Self-Determination Trajectories at Work: A Growth Mixture Analysis

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Abstract

The many theoretical and empirical studies of work motivation to date have not fully clarified how it develops and evolves over time. We therefore investigated profiles of employees to identify their self-determination trajectories, and we examined differences among these profiles with respect to diverse predictors and outcomes. We gathered data (at 0, 6, 12, and 24 months over a two-year period) from a sample of 660 nurses employed in public health care establishments. Longitudinal growth mixture analyses (GMA) revealed three distinct trajectory profiles, characterized by Increasing, Slightly Decreasing, and Decreasing global levels of self-determination at work. Importantly, when employees perceived supervisors' transformational leadership behaviors and task-level socialization more positively, they were more likely to belong to the Increasing profile. Moreover, higher levels of affective commitment to the occupation and the organization and lower levels of intentions to leave the occupation and the organization were also associated with the Increasing profile.

Keywords: work motivation, self-determination theory, leadership, socialization, commitment, turnover intentions, growth mixture analysis

Organizational scientists and practitioners share a keen interest in understanding employee motivation, which has been defined as the "energetic forces that initiate work-related behavior and determine its form, direction, intensity, and duration" (Pinder, 2008, p. 11). The concern is to get a better handle on how workers' efforts translate into benefits for both employees (e.g., growth, development, and well-being) and the organization (e.g., commitment, retention, and performance). However, and despite tremendous research into the nature of motivation as well as its antecedents and outcomes, scant empirical research exists on how motivation develops over time. This is a significant limitation, given that, across definitions and operationalizations, motivation is systematically viewed as a process that develops and evolves over time. Yet most studies have focused on theoretical antecedents and consequences of static motivational states captured at a specific point in time. Although this approach is useful for determining why certain types of motivation are distinctly associated with specific covariates, such as workplace commitment, job satisfaction, or work performance (Deci, Olafsen, & Ryan, 2017; Gagné & Deci, 2005), it has limitations for explaining how motivation develops, persists, and fades out. Unfortunately, research has relied heavily on designs that preclude considering how motivation unfolds over time and how this development differs across subgroups of employees. To provide theoretical and empirical answers to this question, we build on recent developments in self-determination theory (SDT; Ryan & Deci, 2017) and longitudinal person-centered analyses to examine the development of distinct trajectories of self-determined motivation.

The present study offers three key contributions to research on work motivation. First, it responds to recent calls to examine the complex motivational processes known to drive employees (Fernet et al., 2020; Gillet, Fouquereau, Vallerand, Abraham, & Colombat, 2018; Graves, Cullen, Lester, Ruderman, & Gentry, 2015; Howard, Gagné, Morin, & Van den Broeck, 2016). Whereas classical variable-centered analyses of rank-order stability or individual trajectories assume that results would generalize to the whole sample, the person-centered approach seeks to identify subpopulations, or profiles, of employees characterized by distinct self-determination trajectories. For instance, observing that self-determination levels remain high in a sample does not exclude that a subset of employees may present chronically low levels of self-determination (e.g., Morin, Maïano, Marsh, Nagengast, & Janosz, 2013). Previous cross-sectional research has already demonstrated the value of the person-centered approach for research on work motivation (Gillet et al., 2018; Graves et al., 2015; Howard et al., 2016). By applying this approach, this study seeks to achieve a far more realistic and holistic view of the development of self-determined motivation at work.

Second, we draw on theories of leadership (transformational: Bass, 1985; and abusive: Tepper, 2002) and socialization (learning and internalization: Bauer, Morrison, & Callister, 1998; Louis, 1980; Perrot & Campoy, 2009; Van Maanen & Schein, 1979) to explain work motivation trajectories. Although SDT cross-sectional research has produced evidence for the role of the social context, and more particularly leadership practices, as predictors of work motivation (e.g., Fernet, Trépanier, Austin, Gagné, & Forest, 2015), the role of socialization has been neglected. We argue that the first few years into a career is a pivotal time for employees, and examine the simultaneous contribution of leadership behaviors—both positive (transformational) and negative (abusive)—and of the amount of socialization (the degree to which employees have been socialized) to the development of employees' self-determination trajectories during this critical period. To do so, we introduce aspects of socialization (task-, team- and organizational-level) that are liable to foster or hinder the internalization process, as described in SDT. Our study therefore adds to the understanding of how certain work environment factors act on the development of self-determination at work.

Third, whereas commitment and turnover intentions are known antecedents of actual turnover (Lee, Carswell, & Allen, 2000; Meyer, Morin, & Vandenberghe, 2015; Spurk, Hofer, Burmeister, Muehlhausen, & Volmer, 2019), little research has looked at how work motivation is associated with commitment and turnover intentions directed at distinct targets such as the occupation and the organization. Although turnover intentions generally refer to a conscious and deliberate willingness to leave the organization or the occupation (Tett & Meyer, 1993), commitment is a multidimensional concept referring to a force that binds an individual to a course of action of relevance to one or more targets (Meyer & Herscovitch, 2001). For Meyer, Allen, and Smith (1993), different mindsets may underpin this force as it relates to distinct targets or foci. The most distinguishable mindsets are the affective commitment (reflecting an emotional attachment) and the continuance commitment (the desire to stay due to the perceived costs of leaving) (Meyer & Herscovitch, 2001; Meyer, Stanley, &

Parfyonova, 2012). The scientific and managerial interest in integrating mindsets (affective, continuance) and targets (organization, occupation) of commitment is to get a better grasp of how motivation helps maintain high-quality commitment and limit turnover intentions. This can lower direct (e.g., replacement, recruitment) and indirect (e.g., loss of productivity and/or organizational knowledge) organizational costs, as well as some of the social costs of turnover (Hayes et al., 2012). We now turn our attention to the theoretical grounding for our study.

Theory and Hypotheses

Self-determination theory (SDT)

SDT (Deci & Ryan, 2000; Ryan & Deci, 2017) offers a multidimensional perspective on work motivation. The central idea is that people engage in various activities for reasons (i.e., behavioral regulations) that are more or less self-determined, and which wield considerable influence on psychological functioning. On the job, behavioral regulations correspond to the different reasons for employees to expend their efforts. SDT distinguishes three broad forms of behavioral regulations: autonomous regulation, controlled regulation, and amotivation. Employees are governed by autonomous regulation when they perform their tasks for the pleasure and satisfaction of doing them (intrinsic motivation) or when they want to achieve objectives that align with their personal values (identified regulation). They are governed by controlled regulation when they perform their job under some form of pressure, either internal (introjected regulation, e.g., to avoid anxiety or guilt, or to bolster feelings of self-worth) or external (external regulation, e.g., to avoid negative consequences, or to obtain material or social reward). In contrast, amotivation refers to the absence of autonomous or controlled forms of regulation, and thus a complete lack of volition to act. This translates into a lack of self-determination. Employees are amotivated when they perform their job mechanically, perceive that their actions are not aligned with the outcomes, or else they feel unable to achieve their goals.

SDT expects these different regulations to be organized along a global continuum of self-determination varying from purely intrinsic types of regulation to purely extrinsic types of regulations and amotivation (e.g., Ryan & Deci, 2017). Recent research has shown that the application of a bifactor-ESEM (B-ESEM; Morin, Arens, & Marsh, 2016) model provided a way to obtain a direct and explicit estimate of participants global levels of self-determination that matched the continuum structure proposed by SDT (Howard, Gagné, Morin, & Forest, 2018; Litalien, Morin, Gagné, Vallerand, Losier, & Ryan, 2017). On this global factor, the intrinsic motivation items display strong positive loadings, the identified regulation items display moderate positive loadings, the introjected regulation items display weak positive loadings, the external regulation items displayed negligible or small negative loadings, and the amotivation items displayed moderate negative loadings. Specific factors are also simultaneously incorporated to the model to capture the variance that is uniquely attributable to each behavioral regulation type beyond the variance already explained by the global factor. In addition, these studies have demonstrated that the global self-determination factor was the strongest predictor of outcomes, whereas the predictive role of the specific subscales was more limited. A similar approach was implemented in the present study, allowing us to estimate a factor scores (Morin, Boudrias et al., 2016, 2017) reflecting participants global levels of self-determined motivation, which was used to estimate longitudinal trajectories (Gillet et al., 2018).

Of direct relevance to the present study, the literature generally shows that higher global levels of self-determination or of the more autonomous forms of behavioral regulation (i.e., intrinsic motivation, identified regulation) tend to be associated with adaptive attitudes, including job satisfaction and affective commitment to the organization and to an occupation. In contrast, the behavioral regulations located at the other end of the continuum (introjected regulation, external regulation, amotivation), tend to be positively related to continuance commitment to the organization and intentions to leave the organization or the occupation, and to be negatively associated with affective commitment to the organization and to the occupation (for recent reviews, see Deci et al., 2017 and Fernet, Trépanier, Demers, & Austin, 2017). Although these findings shed some light on cross-sectional associations between employee attitudes and regulations located at different positions on the self-determination continuum, they were all obtained by variable-centered analyses, which fail to account for the possibility of that relations could differ across employees following distinct motivation trajectories. In contrast, person-centered analyses (Meyer & Morin, 2016) account for this possibility by identifying subpopulations of employees with distinct self-determination trajectories.

A longitudinal person-centered approach to the study of work motivation

For decades, SDT-based research has produced evidence that self-determined motivation varies as a function of work environment characteristics, and to a lesser extent, according to individual employee characteristics (Deci et al., 2017; Gagné & Deci, 2005). However, little is known about how self-determined motivation develops and evolves on the job. The question persists because, despite the theoretical expectation of a developmental process, studies have found little change over time in employees' self-determined motivation. This conclusion appears to hold across motivation measures (e.g., Fernet, Austin, & Vallerand, 2012; Olafsen, Deci, & Halvari, 2018). For example, Fernet et al. (2012) found relatively stable correlation coefficients for autonomous (r = .61) and controlled (r = .60) regulations across two time points over a nine-month period. Olafsen et al. (2018) obtained comparable stable coefficients for autonomous regulation across four time points over 14 months (r = .54 to 64; mean r = .59). Albeit useful for examining rank order stability and the directionality of associations among variables, the methods used in these studies would be inadequate to capture how self-determined motivation develops on the job in employees.

More specifically, the statistical analyses (e.g., bivariate correlation, cross-lagged analysis) adopted in previous longitudinal studies make it impossible to consider the potentially distinct developmental trajectories followed by distinct subpopulations of employees. Despite their interest, these studies do not focus on longitudinal trajectories, but on the rank-order stability of behavioral regulations. However, rank-order stability does not exclude the presence of normative increases or decreases in regulations over time, which leaves open the possibility that a substantial proportion of employees might undergo changes. This suggests that individual trajectories of self-determined motivation could present considerable inter-individual heterogeneity, due in part to the presence of subpopulations characterized by distinct self-determination trajectories, a direction that researchers have neglected to date. Latent Curve Models (Bollen & Curran, 2006) could account for the shape of longitudinal individual trajectories, and even account for inter-individual variations in the shape of these trajectories. However, these models are unable to account for the existence of unobserved subpopulations of employees following qualitatively distinct longitudinal trajectories reflecting their involvement in distinct organizational socialization scenarios. In this study, we address this limitation by applying person-centered growth mixture analyses (GMA; Muthén, 2002) for examining changes in self-determined motivation via the identification of employee profiles that shows qualitatively and quantitatively distinct self-determination trajectories.

On the Development of Self-Determination Trajectories at Work

In this study, we assume that stability and change in self-determination trajectories would be influenced by early work experiences (i.e., within the first five years; Rudman, Gustavsson, & Hultell, 2014) as employees come to confront their early expectations to the reality of their new work roles before eventually becoming accommodated to their occupation (Louis, 1980; Weiss, 1978). In this sense, we expect longitudinal trajectories of self-determination to reflect whether socialization scenarios occurring early in their career meet or fall short of employees' expectations (Solinger, Van Olffen, & Hofmans, 2013; Weiss, 1978). Some employees might have to lower their expectations to reach an accommodation between professional demands and their own needs (a Learning to Love scenario). Others might start out enthusiastic but become increasing disappointed (a Honeymoon–Hangover scenario). Still others might find that their early expectations, whether high or low, match the reality quite well (Matching scenarios; Solinger et al., 2013).

In any case, the reality of organizational socialization and integration varies greatly from employee to employee (Dinmohammadi, Peyrovi, & Mehrdad, 2013). Person-centered approaches are required to capture this inter-individual heterogeneity, providing a way to directly identify profiles of employees characterized by longitudinal trajectories reflecting exposure to distinct socialization scenarios. To our knowledge, only one study to date has used person-centered GMA to investigate the development of self-determined work motivation, but in 1,676 students enrolled in a nine-month full-time police training program (Gillet et al., 2018). In this study, three distinct and generally stable self-determination trajectories were identified. The first trajectory included 47.6% of the students who showed average initial levels of self-determined motivation with a very slight decreasing tendency over time (Moderate). The second included 29.7% of the students who showed high initial levels of self-determined motivation that tended to increase slightly over time (High). The third included 22.7% of the students who showed low initial levels of self-determined motivation that tended to decrease over time (Low). These trajectories—identified prior to job entry—echo the three matching scenarios

(High, Moderate, Low) proposed by Solinger et al. (2013), but without showing the marked change that can be expected to be associated with the Learning to Love and Honeymoon–Hangover scenarios.

Although insightful, this study was conducted in students enrolled in a vocational training program, which fails to account for how these trajectories might operate in a true professional setting. It is plausible that scenarios that feature more drastic changes (Learning to Love and Honeymoon–Hangover) would require a more realistic entry into the job, along with diminished possibilities of rationalizing expectations (e.g., “Things will be different when I get a job”) (Schneider, 1987). It is also possible that these scenarios could extend over a longer period, given that they involve the internalization of behavioral regulations, which is largely contingent on the prevailing practices in the work environment (Deci & Ryan, 2000) as well as the complex set of skills to be developed in some occupations. For instance, in nursing, the development of clinical judgement is typically viewed as a product of critical thinking in practice (Oermann 1997). Because critical thinking is developed through experience and involves making decisions based on practical knowledge, most education and training programs are unable to teach this skill to a level that meets professional standards (Fergusson & Day, 2001). However, the relevance of applying SDT to investigate organizational socialization does not stem solely from the potential to reproduce scenarios described in the literature (Solinger et al., 2013). SDT allows a deeper exploration of the experience of choice, thus going beyond the contingency between behaviors and outcomes. Hence, the development of self-determined work motivation is liable to wield a strong influence on employees’ actual and subsequent attitudes (e.g., commitment), affect (e.g., vitality), and behaviors (e.g., voluntary turnover).

The lack of studies on the development of self-determined work motivation makes it difficult to formulate precise hypotheses concerning identifiable profiles. Nevertheless, based on Gillet et al.’s (2018) results, we expected to find a small number of trajectories (3 to 4) similar to those described in the socialization literature. Based on Solinger et al. (2013) propositions, we expect these trajectories to reflect the Learning to Love (characterized by an initially moderate level of self-determined motivation followed by a moderately increasing trajectory), Honeymoon–Hangover (characterized by an initially high level of self-determined motivation followed by a sharp decreasing trajectory), and Matching (characterized by stable self-determined motivation trajectories) scenarios.

Predictors of Self-Determination Trajectories

According to SDT, self-determined work motivation should be largely influenced by multiple “aspects of the social environment, including both aspects of the job and the work climate” (Gagné & Deci, 2005, p.340). More precisely, environmental conditions that support the satisfaction of employees’ basic needs for autonomy, competence, and relatedness are likely to influence the development of more autonomous types of behavioral regulations, thus contributing to higher global levels of self-determination (Deci & Ryan, 2000; Gagné & Deci, 2005; Ryan & Deci, 2017). In contrast, heavy pressures and constraints surrounding task performance, because they tend to frustrate basic needs, should generate more controlled types of behavioral regulations, and even amotivation, thus leading to lower global self-determination (Deci & Ryan, 2000; Gagné & Deci, 2005; Ryan & Deci, 2017). In the absence of empirical evidence on predictors of motivation trajectories during the first years in employment, we felt it important to focus on elements that were liable to produce substantial gains or losses (having the potential to satisfy or frustrate basic needs) in overall self-determined work motivation. Based on past research showing that supervisors play a unique and critical role in employees learning, interaction, development, and adjustment outcomes (Deci et al., 2017), we considered the role of immediate superior’s leadership behaviors perceived as both positive (transformational) and negative (abusive) by the employees, as well as employees’ socialization in terms of capacity to learn work-related skills (Van Maanen & Schein, 1979) and to internalize the values, skills, expected behaviors, and social knowledge needed to perform their role (Louis, 1980).

Transformational leadership. Bass (1985) defines transformational leadership as encompassing behaviors related to idealized influence, inspirational motivation, intellectual stimulation, and individualized consideration. Transformational leaders exert a charismatic force (i.e., idealized influence) that inspires employees to identify with them emotionally and to view them as a model, or an example to follow. Transformational leaders can lever inspirational motivation to exhort a group to go forward. By sending a clear message of their (and the organization’s) values, goals, and mission, transformational leaders give the work a sense of purpose, so that employees can buy into the vision and think of their work as meaningful and challenging. They provide employees with intellectual stimulation by encouraging creativity and innovation, and by seeking employee feedback to improve ways of doing things. They pay attention to individual employee needs by showing individualized consideration through coaching, mentoring, and other behaviors meant to support personal and professional development. In the research, these types of behaviors are generally found to be strongly correlated (e.g., Judge & Piccolo, 2004), forming a single overarching transformational leadership construct that is positively associated with global levels of self-determination (i.e., through positive associations with autonomous behavioral regulations, and to a lesser extent, negative associations with controlled behavioral regulations; Bono & Judge, 2003; Fernet et al., 2015). Despite the lack of empirical evidence on self-determination trajectories, these theoretical expectations suggest that:

> *Hypothesis 1:* More positive perceptions of a supervisor's transformational leadership will increase the likelihood of employee membership in a more adaptive self-determination trajectory.

