-	-	-
First-Order Configural Invariance	4130.538*(2690)	.958	.954	.036	[.033, .038]	-	-	-	-
First-Order Weak Invariance	4150.193*(2719)	.959	.954	.035	[.033, .037]	205.324*(171)	.001	.000	-.001
First-Order Strong Invariance	4312.223*(2890)	.959	.957	.034	[.032, .036]	28.719(29)	.000	.003	-.001
First-Order Strict Invariance	4362.203*(2929)	.959	.958	.034	[.032, .036]	110.902**(39)	.000	.001	.000
First-Order Cor. Uniquenesses Invariance	4364.023*(2932)	.959	.958	.034	[.032, .036]	0.857(3)	.000	.000	.000
First-Order Latent Var.-Covar. Invariance	4129.765*(2987)	.967	.967	.030	[.028, .032]	62.045(55)	.008	.009	-.004
First-Order Latent Means Invariance	4110.373*(2997)	.968	.968	.030	[.027, .032]	8.584(10)	.001	.000	-.001
Second-Order Configural Invariance	4927.709*(3044)	.946	.946	.038	[.036, .040]	-	-	-	-
Second-Order Weak Invariance	4898.916*(3048)	.946	.947	.038	[.036, .040]	4.136(4)	.000	.001	.000
Second-Order Strong Invariance	4902.409*(3052)	.947	.947	.038	[.036, .040]	9.053(4)	.001	.000	.000
Second-Order Strict Invariance	4889.159*(3058)	.947	.948	.038	[.036, .040]	4.659(6)	.000	.001	.000
Second-Order Latent Var.-Covar. Invariance	4689.448*(3079)	.953	.955	.035	[.033, .037]	24.227(21)	.006	.007	-.003
Second-Order Latent Means Invariance	4663.279*(3085)	.954	.956	.035	[.033, .037]	3.498(6)	.001	.001	.000

Note. *p < .01; B-ESEM = bifactor exploratory structural equation modeling; χ^2: Chi-square; *df*: Degrees of freedom; CFI: Comparative fit index; TLI: Tucker-Lewis index; RMSEA: Root mean square error of approximation; 90% CI: 90% confidence interval of the RMSEA; MD $\Delta\chi^2$: Chi-square difference tests calculated with the Mplus DIFFTEST function for WLSMV estimation.

Table S2

Latent Correlations from the Fully Invariant Longitudinal Model Models

	SDT_T1	MINT_T1	MIDE_T1	MROJ_T1	MET_T1	AMOT_T1	DEM_T1	RESS_T1	EE_T1	IPE_T1	INTE_T1	INTP_T1
SDT_T1	-											
MINT_T1	-.013	-										
MIDE_T1	.092	-.036	-									
MROJ_T1	.024	-.045	.104*	-								
MEXT_T1	-.035	-.028	.070	.138**	-							
AMOT_T1	-.059	-.017	-.117*	.089	.152**	-						
DEM_T1	-.045	-.045	.110*	.123*	.109*	.037	-					
RESS_T1	.318**	.006	.038	-.041	.009	.009	-.540**	-				
EE_T1	-.365**	-.153**	.023	.137**	.099*	.108*	.521**	-.442**	-			
IPE_T1	.363**	-.055	.077	-.005	-.092	-.123*	-.205**	.326**	-.403**	-		
INTE_T1	-.322**	-.120*	.026	.027	.009	.164**	.250**	-.270**	.388**	-.166**	-	
INTP_T1	-.414**	-.133**	.002	.093	.081	.167**	.288**	-.323**	.590**	-.304**	.640**	-
SDT_T2	.618**	-.027	.159*	-.035	-.130*	-.097	-.148**	.360**	-.348**	.378**	-.243**	-.346**
MINT_T2	.091	.290**	.015	.016	-.149*	-.027	-.043	.160**	-.131*	-.021	-.124	-.091
MIDE_T2	.262**	-.046	.442*	.163**	-.042	-.090	.072	.125*	.038	.030	-.098	-.108
MROJ_T2	.000	-.073	.011	.485**	.055	-.004	.134*	.013	.068	.024	.035	.075
MEXT_T2	-.076	-.029	.099	.109	.422**	.059	.172**	-.045	.132*	-.148*	.087	.107
AMOT_T2	-.054	-.103	-.002	.042	.058	.489**	.110	-.089	.089	-.131*	.089	.138*
DEM_T2	.014	-.039	.124*	.122*	.112*	.028	.969**	-.436**	.481**	-.181**	.203**	.238**
RESS_T2	.220**	-.024	.008	-.054	.004	.025	-.517**	.842**	-.398**	.287**	-.207**	-.262**
EE_T2	-.287**	-.093	.027	.092	.127**	.101*	.467**	-.411**	.793**	-.507**	.244**	.429**
IPE_T2	.341**	-.049	.096	-.040	-.021	-.132**	-.174**	.300**	-.375**	.751**	-.235**	-.380**
INTE_T2	-.222**	-.084	.002	.042	.041	.136**	.255**	-.283**	.404**	-.256**	.532**	.392**
INTP_T2	-.369**	-.133**	-.011	.086	.089	.159**	.293**	-.338**	.594**	-.280**	.335**	.730**

Note. **$p < .01$, *$p < .05$; These variables are factor scores with mean of 0 and a standard deviation of 1; for the motivation components, all factors were saved from an orthogonal model (not-correlated); SDT = global self-determined motivation; MINT = intrinsic motivation; MIDE = identified regulation; MROJ = introjected regulation; MET = external regulation; AMOT = amotivation; DEM = demands; RESS = resources; EE = emotional exhaustion; IPE = in-role performance; INTE = intention to quit the organization; INTP = intention to quit the profession; T1 = first point of measurement; T2 = second point of measurement.

Table S2 (Continued)

	SDT_T2	MINT_T2	MIDE_T2	MROJ_T2	MET_T2	AMOT_T2	DEM_T2	RESS_T2	EE_T2	IPE_T2	INTE_T2	INTP_T2
SDT_T2	-											
MINT_T2	.136*	-										
MIDE_T2	.176**	.010	-									
MROJ_T2	.010	.110	.128*	-								
MET_T2	-.002	-.093	.018	.048	-							
AMOT_T2	-.119	-.037	-.076	.175**	.234**	-						
DEM_T2	-.121*	-.027	.095	.140*	.182**	.119	-					
RESS_T2	.388**	.117*	.098	.011	-.044	-.099	-.521**	-				
EE_T2	-.411**	-.104	.050	.074	.175**	.176**	.493**	-.493**	-			
IPE_T2	.397**	.024	.048	.043	-.043	-.088	-.148**	.319**	-.446**	-		
INTE_T2	-.394**	-.211**	-.004	-.017	.036	.126*	.259**	-.348**	.455**	-.289**	-	
INTP_T2	-.437**	-.152**	-.053	.032	.058	.185**	.278**	-.370**	.622**	-.344**	.604**	-

Note. **$p < .01$, *$p < .05$; These variables are factor scores with mean of 0 and a standard deviation of 1; for the motivation components, all factors were saved from an orthogonal model (not-correlated); SDT = global self-determined motivation; MINT = intrinsic motivation; MIDE = identified regulation; MROJ = introjected regulation; MET = external regulation; AMOT = amotivation; DEM = demands; RESS = resources; EE = emotional exhaustion; IPE = in-role performance; INTE = intention to quit the organization; INTP = intention to quit the profession; T2 = second point of measurement.