Abusive leadership. Abusive leadership behaviors are likely to have a detrimental effect on employees' levels of self-determination. Tepper (2000) describes abusive leadership as sustained forms of nonphysical hostility perpetrated by supervisors against subordinates (e.g., loud outbursts, undermining, and belittling). Krasikova, Green, and LeBreton (2013) explain that the behaviors of an abusive leader may take many forms, ranging from simply turning a blind eye to practices that go against the organization's values, to active use of offensive verbal or nonverbal communication with subordinates, such as intimidation, public criticism, rudeness, and coercion (Bies, 2001). From a self-determination standpoint, such behaviors are likely to be harmful for employee functioning insofar as they conflict with their ability to experience feelings of volition, freedom, and self-endorsement of their choices and actions (deCharms, 1968; Deci & Ryan, 2000). The research provides empirical evidence of a negative relation between abusive leadership and employees' self-determination. For instance, Trépanier, Fernet, and Austin (2015) found that perceptions of abusive behaviors (person-related behaviors, work-related behaviors, and physical intimidation) were negatively related to employees' basic need satisfaction, known to be closely related to self-determination (Gagné & Deci, 2005). Indeed, when exposed to such behaviors, employees also reported higher levels of controlled regulations and lower levels of autonomous regulations (Trépanier, Fernet, & Austin, 2013). In addition, a recent cross-sectional study in nurses (Lavoie-Tremblay, Fernet, Lavigne, & Austin, 2016) suggests that perceived abusive leadership behaviors predict intentions to leave the organization and the occupation over and above perceived transformational leadership behaviors. Based on this theoretical rationale and the available findings, we propose that:

> *Hypothesis 2:* Stronger perceptions of a supervisor's abusive leadership behaviors will increase the likelihood of employee membership in a less adaptive self-determination trajectory.

Socialization. Socialization refers to whether and how employees learn to adjust to their new work environment and to assume the behaviors, attitudes, and skills they need to acquit themselves successfully of their role as a member of the organization (Bauer, Bodner, Erdogan, Truxillo, & Tucker, 2007). Because early career employees typically have not had previous opportunities to get acquainted with the roles and requirements of ongoing organizational life, their socialization experiences during this critical period of their professional life are likely to exert a lasting impact on their work attitudes, knowledge, confidence, and motivation (Kammeyer-Mueller & Wanberg, 2003). Although some authors suggest that professional integration, in which socialization figures predominantly, takes about six months to run its course (e.g., Ashforth & Saks, 1996), others more realistically extend this time frame to five years for more complex occupations such as nursing (e.g., Rudman, Gustavsson, & Hultell, 2014), given the multiple skills needing to be developed (e.g., clinical judgment) and the complexity of health care tasks and systems. Benner, Tanner, and Chelsa (2009) point out that nurses' knowledge, skills, and reasoning abilities are developed with experience and over time. Whereas this rich mix of skills and experience allows expert nurses to intuitively grasp and respond to complex health care situations, such high-caliber performance cannot be expected from nurses with less than six months of practice. At this stage, most nurses are still focused on learning their new roles along with the policies and procedures of their practice setting, while having to manage multiple competing priorities (Benner et al., 2009).

We take this position in the present study, to account for the specificities of the nursing profession and the nature of self-determined motivation. According to SDT, the development of motivation can be explained by Organismic Integration Theory. This theory suggests that individuals construct a coherent sense of identity by internalizing their perceptions of themselves and of the situations and experiences that they encounter (Deci & Ryan, 2000). Although integration into a new work role may be considered as a natural developmental tendency, it should not be assumed to be automatic or instantaneous. When employees are exposed to an environment not fully consistent with their own goals and values, socialization may be delayed or blocked (O'Reilly, Chatman, & Caldwell, 1991). This logic is based on the SDT principle of internalization, whereby initially external motives are progressively integrated into one's professional identity (Deci & Ryan, 2000).

Internalization is also a central concept in classic definitions of organizational socialization. The internalization process is more effective when the individual accepts and progressively integrates the organization's goals and values, beyond the acquired knowledge and know-how that help employees settle into a new work environment (e.g., Chao et al., 1994). The same observation is made in a critical literature review by Perrot and Campoy (2008), who noted a substantial disparity between the conceptualization and operationalization of the socialization constructs used in the field. More specifically, this review identified two central elements of organizational socialization, as reflected in the instruments used to measure them (e.g., Chao et al., 1994): learning and internalization. Assuming that socialization essentially involves a process of assimilation whereby employees learn relevant work-related skills (Van Maanen & Schein, 1979) and internalize the values, skills, expected behaviors, and social knowledge they need to perform their work role (Louis, 1980), we anticipated relations between socialization (i.e., the degree to which employees have been socialized) and self-determination trajectories. To the extent that employees have been able to acquire and freely adopt the norms, values, and behaviors required to achieve their objectives at the task, team, and organization level, their motivation should become more self-determined over time. Conversely, the inability to learn or meet job expectations and the failure to understand or endorse organizational values and norms should impair the development of self-determination. In this case, employees' actions should remain contingent on external constraints, and they would be unable to develop a real sense of volition and choice (Deci & Ryan, 2000). This rationale suggests that:

Hypothesis 3: Higher levels of socialization will increase the likelihood of employee membership in a more adaptive self-determination trajectory.

Self-Determination Trajectories, Commitment, and Turnover Intentions

Finally, the present study explores the relevance of the identified self-determination trajectories by assessing their associations with organizationally and occupationally relevant work outcomes related to employees' commitment and turnover intentions. Given our focus on the nursing profession, it appeared critical to consider employee intentions to leave their occupation and the organizations as key outcomes. Actual turnover rates exact a high toll on health care systems, as they incur substantial costs (e.g., recruitment, replacement, training) that must be assumed by already overloaded institutions. This turnover problem is particularly marked in nursing (e.g., Kovner, Brewer, Fatehi, & Jun, 2014), calling for efforts to develop ways to ensure retention at this critical time. In the absence of objective turnover data, the present study focuses on the two most strongly established predictors of turnover: turnover intentions and commitment (Lee et al., 2000; Meyer et al., 2002). Both factors have been closely related to self-determined work motivation (Fernet et al., 2012; Meyer et al., 2012), and they can be conceptualized as a function of whether the target is the occupation or the organization. Moreover, both variables have been deemed as important outcomes of employees' socialization (Bauer et al., 2007).

Commitment may be defined as a force that binds an employee to an ongoing course of action related to a specific target (Meyer & Herscovitch, 2001), such as the organization or the occupation (Morin, Meyer, McInerney, Marsh, & Ganotice, 2015). Furthermore, commitment is a natural outcome of work motivation (Meyer, Becker, & Vandenberghe, 2004). Although Meyer et al. (1993) differentiate three mindsets underlying commitment, studies and meta-analyses point to the affective (i.e., emotional attachment) and continuance (i.e., perceived costs of leaving) mindsets as the most relevant from an occupational and organizational perspective (e.g., Lee et al., 2000; Meyer, Stanley, Herscovitch, & Topolnytsky, 2002). Theory and research findings also position these two commitment mindsets as being the most clearly related to the two extremities of the self-determination continuum. Thus, they show clear associations with the more autonomous types of behavioral regulations and affective commitment and with the more controlled types of behavioral regulations and continuance commitment (Meyer et al., 2012). The scientific and managerial interest in integrating the mindsets (affective, continuance) and targets (organization, occupation) of commitment seeks to get a better grasp on how motivation helps maintain high-quality commitment and limit turnover intentions. To our knowledge, only one study to date (Fernet et al., 2017) has examined the differentiated contribution of motivation in nurses in connection with commitment and intentions to leave the occupation and the organization. Their cross-sectional results suggest that both autonomous and controlled motivation are more strongly associated with commitment and intentions to leave the occupation than the organization. We therefore propose that occupational and organizational outcomes are distinctly predicted by diverse self-determination trajectories.

Hypothesis 4: The more adaptive self-determination trajectories will be positively associated with affective commitment to the occupation (H4a) and the organization (H4b), negatively associated with continuance commitment to the occupation (H4c) and the organization (H4d), and negatively associated with intentions to leave the occupation (H4e) and the organization (H4f).

Method

Procedure and Participants

This study was conducted over a 24-month period. Data was collected at four time points (October 2014, April 2015, October 2015, and October 2016) from registered French Canadian nurses having three years or less of experience in the profession. All participants were working in the public health care sector, in the province of Quebec, Canada and were members of the *Ordre des Infirmières et des Infirmiers du Québec* (The Quebec professional nursing association – OIIQ). Potential participants were contacted via a letter sent to their home address explaining the study purpose and inviting them to participate in the study by completing an online questionnaire. In the letter, it was emphasized that responses would remain anonymous and that participation was voluntary.

A total of 660 nurses took part in this study. Participants were mostly women (87.9%), with a mean age of 26.7 years (SD = 6.67) and 0 to 3 (M = 1.85; SD =.86) years of experience in the nursing profession (occupational tenure). The majority of participants (76.3%) held a permanent position, and fewer than half (43.5%) were working full time. The sample is fairly representative of the demographics of novice nurses (with three years or less of experience in the profession) enrolled in the OIIQ at the time (e.g., 43% worked full time; 87% were women; mean age 27.8 years).

Measures

All measures were administered in French. Measures not previously validated in French (i.e., transformational and abusive leadership, commitment to the organization and occupation) were adapted to this language using a classical translation back-translation procedure (Brislin, 1980) involving independent bilingual translators. With the exception of the control variables, which were only assessed at Time 1, all other variables were assessed at all time points.

Work motivation. We used the Multidimensional Work Motivation Scale (Gagné et al., 2015) to assess behavioral regulations. On a scale ranging from 1 (*not at all for this reason*) to 7 (*exactly for this reason*), participants rated their main reasons for investing efforts in their job: amotivation (3 items; e.g., “I do little because I don’t think this work is worth putting efforts into”; α = .759 to .783 between T1 and T4, M_α= .747), external regulation (3 items; e.g. “To get others’ approval”; α = .724 to .816, M_α= .778), introjected regulation (4 items; e.g. “Because otherwise, I would be ashamed of myself”; α = .626 to .685, M_α= .660), identified regulation (3 items; e.g. “Because this job has a personal significance for me”; α = .600 to .704, M_α= .632), and intrinsic motivation (3 items; e.g. “Because my work is stimulating”; α = .882 to .911, M_α= .893). In this study, we used a total score capturing global levels of self-determination at work according to participants’ position on the SDT continuum (α = .667 to .743, M_α= .712). Additional details on this score are provided in the preliminary analysis and online supplement sections.

Transformational leadership. We assessed transformational leadership with the seven-item Global Transformational Leadership scale (GTL; Carless, Wearing, & Mann, 2000). Participants rated their perceptions of their supervisor’s leadership behaviors (e.g., “He/she encourages us and recognizes our work”; α = .939 to .957, M_α= .948) on a scale ranging from 1 (*never*) to 5 (*almost always*). The GTL has shown convergent validity with established questionnaires such as the Multifactor Leadership Questionnaire and the Leadership Practice Inventory (Carless et al., 2000).

Abusive leadership. We assessed abusive leadership with a 15-item scale developed by Tepper (2000). Participants rated their perceptions of their supervisor’s leadership behaviors (e.g., “He/she blames me to save himself/herself embarrassment”; α = .867 to .908, M_α= .888) on a scale ranging from 1 (*never*) to 5 (*almost always*). Tepper demonstrated the scale’s score reliability and the construct validity of obtained responses by reporting positive associations with several variables, including continuance organizational commitment and by negative associations with affective organizational commitment and job and life satisfaction.

Socialization. Employee socialization was assessed with six four-item subscales addressing learning and internalization related to tasks, the team, and the organization (Perrot & Campoy, 2009): (a) task-level learning (e.g., “I know the responsibilities, tasks, and projects that I was hired for”; α = .797 to .824, M_α= .808); (b) task-level internalization (e.g., “I fully agree with the work mission”; α = .886 to .898, M_α= .891); (c) team-level learning (e.g., “I understand how my team contributes to my organization’s goals”; α = .869 to .888, M_α= .877); (d) team-level internalization (e.g., “My team’s objectives are also my own objectives”; α = .909 to .937, M_α= .921); (e) organization-level learning (e.g., “I understand the objectives and goals of my organization”; α = .888 to .921, M_α= .904); (f) organization-level internalization (e.g., “I have incorporated the values of my organization into my own value system”; α = .897 to .922, M_α= .909). Each item was scored on a scale ranging from 1 (*strongly disagree*) to 7 (*strongly agree*). Perrot and Campoy (2009) confirmed the scale’s convergent validity with organizational commitment as well as person–job fit, person–team fit, and person–organization fit. Due to a high level of interrelations between the internalization and learning facets of each socialization level, we used global scores reflecting socialization at the task (α = .895 to .905, M_α= .900), team (α = .924 to .940, M_α= .930), and organization (α = .912 to .937, M_α= .922) level. Details on these global scores are provided in the online supplements.

Commitment. We assessed affective and continuance commitment to the organization and occupation with Meyer, Allen, and Smith’s (1993) instrument, slightly adapted to the nursing context. Three items were used to capture each dimension: (a) affective commitment to the occupation (e.g., “The nursing profession means a lot to me”; α = .868 to .893, M_α= .876); (b) affective commitment to the organization (e.g., “I am proud to belong to this organization”; α = .785 to .858, M_α= .833); (c) continuance commitment to the occupation (e.g., “I will not leave the nursing profession because I have spent too much energy learning it”; α = .798 to .862, M_α= .825); and (d) continuance commitment to the organization (e.g., “Leaving my current organization would have many more disadvantages than advantages”; α = .699 to .779, M_α= .748). Each item was rated on a scale ranging from 1 (*strongly disagree*) to 5 (*strongly agree*). The validation study conducted by Meyer et al. (1993), as well as extensive international research (Meyer, Stanley, Jackson, McInnis, Maltin, & Sheppard, 2012) support the scale’s factor structure and the scale score reliability, and validity.

Turnover Intentions. Employee intentions to leave the occupation and the organization were assessed with respectively three and four items adapted from O’Driscoll and Beehr (1994): “I’m thinking about leaving the nursing profession” (intentions to leave the occupation; α = .853 to .926, M_α= .895) and “I’m thinking about leaving my current health care facility” (intentions to leave the organization; α = .851 to .867, M_α= .861). Each item was scored on a scale ranging from 1 (*strongly disagree*) to 7 (*strongly agree*). Previous studies support the reliability and validity of the version used in the present study (e.g., Fernet et al., 2015; Trépanier et al., 2015).

Control variables. Although largely overlooked in the work motivation research, a number of variables that could account for variation in self-determination profiles were also considered: age, gender, occupational tenure, employment status (permanent, temporary), and work schedule (full time, part time). Some studies suggest that self-determined motivation is more prevalent for women (e.g., Fernet, 2011; Fernet, Trépanier, Austin, & Levesque-Côté, 2016) and less with increasing years of experience in the profession (e.g., Fernet et al., 2016). In addition, we took age, employment status, and work schedule as control variables because they have been shown or suggested to account for variance in employee motivation (e.g., Blais, Brière, Lachance, Riddle, & Vallerand, 1993; Dysvik, & Kuvaas, 2008; Philippe, Lopes, Houlfort, & Fernet, 2019).

Analysis

Preliminary Analyses

Growth mixture trajectories, predictors, and outcomes were estimated from standardized (with a mean of 0 and a SD of 1) factor scores obtained in the context of preliminary analyses aiming to ensure the longitudinal measurement invariance (Millsap, 2011) of the variables included in the present study. Among the various advantages of factor scores, which are able to preserve the underlying nature of the measurement models used to generate them (i.e., bifactor, longitudinal invariance, etc.), factor scores also afford a partial control for measurement error present at the item level (Skrondal & Laake, 2001; Morin, Boudrias et al., 2016, 2017).

For the repeated motivation measures, these preliminary analyses are based on bifactor exploratory structural equation models (B-ESEM; Morin, Arens, & Marsh, 2016). Indeed, accumulating evidence supports the value of B-ESEM for the representation of motivation measures across domains, including the work area (Howard et al., 2018). More precisely, these studies have shown that B-ESEM yields a direct estimate of participants' global levels of self-determination in a way that perfectly matches the theoretical SDT continuum (i.e., defined by factor loadings aligned with items' location on the continuum). In this study, participants' self-determination trajectories are estimated from this global indicator. Details on the measurement models (and missing data treatment), their longitudinal invariance, correlations and reliability can be found in the online supplements.

Growth Mixture Analyses (GMA)

Our main analyses were conducted with Mplus 7.31 (Muthén & Muthén, 2015), using the Maximum Likelihood-Robust (MLR) estimator, 10,000 random start values and 1000 iterations. Final optimization was conducted on the 500 most optimal solutions. These procedures were implemented in order to ensure converge on a true local maximum (Hipp & Bauer, 2006; McLachlan & Peel, 2000). Missing data were handled via Full Information Maximum Likelihood (FIML) procedures, which allows missingness to be conditioned on all variables included in the analytic model (e.g., Enders, 2010). In the present study, 660 participants produced 1,747 occasion-specific ratings (M = 2.65 per participant), with 201 (30.5%) completing all four time points, 175 (26.5%) three time points, 134 (20.3%) two time points, and 150 (22.7%) one time point. We also conducted a series of preliminary verifications to more precisely ascertained attrition mechanisms. First, we assess the extent to which the number of time of measurement completed by each participant were related to all variables included in this study. These results can be consulted in the online supplements (Table S6) and show very few statistically significant correlations, limited to showing a weak negative association between the number of completed time points and participants turnover intentions from their occupation (r = -.111) and organization (r = -.128) at Time 3 only, and levels of team-related socialization at Time 4 only (r = -.116). We also found no evidence of any statistically significant associations between participants' membership into any of the profiles and the number of completed time of measurements.