Selecting the Optimal Number of Profiles at Each Time Point

Statistical Considerations

Selecting the appropriate number of profiles can be challenging when conducting LPA. The choice of a specific solution should certainly be informed by its substantive meaning and its statistical and theoretical adequacy (Bauer & Curran, 2003; Marsh, Lüdtke, Trautwein, & Morin, 2009; Muthén, 2003). Several statistical indices are also available to support this choice (McLachlan & Peel, 2000): 1- The Akaïke Information Criterion (AIC); 2- the Consistent AIC (CAIC); 3- the Bayesian Information Criterion (BIC); 4- the sample-size Adjusted BIC (ABIC); 5- the standard and adjusted Lo, Mendel and Rubin's (2001) Likelihood Ratio Test (LRTs, in this study, we present the adjusted test [aLMR]); and 6- the Bootstrap Likelihood Ratio Test (BLRT). AIC, CAIC, BIC, or ABIC are compared across competing models, with lowest values indicating a better fit. The aLMR and BLRT compare a model including two or more profiles with a model comprising one less profile. When statistically significant, these tests suggest that the model with the higher number of profiles should be retained. Entropy is an indicator of classification uncertainty, with values ranging from 0 to 1. Although higher values indicate more precision in cases assignment, researchers should not solely rely on this indicator to select the optimal profile solution (Lubke & Muthén, 2007).

Results from various studies using simulation reveal that the CAIC, BIC, ABIC, and BLRT are particularly informative (Henson, Reise, & Kim, 2007; Nylund, Asparouhov, & Muthén, 2007; Peugh & Fan, 2013; Tein, Coxe, & Cham, 2013; Tofighi & Enders, 2008). Based on a simulation study, Diallo, Morin, and Lu (2017) suggest that when the level is high (e.g., ≥ .800), BIC and CAIC performed better. In contrast, when the level of entropy is rather low (e.g., ≤ .600), ABIC and BLRT were more efficient. In contrast, the bulk of current research evidence suggests that, like the entropy, the AIC and the LMR/ALMR should be avoided in determining the optimal number of profiles (Diallo et al., 2017; Henson et al., 2007; Nylund et al., 2007; Peugh & Fan, 2013; Tofighi & Enders, 2007). In the present study, we report these indices for reader's convenience although we do not rely on them for the choice of the optimal solution. As all these information criteria are strongly affected by sample size (Marsh et al., 2009) and with a sufficiently large number of cases, they may continue to support the addition of profiles without reaching a minimum value. When such situation occurs, researchers can rely on graphical representation of these indicators through elbow plots to better grasp the improvement associated to each additional profile (Morin, Maïano et al., 2011). The optimal solution can thus be identified when the slope starts to level off.

Results

Fit indices for the various LPA models at both measurement times are presented in Table S3. At both times, the CAIC and BIC respectively support solutions including two and three profiles, while the ABIC supports the 5-profile solution at T1 and keeps on increasing at T2. Finally, the BLRT appears to support the 3-profile solution at T1, and either the 4- or 6- profile solution at T2. Entropy values were also relatively weak (.480 to .859 across models and time points). Thus, following Diallo et al.'s (2017) recommendations, the choice of the optimal number of profiles should mainly rely on the ABIC and BLRT, which oscillate between supporting solutions including 3 to 5 profiles across time points, an interpretation that is also supported by considering a graphical representation of these indices (see Figures S1 and S2). All these profile solutions were statistically appropriate. The additional profile brought by the four-profile solution was well-defined and theoretically meaningful. In contrast, adding a fifth profile did not bring much additional information, but rather divide an existing profile into smaller ones (e.g., the new profile only corresponded to 4 participants at T2) which only differed quantitatively. The 4-profile solution was thus retained at both measurement times, providing support to the *configural similarity* of this LPA solution across time points. With an entropy value of .662 in T1 and .769 in T2, this solution provides a reasonable level of classification accuracy.

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Table S3

Results from the Latent Profile Analysis Models Estimated Separately at Each Time Point

Model	LL	#fp	Scaling	AIC	CAIC	BIC	ABIC	Entropy	aLMR	BLRT
Time 1 (n=438)										
1 profile	-2958.914	12	1.0764	5941.828	6002.814	5990.814	5952.732	Na	Na	Na
2 profile	-2879.073	25	1.0245	5808.145	5935.201	5910.201	5830.863	.480	≤.001	≤.001
3 profile	-2836.642	38	0.9910	5749.284	5942.408	5904.408	5783.815	.683	.044	≤.001
4 profile	-2813.863	51	1.0484	5729.725	5988.919	5937.919	5776.070	.662	.273	.140
5 profile	-2785.277	64	0.9988	5698.554	6023.816	5959.816	5756.712	.706	.527	.351
6 profile	-2773.694	77	0.9898	5701.387	6092.718	6015.718	5771.359	.732	.078	.080
7 profile	-2751.358	90	0.9703	5682.716	6140.115	6050.115	5764.500	.775	.107	.111
8 profile	-2736.439	103	1.0463	5678.877	6202.346	6099.346	5772.476	.732	.518	.090
Time 2 (n=234)										
1 profile	-1562.704	12	1.0537	3149.408	3202.872	3190.872	3152.838	Na	Na	Na
2 profile	-1508.652	25	1.0293	3067.305	3178.688	3153.688	3074.449	.620	.003	≤.001
3 profile	-1472.408	38	1.0455	3020.815	3190.117	3152.117	3031.675	.669	.064	≤.001
4 profile	-1440.562	51	0.9991	2983.123	3210.345	3159.345	2997.698	.769	.029	≤.001
5 profile	-1417.221	64	1.0316	2962.442	3247.583	3183.583	2980.732	.815	.317	.040
6 profile	-1393.241	77	0.9349	2940.482	3283.542	3206.542	2962.487	.841	.285	≤.001
7 profile	-1376.667	90	0.9500	2933.335	3334.314	3244.314	2959.055	.858	.170	.532
8 profile	-1359.155	103	1.0709	2924.310	3383.208	3280.208	2953.745	.859	.641	.143

Note. LL = Model LogLikelihood; #fp = Number of free parameters; Scaling = scaling factor; AIC = Akaïke Information Criteria; CAIC = Consistant AIC; BIC = Bayesian Information Criteria; ABIC = Sample-Size adjusted BIC; aLMR = Adjusted Lo-Mendell-Rubin likelihood ratio test; BLRT = Bootstrap Likelihood ratio test.