Linear GMA models[1] were estimated for solutions ranging from one to eight profiles of participants following distinct longitudinal trajectories of self-determination (Grimm, Ram, & Estabrook, 2010; Morin, Maïano, Nagengast, Marsh, Morizot, & Janosz, 2011). These trajectories are each characterized by a random intercept factor (i.e., the initial level, defined by fixing to 1 the loadings of the time-specific measures on this factor) and a random slope factor (i.e., the rate of change over time, defined by fixing the loadings of the time-specific measures on this factor in a way that reflects the passage of time) (e.g., Bollen & Curran, 2006). In GMA, the variances of these factors reflect the degree of inter-individual variability present within each profile.

In the present study, the passage of time was reflected by fixing factor loadings on the slope factors to 0, 0.5, 1, and 2, in order to represent the six-month intervals between the first three times points and the one year interval between the last two time points. Any study involving the estimation of growth trajectories (e.g., latent curve models or GMM), relies on the strong assumption that these trajectories can be modeled on the basis of meaningful time units (Metha & West, 2000). For studies, such as this one, where more than one time referent co-exist (i.e., participants differed from one another regarding the length of their work experience in the nursing occupation, which creates a potential confound with the time of measurements, which occurred at different career moments across participants), Metha and West (2000; also see Morin & Litalien, 2020) proposed a way to verify whether the reliance on uniform time codes remains appropriate despite this variation. As applied to the present context, this approach states that the added effects of occupational tenure (i.e., the length of

[1] The decision to use linear versus quadratic GMA stemmed from a preliminary estimation of linear and quadratic latent curve models (Bollen & Curran, 2006). Both models afforded an equivalent fit to the data ($\Delta\chi^2$ = 0.978; Δdf = 4; $p \geq .05$), despite the greater parsimony of the linear model. The results also revealed non-significant mean and variance parameters associated with the quadratic slope, consistent with the absence of quadratic trends. This conclusion was supported by attempts to estimate quadratic GMA, which resulted in nonconverging or improper solutions revealing a lack of quadratic trends, consistent with overparameterization (Bauer & Curran, 2003; Chen et al., 2001).

their work experience in the nursing profession) can be deemed to be ignorable if: (1) the regression of the intercept of trajectories defined based on a latent curve model on tenure is equal to the slope of these same trajectories, and (2) the regression of the slope of the trajectories on tenure is equal to zero. Yet, in order to ascertain the robustness of this decision, we also directly assess the role of tenure (see the section on predictors below) as a possible predictor of profile membership, trajectories intercept, and trajectory slopes, as part of our final GMM solution. This verification supported the idea that tenure had no additional effect on the results ($\Delta\chi^2 = 4.463$; $\Delta df = 2$; $p \geq .05$). Similar tests were conducted as a function of age supported the same conclusion ($\Delta\chi^2 = 2.157$; $\Delta df = 2$; $p \geq .05$).

Statistical guidance recommends GMA to be estimated while allowing all parameters to differ across profiles (Diallo, Morin, & Lu, 2016; i.e., the mean of the intercept and slope factor, the variance-covariance of the intercept and slope factors, and the residuals associated with the occasion-specific measures). Yet, this globally free estimation process often results in estimation problems (Diallo et al., 2016), due to overparameterization (Bauer & Curran, 2003; Chen et al., 2001), which happened here. When this happens, more parsimonious models should be estimated via the progressive implementation of equality constraints across profiles on subset of parameters (Diallo et al., 2016). For this reason, we constrained the latent variance-covariance matrix to equality across profiles (i.e., the Mplus default parameterization), and allowed the occasion-specific residuals to differ across profiles, but not time points (i.e., homoscedasticity; e.g., Li & Hser, 2011; Tofighi & Enders, 2007). Residual homoscedasticity is consistent with the way growth models are generally estimated in the multilevel framework and yields results in which all repeated measures are assumed to be equally well represented by the growth trajectories, at least within each profile. The online supplements include a more technical discussion of GMA and annotated input files to guide model estimation.

When GMA solutions including increasing numbers of profiles are compared, deciding on the optimal solution might prove challenging, and need to be anchored in an examination of the statistical adequacy, heuristic value, and theoretical meaningfulness of the solutions (Marsh, Lüdtke, Trautwein, & Morin, 2009; Muthén, 2003). Fortunately, this decision process can also be supported by statistical indicators (McLachlan & Peel, 2000). Among those, the Bootstrap Likelihood Ratio Test (BLRT) and Lo, Mendel and Rubin’s (2001) adjusted LRT (aLMR) seek to compare a target solution with a matching solution including one fewer profile. For these indices, statistical significance support the target solution. In addition, lower values on the Bayesian Information Criterion (BIC) and its sample-size adjusted version (ABIC), as well as on the Akaïke Information Criterion (AIC) and its consistent version (CAIC) all indicate a better fitting solution. Statistical work on the relative performance of these indicators support the efficacy of the BLRT, BIC, ABIC, and CAIC (e.g., Diallo et al., 2016, 2017; Nylund, Asparouhov, & Muthén, 2007; Peugh & Fan, 2013).

Predictors and Outcomes of Membership into the Final Set of Profiles. Relations between the final set of profiles and various predictors and outcomes were then investigated. To ensure that covariate inclusion did not result in a change in the nature of the profiles (e.g., Diallo et al., 2017; Morin, Morizot, Boudrias, & Madore, 2011), start values were defined from the results of the final solution rather than randomly estimated (Diallo et al., 2017; Morin, Meyer, Creusier, & Biétry, 2016).

A series of alternative predictive models was then contrasted, following Diallo et al.’s (2017) recommendations. We first considered the demographic controls assessed at Time 1 (age, sex, tenure, employment status, and work schedule) to verify the need to incorporate these controls as additional time-invariant predictors (TIP) in further models. First, we estimated a null effects model in which the relations between these controls and the probability of membership in all profiles and the growth factors were constrained to be zero. In a second model, the controls were allowed to predict profile membership via a multinomial logistic regression. We then tested additional models in which the controls were also allowed to influence within-profile variation in the intercept and slope factors (via a multiple regression equation), and in which these effects were allowed to vary across profiles.

A second series of models was then estimated following the same sequence to assess the effects of the predictors (transformational leadership; abusive leadership; and task, team, and organizational socialization). To ensure a temporal ordering of the predictors relative to the predicted variables (i.e., the latent profiles and the latent trajectory factors), we considered only the Time 1 measures of these predictors, specified as TIP. Then, starting with the final model retained in the previous steps, we added the Time 2-3-4 measures of these predictors as time-varying predictors (TVP) to verify whether changes in these predictors over time would influence the self-determination trajectories over and above the initial effects. For models including TVP, we contrasted five alternative models. In a first model, the effects of the TVP on time-specific fluctuations in repeated measures of global self-determination (taken at the matching time point) were constrained to be zero. These effects were then estimated, but constrained to be equivalent across profiles and time points. In the third and fourth models, these effects were respectively freely estimated across profiles but constrained to be equivalent across time points, or freely estimated across time points but constrained to be equivalent across profiles. Finally, these effects were allowed to be freely estimated across both time points and profiles. As recommended by Diallo et al. (2017, see also Morin, Meyer et al., 2016), we contrasted the fit of the alternative control, TIP, and TVP models using the information criteria (AIC, CAIC, BIC, ABIC), with lower values indicating better model fit.

Finally, we compared time-specific outcome levels across profiles (affective commitment, continuance commitment, and intentions to leave, all estimated in relation to the occupation and organization) with a model-based weighted ANOVA approach developed by Bakk and Vermunt (2016) based on work by Bolck, Croon, and Hagenars (2004). This approach is implemented in Mplus via the Auxiliary (BCH) command (Asparouhov & Muthén, 2015).

Results

Unconditional Models

The results of unconditional GMA are reported in the top section of Table 1. With the sole exception of the AIC, which reached its lowest point for the 7-profile solution, all remaining indices converged to support the 3-profile solution. Examination of this 3-profile solution and the adjacent 2- and 4- profile solutions supported this statistical information: the 3-profile solution resulted in the addition of a meaningful and well-defined third profile, whereas the 4-profile solution resulted in the arbitrary division of one profile into two highly similar profiles. We therefore retained the 3-profile solution, which is graphically illustrated in Figure 1. Specific parameter estimates are reported in Table 2. In interpreting these results, it should be kept in mind that growth trajectories are estimated from standardized (M = 0; SD = 1) time-invariant factor scores reflecting global self-determination levels (see online supplements for details). Thus, a score of 0 corresponds to the sample mean level of global self-determination, with deviations expressed in standard deviation units.

Comparing the profiles, we first noted that all three were characterized by initial levels (i.e., the mean on the intercept factors) that were not statistically different ($p \leq .05$) from the sample average (i.e., 0), or from each another. This observation was consistent with the fact that this sample comprises employees having three years or less of experience in the profession. However, the profiles became more clearly differentiated as employees settled into their career. Profile 1 characterized 51.26% of the employees presenting initially m*oderate* self-determination levels and showing a *Slightly Decreasing* trajectory over time (corresponding to -.153 *SD* units per year). In contrast, Profile 2 characterized 41.04% of the employees, who presented an *Increasing* trajectory of global self-determination, with a slope factor indicating an increase of .186 *SD* units per year. Profile 3 was the most concerning, and characterized 7.70% of the employees, who presented a marked *Decreasing* trajectory of global self-determination (corresponding to -.510 *SD* units per year, for a total decrease of -1 *SD* over the study period).

The classification accuracy of employees into their most likely profile is reported in Table 3, revealing a high classification accuracy for the *Decreasing* profile (i.e., members have an average 82.3% probability of belonging to this profile). Results also revealed a moderately high classification accuracy for the *Slightly Decreasing* (65.6%) and *Increasing* (68.2%) profiles, which showed a slight overlap, likely due to similar levels of self-determination at the first two time points. At this stage, it is important to reinforce that the profiles themselves, as latent prototypes located at the population levels are naturally controlled for classification inaccuracies (e.g., Morin, Bujacz, & Gagné, 2018; Morin & Litalien, 2019), allowing us to have confidence in our results.

Predictors of the Self-Determination Trajectories

The results of the models incorporating controls, TIP, and TVP up to the final 3-profile solution are reported in the lower section of Table 1. Starting with the models that included the controls (age, sex, occupational tenure, employment status, and work schedule), the AIC supported the model in which the controls were allowed to predict the probability of profile membership as well as the intercept and slope factors in a profile-invariant manner (model M13 in Table 1). In contrast, all other indices (CAIC, BIC, ABIC) supported the null effects model (model M9 in Table 1). Examination of the parameter estimates from these models supported this last conclusion regarding the lack of meaningful associations between the control variables and the profiles. More importantly, this conclusion supports the idea that participants' inter-individual variations in terms of early career tenure in the nursing occupation (or age) did not play any additional impact on participants likelihood of membership into any of the profiles, or on the shape of their longitudinal trajectories, beyond the effects already captured by the passage of time. The control variables were therefore removed from further analysis. Conversely, models that included the TIP (Time 1 predictors: transformational leadership; abusive leadership; and task, team, and organizational socialization) were consistent with the presence of significant relations between the predictors and the growth trajectories. More precisely, the CAIC and BIC supported a model in which the TIP significantly predicted the probability of profile membership and the intercept factor in a profile-invariant manner (model M17, Table 1), whereas the AIC and ABIC suggested that these predictors may also present a significant association with the slope factor (invariant across profiles: Model M18, Table 1). Parameter estimates from these models were consistent with the presence of significant effects of the predictors on the slope factor. Model M18 was therefore retained for interpretation.

The results of the predictions estimated as part of model M18 are reported in Table 4. First, these results highlight the importance of transformational leadership, showing that more positive perceptions of supervisors' transformational leadership behaviors were associated with greater likelihood of membership into the *Increasing* and *Slightly Decreasing* profiles relative to the *Decreasing* profile, and into the *Increasing* profile relative to the *Slightly Decreasing* profile. Above these effects on profile membership, transformational leadership was also associated with more stable self-determination trajectories (evidenced by a negative relation with the slope factor). These results were consistent with Hypothesis 1, which proposed that transformational leadership would increase the likelihood of membership in the most adaptive profiles. The effects of employees' perceptions of supervisor's abusive leadership behaviors were more limited, being mainly associated with a slight stabilization of the trajectories once the effects of the various predictors on profile membership were taken into account. These results do not support Hypothesis 2, which suggested that abusive leadership behaviors would increase the likelihood of membership into the least adaptive profiles.

The effects of socialization are particularly interesting. First, they showed that whereas task-level socialization predicted a greater likelihood of membership into the *Increasing* profile relative to the *Slightly Decreasing* profile, team-level socialization predicted the opposite pattern: a greater likelihood of membership into the *Slightly Decreasing* profile relative to the *Increasing* one. In addition, both socialization levels were associated with higher initial levels of self-determination for all employees (evidenced by a significant positive relation with the intercept factor). No relations between organizational socialization and employee trajectories of global self-determination were identified. These results support Hypothesis 3 when considering task-level socialization, whereas those related to team- and organization-level socialization were inconsistent with Hypothesis 3.

To test whether the effects of these predictors on global self-determination were limited to the initial time point (consistent with the importance of employee socialization efforts) or whether fluctuations in predictors levels over time could still influence fluctuations in global self-determination over and above the effects of the TIP, TVP representing the effects of time-specific measures of the predictors on the time-specific measures of global self-determination were added to M18. For these additional models, all information criteria (AIC, CAIC, BIC, and AIC) supported a model in which the TVP were allowed to influence time-specific fluctuations in motivation levels in a way that was equivalent (i.e., invariant) across time and profiles (Model M22, Table 1). These results thus suggest that some TVP had an additional effect on global self-determination level over and above their initial effects on the intercepts and slope factors. Inspection of the results associated with model M22, however, revealed that these effects were limited to task-level socialization which predicted time-specific increases in global self-determination levels ($b = .169$; s.e. $= .059$; $\beta = .153$; $p \leq .01$) over and above its effects on profile membership and initial levels of self-determination[2].

Outcomes of the Self-Determination Trajectories

[2] Alternative TVP models in which the TVP were allowed to predict fluctuations in self-determination levels at the next time point, and in which they were allowed to directly influence the slope factors, were also estimated and revealed no additional effect. These alternative results are available upon request from the authors.

The results of the comparison of the time-specific outcome levels across profiles are reported in the online supplements (Table S7), revealing clear differences across profiles that varied across outcomes and time points. For the first two time points, levels of affective commitment to the occupation were higher in the *Increasing* and *Decreasing* profiles relative to the *Slightly Decreasing* profile, consistent with the initially higher global levels of self-determination (although this difference was not statistically significant). Levels of affective commitment to the occupation increased over time (at Times 3 and 4) in the *Increasing* profile, matching the increases in global levels of self-determination observed in this profile, whereas these levels became indistinguishable between the *Slightly Decreasing* and *Decreasing* profiles. Levels of affective commitment to the organization showed similar trends over time, except that they were systematically highest in the *Increasing* profile, in which they were indistinguishable from those observed in *Slightly Decreasing* profile at Time 1 but not at Times 2 to 4. In addition, levels of affective commitment to the organization were higher in the *Slightly Decreasing* profile relative to the *Decreasing* profile at Times 1 to 3, but equivalent at Time 4. Overall, these results, which are illustrated in Figure 2, showed that levels of affective commitment to the occupation and organization closely followed employees' self-determination trajectories. These results supported Hypotheses H4a and 4b, showing that the most adaptive self-determination trajectories are positively associated with affective commitment to the occupation but also, to a lesser extent to the organization. However, the results also revealed a distinguishing characteristic of the *Decreasing* profile: it was initially characterized by high levels of affective commitment to the occupation, but low levels of affective commitment to the organization. In contrast, the *Increasing* profile systematically presented the highest levels of affective commitment to these targets.

Conversely, the three self-determination profiles showed very few differences in continuance commitment to the occupation and organization. In fact, the only significant difference was related to a higher level of continuance commitment to the organization in the *Slightly Decreasing* relative to the *Increasing* profile at Times 2 and 4, suggesting that continuance commitment to the organization may be a defining characteristic of the *Slightly Decreasing* profile. These results fail to support Hypothesis H4c, as they revealed no differences across profiles in terms of continuance commitment to the occupation. However, Hypothesis H4d is partially supported by some negative associations between adaptive self-determination trajectories and continuance commitment to the organization.

Regarding turnover intentions, the results were relatively consistent with those obtained for affective commitment: the *Decreasing* and *Slightly Decreasing* profiles presented the highest levels of intentions to leave the occupation at all time points. Similar results were observed for intentions to leave the organization, although statistically significant differences were limited to Time 2 (with the highest intentions to leave observed in the *Decreasing* profile) and Time 3 (with the highest intentions to leave observed in the *Slightly Decreasing* and *Decreasing* profiles). These results supported Hypotheses H4e and H4f, with negative associations between the most adaptive self-determination trajectories and turnover intentions. Results on continuance commitment and intentions to leave are graphically illustrated in Figures S2 and S3 in the online supplements.

Discussion

The present study aimed to enrich the understanding of how work motivation evolves at work. Three profiles were identified with distinct longitudinal trajectories of self-determination: *Increasing*, *Slightly Decreasing*, and *Decreasing*. One noteworthy finding was that employees' perceptions of transformational leadership predicted membership into these self-determination trajectories, whereas abusive leadership played only a minimal role. In contrast, socialization appeared to be a double-edged sword. Whereas team-level socialization decreased the likelihood of membership into the most adaptive self-determination trajectory (i.e., *Increasing*), task-level socialization increased that likelihood. However, both types of socializations were associated with increases in initial levels of self-determination across all profiles. In addition, variations over time in task-level socialization also predicted time-specific increases in self-determination levels across all profiles. Furthermore, the *Increasing* self-determination trajectory was found to promote affective commitment to the occupation and organization while limiting employee intentions to leave the occupation and the organization. These findings have several important theoretical and managerial implications.