Table S4

Detailed Results from the Final Longitudinal Latent Profile Analysis (Distributional Similarity)

	Profile 1		**Profile 2**		**Profile 3**		**Profile 4**		
	Mean	CI	Mean	CI	Mean	CI	Mean	CI	Significant Differences ($p \leq .05$)
Global self-determined motivation	.246	[-.003; .495]	-.570	[-.730; -.409]	.047	[-.271; .364]	1.564	[1.420; 1.708]	2 < 1 = 3 < 4
Intrinsic motivation	-.136	[-.287; .015]	.041	[-.063; .144]	.329	[.098; .561]	-.060	[-.355; .234]	1 = 2 = 4 < 3
Identified regulation	.002	[-.158; .161]	-.106	[-.232; .019]	.079	[-.116; .273]	.567	[.328; .806]	1 = 2 = 3 < 4
Introjected regulation	-.025	[-.284; .234]	.100	[-.038; .238]	-.374	[-.608; -.139]	.629	[.208; 1.049]	3 < 1 = 2 < 4
External regulation	.024	[-.129; .177]	.234	[.086; .382]	-.719	[-1.115; -.324]	.509	[-.208; 1.226]	3 < 1 = 2 = 4
Amotivation	-.028	[-.147; .092]	.494	[.326; .662]	-.470	[-.618; -.322]	.146	[.018; .274]	3 < 1 = 4 < 2

Note. Profile indicators are factor scores with mean of 0 and a standard deviation of 1; CI = 95% Confidence Interval; Profile 1 = Moderately Motivated; Profile 2 = Poorly Motivated; Profile 3 = Self-Determined; Profile 4 = Strongly Motivated

Table S5

Supplementary Results Regarding Possible Associations between Demographics and Profile Membership.

Model	LL	#fp	Scaling	CAIC	BIC	ABIC
Profile-Specific Free Relations with Pred.	-694.657	105	.3068	2132.707	2027.707	1694.491
Free Relations with Predictors	-740.698	45	1.1973	1799.993	1754.993	1612.186
Equal Relations with Predictors	-747.684	30	.9561	1707.766	1677.766	1582.561
Null Effects Model	-765.498	15	.9333	1637.195	1622.195	1574.593

Note. LL = Model LogLikelihood; #fp = Number of free parameters; Scaling = scaling factor; AIC = Akaïke Information Criteria; CAIC = Consistant AIC; BIC = Bayesian Information Criteria; ABIC = Sample-Size adjusted BIC.

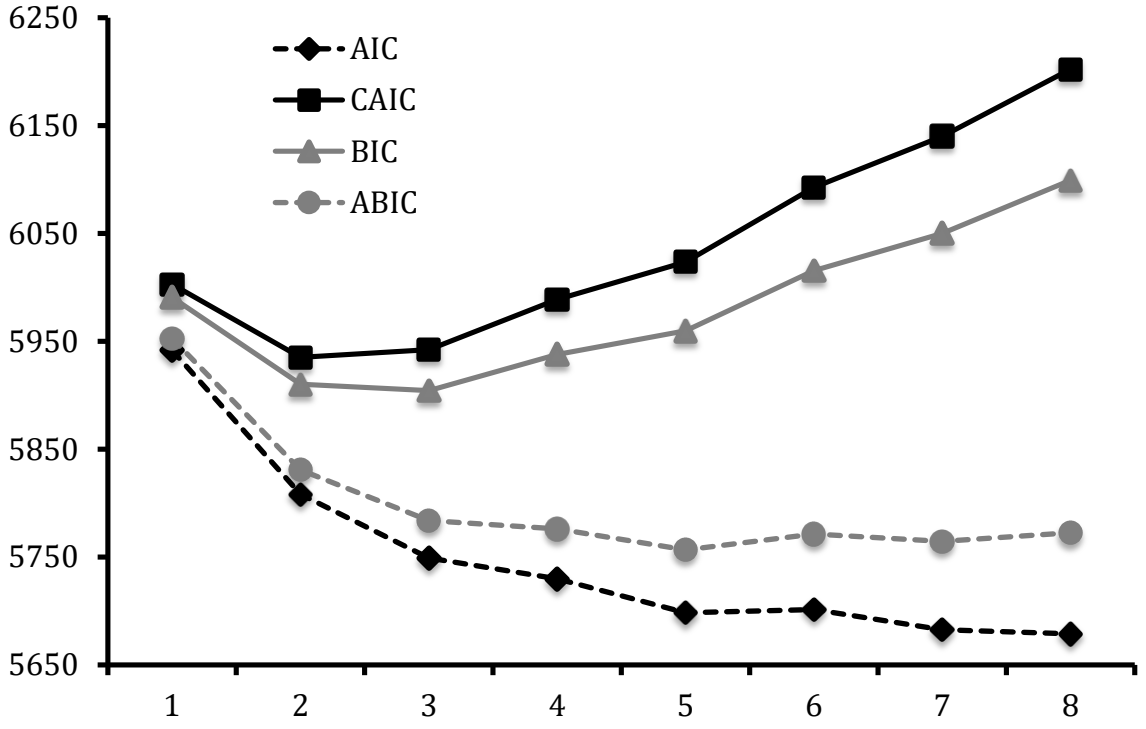

Figure S1. Elbow Plot of the Information Criteria for the Latent Profile Analyses (Time 1).

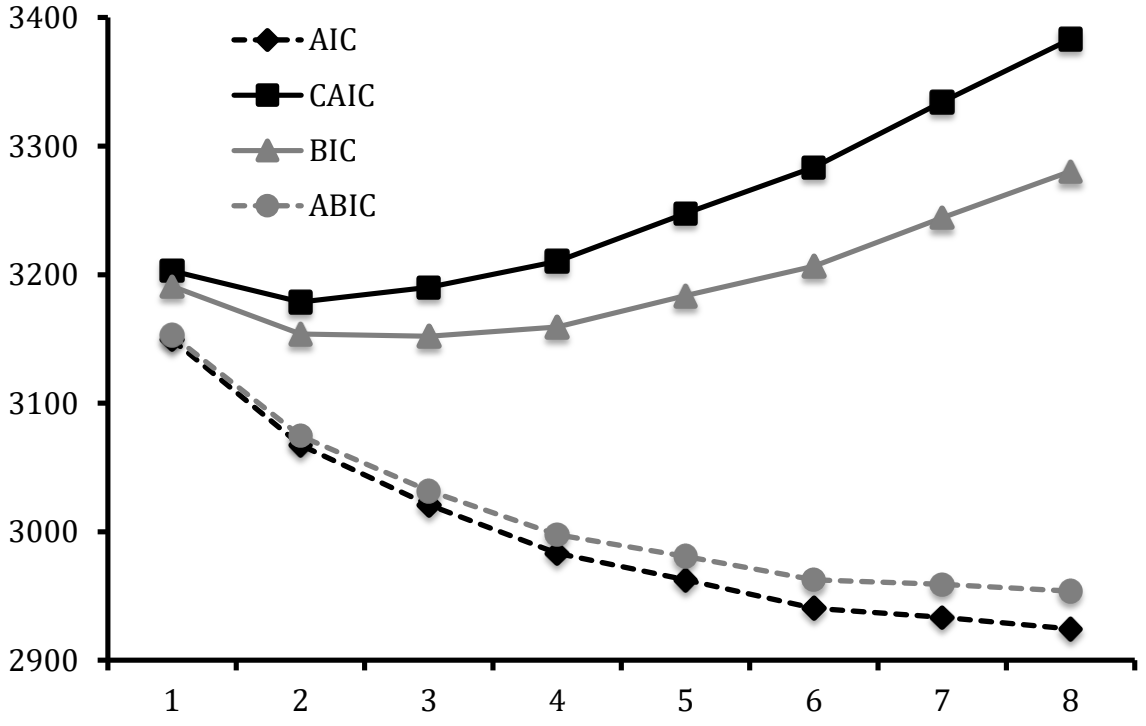

Figure S2. Elbow Plot of the Information Criteria for the Latent Profile Analyses (Time 2).