Theoretical Contributions

Distinct Motivation Scenarios. The main contribution of this study arguably lies in the identification of the distinct self-determination trajectories that characterize employee motivation. The results showed that these distinct trajectories could be differentiated both in terms of intensity (a quantitative aspect: high or low levels) and evolution (a qualitative aspect: increasing, slightly decreasing, or decreasing levels) of self-determination, and presented differentiated associations with specific predictors and outcomes. While this confirms the developmental nature of work motivation, our results reveal a relatively small number of self-determination trajectories. The most worrisome trajectory (i.e., *Decreasing*), despite showing initially high levels of self-determination, displayed a marked decline over time so that the levels of self-determination observed in this profile were the lowest by the end of the study. This profile characterizes only a limited number of employees (7.7%). The results also revealed a second worrisome trajectory, initially characterized by moderate levels of self-determination and presenting a *Slightly Decreasing* trend over time. What is most concerning is that this profile describes what we might call the “silent majority”, corresponding to 51.23% of the sample. Moreover, it is also important to note that, by the end of the study, the levels of self-determined motivation observed in these two profiles (*Slightly Decreasing* M_{t4} = -.413; *Decreasing* M_{t4} = -.642) did not differ from one another in a statistically significant manner (p = .723). Fortunately, the third profile also represents a considerable proportion of employees (41.04%) characterized by an *Increasing* trajectory of global self-determination.

It is noteworthy that the *Increasing* and *Decreasing* trajectories appear to respectively reflect the “Learning to Love” and “Honeymoon–Hangover” adjustment scenarios respectively, as proposed in the socialization research (Solinger et al., 2013). More precisely, the Honeymoon–Hangover effect describes an initially high level of job satisfaction followed by a marked decline once an employee becomes acquainted with his or her new work environment. This scenario has been previously attributed to growing disappointment with the work environment, possibly due to a perceived breach of the psychological contract linking an employee with his or her workplace, following an initial period of exuberance (e.g., Solinger et al., 2013). In contrast, the Learning to Love scenario is purported to occur when an employee achieves an optimal level of adjustment to a job through a less exuberant but more efficient process of meeting the organization’s expectations which slowly become part of one’s identity (e.g., Solinger et al., 2013; Weiss, 1978). Our empirical results complement these findings and those of Gillet et al.’s (2018) study of students in a vocational training program, in the sense that these scenarios also apply to motivation trajectories in real organizational life. In addition, our results revealed that an additional scenario, which we call “Fading Away”, characterizes self-determination trajectories presenting on less pronounced, but ongoing, decrease over time. In their study, Solinger et al. (2013) referred to a similar commitment trajectory as depicting a “low match” between employees’ expectations and the characteristics of their workplaces, which causes initially moderate levels of commitment (or self-determination in this study) to diminish gradually over time.

In addition to showing how research focusing on organizational socialization and commitment extends and translates to the field of work motivation, our results contribute to a growing person-centered research stream in organizational psychology (Howard, Gagné, Morin, & Van den Broeck, 2016). This longitudinal study adopts a person-centered approach to obtain a finer-grained picture of how self-determined motivation unfolds over time among distinct subpopulations of employees. It would be informative to pursue this line of questioning by describing how self-determination trajectories emerge during the entry into the workplace and evolve over the course of a career.

The role of Leadership and Socialization. Our study also sheds new light on factors likely to be involved in the development of these distinct of self-determination trajectories at work. More precisely, we found that employees who initially perceive transformational leadership behaviors in their supervisor are more likely to belong to more adaptive self-determination trajectories. While there is abundant evidence of the motivational benefits of transformational leadership (e.g., Montano, Reeske, Franke, & Hüffmeier, 2017), our results provide new empirical evidence on how these behaviors influence the development of self-determination trajectories. From a job crafting perspective (Wrzesniewski & Dutton, 2001), it is plausible that the trajectory captures, to some extent, the manner in which employees shape and redefine their work reality. Thus, employees in the *Increasing* trajectory would be more inclined toward transformational leadership behaviors that support their actions, and this would strengthen feelings of self-determination over time.

Our results also showed that, once employees’ perceptions of transformational leadership were taken into account, abusive leadership behaviors were not related to membership into any of the self-determination trajectories identified in this study. In light of the well-documented harmful effects of such behaviors on employee motivation and functioning (Tepper, Simon, & Park, 2017; Trépanier et al., 2015), this result was unexpected. Considering that self-determination is characterized by volition and self-endorsement of one's choices and actions, our results suggested that abusive leadership behaviors are unable to make a real dent in employee motivation. Although our results may suggest that the harmful effects of abusive leadership behaviors could be limited to decreasing employee's exposure to more desirable forms of leadership behaviors (i.e., transformational ones in the present study), they also raise the possibility that abusive leadership behaviors may take time to take a toll on employees' motivation. Alternatively, employees may need time to come to recognize the unacceptable nature of these behaviors. Future studies would do well to consider the ability of employees to recognize specific leadership behaviors as being abusive in nature, as well as the role of persistent abusive behaviors on employee motivation later in their career.

Our study also extends the knowledge of the social antecedents of work by considering the role of organizational socialization. Although the socialization research describes the learning and the internalization of the values, skills, expected behaviors, and social knowledge that are required for proper job functioning (Perrot & Campot, 2009), no studies to date have considered that socialization may play a role on employee self-determination. Consistent with SDT predictions, our results showed that, irrespective of profile membership, task- and team-level socialization were associated with higher average levels of self-determined motivation over time, and that time-specific variations in task-level socialization further predict time-specific increases in self-determined motivation levels. However, the results also showed that task-level socialization increased the likelihood of belonging to the most adaptive self-determination trajectory, whereas team-level socialization decreased this likelihood. Given that, from a theoretical standpoint, the amount of socialization should contribute to the development of self-determined motivation, we offer a tentative explanation for this partly unexpected finding. Whereas learning and internalization occurring at the task level should help to meet the needs for autonomy (aligning with the objectives and mission of one's job), competence (understanding one's responsibilities and work role), and relatedness (knowing who to ask for assistance when needed), these processes could differ at the team level. The processes involved in team learning (understanding how each team member can contribute to achieve team objectives) and internalization (representing the team's values) may generate pressure on employees to buy into established team rules, norms, and values. For instance, novice nurses may rely on more experienced nurses in the team, to identify client values, and may relinquish some of their decision-making responsibilities to these nurses (Fergusson & Day, 2001). As being less autonomous in decision-making, they are likely to experience excessive guilt and accept full responsibility for poor outcomes in care (Benner et al., 2009). This perceived pressure could lead employees to regulate their actions to suit the circumstances (i.e., contingently) in order to maximize their degree of fit with their teammates. According to SDT (Ryan & Deci, 2017), such externally-driven pressures should be accompanied by a decrease in employee interest and enjoyment at work.

Alternatively, it is plausible that, in the nursing profession, team-level socialization could provide a greater and more realistic exposure to the challenges of the job (e.g., increasing pressure to meet performance targets in the face of labor shortages). Team socialization enables the transmission of the organizational culture (Bauer et al., 1989) and provides an interpretation scheme to guide the construction of meaning (Louis, 1980). It can thus expose nurses to certain aggravating circumstances that are not fully aligned with their personal motives, goals, and values, thereby impeding the development of self-determined motivation. Further studies are needed to clarify this issue and to achieve a more nuanced understanding of the role of socialization at the organization level.

The Importance of Self-Determination Trajectories from an Outcomes' Perspective. Finally, this study broadens the knowledge of the potential effects of self-determined work motivation on employee commitment and turnover intentions. A key finding is that the most adaptive trajectories, particularly the *Increasing* trajectory, appear to facilitate affective commitment to the occupation and the organization, while limiting turnover intentions. Nonetheless, one notable characteristic of the decreasing profile was an initial association with high levels of affective commitment to the occupation but low levels of affective commitment to the organization. A good person-environment match being a basic component of employee adaptation (O'Reilly et al., 1991), it is plausible that an inadequate match between affective commitment to the occupation—arguably a self-defining characteristic of employees (Meyer et al., 1993)—and affective commitment to the organization could be accompanied by a drastic diminishment in global self-determination during the first years of employment. This decrease is consistent with the idea that the Honeymoon-Hangover scenario (corresponding to the *Decreasing* trajectory) could be caused by a growing sense of disappointment with the work environment as it fails to meet one's personal or professional expectations. This is well illustrated by the situation where, after heavily investing in a demanding training program, nurses find themselves stuck in a workplace that falls short of their expectations. In addition, the results revealed differences in levels of continuance commitment to the organization between the *Slightly Decreasing* and *Increasing* profiles at Time 2 (6 months) and Time 4 (24 months), suggesting that this commitment mindset could be a defining characteristic of the *Slightly Decreasing* profile. While consistent with the research on commitment, which demonstrates the need to consider multiple mindsets and targets in order to obtain a complete picture of employees' commitment (Meyer et al., 2015; Morin, Meyer et al., 2015), these results are also consistent with the idea that continuance commitment might be more closely related to less self-determined forms of motivation (Fernet et al., 2017; Meyer et al., 2012). In future studies, it would be useful to disentangle the temporal effects of sources and targets of commitment in relation to self-determined motivation.

Limitations and Future Directions

This study includes limitations that should be acknowledged and open the way to further research. First, we used self-report measures exclusively, which are susceptible to social desirability and self-evaluation biases. Upcoming longitudinal studies should include data from other sources (e.g., peer perceptions of leadership) and outcomes (e.g., job performance, actual turnover) to increase the scope of the findings. Second, profiles of longitudinal trajectories, albeit a rich source of information, are not sufficient to identify causality, to study the dynamic interplay between employees and their environments, or to investigate how new employees become socialized into their new workplaces. Although studies supported some of the proposed associations (e.g., Fernet et al., 2012) and the present results established these relations longitudinally, we should not rule out the possibility of reciprocal or inverse relations. Thus, it remains plausible that some commitment mindsets or targets would act on employee motivation (Meyer et al., 2004), or that additional variables (e.g., personality, social interactions) could have impacted both. Future studies could use experimental designs to clarify the nature of observed relations. Third, although we adopted a recognized theoretical perspective to determine the choice of predictors liable to act on trajectory membership, the analysis was based on a limited number of theoretical antecedents. Whereas the developmental nature of self-determined work motivation has been established, further studies are needed to enrich our understanding of the factors that predict the emergence of these trajectories. In addition to deepening the understanding of leadership practices (e.g., authentic, transactional, laissez-faire), one promising research avenue would be to examine individual (i.e., basic psychological need satisfaction) and work design characteristics, of which the motivational potential has been extensively studied (see Parker, Morgeson, & Johns, 2017), yet not necessarily longitudinally.

Fourth, we examined the trajectories at only four intervals (0, 6, 12, and 24 months) and in employees with varying length of experience, although all within their three first years in the nursing profession. Despite the fact that results obtained from extensive verifications conducted as part of the present study support the idea that this inter-individual variability in terms of early career tenure played no additional role in the present study, it remains important for future studies to, whenever possible, investigate whether and how the present results would generalize to the estimation of trajectories among a sample of participants showing fewer variations in this regard, or directly reflecting the length of early career socialization. Furthermore, our data did not allow examining the contribution of previous job experience at T1 (e.g., internships in the studied or other organizations) or the effect of turnover in units and actual organizational and occupational turnover. Nevertheless, it is worth noting that in the province of Quebec (Canada), where this study was conducted, health care facilities are organized by socio-health regions, which substantially restricts staff rotation between facilities. To extend the understanding, future studies could address larger samples, attempt to recruit upcoming employees and follow them across the transition into employment, and consider distinct time periods and intervals. It would also be useful to examine self-determination trajectories at different career stages and during career transitions (e.g., internal job changers, organizational insiders). Fifth, in terms of generalizability, our results are based uniquely on a sample of nurses in a single Canadian province. Our findings should be replicated in employees from various occupations and cultures, especially because most occupations lack consensus on the optimal duration of professional integration or organizational socialization. Finally, it is worth noting that, although the results reported here can be considered to be robust to the inherent degree of classification inaccuracy present in any person-centered analysis, the low level of entropy observed in this study (anchored in the lower levels of classification accuracy of participants into Profiles 1 and 2) suggest that any attempt to physically assign participants into their most likely profile should be done with caution. Interestingly, our results do suggest that the simultaneous consideration of predictors seems to help increase this classification accuracy, as shown by the higher levels of entropy associated with the models including predictors.

Managerial Implications

Despite these limitations, the present study has managerial implications for nurturing employee self-determination. From an organizational perspective, managers would benefit from questioning and nurturing the transformational leadership skills of supervisors insofar as they appear to wield considerable influence on employees' self-determination trajectories, and hence play a key role in optimizing task-related socialization. When supervisors are in a position to define and shape the workplace reality, they embody the attitudes and behaviors that employees should develop (Smircich & Morgan, 1982). Supervisors who demonstrate transformational leadership behaviors can help lighten work demands, for example, by providing a meaningful rationale for the needs and merits of each task. They can also be available to dispense information, clarify ambiguities related to roles and tasks, answer questions, and provide assistance or guidance as needed. Supervisors can stimulate the perception of resources by creating an environment that is conducive to collaboration, information sharing, and recognition. Studies have supported these proposals by showing that transformational leadership behaviors are associated with employee attitudes, performance, and well-being, and that these behaviors foster favorable perceptions of the workplace, including more resources and fewer demands (Fernet et al., 2015; Piccolo & Colquitt, 2006).

Conclusion

Our results revealed that global levels of self-determined work motivation tended to follow one out of three distinct developmental trajectories. In addition, our resulted identified trajectory predictors which could prove to be particularly useful for intervention purposes. Notably, task-level socialization and transformational leadership behaviors appeared to promote self-determination, which itself was found to help achieve greater commitment and intentions to remain in the occupation and the organization.

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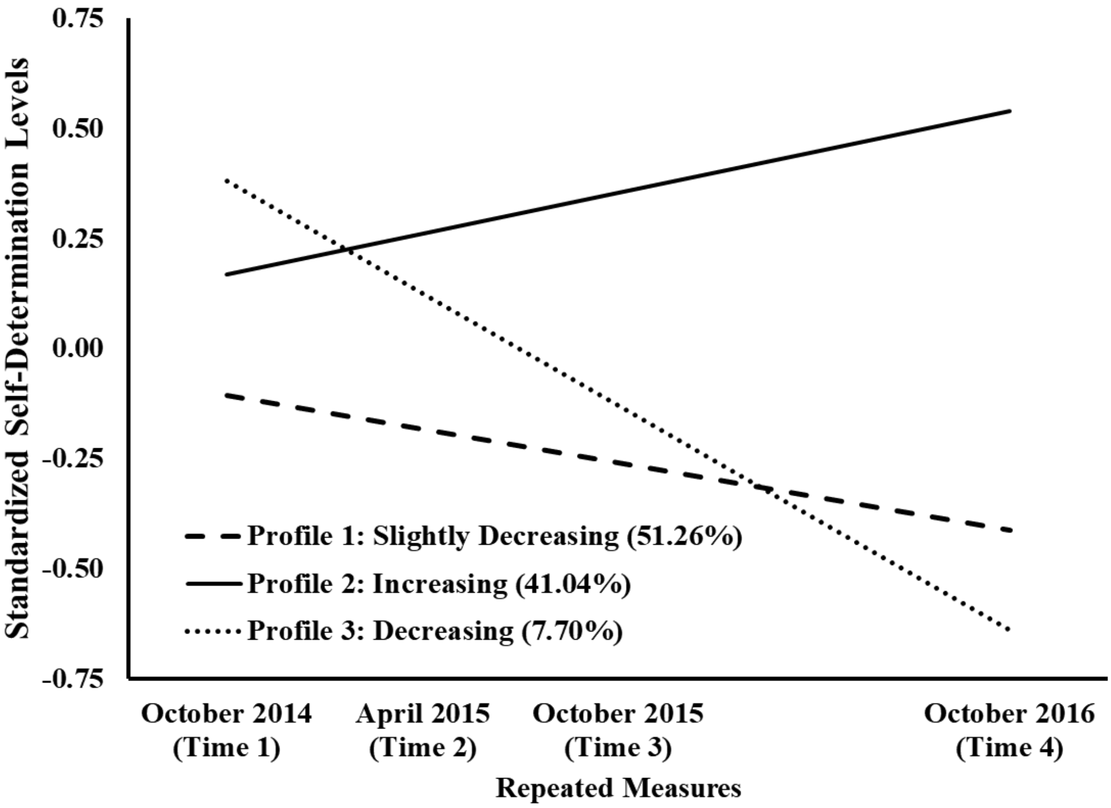

Figure 1. Estimated growth trajectories for the three motivation profiles

Note. Trajectories are estimated based on invariant factor scores with a mean of 0 and a standard deviation of 1 obtained on the global self-determination factor in the preliminary analysis, as reported in the online supplements.

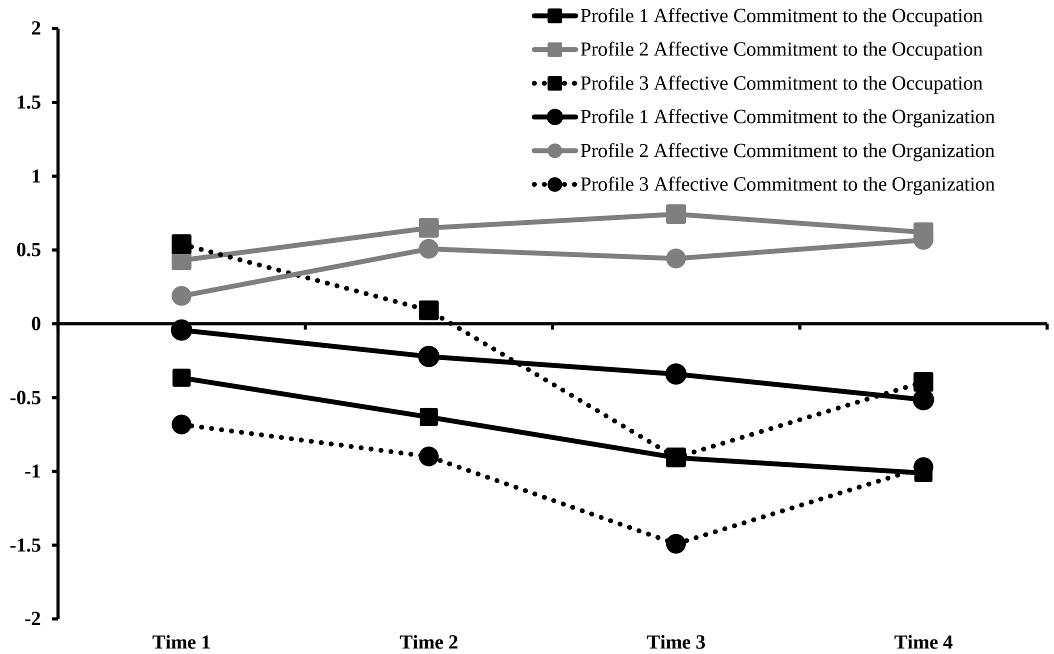

Figure 2. Affective commitment in the three motivation profiles

Note. Trajectories are estimated based on invariant factor scores with a mean of 0 and a standard deviation of 1 obtained from the preliminary analysis, as reported in the online supplements.

Table 1. *Results for the Growth Mixture Analyses*

Model		LL	#fp	AIC	CAIC	BIC	ABIC	Entropy	aLMR	BLRT
Unconditional models										
M1	Profile 1	-2165.454	6	4342.908	4375.862	4369.862	4350.812	Na	Na	Na
M2	Profile 2	-2148.278	10	4316.557	4371.479	4361.479	4329.729	.435	.002	≤.001
M3	Profile 3	-2133.118	14	4294.237	4371.128	4357.128	4312.678	.446	.036	.006
M4	Profile 4	-2128.582	18	4293.164	4392.024	4374.024	4316.874	.459	.449	1.000
M5	Profile 5	-2121.723	22	4287.446	4408.275	4386.275	4316.424	.461	.216	.118
M6	Profile 6	-2116.264	26	4284.528	4427.326	4401.326	4318.775	.457	.198	.333
M7	Profile 7	-2109.890	30	4279.780	4444.547	4414.547	4319.296	.623	≤.001	≤.001
M8	Profile 8	-2108.150	34	4284.301	4471.037	4437.037	4329.086	.564	.182	.182
Models with time-invariant (Time 1) controls, from M3										
M9	Null effects of controls	-2101.151	14	4230.303	4307.002	4293.002	4248.552	.449	Na	Na
M10	Effects of controls on C	-2092.027	24	4232.054	4363.539	4339.539	4263.339	.425	Na	Na
M11	Effects of controls on C, I (Inv.)	-2087.715	29	4233.430	4392.307	4363.307	4271.232	.446	Na	Na
M12	Effects of controls on C, I, S (Inv.)	-2081.886	34	4231.772	4418.041	4384.041	4276.092	.465	Na	Na
M13	Effects of controls on C, I (free across profiles)	-2071.038	39	4220.077	4433.739	4394.739	4270.914	.398	Na	Na
M14	Effects of controls on C, I, S (free across profiles)	-2060.423	54	4228.846	4524.685	4470.685	4299.236	.511	Na	Na
Models with time-invariant predictors (TIP; Time 1), from M3										
M15	Null effects of TIP	-1816.468	14	3660.937	3735.199	3721.199	3676.757	.465	Na	Na
M16	Effects of TIP on C	-1725.511	24	3499.022	3626.329	3602.329	3526.143	.722	Na	Na
M17	Effects of TIP on C, I (Inv.)	-1698.863	29	3455.727	3609.556	3580.556	3488.498	.480	Na	Na
M18	Effects of TIP on C, I, S (Inv.)	-1687.200	34	3442.400	3622.751	3588.751	3480.822	.513	Na	Na
M19	Effects of TIP on C, I (free across profiles)	-1689.578	39	3457.157	3664.030	3625.030	3501.228	.490	Na	Na
M20	Effects of TIP on C, I, S (free across profiles)	-1669.031	54	3446.062	3732.502	3678.502	3507.085	.429	Na	Na
Models with time-varying predictors (TVP), from M18										
M21	Null effects of TVP	-8842.634	294	18273.267	19887.986	19593.986	18660.528	.673	Na	Na
M22	Effects of TVP Inv. across time & profiles	-8804.921	299	18207.843	19850.022	19551.022	18601.689	.685	Na	Na
M23	Effects of TVP Inv. across time & free across profiles	-8802.151	309	18222.302	19919.404	19610.404	18629.320	.686	Na	Na
M24	Effects of TVP free across time & Inv. across profiles	-8792.664	314	18213.329	19937.892	19623.892	18626.933	.684	Na	Na
M25	Effects of TVP free across time & profiles	-8760.564	354	18229.129	20173.382	19819.382	18695.422	.727	Na	Na

Note. LL: Model log likelihood; #fp: Number of free parameters; AIC: Akaïke information criterion; CAIC: Constant AIC; BIC: Bayesian information criterion; ABIC: Sample-size adjusted BIC; na: Not applicable; C: Profile membership; I: Intercept factor; S: Slope factor.

Table 2. *Parameters Estimates for the Final Unconditional Growth Mixture Analysis Solution*

Parameter	Profile 1 (Slightly Decreasing) Estimate (t)	Profile 2 (Increasing) Estimate (t)	Profile 3 (Decreasing) Estimate (t)
Intercept mean	-0.107 (-1.128)	0.167 (1.242)	0.379 (1.079)
Slope mean	-0.153 (-2.910)**	0.186 (2.032)*	-0.510 (-2.561)**
Intercept variability ($SD = \sqrt{\sigma}$)	0.824 (11.909)**	0.824 (11.909)**	0.824 (11.909)**
Slope variability ($SD = \sqrt{\sigma}$)	0.173 (2.130)*	0.173 (2.130)*	0.173 (2.130)*
Intercept-slope correlation	-0.444 (-2.935)*	-0.444 (-2.935)*	-0.444 (-2.935)*
$SD(\varepsilon_{yi})$	0.401 (5.141)**	0.650 (4.580)**	0.965 (4.965)**

Note. t = Estimate / standard error of the estimate (t values are computed from the original variance estimate and not from the square root); SD(ε_{yi}) = Standard deviation of the time-specific residual. The square root of the estimate of variability (trajectory factor, time-specific residual) is presented so that the results can be interpreted in the same unit as the construct used in the model (here, standardized factor score with a mean of 0 and an SD of 1); * $p \leq .05$; ** $p \leq .01$.

Table 3. *Classification Accuracy: Average Probability of Membership in Each Latent Profile (Column) as a Function of the Most Likely Profile Membership (Row).*

	Profile 1 (Slightly Decreasing)	Profile 2 (Increasing)	Profile 3 (Decreasing)
Profile 1 (Slightly Decreasing)	0.656	0.296	0.047
Profile 2 (Increasing)	0.227	0.682	0.091
Profile 3 (Decreasing)	0.019	0.158	0.823

Table 4. *Predictor Effects on Profile Membership and on the Intercept and Slope Factors*

	Profile 1 (Slightly Decreasing) vs. 3 (Decreasing)		Profile 2 (Increasing) vs. 3 (Decreasing)		Profile 1 (Slightly Decreasing) vs. 2 (Increasing)		Intercept factor		Slope factor	
	Coef. (SE)	OR	Coef. (SE)	OR	Coef. (SE)	OR	Coef. (SE)	β	Coef. (SE)	β
Transformational leadership	1.826(0.859)*	6.207	3.361 (0.971)**	28.821	-1.535 (0.458)**	0.215	-0.123 (0.117)	-0.137	-0.118 (0.056)*	-0.621
Abusive leadership	1.013(0.716)	2.753	2.041 (1.073)	7.700	-1.029 (0.576)	0.357	-0.125 (0.088)	-0.144	-0.088 (0.038)*	-0.481
Task-level socialization	-0.896 (0.610)	0.408	0.020 (0.982)	1.021	-0.916 (0.375)*	0.400	0.392 (0.078)**	0.496	-0.001 (0.043)	-0.008
Organization-level socialization	0.607 (0.704)	1.834	1.469 (1.075)	4.344	-0.862 (0.592)	0.422	-0.171 (0.090)	-0.212	-0.128 (0.071)	-0.751
Team-level socialization	-0.372 (1.207)	0.689	-2.008 (1.558)	0.134	1.635 (0.542)**	5.129	0.316 (0.108)*	0.396	0.043 (0.088)	0.254

Notes. **: $p < .01$; *: $p < .05$. Coef: Regression coefficient (these are multinomial logistic regression coefficients for the prediction of profile membership, and unstandardized multiple regression coefficients for the prediction of the intercept and slope factors); SE: standard error of the coefficient; OR: Odds ratio; β: standardized multiple regression coefficients. The multinomial logistic regression coefficients and OR reflect the predictor effects on the likelihood of membership in the first listed profile relative to the second listed profile.

Online Supplements for:

Self-Determination Trajectories at Work: A Growth Mixture Analysis

Authors' note:

These online technical appendices are to be posted on the journal website and hot-linked to the manuscript. If the journal does not offer this possibility, these materials can alternatively be posted on one of our personal websites (we will adjust the in-text reference upon acceptance).

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

Preliminary Measurement Models

Preliminary measurement models were estimated using Mplus 7.31 (Muthén & Muthén, 2015). Due to the complexity of the longitudinal models underlying all constructs assessed in the present study, these analyses were conducted separately for the motivation variables, the predictors related to employees' perceptions of their supervisors' transformational and abusive leadership, the predictors related to employees' socialization (tasks, organization, and team) and the outcomes (affective commitment to, continuance commitment to, and intentions to leave the organization and the occupation). 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-determination) and six specific orthogonal factors (S-factors: intrinsic motivation, identified regulation, introjected regulation, external regulation, and amotivation) was estimated based on Howard, Gagné, Morin, and Forest's (2018; also see Litalien et al., 2017) recommendations.

For the leadership model, a confirmatory factor analytic (CFA) approach including two correlated first-order factors (transformational and abusive) was estimated. For the socialization model, we relied on a confirmatory factor analytic (CFA) approach including six first-order factors (learning and internalization related to the tasks, the organization, and team) and three correlated higher-order factors (tasks, organization, and team) estimated from two first-order factors each (learning and internalization). For the outcomes model, we relied on an exploratory structural equation model (ESEM), following recent recommendations from Morin and colleagues (Morin, Boudrias et al., 2017; Morin, Meyer et al., 2015). This choice reflects the conceptually-related nature of ratings of a variety of constructs directed at similar foci (e.g., affective and continuance commitment to the organization) as well as that of ratings of similar constructs related to distinct foci (e.g., affective commitment to the organization and occupation). In these conditions, ESEM has been shown to result in more precise estimates of correlations among psychological constructs relative to CFA (Asparouhov, Muthén, & Morin, 2015; Morin, Arens, & Marsh, 2016). To reflect the fact that outcomes measures of commitment and intentions to leave are taken from different instruments, two distinct sets of ESEM factors (one set of four commitment factors and one set of two intentions to leave factors) were estimated into the same model, with cross-loadings allowed between factors from the same set but not across factors from different sets. All factors were freely allowed to correlate within and across sets.

Longitudinal models were directly estimated across all four time waves and included a total of 28 factors ([1 G-factor + 6 S-factors] x 4 time waves) for the motivation measure, 8 factors for the leadership measure (2 factors x 4 time waves), 36 factors for the socialization measure ([6 first-order factors +3 higher-order factors] x 4 time waves), and 24 factors for the outcomes measures (6 factors x 4 time waves). All factors were freely 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 between: (a) 3 pairs of items presenting parallel wording in the socialization model, (b) 7 pairs of items (4 for commitment and 3 for intentions to leave) presenting parallel wording in the outcomes model, and (c) the 5 negatively-worded items used in the commitment measure in the outcomes model (e.g., Marsh, Abduljabbar et al., 2013; Marsh, Scalas, & Nagengast, 2010). The B-ESEM (motivation) and ESEM (outcomes) models were estimated using confirmatory target rotation, in which all target loadings of items on their a priori were freely estimated, and all cross-loadings targeted to be as close to zero as possible (Asparouhov & Muthén, 2009; Browne, 2001; Reise, Moore, & Maydeu-Olivares, 2011).

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 5 or less responses categories are used (as in the leadership and commitment measures) or when the response categories follow asymmetric thresholds (as is the case for all measures used 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; Lei, 2009; Lubke & Muthén, 2004; Rhemtulla, Brosseau-Liard, & Savalei, 2012). In particular, WLSMV estimation has previously been showed to be appropriate for motivation measures (Guay et al., 2015; Litalien et al., 2015).

Before saving the factor scores for our main analyses, we verified that the measurement model operated in the same manner across time waves, through sequential tests of measurement invariance (Millsap, 2011). For the motivation measure, 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 outcomes model, an additional step (4b) was included to test the invariance of the correlated uniquenesses included between the seven pairs of parallel-worded items as well as between the 5 negatively-worded items. For the socialization model, because of the presence of higher-order factors, 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.

In the socialization model, all higher-order factors (tasks, the organization, and team) were estimated based on two first-order factors each (learning and internalization), creating locally underidentified constructs (although the overall model remains overidentified). These variables were locally-identified using essentially tau-equivalent constraints (ETEC; Little, Lindenberger & Nesselroade, 1999). This technique involves placing equality constraints on the loadings of both indicators to help locate the construct at the true intersection of the indicators and essentially tests whether both first-order factors can be considered as equivalent indicators of the higher-order factors. These ETEC were incorporated as an additional step in the higher-order invariance sequence (2b). Indeed, if these ETEC had been directly included from the model of higher-order configural invariance, then the model of higher-order weak invariance would have the same number of degrees of freedom as the model of model higher-order configural invariance (freeing up three variances while constraining three pairs of loadings to equality).

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; Yu, 2002): 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 the context of tests of measurement invariance. A ΔCFI of .010 or less and a ΔRMSEA of .015 or less between a more restricted model and the previous one supports the invariance hypothesis.

Longitudinal B-ESEM (motivation variables) and CFAs (predictors and outcomes) models were estimated using the data from all respondents who completed at least one wave of data rather than a listwise deletion strategy focusing only on employees having answered all, or a subset, of the time waves (Enders, 2010; Graham, 2009). In total, 660 participants provided a total of 1,747 time-specific ratings (M = 2.65 time-specific ratings per participant), with 201 participants (30.5%) completing all four time-points, 175 (26.5%) completing 3 time-points, 134 (20.3%) completing 2 time-points, and only 150 (22.7%) completing a single time-point. To account for missing responses, models were estimated based on the full available information, based on algorithms implemented in Mplus for WLSMV (Asparouhov & Muthén, 2010a). This procedure 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. Still, a key limitation of WLSMV estimation, when compared to ML/MLR, is the reliance on a slightly less efficient way of handling missing data (Asparouhov & Muthén, 2010a). For this reason, factor scores were saved using start values taken from the final WSLMV longitudinal model, but using a Bayes estimator which handles missing data in a manner comparable to ML/MLR (Asparouhov & Muthén, 2010b; Enders, 2010). This procedure has comparable efficacy to multiple imputation, while being more efficient (Enders, 2010; Jeličič, Phelps, & Lerner, 2009; Larsen, 2011). The reason why initial measurement models and tests of measurement invariance where not directly conducted with Bayes is to be able to properly assess the adequacy of the measurement model, and its measurement invariance over time, using typical goodness-of-fit information which is not available with Bayes. This approach thus provided a relatively efficient way of handling participants' missing responses on subsets of items at specific time-points (participants who completed one specific time point left on average 5.77% of missing responses on specific items (SD = 5.31%). However, because these longitudinal measurement models are not "time-structured" (they do not take into account the specific shape of employees longitudinal growth trajectories, which requires latent curve models or growth mixture models), these factors scores were not used to impute (i.e. replace) scores for missing time points. Indeed, doing so would have induced the risk of inflating the apparent stability of employees' trajectories by relying on an imputation model taking into account adjacent time points, but not time-structured evolution. Missing time points were directly handled in the main growth mixture models reported in the main manuscript, using Full Information Maximum Likelihood (FIML) in conjunction with the MLR estimator (Enders, 2010; Graham, 2009).

The goodness-of-fit results from all models are reported in Table S1. These results support the adequacy of the a priori longitudinal measurement models underlying all constructs (with all CFI/TLI ≥ .95 and all RMSEA ≤ .06), as well as their complete measurement invariance across time waves 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). All of the completely invariant measurement models even fitted the data as well as the baseline models of configural invariance. To ensure that the latent profiles estimated at each time wave 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, correlated uniquenesses when appropriate, latent variance-covariance, and latent means). Although only strict measurement invariance is required to ensure that measurement of the constructs remains equivalent across time waves 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 waves) provides scores on profile indicators that can be readily interpreted as deviation from the grand mean expressed in standard deviation units. The observation of latent mean invariance across time point for the motivation measure indicates that, on the average, the sample is neither characterized by growth or decline in levels of global self-determination over time. However, observed levels of between-person variability in latent means and individual trajectories are consistent with the presence of substantial inter-individual variability in growth trajectories, supporting the use of methods specifically designed to model this variability (i.e., latent curve models) and specific growth profiles (i.e., growth mixture analyses). Figure S1 graphically represents observed individual trajectories.