Mplus Input to Estimate a 4-Profile Latent Profile Analysis (Time 1)

```
! In all input files, statements preceded by "!" are annotations.
! Use the following statement to identify the data set. Here, the data set is labelled Data.dat.
DATA:
FILE IS Data.dat;
! The variables names function identifies all variables in the data set, in order of appearance,
! whereas the usevariable command identifies the variables used in the analysis.
NAMES = Expet_1 ID Age_1 Sexe_1 Exp_1 Mi1_1 Mi2_1 Mi3_1 Id1_1 Id2_1 Id3_1 Ij_ap1_1
Ij_ap2_1 Ij_av1_1 Ij_av2_1 Ex_sa1_1 Ex_sa2_1 Ex_sa3_1 Ex_ma1_1 Ex_ma2_1 Ex_ma3_1 Am1_1
Am2_1 Am3_1 Dcog1_1 Dcog2_1 Dcog3_1 Dcog4_1 Demo1_1 Demo2_1 Demo3_1 Demo4_1
Dphy1_1 Dphy2_1 Dphy3_1 Dphy4_1 Remo1_1 Remo2_1 Remo3_1 Remo4_1 Rphy1_1 Rphy2_1
Rphy3_1 Rphy4_1 Rcog1_1 Rcog2_1 Rcog3_1 Rcog4_1 Mi1_2 Mi2_2 Mi3_2 Id1_2 Id2_2 Id3_2
Ij_ap1_2  Ij_ap2_2 Ij_av1_2 Ij_av2_2 Ex_sa1_2 Ex_sa2_2 Ex_sa3_2 Ex_ma1_2 Ex_ma2_2
Ex_ma3_2 Am1_2 Am2_2 Am3_2 Ee1_2 Ee2_2 Ee3_2 Ee4_2 Ee5_2 Ipe1_2 Ipe2_2 Ipe3_2 Ipe4_2
Iq1_2 Iq4_2 Iq6_2 Iq3_2 Iq5_2 Iq7_2 SDT_1 mint_1 mide_1 mroj_1 mext_1 amot_1 SDT_2 mint_2
mide_2 mroj_2 mext_2 amot_2;
USEVARIABLES = SDT_1 mint_1 mide_1 mroj_1 mext_1 amot_1;
! Missing data are identified with the following (the same code * is used for all missing).
MISSING ARE ALL *;
! The following identifies the unique identifier for participants
IDVARIABLE = ID;
! The following identifies the number of latent profiles requested in the analysis.
CLASSES = c (4);
ANALYSIS:
! The following identifies that mixture modeling is requested.
type = mixture; estimator = MLR;
! The following set up is to estimate the model using 3 processors, 3000 starts values, 100 final stage
optimizations, and 100 iterations.
Process = 3;
STARTS = 3000 100; STITERATIONs = 100;
! In this input, the overall model statement defines sections that are common across profiles.
! Here, there is no need to include anything in this section.
! The %c#1% to %c#4% sections are class-specific statement to specify which part of the
! model is freely estimated in each profile.
! For a simple latent profile model, include only the means of the indicators (using []) in all profiles.
! To also freely estimate all variances, as in this study, the following is added in each class-specific
! statement: SDT_1 mint_1 mide_1 mroj_1 mext_1 amot_1
MODEL:
%OVERALL%
%c#1%
[SDT_1 mint_1 mide_1 mroj_1 mext_1 amot_1];
SDT_1 mint_1 mide_1 mroj_1 mext_1 amot_1;
%c#2%
[SDT_1 mint_1 mide_1 mroj_1 mext_1 amot_1];
SDT_1 mint_1 mide_1 mroj_1 mext_1 amot_1;
%c#3%
[SDT_1 mint_1 mide_1 mroj_1 mext_1 amot_1];
SDT_1 mint_1 mide_1 mroj_1 mext_1 amot_1;
%c#4%
[SDT_1 mint_1 mide_1 mroj_1 mext_1 amot_1];
SDT_1 mint_1 mide_1 mroj_1 mext_1 amot_1;
! Specific sections of output are requested. TECH11 estimates LMR, and TECH14 estimates BLRT.
OUTPUT:
STDYX SAMPSTAT CINTERVAL MODINDICES (10) SVALUES
RESIDUAL TECH1 TECH7 TECH11 TECH13 TECH14;
```

Mplus Input to Estimate a Configural Similarity Model for a Longitudinal Latent Profile Analysis

```
! Annotations only focus on functions not previously defined.
[…]
USEVARIABLES =
SDT_1 mint_1 mide_1 mroj_1 mext_1 amot_1 SDT_2 mint_2 mide_2 mroj_2 mext_2 amot_2;
! The following identifies the number of latent profiles (4) requested in the analysis
! One latent profile variable (c1, c2) is required for each specific time wave.
CLASSES = c1 (4) c2 (4);
Analysis:
type = mixture;
estimator = MLR;
Process = 3;
STARTS = 10000 500;
STITERATIONs = 1000;
! In this input, subsections corresponding to the various latent profile variables (one per time waves;
! MODEL C1 to C2).
! The labels in parentheses are used to impose equality constraints on parameters (parameters
! with the same labels are constrained to invariance). Here, no invariance constraint is added.
MODEL:
%OVERALL%
MODEL C1:
%c1#1%
[SDT_1 mint_1 mide_1 mroj_1 mext_1 amot_1](ma1-ma6);
SDT_1 mint_1 mide_1 mroj_1 mext_1 amot_1(va1-va6);
%c1#2%
[SDT_1 mint_1 mide_1 mroj_1 mext_1 amot_1](ma7-ma12);
SDT_1 mint_1 mide_1 mroj_1 mext_1 amot_1(va7-va12);
%c1#3%
[SDT_1 mint_1 mide_1 mroj_1 mext_1 amot_1](ma13-ma18);
SDT_1 mint_1 mide_1 mroj_1 mext_1 amot_1(va13-va18);
%c1#4%
[SDT_1 mint_1 mide_1 mroj_1 mext_1 amot_1](ma19-ma24);
SDT_1 mint_1 mide_1 mroj_1 mext_1 amot_1(va19-va24);
MODEL C2:
%c2#1%
[SDT_2 mint_2 mide_2 mroj_2 mext_2 amot_2](mb1-mb6);
SDT_2 mint_2 mide_2 mroj_2 mext_2 amot_2(vb1-vb6);
%c2#2%
[SDT_2 mint_2 mide_2 mroj_2 mext_2 amot_2](mb7-mb12);
SDT_2 mint_2 mide_2 mroj_2 mext_2 amot_2(vb7-vb12);
%c2#3%
[SDT_2 mint_2 mide_2 mroj_2 mext_2 amot_2](mb13-mb18);
SDT_2 mint_2 mide_2 mroj_2 mext_2 amot_2(vb13-vb18);
%c2#4%
[SDT_2 mint_2 mide_2 mroj_2 mext_2 amot_2](mb19-mb24);
SDT_2 mint_2 mide_2 mroj_2 mext_2 amot_2(vb19-vb24);

[…]
```