The final parameter estimates from these measurement models are reported in Tables S2 to S5, while the correlations between all variables used in the main analyses (i.e., the factor scores saved from these final measurement models) are reported in Tables S6, together with reliability information. Generally, all covariates models resulted in factors that were well-defined through high target factor loadings ($M_{|\lambda|}$ = .810), resulting in fully acceptable composite reliability coefficients (ω; McDonald, 1970[3]): (a) transformational leadership ($M_{|\lambda|}$ = .892; ω = .965); (b) abusive leadership ($M_{|\lambda|}$ = .892; ω =

[3] Composite reliability coefficients associated with each of the a priori factors are calculated from the model standardized parameters using McDonald (1970) omega (ω) coefficient:

$$\omega = \frac{(\sum|\lambda_i|)^2}{[(\sum|\lambda_i|)^2 + \sum \delta_i]}$$

where $|\lambda_i|$ are the standardized factor loadings associated with a factor in absolute values, and δi, the item uniquenesses. The numerator, were the factor loadings are summed, and then squared, reflects the proportion of the variance in in indicators that reflect true score variance, whereas the denominator reflects total amount of variance in the items including both true score variance and random measurement errors (reflects by the sum of the items uniquenesses associated with a factor).

.965); (c) task-related socialization ($M_{|\lambda|}$ = .905; ω = .900); (d) organization-related socialization ($M_{|\lambda|}$ = .854; ω = .843); (e) team-related socialization ($M_{|\lambda|}$ = .915; ω = .911); (f) affective commitment to the occupation ($M_{|\lambda|}$ = .892; ω = .923); (g) continuance commitment to the occupation ($M_{|\lambda|}$ = .641; ω = .864); (h) affective commitment to the organization ($M_{|\lambda|}$ = .721; ω = .891); (i) continuance commitment to the organization ($M_{|\lambda|}$ = .644; ω = 853); (j) intentions to leave the occupation ($M_{|\lambda|}$ = .913; ω = .952); (h) intentions to leave the organization ($M_{|\lambda|}$ = .784; ω = .912). The estimated global self-determination factor was also fully in line with Howard et al. (2018), supporting its interpretation as a reliable (ω = .708) estimate of global levels of self-determination, with strong positive loadings from the intrinsic motivation ($M_{|\lambda|}$ = .869) and identified regulation ($M_{|\lambda|}$ = .609) items, weak loadings from the introjected regulation ($M_{|\lambda|}$ = .265) and external regulation ($M_{|\lambda|}$ = .111) items, and moderate negative loadings from the amotivation items (M_{λ} = -.569).

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A More Technical Presentation of Growth Mixture Analyses.

GMA aim to represent longitudinal heterogeneity by the identification of subgroups (i.e., profiles) of participants following distinct trajectories. A linear GMA for the repeated measure y_{it} for individual *i* at time *t* is estimated within *k* distinct levels (k = 1, 2, …, K) of an unobserved latent categorical variable *c* representing the profiles, with each individual having a probability (*p*) of membership in the *k* levels of this latent categorical variable.

$$y_{it} = \sum_{k=1}^{K} p_k[\alpha_{iyk} + \beta_{iyk}\lambda_t + \varepsilon_{yitk}] \tag{1}$$

$$\alpha_{iyk} = \mu_{\alpha yk} + \zeta_{\alpha yik} \tag{2}$$

$$\beta_{iyk} = \mu_{\beta yk} + \zeta_{\beta yik} \tag{3}$$

The *k* subscript indicates that most parameters can be freely estimated across profiles. In this equation, α_{iyk} and β_{iyk} represent the random intercept and random linear slope of the trajectory for individual *i* in profile *k*; $\mu_{\alpha yk}$ and $\mu_{\beta yk}$ represent the average intercept and linear slope in profile *k* and $\zeta_{\alpha yik}$ and $\zeta_{\beta yik}$ represent the variability of the intercepts and slopes across cases within profiles. ε_{yitk} represents a diagonal matric of time- individual- and class- specific residuals. p_k defines the probability that an individual *i* belongs to class *k* with all $p_k \geq 0$ and $\sum_{k=1}^{K} p_k = 1$. The variance parameters ($\zeta_{\alpha yik}, \zeta_{\beta yik}$) have a mean of zero and a Φ_{yk} variance-covariance matrix:

$$\Phi_{yk} = \begin{bmatrix} \psi_{\alpha\alpha yk} & \\ \psi_{\alpha\beta yk} & \psi_{\beta\beta yk} \end{bmatrix} \tag{4}$$

In these models, Time is represented by λ_t , the factor loading matrix relating the time-specific indicators to the linear slope factor. Time is coded to reflect the passage of time and is thus a function of the intervals between measurement points. Assuming a study including four equally space monthly measurement points of newcomers starting a new employment, it is reasonable to set the intercept at Time 1 [$E(\alpha_{iyk}) = \mu_{y1k}$]. Thus, for a linear GMM, time would be coded $\lambda_1 = 0$, $\lambda_2 = 1$, $\lambda_3 = 2$, $\lambda_4 = 3$. In the present study, to reflect the fact that Times 1-2-3 assessments were conducted 6 months apart and that Time 4 assessment was conducted one year after Time 3, time was coded: $\lambda_1 = 0$, $\lambda_2 = .5$, $\lambda_3 = 1$, $\lambda_4 = 2$. As noted in the manuscript, this study relies on a more constrained estimation of GMA through which the latent variance-covariance matrix was specified as invariant across classes, whereas the residuals were specified as homoscedastic, leading to the following model equations:

$$y_{it} = \sum_{k=1}^{K} p_k[\alpha_{iyk} + \beta_{iyk}\lambda_t + \varepsilon_{yik}] \tag{5}$$

$$\alpha_{iyk} = \mu_{\alpha yk} + \zeta_{\alpha yi} \tag{6}$$

$$\beta_{iyk} = \mu_{\beta yk} + \zeta_{\beta yi} \tag{7}$$

$$\Phi_{y} = \begin{bmatrix} \psi_{\alpha\alpha y} & \\ \psi_{\alpha\beta y} & \psi_{\beta\beta y} \end{bmatrix} \tag{8}$$

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									
Configural Invariance	1459.146*(1380)	.997	.996	.009	[.000; .014]	-	-	-	-
Weak Invariance	1660.167*(1560)	.996	.995	.010	[.003; .014]	218.879(180)	-.001	-.001	+.001
Strong Invariance	1879.354*(1758)	.995	.995	.010	[.004; .014]	241.202(198)	-.001	.000	.000
Strict Invariance	1969.439*(1806)	.994	.993	.012	[.007; .015]	101.920*(48)	-.001	-.002	+.002
Latent Variance-Covariance Invariance	2126.398*(1869)	.990	.989	.014	[.011; .017]	119.564*(63)	-.004	-.004	+.002
Latent Means Invariance	2192.385*(1887)	.988	.988	.016	[.012; .018]	47.753*(18)	-.002	-.001	+.002
Leadership Measurement Models									
Configural Invariance	4720.008*(3584)	.972	.970	.023	[.021; .024]	-	-	-	-
Weak Invariance	4772.500*(3644)	.972	.971	.022	[.022; .024]	69.292(60)	.000	+.001	-.001
Strong Invariance	4917.982*(3808)	.973	.973	.022	[.020; .023]	185.074(164)	+.001	+.002	.000
Strict Invariance	5010.239*(3874)	.972	.973	.022	[.020; .024]	162.169*(66)	-.001	.000	.000
Latent Variance-Covariance Invariance	5010.311*(3883)	.972	.973	.022	[.020; .023]	23.464*(9)	.000	.000	.000
Latent Means Invariance	4999.928*(3889)	.973	.973	.021	[.020; .023]	5.692(6)	+.001	.000	-.001
Socialization First-Order Measurement Models									
First-Order Configural Invariance	6456.412*(4032)	.966	.961	.031	[.029; .032]	-	-	-	-
First-Order Weak Invariance	6459.167*(4086)	.966	.962	.030	[.029; .031]	43.975(54)	.000	+.001	-.001
First-Order Strong Invariance	6686.868*(4395)	.967	.966	.028	[.027; .030]	341.880(309)	+.001	+.004	-.002
First-Order Strict Invariance	6588.516*(4467)	.970	.969	.027	[.026; .029]	135.719*(72)	+.003	+.003	-.001
First-Order Cor. Uniquenesses Invariance	6598.922*(4476)	.970	.969	.027	[.026; .029]	21.229(9)	.000	.000	.000
First-Order Latent Var.-Covar. Invariance	6267.336*(4539)	.975	.975	.024	[.023; .026]	94.731*(63)	+.005	+.006	-.003
First-Order Latent Means Invariance	6257.548*(4557)	.976	.976	.024	[.023; .026]	24.070(18)	+.001	+.001	.000
Socialization Second-Order Measurement Models									
Second-Order Configural Invariance	7172.937*(4662)	.964	.965	.029	[.028; .030]	-	-	-	-
Second-Order Weak Invariance	7137.607*(4671)	.965	.966	.029	[.027; .030]	13.905(9)	+.001	+.001	.000
Second-Order Weak Invariance + ETEC	7215.289*(4674)	.964	.965	.029	[.028; .030]	40.828*(3)	-.001	.000	.000
Second-Order Strong Invariance	7211.723*(4683)	.964	.965	.029	[.028; .030]	5.972(9)	.000	.000	.000
Second-Order Strict Invariance	7377.685*(4701)	.962	.963	.030	[.028; .031]	126.244*(18)	-.002	-.002	+.001
Second-Order Latent Var.-Covar. Invariance	7048.996*(4719)	.967	.968	.028	[.026; .029]	28.951(18)	+.005	+.006	-.002
Second-Order Latent Means Invariance	7031.215*(4728)	.967	.968	.028	[.026; .029]	13.771(9)	.000	.000	.000
Leadership Measurement Models									
Configural Invariance	7600.911*(6716)	.983	.981	.014	[.012; .016]				
Weak Invariance	7779.495*(6986)	.985	.984	.013	[.011; .015]	313.150(270)	+.002	+.003	-.001
Strong Invariance	8103.325*(7289)	.985	.984	.013	[.011; .015]	404.613(303)	.000	.000	.000
Strict Invariance	8225.817*(7382)	.984	.984	.013	[.011; .015]	161.411*(93)	-.001	.000	.000
Cor. Uniquenesses Invariance	8284.217*(7431)	.984	.984	.013	[.011; .015]	100.672*(49)	.000	.000	.000
Latent Variance-Covariance Invariance	8412.497*(7494)	.983	.983	.014	[.012; .015]	118.586*(63)	-.001	-.001	+.001
Latent Means Invariance	8453.794*(7412)	.982	.982	.014	[.012; .015]	38.433*(18)	-.001	-.001	.000

Note. *p < .01; ETEC: essentially tau-equivalent constraints; χ^2: WLSMV chi-square test of exact fit; *df*: degrees of freedom; CFI: comparative fit index; TLI: Tucker-Lewis index; RMSEA: root mean square error of approximation; 90% CI: 90% confidence interval; MD $\Delta\chi^2$: chi-square difference tests calculated with Mplus' DIFFTEST function.

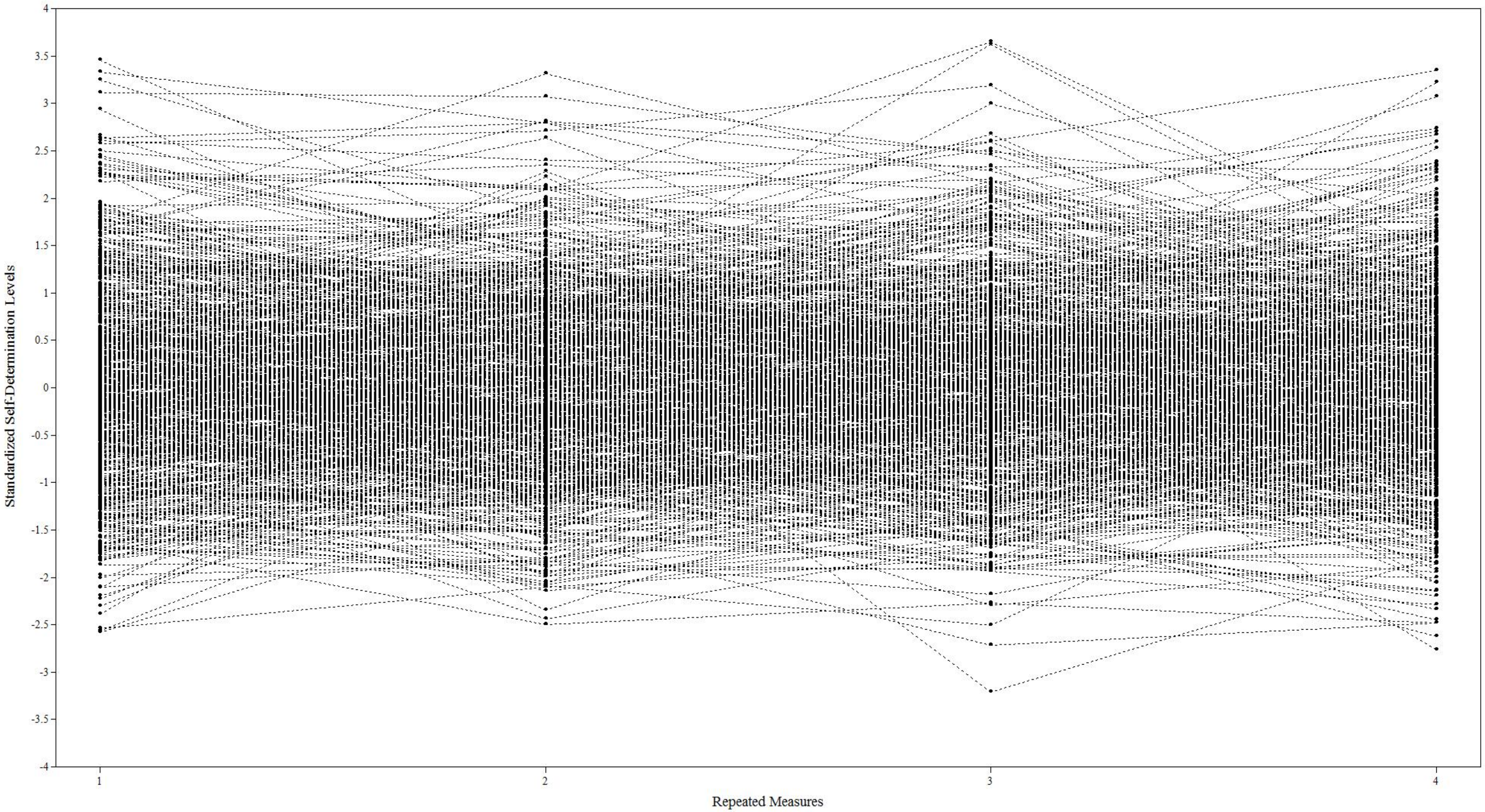

Figure S2. Observed Individual Trajectories of Employees Global Levels of Self-Determination.

Note. Global levels of self-determination are factor scores with a mean of 0 and a standard deviation of 1.

Table S2

Longitudinally Invariant Standardized Factor Loadings (λ) and Uniquenesses (δ) for the Motivation Bifactor-ESEM Measurement Model

Items	Global SD Factor (λ)	S-Factor 1 (λ)	S-Factor 2 (λ)	S-Factor 3 (λ)	S-Factor 4 (λ)	S-Factor 5 (λ)	δ
1. Intrinsic							
Item 1	**0.878**	***0.177***	*-0.015*	0.036	*0.017*	*0.010*	0.196
Item 2	**0.892**	***0.209***	*-0.007*	*-0.012*	*0.012*	*0.011*	0.159
Item 3	**0.837**	***0.265***	0.062	-0.056	*-0.028*	*0.016*	0.220
2. Identified							
Item 1	**0.734**	*0.134*	**0.222**	-0.065	*0.041*	*-0.041*	0.386
Item 2	**0.521**	-0.091	**0.195**	0.454	0.108	*-0.066*	0.460
Item 3	**0.572**	*0.018*	**0.362**	0.203	0.092	*-0.047*	0.490
3. Introjected							
Item 1	**0.245**	-0.333	*-0.162*	**0.391**	0.398	*0.145*	0.471
Item 2	**0.691**	*-0.118*	*-0.042*	**0.333**	0.113	*0.060*	0.380
Item 3	**0.110**	*0.019*	0.063	**0.838**	0.086	*-0.034*	0.272
Item 4	***0.012***	0.109	0.113	**0.779**	0.201	0.127	0.312
4. External							
Item 1	***0.019***	-0.205	*0.029*	0.108	**0.697**	*0.124*	0.444
Item 2	**-0.215**	0.119	*0.010*	0.220	**0.732**	0.154	0.332
Item 3	**-0.099**	*0.024*	*0.030*	0.233	**0.765**	0.146	0.328
5. Amotivation							
Item 1	**-0.561**	*0.005*	*-0.040*	*0.000*	0.093	**0.554**	0.368
Item 2	**-0.631**	-0.174	*0.034*	*0.022*	0.084	**0.689**	*0.088*
Item 3	**-0.514**	*0.208*	*-0.043*	*0.032*	*0.012*	**0.759**	0.113

Note. λ: factor loading; δ: item uniqueness; SD: self-determination; S: specific; Coefficients in italics are statistically non-significant ($p \geq .05$) while bold coefficients reflect the main target loadings.

Table S3

Longitudinally Invariant Standardized Factor Loadings (λ) and Uniquenesses (δ) for the Leadership CFA Measurement Model

	Transformational		Abusive	
	λ	δ	λ	δ
Item 1	0.801	0.358	0.889	0.210
Item 2	0.929	0.137	0.872	0.239
Item 3	0.931	0.134	0.740	0.452
Item 4	0.925	0.144	0.894	0.201
Item 5	0.851	0.275	0.630	0.603
Item 6	0.881	0.225	0.705	0.503
Item 7	0.928	0.138	0.825	0.319
Item 8			0.870	0.243
Item 9			0.703	0.506
Item 10			0.846	0.284
Item 11			0.900	0.190
Item 12			0.826	0.318
Item 13			0.682	0.534
Item 14			0.796	0.367
Item 15			0.822	0.324

Note. λ: factor loading; δ: item uniqueness; All coefficients are statistically significant ($p \leq .05$).

Table S4

Longitudinally Invariant Standardized Factor Loadings (λ) and Uniquenesses (δ) for the Motivation Bifactor-ESEM Measurement Model

Items	Task		Organization		Team	
	λ	δ	λ	δ	λ	δ
First Order Factors						
Learning Item 1	0.840	0.295	0.824	0.320	0.945	0.107
Learning Item 2	0.878	0.230	0.873	0.238	0.914	0.164
Learning Item 3	0.809	0.346	0.929	0.138	0.850	0.277
Learning Item 4	0.704	0.504	0.877	0.231	0.830	0.311
Internalization Item 1	0.875	0.235	0.895	0.199	0.924	0.147
Internalization Item 2	0.808	0.347	0.831	0.309	0.833	0.306
Internalization Item 3	0.916	0.162	0.954	0.090	0.952	0.094
Internalization Item 4	0.931	0.134	0.870	0.244	0.831	0.310
Higher Order Factors						
Learning	0.905	0.181	0.854	0.271	0.915	0.163
Internalization	0.905	0.181	0.854	0.271	0.915	0.163

Note. λ: factor loading; δ: item uniqueness; All coefficients are statistically significant ($p \leq .05$).

Table S5

Longitudinally Invariant Standardized Factor Loadings (λ) and Uniquenesses (δ) for the Outcomes ESEM Measurement Model

Items	Factor 1 (λ)	Factor 2 (λ)	Factor 3 (λ)	Factor 4 (λ)	Factor 5 (λ)	Factor 6 (λ)	δ
1. Affective Commitment to the Occupation							
Item 1R	**-0.765**	*0.028*	*-0.046*	0.080			0.356
Item 2R	**-0.788**	0.087	*0.011*	*0.021*			0.381
Item 3	**0.889**	0.094	-0.059	*0.004*			0.236
Item 4	**0.852**	*0.012*	*0.029*	*0.003*			0.251
Item 5R	**-0.787**	*0.056*	*0.020*	*-0.036*			0.406
Item 6	**0.764**	*0.003*	0.087	-0.096			0.316
2. Continuance Commitment to the Occupation							
Item 1	0.125	**0.742**	*-0.049*	*0.018*			0.415
Item 2	0.361	**0.451**	*0.028*	0.143			0.586
Item 3	-0.037	**0.987**	*0.008*	-0.040			0.057
Item 4	*0.001*	**0.938**	*0.004*	*0.008*			0.114
Item 5	-0.084	**0.362**	*-0.059*	0.388			0.595
Item 6	0.323	**0.365**	*0.014*	0.352			0.562
3. Affective Commitment to the Organization							
Item 1	*0.026*	*0.007*	**0.897**	*0.009*			0.173
Item 2R	*-0.047*	0.054	**-0.762**	0.056			0.378
Item 3R	*-0.050*	0.135	**-0.650**	0.133			0.498
Item 4	0.043	*0.025*	**0.889**	0.068			0.163
Item 5	*0.028*	*0.028*	**0.897**	*-0.004*			0.172
Item 6	*0.004*	*0.031*	**0.230**	0.154			0.915
4. Continuance Commitment to the Organization							
Item 1	*-0.038*	*-0.005*	*-0.023*	**0.724**			0.468
Item 2	*-0.053*	*0.026*	-0.303	**0.731**			0.349
Item 3	-0.090	0.052	-0.327	**0.705**			0.332
Item 4	*0.032*	*0.024*	0.383	**0.638**			0.408
Item 5	-0.151	*0.046*	0.294	**0.468**			0.661
Item 6	*-0.038*	*-0.006*	0.522	**0.595**			0.359
5. Intentions to Leave the Occupation							
Item 1					**0.988**	*-0.002*	*0.027*
Item 2					**0.802**	0.123	0.240
Item 3					**0.948**	*-0.006*	0.108
6. Intentions to Leave the Organization							
Item 1					0.101	**0.871**	0.140
Item 2					0.445	**0.353**	0.515
Item 3					-0.075	**0.978**	0.115
Item 4					*-0.049*	**0.932**	0.176

Note. λ: factor loading; δ: item uniqueness; Coefficients in italics are statistically non-significant ($p \geq .05$) while bold coefficients reflect the main target loadings.

Table S6

Correlations among the variables used in the present study (Part 1)

	α	ω	1-	2-	3-	4-	5-	6-	7-	8-	9-	10-	11-	12-	13-	14-	15-	16-	17-	18-
1- Age	---	---																		
2- Sex	---	---	.184*																	
3- Tenure	---	---	.163*	.003																
4- Emp.	---	---	-.050	.055	-.126**															
5- Sch.	---	---	-.113**	-.030	-.221**	.159**														
6- Compl.	---	---	-.025	-.028	.008	-.020	-.026													
7- SD_1	.695	.708	-.040	-.088*	-.029	-.016	-.065	.030												
8- TFL_1	.942	.965	.027	.023	-.012	-.060	-.117*	.073	.200*											
9- ABL_1	.867	.965	.067	.046	-.012	.008	.026	-.028	-.178*	-.672*										
10- TAS_1	.895	.900	.046	-.015	.050	-.050	-.159*	.019	.528*	.335*	-.261*									
11- ORS_1	.912	.843	.050	-.004	-.030	.009	-.118*	-.029	.418*	.335*	-.237*	.752*								
12- TES_1	.926	.911	.054	.000	-.003	-.023	-.111*	.003	.485*	.381*	-.243*	.780*	.843*							
13- ACOC_1	.868	.923	.015	-.096*	-.012	-.008	-.060	.014	.583*	.273*	-.252*	.458*	.376*	.384*						
14- ACOR_1	.834	.891	-.014	-.050	.007	-.023	-.131*	-.026	.333*	.460*	-.372*	.412*	.474*	.454*	.435*					
15- CCOC_1	.798	.864	-.039	-.044	-.083*	.014	.026	-.016	.029	-.114*	.171*	-.014	.005	.007	.033	-.042				
16- CCOR_1	.699	.853	.023	.000	.046	-.019	-.093*	-.029	-.067	-.015	.039	-.096*	-.041	-.042	-.187*	.036	.325*			
17- ILOC_1	.893	.952	-.014	.102*	-.037	.059	.087*	.013	-.378*	-.249*	.295*	-.317*	-.299*	-.280*	-.671*	-.374*	-.027	.089*		
18- ILOR_1	.851	.912	-.057	.062	-.073	.031	.169*	.016	-.232*	-.263*	.243*	-.230*	-.298*	-.264*	-.314*	-.531*	.088*	-.163*	.527*	
19- SD_2	.667	.708	-.030	-.109*	.007	-.014	-.126*	.030	.668*	.261*	-.208*	.419*	.286*	.336*	.477*	.230*	-.017	-.103*	-.333*	-.223*
20- TFL_2	.957	.965	.040	-.066	.021	-.023	-.053	.066	.223*	.496*	-.343*	.233*	.243*	.232*	.218*	.231*	-.067	-.113*	-.154*	-.080
21- ABL_2	.892	.965	-.006	.076	-.012	.024	-.047	-.050	-.176*	-.384*	.631*	-.266*	-.238*	-.227*	-.198*	-.210*	.099*	.095	.204*	.119*
22- TAS_2	.899	.900	-.008	-.101*	.023	-.075	-.129*	.015	.445*	.261*	-.211*	.761*	.513*	.573*	.376*	.260*	.008	-.085	-.244*	-.146*
23- ORS_2	.921	.843	.036	-.057	-.021	-.047	-.108*	.019	.338*	.262*	-.152*	.568*	.736*	.610*	.327*	.351*	.012	-.074	-.225*	-.195*
24- TES_2	.930	.911	.019	-.045	.008	-.014	-.069	.007	.372*	.267*	-.154*	.588*	.567*	.639*	.324*	.276*	.026	-.059	-.193*	-.134*
25- ACOC_2	.872	.923	-.053	-.153*	-.003	-.021	-.032	-.017	.584*	.258*	-.219*	.404*	.306*	.326*	.856*	.408*	.149*	-.109*	-.621*	-.267*
26- ACOR_2	.858	.891	-.021	-.082	-.012	-.015	-.093	-.025	.306*	.351*	-.282*	.357*	.432*	.393*	.350*	.649*	.035	-.066	-.301*	-.380*
27- CCOC_2	.816	.864	-.101*	.003	.006	.013	.039	-.046	-.096*	-.102*	.154*	-.047	-.042	-.048	-.067	-.067	.644*	.378*	.094	.047
28- CCOR_2	.748	.853	.007	.047	-.012	-.006	-.064	-.051	-.124*	-.062	.137*	-.100*	-.030	-.051	-.179*	.009	.272*	.646*	.159*	-.215*
29- ILOC_2	.853	.952	.120*	.095*	-.038	.012	.062	-.031	-.414*	-.205*	.188*	-.265*	-.210*	-.232*	-.540*	-.310*	-.086	.001	.500*	.263*
30- ILOR_2	.867	.912	-.048	.090	-.044	.045	.084	-.006	-.240*	-.153*	.142*	-.154*	-.229*	-.206*	-.189*	-.341*	.009	-.082	.336*	.529*

Note. * p ≤ .05; α: alpha coefficient of scale score reliability; ω: omega coefficient of model-based composite reliability (identical across time wave due to the complete invariance of the measurement models); sex (1 female, 2 male); age (years); tenure (years); Emp.: Employment status (1 permanent, 2 temporary); Sch.:Work schedule (1 full time, 2 part time); Comp: Number of completed time points (1 to 4); All other variables are time-invariant factor scores with a mean of 0 and a SD of 1; SD: global levels of self-determination; TFL: transformational leadership; ABL: abusive leadership; TAS: task-related socialization; ORS: organization-related socialization; TES: team-related socialization; ACOC: affective commitment to the occupation; ACOR: affective commitment to the organization; CCOC: continuance commitment to the occupation; CCOC: continuance commitment to the organization; ILOC: intentions to leave the occupation; ILOR: intentions to leave the organization, _1 to _4: time of measurement.

Table S6 (Continued)

Correlations among the variables used in the present study (Part 2)

	α	ω	1-	2-	3-	4-	5-	6-	7-	8-	9-	10-	11-	12-	13-	14-	15-	16-	17-	18-
31- SD_3	.742	.708	-.079	-.061	-.055	-.040	-.077	.026	.662*	.270*	-.191*	.545*	.422*	.476*	.524*	.292*	.006	-.153*	-.329*	-.146*
32- TFL_3	.954	.965	-.036	-.066	-.002	.048	-.101	.085	.225*	.389*	-.283*	.230*	.318*	.297*	.194*	.311*	-.012	-.008	-.208*	-.154*
33- ABL_3	.908	.965	.010	.021	-.036	-.014	.024	-.065	-.181*	-.253*	.449*	-.202*	-.267*	-.202*	-.187*	-.241*	.071	.021	.217*	.131*
34- TAS_3	.901	.900	.001	.012	.008	-.060	-.118*	-.023	.445*	.273*	-.216*	.670*	.526*	.561*	.398*	.310*	-.007	-.118*	-.271*	-.137*
35- ORS_3	.937	.843	.035	.038	-.027	-.031	-.059	-.058	.299*	.287*	-.187*	.492*	.626*	.524*	.294*	.346*	-.033	-.069	-.220*	-.161*
36- TES_3	.924	.911	.040	.039	.007	-.027	-.066	-.049	.346*	.287*	-.166*	.511*	.463*	.565*	.263*	.290*	-.023	-.067	-.161*	-.129*
37- ACOC_3	.893	.923	-.023	-.097	-.049	-.031	.033	.087	.545*	.210*	-.204*	.429*	.345*	.362*	.770*	.322*	.093	-.148*	-.526*	-.223*
38- ACOR_3	.855	.891	-.025	-.084	-.020	.006	-.073	.075	.264*	.305*	-.243*	.357*	.407*	.390*	.299*	.636*	-.020	-.099	-.252*	-.242*
39- CCOC_3	.824	.864	-.107*	-.014	.054	-.017	.010	.004	-.036	-.051	.101	-.083	-.090	-.086	-.072	-.037	.519*	.304*	.081	.020
40- CCOR_3	.765	.853	-.062	-.002	.032	-.034	-.159*	.004	-.157*	-.011	.044	-.119*	-.037	-.056	-.207*	.095	.287*	.700*	.059	-.165*
41- ILOC_3	.908	.952	.086	.020	.031	.021	.049	-.111*	-.441*	-.213*	.186*	-.377*	-.308*	-.305*	-.571*	-.258*	.007	.084	.555*	.229*
42- ILOR_3	.862	.912	-.035	.029	-.032	.040	.138*	-.128*	-.147*	-.193*	.132*	-.245*	-.267*	-.245*	-.169*	-.348*	-.016	-.082	.277*	.423*
43- SD_4	.743	.708	-.093	-.067	.026	-.007	-.107	-.065	.521*	.250*	-.196*	.444*	.256*	.290*	.460*	.234*	.077	-.121*	-.363*	-.168*
44- TFL_4	.939	.965	-.038	-.032	.071	.032	-.052	-.022	.098	.304*	-.236*	.188*	.181*	.190*	.116	.119	-.054	-.073	-.187*	-.067
45- ABL_4	.884	.965	.099	.028	-.022	-.064	-.015	-.008	-.122*	-.297*	.486*	-.203*	-.178*	-.204*	-.134*	-.112	.100	.080	.251*	.075
46- TAS_4	.905	.900	.034	-.076	.040	-.090	-.089	-.095	.382*	.258*	-.195*	.679*	.485*	.490*	.347*	.298*	.015	-.093	-.302*	-.224*
47- ORS_4	.918	.843	.064	-.071	-.006	-.054	-.052	-.087	.278*	.227*	-.141*	.493*	.663*	.530*	.253*	.355*	.008	-.105	-.263*	-.233*
48- TES_4	.940	.911	.011	-.062	-.006	-.077	.012	-.116*	.275*	.271*	-.166*	.527*	.516*	.612*	.252*	.318*	.079	-.065	-.239*	-.209*
49- ACOC_4	.872	.923	-.060	-.141*	-.041	-.023	.012	-.089	.535*	.139*	-.092	.412*	.273*	.301*	.749*	.278*	.177*	-.185*	-.419*	-.118*
50- ACOR_4	.785	.891	-.024	-.052	-.073	-.022	-.021	-.035	.262*	.257*	-.123*	.358*	.395*	.387*	.376*	.562*	.072	-.044	-.299*	-.209*
51- CCOC_4	.862	.864	-.073	-.021	.000	-.008	.060	-.059	-.061	-.179*	.249*	-.152*	-.141*	-.131*	-.069	-.083	.598*	.369*	.105	.001
52- CCOR_4	.779	.853	.000	.017	.010	-.051	-.008	-.049	-.070	.007	.094	-.119*	-.067	-.025	-.048	.052	.298*	.530*	.128*	-.139*
53- ILOC_4	.926	.952	.066	.081	-.051	.001	.023	.002	-.393*	-.094	.128*	-.341*	-.219*	-.244*	-.502*	-.254*	-.077	.086	.492*	.210*
54- ILOR_4	.862	.912	.009	.040	-.049	.014	.033	-.025	-.247*	-.093	.004	-.243*	-.235*	-.239*	-.222*	-.304*	-.042	.017	.253*	.254*

Table S6 (Continued)

Correlations among the variables used in the present study (Part 3)