Mplus Input to Estimate a Structural Similarity Model for a Longitudinal Latent Profile Analysis

```
! Annotations only focus on functions not previously defined.
[…]
! Labels in bold indicate newly imposed invariance constraints on means across time waves.
MODEL:
%OVERALL%
MODEL C1:
%c1#1%
[SDT_1 mint_1 mide_1 mroj_1 mext_1 amot_1](ma1-ma6);
SDT_1 mint_1 mide_1 mroj_1 mext_1 amot_1(va1-va6);
%c1#2%
[SDT_1 mint_1 mide_1 mroj_1 mext_1 amot_1](ma7-ma12);
SDT_1 mint_1 mide_1 mroj_1 mext_1 amot_1(va7-va12);
%c1#3%
[SDT_1 mint_1 mide_1 mroj_1 mext_1 amot_1](ma13-ma18);
SDT_1 mint_1 mide_1 mroj_1 mext_1 amot_1(va13-va18);
%c1#4%
[SDT_1 mint_1 mide_1 mroj_1 mext_1 amot_1](ma19-ma24);
SDT_1 mint_1 mide_1 mroj_1 mext_1 amot_1(va19-va24);

MODEL C2:
%c2#1%
[SDT_2 mint_2 mide_2 mroj_2 mext_2 amot_2](ma1-ma6);
SDT_2 mint_2 mide_2 mroj_2 mext_2 amot_2(vb1-vb6);
%c2#2%
[SDT_2 mint_2 mide_2 mroj_2 mext_2 amot_2](ma7-ma12);
SDT_2 mint_2 mide_2 mroj_2 mext_2 amot_2(vb7-vb12);
%c2#3%
[SDT_2 mint_2 mide_2 mroj_2 mext_2 amot_2](ma13-ma18);
SDT_2 mint_2 mide_2 mroj_2 mext_2 amot_2(vb13-vb18);
%c2#4%
[SDT_2 mint_2 mide_2 mroj_2 mext_2 amot_2](ma19-ma24);
SDT_2 mint_2 mide_2 mroj_2 mext_2 amot_2(vb19-vb24);

[…]
```

Mplus Input to Estimate a Dispersion Similarity Model for a Longitudinal Latent Profile Analysis

```
! Annotations only focus on functions not previously defined.
[…]
! Labels in bold indicate newly imposed invariance constraints on variances across time waves.
MODEL:
%OVERALL%
MODEL C1:
%c1#1%
[SDT_1 mint_1 mide_1 mroj_1 mext_1 amot_1](ma1-ma6);
SDT_1 mint_1 mide_1 mroj_1 mext_1 amot_1(va1-va6);
%c1#2%
[SDT_1 mint_1 mide_1 mroj_1 mext_1 amot_1](ma7-ma12);
SDT_1 mint_1 mide_1 mroj_1 mext_1 amot_1(va7-va12);
%c1#3%
[SDT_1 mint_1 mide_1 mroj_1 mext_1 amot_1](ma13-ma18);
SDT_1 mint_1 mide_1 mroj_1 mext_1 amot_1(va13-va18);
%c1#4%
[SDT_1 mint_1 mide_1 mroj_1 mext_1 amot_1](ma19-ma24);
SDT_1 mint_1 mide_1 mroj_1 mext_1 amot_1(va19-va24);

MODEL C2:
%c2#1%
[SDT_2 mint_2 mide_2 mroj_2 mext_2 amot_2](ma1-ma6);
SDT_2 mint_2 mide_2 mroj_2 mext_2 amot_2(va1-va6);
%c2#2%
[SDT_2 mint_2 mide_2 mroj_2 mext_2 amot_2](ma7-ma12);
SDT_2 mint_2 mide_2 mroj_2 mext_2 amot_2(va7-va12);
%c2#3%
[SDT_2 mint_2 mide_2 mroj_2 mext_2 amot_2](ma13-ma18);
SDT_2 mint_2 mide_2 mroj_2 mext_2 amot_2(va13-va18);
%c2#4%
[SDT_2 mint_2 mide_2 mroj_2 mext_2 amot_2](ma19-ma24);
SDT_2 mint_2 mide_2 mroj_2 mext_2 amot_2(va19-va24);

[…]
```

Mplus Input to Estimate a Distribution Similarity Model for a Longitudinal Latent Profile Analysis

```
! Annotations only focus on functions not previously defined.
[…]
! The additions in bold (in %Overall%) constrain class sizes to be invariant across time waves.
! c1, c2 refer to the various latent profile variables (for each time waves), whereas #1, #2, #3
! refer to the specific profile in this model. One less statement than the number of profiles is needed.
MODEL:
%OVERALL%
[c1#1] (p1); [c1#2] (p2); [c1#3] (p3);
[c2#1] (p1); [c2#2] (p2); [c2#3] (p3);
MODEL C1:
%c1#1%
[SDT_1 mint_1 mide_1 mroj_1 mext_1 amot_1](ma1-ma6);
SDT_1 mint_1 mide_1 mroj_1 mext_1 amot_1(va1-va6);
%c1#2%
[SDT_1 mint_1 mide_1 mroj_1 mext_1 amot_1](ma7-ma12);
SDT_1 mint_1 mide_1 mroj_1 mext_1 amot_1(va7-va12);
%c1#3%
[SDT_1 mint_1 mide_1 mroj_1 mext_1 amot_1](ma13-ma18);
SDT_1 mint_1 mide_1 mroj_1 mext_1 amot_1(va13-va18);
%c1#4%
[SDT_1 mint_1 mide_1 mroj_1 mext_1 amot_1](ma19-ma24);
SDT_1 mint_1 mide_1 mroj_1 mext_1 amot_1(va19-va24);
MODEL C2:
%c2#1%
[SDT_2 mint_2 mide_2 mroj_2 mext_2 amot_2](ma1-ma6);
SDT_2 mint_2 mide_2 mroj_2 mext_2 amot_2(va1-va6);
%c2#2%
[SDT_2 mint_2 mide_2 mroj_2 mext_2 amot_2](ma7-ma12);
SDT_2 mint_2 mide_2 mroj_2 mext_2 amot_2(va7-va12);
%c2#3%
[SDT_2 mint_2 mide_2 mroj_2 mext_2 amot_2](ma13-ma18);
SDT_2 mint_2 mide_2 mroj_2 mext_2 amot_2(va13-va18);
%c2#4%
[SDT_2 mint_2 mide_2 mroj_2 mext_2 amot_2](ma19-ma24);
SDT_2 mint_2 mide_2 mroj_2 mext_2 amot_2(va19-va24);

[…]
```

Mplus Input to Build the Manual 3-Step Approach

In this study, the distribution similarity of the model was supported, forcing us to adopt a manual 3-step approach to estimate a latent transition model in which the profiles followed these distributional similarity assumptions (as described in Morin & Litalien, 2017) and further tests of Predictive (predictors) and Explanatory (outcomes) similarity.

Essentially, this approach consists of assigning participants to their most likely profile, while taking into account the probability that each participant has of being a member of each latent profile in the estimation of the model. To achieve this, the approach relies on the exact parameter estimates obtained from the most invariant model from the preceding sequence (here Distributional Similarity). These parameter estimates can be obtained, ready to cut and paste in a new input, while using the SVALUE function of the OUTPUT statement.

Using these exact values (these would need to be fixed with @, rather than used as start values with *), one model is estimated separately for each time point and used to export the class membership information to an external data file. Asparouhov and Muthén (2014) further describe a process using the Auxiliary function through which the variables required for further analyses can be directly exported to this external data file, which can then be automatically used in further analyses. However, doing so poses problem in longitudinal analyses with missing data as the time-specific models will only be estimated using participants who completed the specific time point, so that the final data set will automatically use listwise deletion of participants who have not completed both measurement point. Our recommendation is thus to use your preferred data management package (e.g., SPSS, EXCEL) to combine the saved class membership information into the complete data set.

In these analyses, and all further analyses, the random start function is set to 0, to ensure that the model converges on the same solution as retained before.

Asparouhov, T. & Muthén, B. (2014). Auxiliary variables in mixture modeling: Three-step approaches using Mplus. *Structural Equation Modeling, 21*, 329-341. For the appendices, see: https://www.statmodel.com/download/AppendicesOct28.pdf

Morin, A.J.S., & Litalien, D. (2017). Webnote: Longitudinal tests of profile similarity and latent transition analyses. Montreal, QC: Substantive Methodological Synergy Research Laboratory. http://smslabstats.weebly.com/uploads/1/0/0/6/100647486/lta_distributional_similarity_v02.pdf

```
! Annotations only focus on functions not previously defined.
! This is a model estimated only for Time 1 data, using the SVALUES from the model of Distributional
! Similarity and replacing * by @.
CLASSES = c1 (4);
! The random start function is turned off.
Analysis:
TYPE = MIXTURE ;
ESTIMATOR = MLR;
process = 3;
STARTS = 0;

MODEL:
%OVERALL%
[ c1#1@1.97929 ] (p1);    [ c1#2@1.90202 ] (p2);    [ c1#3@1.21559 ] (p3);

%C1#1%
[ sdt_1@0.24577 ] (ma1);    [ mint_1@-0.13567 ] (ma2);    [ mide_1@0.00157 ] (ma3);
[ mroj_1@-0.02464 ] (ma4);    [ mext_1@0.02397 ] (ma5);    [ amot_1@-0.02769 ] (ma6);
sdt_1@0.43624 (va1);    mint_1@0.46535 (va2);    mide_1@0.28164 (va3);
mroj_1@0.61924 (va4);    mext_1@0.50610 (va5);    amot_1@0.04785 (va6);
%C1#2%
[ sdt_1@-0.56955 ] (ma7);    [ mint_1@0.04067 ] (ma8);    [ mide_1@-0.10648 ] (ma9);
mroj_1@0.09986 ] (ma10);    [ mext_1@0.23394 ] (ma11);    [ amot_1@0.49414 ] (ma12);
sdt_1@0.70419 (va7);    mint_1@0.37103 (va8);    mide_1@0.42634 (va9);
```

```
mroj_1@0.64892 (va10);     mext_1@0.73979 (va11);     amot_1@0.56922 (va12);
%C1#3%
[ sdt_1@0.04677 ] (ma13);     [ mint_1@0.32922 ] (ma14);     [ mide_1@0.07851 ] (ma15);
[ mroj_1@-0.37371 ] (ma16);     [ mext_1@-0.71937 ] (ma17);     [ amot_1@-0.47014 ] (ma18);
sdt_1@0.83764 (va13);     mint_1@0.57841 (va14);     mide_1@0.44538 (va15);
mroj_1@0.86255 (va16);     mext_1@0.39278 (va17);     amot_1@0.05531 (va18);
%C1#4%
[ sdt_1@1.56381 ] (ma19);     [ mint_1@-0.06015 ] (ma20);     [ mide_1@0.56694 ] (ma21);
[ mroj_1@0.62855 ] (ma22);     [ mext_1@0.50931 ] (ma23);     [ amot_1@0.14626 ] (ma24);
sdt_1@0.07316 (va19);     mint_1@0.30576 (va20);     mide_1@0.00921 (va21);
mroj_1@0.89544 (va22);     mext_1@0.56651 (va23);     amot_1@0.06591 (va24);

! The SAVEDATA function is used to export the class membership information to an external data file,
! that is labelled C1.dat here.
SAVEDATA: file=c1.dat; save=cprob;
```

The end of the output file will indicate the name, and order, of the variables that are saved into C1.dat.

```
SAVEDATA INFORMATION
  Save file
    c1.dat
  Order and format of variables
    SDT_1          F10.3
    MINT_1         F10.3
[…]
    CPROB1         F10.3
    CPROB2         F10.3
    CPROB3         F10.3
    CPROB4         F10.3
    C1             F10.3
```

The variable C1 refers to the most likely class membership of each participant. This is the variable that needs to be brought back into the main data file, where it is relabelled N1 to avoid confusion with the way Mplus labels latent profiles. The same process is then repeated for Time 2 (and all other time points, whenever necessary). Using this information (N1 and N2), it then becomes possible to build an input file that will automatically, and systematically, result in the same classification of participants, while taking into account the class probabilities. More precisely, these variables are used directly in the model estimation process to force the assignment of participants into each profile.

Before doing so, however, we need further information from the outputs associated with the constrained estimations of the Time 1 and Time 2 models. Just before the MODEL RESULTS section, at the end of the MODEL FIT INFORMATION section, there is a Table of logits:

Logits for the Classification Probabilities for the Most Likely Latent Class Membership (Column) by Latent Class (Row)

	1	2	3	4
1	4.130	1.898	1.335	0.000
2	5.057	6.630	3.842	0.000
3	3.569	2.533	4.911	0.000
4	-3.685	-4.454	-4.207	0.000

These logits (as well as those obtained for Time 2) reflect the class probabilities of assignments of the participants into the various profiles and are used in the input to “correct” the class assignment of the participants into each profile while taking into account their probability of membership into the other profiles. This process is akin to modeling class assignment while controlling for the imprecise nature of this assignment, a process akin to controlling for measurement errors.

On next page is the input used to provide an exact replication of the model of Distributional Similarity.

```
! The only variables that need to be used are N1 and N2, which are nominal in nature and reflect the
! most likely profile membership of each participant at each time point.
! Then, in the class-specific statement, this membership is "corrected" using the logit values (@).
USEVARIABLES =  N1 N2 ;
nominal = N1 N2;
missing are all *;
IDVARIABLE = ID;
CLASSES = C1 (4) c2 (4);
Analysis:
TYPE = MIXTURE ; ESTIMATOR = MLR; process = 3;
STARTS = 0;
MODEL:
%OVERALL%
Model C1:
%c1#1%
[n1#1@4.130]; [n1#2@1.898]; [n1#3@1.335];
%c1#2%
[n1#1@5.057]; [n1#2@6.630]; [n1#3@3.842];
%c1#3%
[n1#1@3.569]; [n1#2@2.533]; [n1#3@4.911];
%c1#4%
[n1#1@-3.685]; [n1#2@-4.454]; [n1#3@-4.207];

MODEL c2:
%c2#1%
[n2#1@4.034]; [n2#2@1.289]; [n2#3@1.336];
%c2#2%
[n2#1@4.197]; [n2#2@5.536]; [n2#3@3.090];
%c2#3%
[n2#1@4.407]; [n2#2@3.076]; [n2#3@6.047];
%c2#4%
[n2#1@-3.951]; [n2#2@-13.795]; [n2#3@-6.413];
```

This model is then converted to a Latent Transition Analysis, and used to incorporate predictors and outcomes, as shown in the following sections.

Mplus Input to Estimate a Latent Transition Analysis Build from a Longitudinal Model of Distributional Similarity Using the 3-Step Approach.

```
! Annotations only focus on functions not previously defined.
MODEL:
%OVERALL%
! The following statement is used to convert a longitudinal LPA into a LTA providing a
! direct estimate of participants' longitudinal transitions across profiles.
C2 ON C1;

Model C1:
%c1#1%
[n1#1@4.130]; [n1#2@1.898]; [n1#3@1.335];
%c1#2%
[n1#1@5.057]; [n1#2@6.630]; [n1#3@3.842];
%c1#3%
[n1#1@3.569]; [n1#2@2.533]; [n1#3@4.911];
%c1#4%
[n1#1@-3.685]; [n1#2@-4.454]; [n1#3@-4.207];

MODEL c2:
%c2#1%
[n2#1@4.034]; [n2#2@1.289]; [n2#3@1.336];
%c2#2%
[n2#1@4.197]; [n2#2@5.536]; [n2#3@3.090];
%c2#3%
[n2#1@4.407]; [n2#2@3.076]; [n2#3@6.047];
%c2#4%
[n2#1@-3.951]; [n2#2@-13.795]; [n2#3@-6.413];
```

Mplus Input to Estimate a Latent Transition Analysis with Effects of Predictors Freely Estimated Across Time Points and Time 1 Profiles

```
! Annotations only focus on functions not previously defined.
! Predictors are added to the USEVARIABLES list.
[…]
USEVARIABLES = N1 N2 DEM1 RESS1 DEM3 RESS3;
[…]
MODEL:
%OVERALL%
C2 ON C1;
! The following statements indicate that class membership at each specific time wave is predicted by
! the predictors. The prediction of C2 is also allowed to be profile specific.
C1 ON DEM1 RESS1;
C2 ON DEM3 RESS3;
Model C1:
%c1#1%
[n1#1@4.130]; [n1#2@1.898]; [n1#3@1.335];
C2 ON DEM3 RESS3;
%c1#2%
[n1#1@5.057]; [n1#2@6.630]; [n1#3@3.842];
C2 ON DEM3 RESS3;
%c1#3%
[n1#1@3.569]; [n1#2@2.533]; [n1#3@4.911];
C2 ON DEM3 RESS3;
%c1#4%
[n1#1@-3.685]; [n1#2@-4.454]; [n1#3@-4.207];
C2 ON DEM3 RESS3;
MODEL c2:
%c2#1%
[n2#1@4.034]; [n2#2@1.289]; [n2#3@1.336];
%c2#2%
[n2#1@4.197]; [n2#2@5.536]; [n2#3@3.090];
%c2#3%
[n2#1@4.407]; [n2#2@3.076]; [n2#3@6.047];
%c2#4%
[n2#1@-3.951]; [n2#2@-13.795]; [n2#3@-6.413];
```

Mplus Input to Estimate a Latent Transition Analysis with Effects of Predictors Freely Estimated Across Time Points.

```
! Annotations only focus on functions not previously defined.
 […]
MODEL:
%OVERALL%
C2 ON C1;
! The following statements indicate that class membership at each specific time wave is predicted by
! the predictors.
C1 ON DEM1 RESS1;
C2 ON DEM3 RESS3;
Model C1:
%c1#1%
[n1#1@4.130]; [n1#2@1.898]; [n1#3@1.335];
%c1#2%
[n1#1@5.057]; [n1#2@6.630]; [n1#3@3.842];
%c1#3%
[n1#1@3.569]; [n1#2@2.533]; [n1#3@4.911];
%c1#4%
[n1#1@-3.685]; [n1#2@-4.454]; [n1#3@-4.207];

MODEL c2:
%c2#1%
[n2#1@4.034]; [n2#2@1.289]; [n2#3@1.336];
%c2#2%
[n2#1@4.197]; [n2#2@5.536]; [n2#3@3.090];
%c2#3%
[n2#1@4.407]; [n2#2@3.076]; [n2#3@6.047];
%c2#4%
[n2#1@-3.951]; [n2#2@-13.795]; [n2#3@-6.413];
```

Mplus Input to Estimate a Latent Transition Analysis with Predictive Similarity.

```
! Annotations only focus on functions not previously defined.
[…]
MODEL:
%OVERALL%
C2 ON C1;
! The following statements constrain the predictions to be equal across time waves (one less label
! than profiles)
C1 ON DEM1(de1-de3);
C1 ON RESS1(re1-re3);
C2 ON DEM3(de1-de3);
C2 ON RESS3(re1-re3);
Model C1:
%c1#1%
[n1#1@4.130]; [n1#2@1.898]; [n1#3@1.335];
%c1#2%
[n1#1@5.057]; [n1#2@6.630]; [n1#3@3.842];
%c1#3%
[n1#1@3.569]; [n1#2@2.533]; [n1#3@4.911];
%c1#4%
[n1#1@-3.685]; [n1#2@-4.454]; [n1#3@-4.207];

MODEL c2:
%c2#1%
[n2#1@4.034]; [n2#2@1.289]; [n2#3@1.336];
%c2#2%
[n2#1@4.197]; [n2#2@5.536]; [n2#3@3.090];
%c2#3%
[n2#1@4.407]; [n2#2@3.076]; [n2#3@6.047];
%c2#4%
[n2#1@-3.951]; [n2#2@-13.795]; [n2#3@-6.413];
```

Mplus Input to Estimate a Latent Transition Analysis with Outcomes Levels Freely Estimated Across Time Points

```
! Annotations only focus on functions not previously defined. Outcomes added to USEVARIABLES list.
USEVARIABLES =  N1 N2 EE1 IPE1 INTETA1 INTPROF1 EE3 IPE3 INTETA3 INTPROF3;
[…]
! The additions in bold request the free estimation of the outcomes levels in each profile
MODEL:
%OVERALL%
C2 ON C1;
Model C1:
%c1#1%
[n1#1@4.130]; [n1#2@1.898]; [n1#3@1.335];
 [EE1] (o1p1t1);[IPE1] (o2p1t1) ; [INTETA1] (o3p1t1);[INTPROF1] (o4p1t1);
%c1#2%
[n1#1@5.057]; [n1#2@6.630]; [n1#3@3.842];
 [EE1] (o1p2t1);[IPE1] (o2p2t1) ; [INTETA1] (o3p2t1);[INTPROF1] (o4p2t1);
%c1#3%
[n1#1@3.569]; [n1#2@2.533]; [n1#3@4.911];
 [EE1] (o1p3t1);[IPE1] (o2p3t1) ; [INTETA1] (o3p3t1);[INTPROF1] (o4p3t1);
%c1#4%
[n1#1@-3.685]; [n1#2@-4.454]; [n1#3@-4.207];
 [EE1] (o1p4t1);[IPE1] (o2p4t1) ; [INTETA1] (o3p4t1);[INTPROF1] (o4p4t1);
MODEL c2:
%c2#1%
[n2#1@4.034]; [n2#2@1.289]; [n2#3@1.336];
 [EE3] (o1p1t2);[IPE3] (o2p1t2) ; [INTETA3] (o3p1t2);[INTPROF3] (o4p1t2);
%c2#2%
[n2#1@4.197]; [n2#2@5.536]; [n2#3@3.090];
 [EE3] (o1p2t2);[IPE3] (o2p2t2) ; [INTETA3] (o3p2t2);[INTPROF3] (o4p2t2);
%c2#3%
[n2#1@4.407]; [n2#2@3.076]; [n2#3@6.047];
 [EE3] (o1p3t2);[IPE3] (o2p3t2) ; [INTETA3] (o3p3t2);[INTPROF3] (o4p3t2);
%c2#4%
[n2#1@-3.951]; [n2#2@-13.795]; [n2#3@-6.413];
 [EE3] (o1p4t2);[IPE3] (o2p4t2) ;[INTETA3] (o3p4t2);[INTPROF3] (o4p4t2);
```

Mplus Input to Estimate an a Latent Transition Analysis with Explanatory Similarity

```
! Annotations only focus on functions not previously defined.
! The additions in bold constrain outcome levels to be invariant across time waves.
[…]
MODEL:
%OVERALL%
C2 ON C1;
Model C1:
%c1#1%
[n1#1@4.130]; [n1#2@1.898]; [n1#3@1.335];
 [EE1] (o1p1t1);[IPE1] (o2p1t1) ;[INTETA1] (o3p1t1);[INTPROF1] (o4p1t1);
%c1#2%
[n1#1@5.057]; [n1#2@6.630]; [n1#3@3.842];
 [EE1] (o1p2t1);[IPE1] (o2p2t1) ;[INTETA1] (o3p2t1);[INTPROF1] (o4p2t1);
%c1#3%
[n1#1@3.569]; [n1#2@2.533]; [n1#3@4.911];
 [EE1] (o1p3t1);[IPE1] (o2p3t1) ;[INTETA1] (o3p3t1);[INTPROF1] (o4p3t1);
%c1#4%
[n1#1@-3.685]; [n1#2@-4.454]; [n1#3@-4.207];
 [EE1] (o1p4t1);[IPE1] (o2p4t1) ;[INTETA1] (o3p4t1);[INTPROF1] (o4p4t1);
MODEL c2:
%c2#1%
[n2#1@4.034]; [n2#2@1.289]; [n2#3@1.336];
 [EE3] (o1p1t1);[IPE3] (o2p1t1) ;[INTETA3] (o3p1t1);[INTPROF3] (o4p1t1);
%c2#2%
[n2#1@4.197]; [n2#2@5.536]; [n2#3@3.090];
 [EE3] (o1p2t1);[IPE3] (o2p2t1) ;[INTETA3] (o3p2t1);[INTPROF3] (o4p2t1);
%c2#3%
[n2#1@4.407]; [n2#2@3.076]; [n2#3@6.047];
 [EE3] (o1p3t1);[IPE3] (o2p3t1) ;[INTETA3] (o3p3t1);[INTPROF3] (o4p3t1);
%c2#4%
[n2#1@-3.951]; [n2#2@-13.795]; [n2#3@-6.413];
 [EE3] (o1p4t1);[IPE3] (o2p4t1) ;[INTETA3] (o3p4t1);[INTPROF3] (o4p4t1);
! The model constraint function uses the labels used with the outcomes to request mean level
! comparisons on the outcomes across profiles.
MODEL CONSTRAINT:
NEW (o1p1p2); o1p1p2 = o1p1t1 - o1p2t1;
NEW (o1p1p3); o1p1p3 = o1p1t1 - o1p3t1;
NEW (o1p1p4); o1p1p4 = o1p1t1 - o1p4t1;
NEW (o1p2p3); o1p2p3 = o1p2t1 - o1p3t1;
NEW (o1p2p4); o1p2p4 = o1p2t1 - o1p4t1;
NEW (o1p3p4); o1p3p4 = o1p3t1 - o1p4t1;
NEW (o2p1p2); o2p1p2 = o2p1t1 - o2p2t1;
NEW (o2p1p3);o2p1p3 = o2p1t1 - o2p3t1;
NEW (o2p1p4);o2p1p4 = o2p1t1 - o2p4t1;
NEW (o2p2p3);o2p2p3 = o2p2t1 - o2p3t1;
NEW (o2p2p4);o2p2p4 = o2p2t1 - o2p4t1;
NEW (o2p3p4); o2p3p4 = o2p3t1 - o2p4t1;
NEW (o3p1p2); o3p1p2 = o3p1t1 - o3p2t1;
NEW (o3p1p3);o3p1p3 = o3p1t1 - o3p3t1;
NEW (o3p1p4);o3p1p4 = o3p1t1 - o3p4t1;
NEW (o3p2p3);o3p2p3 = o3p2t1 - o3p3t1;
NEW (o3p2p4);o3p2p4 = o3p2t1 - o3p4t1;
NEW (o3p3p4); o3p3p4 = o3p3t1 - o3p4t1;
NEW (o4p1p2); o4p1p2 = o4p1t1 - o4p2t1;
```

```
NEW (o4p1p3);o4p1p3 = o4p1t1 - o4p3t1;
NEW (o4p1p4);o4p1p4 = o4p1t1 - o4p4t1;
NEW (o4p2p3);o4p2p3 = o4p2t1 - o4p3t1;
NEW (o4p2p4);o4p2p4 = o4p2t1 - o4p4t1;
NEW (o4p3p4); o4p3p4 = o4p3t1 - o4p4t1;
```