		19-	20-	21-	22-	23-	24-	25-	26-	27-	28-	29-	30-	31-	32-	33-	34-	35-
20-	TFL_2	.329*																
21-	ABL_2	-.247*	-.689*															
22-	TAS_2	.488*	.314*	-.266*														
23-	ORS_2	.385*	.325*	-.253*	.763*													
24-	TES_2	.427*	.322*	-.238*	.796*	.849*												
25-	ACOC_2	.548*	.303*	-.230*	.389*	.335*	.346*											
26-	ACOR_2	.379*	.411*	-.309*	.386*	.526*	.448*	.467*										
27-	CCOC_2	-.113*	-.111*	.152*	-.026	-.016	-.007	.049	-.034									
28-	CCOR_2	-.113*	-.118*	.151*	-.061	-.012	-.040	-.182*	.036	.409*								
29-	ILOC_2	-.443*	-.271*	.224*	-.275*	-.246*	-.252*	-.750*	-.395*	-.072	.077							
30-	ILOR_2	-.343*	-.252*	.249*	-.198*	-.270*	-.232*	-.321*	-.571*	.063	-.209*	.445*						
31-	SD_3	.673*	.305*	-.212*	.508*	.418*	.468*	.538*	.350*	-.082	-.211*	-.413*	-.236*					
32-	TFL_3	.198*	.555*	-.370*	.179*	.248*	.203*	.174*	.383*	-.036	-.046	-.205*	-.293*	.335*				
33-	ABL_3	-.147*	-.528*	.724*	-.165*	-.193*	-.143*	-.163*	-.266*	.085	.065	.200*	.288*	-.277*	-.678*			
34-	TAS_3	.446*	.254*	-.222*	.700*	.531*	.607*	.428*	.370*	-.039	-.118*	-.334*	-.233*	.525*	.321*	-.281*		
35-	ORS_3	.290*	.274*	-.234*	.378*	.574*	.490*	.310*	.432*	-.002	-.050	-.232*	-.258*	.425*	.378*	-.307*	.783*	
36-	TES_3	.389*	.301*	-.218*	.549*	.522*	.659*	.314*	.395*	-.013	-.066	-.236*	-.258*	.457*	.362*	-.288*	.827*	.863*
37-	ACOC_3	.522*	.305*	-.259*	.430*	.353*	.369*	.820*	.386*	.023	-.216*	-.710*	-.311*	.625*	.304*	-.309*	.502*	.391*
38-	ACOR_3	.279*	.341*	-.219*	.307*	.440*	.377*	.344*	.678*	-.011	-.017	-.300*	-.404*	.435*	.507*	-.375*	.391*	.486*
39-	CCOC_3	-.068	-.072	.095	-.075	-.115*	-.103	.077	-.088	.594*	.232*	-.086	.031	-.053	.008	.032	-.049	-.064
40-	CCOR_3	-.151*	-.015	.002	-.094	-.027	-.077	-.100	.047	.378*	.774*	-.074	-.146*	-.157*	.023	.004	-.134*	-.039
41-	ILOC_3	-.394*	-.231*	.186*	-.331*	-.286*	-.285*	-.561*	-.303*	-.018	.095	.761*	.306*	-.503*	-.380*	.321*	-.396*	-.317*
42-	ILOR_3	-.234*	-.221*	.169*	-.246*	-.312*	-.292*	-.199*	-.448*	-.062	-.101	.321*	.644*	-.343*	-.420*	.348*	-.282*	-.340*
43-	SD_4	.602*	.352*	-.258*	.436*	.320*	.337*	.527*	.281*	-.053	-.110	-.422*	-.227*	.674*	.299*	-.258*	.447*	.291*
44-	TFL_4	.179*	.320*	-.275*	.226*	.260*	.243*	.122	.231*	-.094	-.072	-.176*	-.196*	.225*	.435*	-.337*	.280*	.279*
45-	ABL_4	-.196*	-.279*	.549*	-.224*	-.174*	-.198*	-.082	-.176*	.146*	.084	.132*	.185*	-.234*	-.312*	.621*	-.288*	-.270*
46-	TAS_4	.376*	.250*	-.234*	.688*	.539*	.555*	.376*	.327*	-.051	-.080	-.305*	-.198*	.459*	.308*	-.245*	.752*	.548*
47-	ORS_4	.263*	.251*	-.168*	.441*	.699*	.501*	.301*	.475*	-.010	-.014	-.270*	-.257*	.376*	.369*	-.261*	.595*	.758*
48-	TES_4	.285*	.238*	-.194*	.509*	.608*	.610*	.346*	.405*	.036	-.010	-.279*	-.237*	.373*	.311*	-.191*	.577*	.575*
49-	ACOC_4	.467*	.244*	-.146*	.426*	.371*	.356*	.756*	.397*	.003	-.120	-.549*	-.149*	.510*	.243*	-.259*	.413*	.295*
50-	ACOR_4	.264*	.331*	-.150*	.319*	.463*	.365*	.403*	.655*	.021	.073	-.351*	-.402*	.321*	.404*	-.237*	.361*	.480*
51-	CCOC_4	-.088	-.176*	.252*	-.133*	-.119	-.115	.037	-.125*	.693*	.485*	-.047	.015	-.166*	-.190*	.160*	-.259*	-.266*
52-	CCOR_4	-.018	-.108	.112	-.070	-.060	-.039	-.065	-.011	.410*	.707*	-.040	-.228*	-.108	-.039	.038	-.108	-.065
53-	ILOC_4	-.354*	-.192*	.173*	-.327*	-.270*	-.264*	-.545*	-.338*	-.012	.037	.677*	.350*	-.424*	-.243*	.289*	-.329*	-.251*
54-	ILOR_4	-.249*	-.123	.038	-.245*	-.275*	-.276*	-.270*	-.353*	-.039	-.134*	.325*	.514*	-.341*	-.273*	.200*	-.268*	-.327*

Table S6 (Continued)

Correlations among the variables used in the present study (Part 4)

		36-	37-	38-	39-	40-	41-	42-	43-	44-	45-	46-	47-	48-	49-	50-	51-	52-	53-
37-	ACOC_3	.401*																	
38-	ACOR_3	.455*	.481*																
39-	CCOC_3	-.043	-.014	-.034															
40-	CCOR_3	-.039	-.181*	.078	.400*														
41-	ILOC_3	-.331*	-.738*	-.430*	-.075	.039													
42-	ILOR_3	-.347*	-.344*	-.638*	-.029	-.222*	.523*												
43-	SD_4	.360*	.533*	.265*	-.017	-.099	-.441*	-.283*											
44-	TFL_4	.314*	.175*	.250*	-.165*	-.047	-.211*	-.231*	.317*										
45-	ABL_4	-.312*	-.168*	-.195*	.111	.004	.150*	.163*	-.275*	-.693*									
46-	TAS_4	.605*	.422*	.337*	-.088	-.066	-.373*	-.304*	.539*	.325*	-.267*								
47-	ORS_4	.622*	.368*	.487*	-.092	.005	-.353*	-.355*	.404*	.336*	-.250*	.752*							
48-	TES_4	.635*	.360*	.416*	-.082	-.025	-.314*	-.323*	.458*	.336*	-.239*	.802*	.831*						
49-	ACOC_4	.295*	.799*	.240*	-.082	-.258*	-.572*	-.093	.503*	.163*	-.108	.425*	.361*	.350*					
50-	ACOR_4	.427*	.399*	.709*	.019	.126	-.408*	-.482*	.380*	.347*	-.222*	.413*	.547*	.494*	.471*				
51-	CCOC_4	-.258*	-.064	-.137*	.642*	.427*	-.005	.049	-.053	-.115	.172*	-.059	-.090	-.016	.034	.014			
52-	CCOR_4	-.028	-.059	-.082	.326*	.654*	-.037	-.137*	-.113	-.040	.008	-.049	-.030	-.010	-.108	.075	.476*		
53-	ILOC_4	-.270*	-.647*	-.285*	.036	.014	.758*	.397*	-.472*	-.240*	.199*	-.385*	-.327*	-.298*	-.706*	-.439*	-.059	.074	
54-	ILOR_4	-.330*	-.327*	-.357*	-.113	-.148*	.511*	.623*	-.338*	-.287*	.207*	-.278*	-.317*	-.271*	-.313*	-.611*	-.091	-.213*	.554*

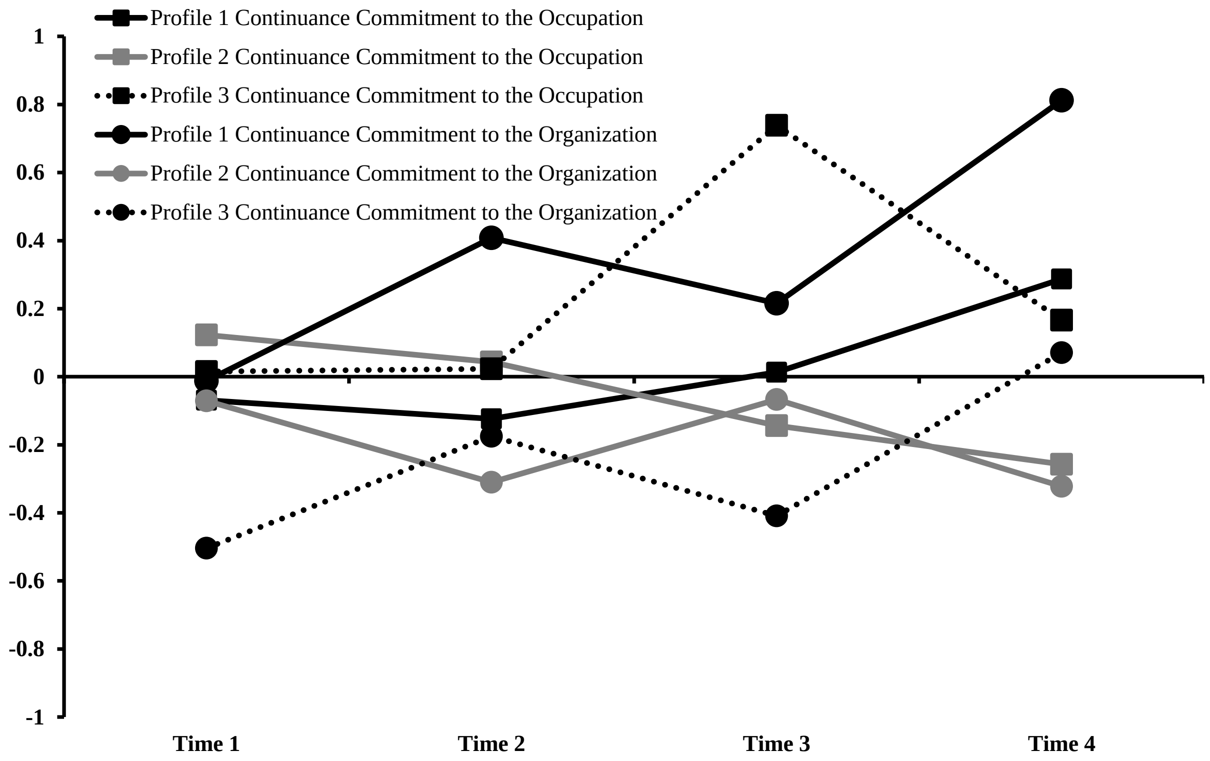

Figure S2. Levels of Continuance Commitment Observed in the Three Motivational Profiles.
Note. Trajectories are estimated on the basis of invariant factor scores with a mean of 0 and a standard deviation of 1 obtained in the context of preliminary analyses reported in the online supplements.

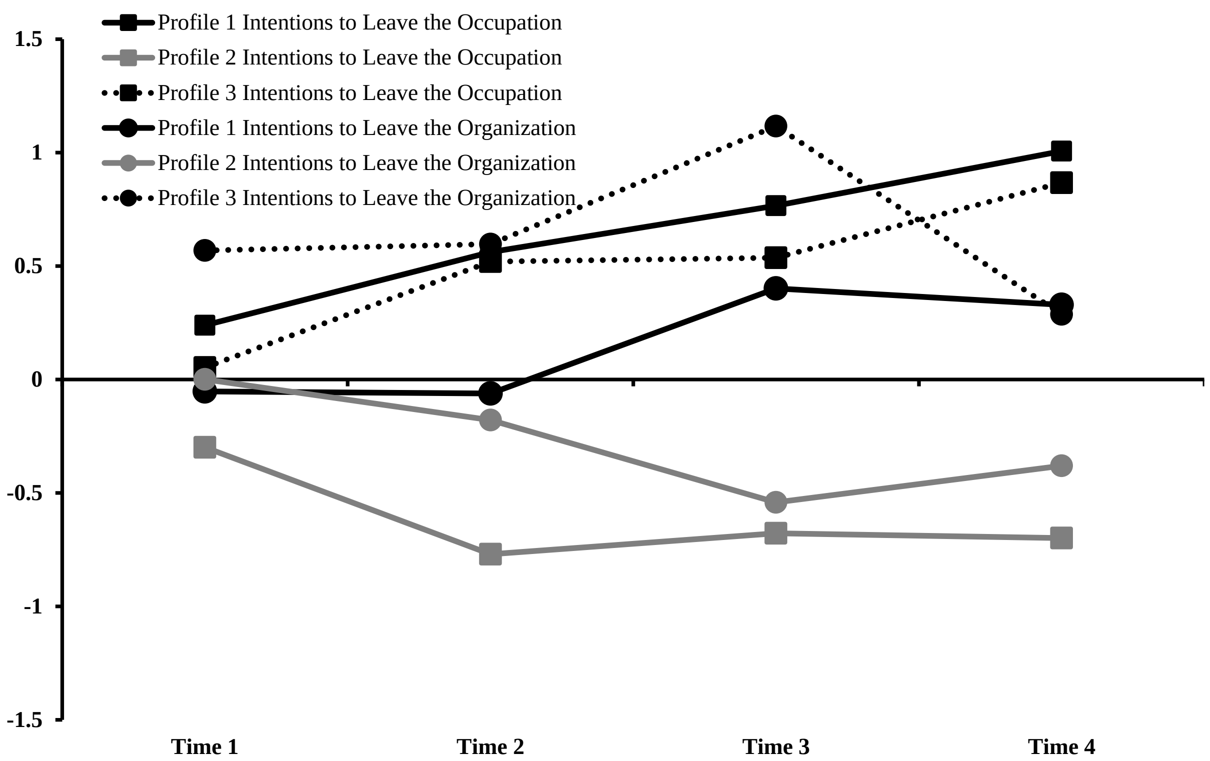

Figure S3. Levels of Intentions to Leave Observed in the Three Motivational Profiles.
Note. Trajectories are estimated on the basis of invariant factor scores with a mean of 0 and a standard deviation of 1 obtained in the context of preliminary analyses reported in the online supplements.

Comprehensive Mplus Input to Estimate a 3-Profile Quadratic Growth Mixture Analysis with all Model Parameter Freely Estimated in all Profiles

```
! 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 = ID Age Sex Emp Sched Ten
SDT_1 SDT_2 SDT_3 SDT_4
ACP_1 CCP_1 ACE_1 CCE_1 IQE_1 IQP_1
ACP_2 CCP_2 ACE_2 CCE_2 IQE_2 IQP_2
ACP_3 CCP_3 ACE_3 CCE_3 IQE_3 IQP_3
ACP_4 CCP_4 ACE_4 CCE_4 IQE_4 IQP_4
TFL_1 ABL_1 TFL_2 ABL_2 TFL_3 ABL_3 TFL_4 ABL_4
SOTA_1 SOET_1 SOEQ_1 SOTA_2 SOET_2 SOEQ_2
SOTA_3 SOET_3 SOEQ_3 SOTA_4 SOET_4 SOEQ_4 ;
USEVARIABLES = SDT_1 SDT_2 SDT_3 SDT_4;
! Missing data are identified with the following (the same code * is used for all missing).
MISSING ARE ALL (-999);
! The following identifies the unique identifier for participants
IDVARIABLE = ID;
! The following identifies the number of latent profiles requested in the analysis.
CLASSES = c (3);
ANALYSIS:
! The following identifies that mixture modeling is requested.
type = mixture; estimator = MLR;
! Using 3 processors, 10000 starts values, 500 final stage optimizations, and 1000 iterations.
Process = 3; STARTS = 10000 500; STITERATIONs = 1000;
! In this input, the overall model statement defines sections that are common across profiles.
! Here, we specify a quadratic growth model, with time codes fixed to 0, .5, 1, 2.
! The %c#1% to %c#3% sections are class-specific statement to specify which part of the
! model is freely estimated in each profile.
MODEL:
%OVERALL%
I S Q | SDT_1@0 SDT_2@.5  SDT_3@1 SDT_4@2;
%c#1%
! To request the free estimation of the growth factors means.
[I S Q];
! To request the free estimation of the growth factors variances and covariances (WITH).
I S Q; I WITH S Q; S WITH Q;
! To request the free estimation of the time specific residuals.
SDT_1 SDT_2 SDT_3 SDT_4;
%c#2%
[I S Q];
I S Q; I WITH S Q; S WITH Q;
SDT_1 SDT_2 SDT_3 SDT_4;
%c#3%
[I S Q];
I S Q; I WITH S Q; S WITH Q;
SDT_1 SDT_2 SDT_3 SDT_4;
OUTPUT:
STDYX SAMPSTAT CINTERVAL SVALUES RESIDUAL TECH1 TECH7 TECH11 TECH14;
PLOT:
TYPE IS PLOT3;
SERIES = SDT_1-SDT_4 (*);
```

Mplus Input to Estimate the 3-Profile Quadratic Growth Mixture Analysis with Invariant Latent Variance-Covariance and Homoscedastic Residuals used in this Study

```
! Annotations only focus on functions not previously defined.
[…]
MODEL:
%OVERALL%
I S  | SDT_1@0 SDT_2@.5  SDT_3@1 SDT_4@2;
%c#1%
[I S ];
! Labels used in parentheses constrain the residuals to equality within each profiles, but using
! different labels in each profiles allows the residuals to take a different value across profiles
 SDT_1 SDT_2 SDT_3 SDT_4 (r1);
%c#2%
[I S ];
SDT_1 SDT_2 SDT_3 SDT_4 (r2);
%c#3%
[I S ];
 SDT_1 SDT_2 SDT_3 SDT_4 (r3);
[…]
```

Mplus Input to Estimate the 3-Profile Quadratic Growth Mixture Analysis with Time-Invariant Predictors: Null Effects Model (Model M15)

```
! Annotations only focus on functions not previously defined.
! To ensure stability, the starts values from the final unconditional model (obtained with the SVALUE
! command of the OUTPUT Section) can be used, and the STARTS function set to 0 (STARTS = 0;).
! Predictors need to be added to the USEVARIABLE list.
[…]
%OVERALL%
! To specify the effects of predictors on profile membership (c#1-c#2: one less statement than the total
! number of profiles is necessary). These predictions are set to be null (@0).
c#1-c#2 on TFL_1@0  ABL_1@0  SOTA_1@0  SOET_1@0  SOEQ_1@0 ;
! To specify the effects of predictors on the latent intercept and slope factors.
! These predictions are set to be null (@0).
i on TFL_1@0 ABL_1@0  SOTA_1@0  SOET_1@0  SOEQ_1@0 ;
s on TFL_1@0  ABL_1@0  SOTA_1@0  SOET_1@0  SOEQ_1@0 ;
i s | sdt_1@0 sdt_2@.5 sdt_3@1 sdt_4@2;
%c#1%
[I S ];
SDT_1 SDT_2 SDT_3 SDT_4 (r1);
%c#2%
[I S ];
SDT_1 SDT_2 SDT_3 SDT_4 (r2);
%c#3%
[I S ];
 SDT_1 SDT_2 SDT_3 SDT_4 (r3);
[…]
```

Mplus Input to Estimate the 3-Profile Quadratic Growth Mixture Analysis with Time-Invariant Predictors: Effects on Class Membership (Model M16)

```
! Annotations only focus on functions not previously defined.
[…]
%OVERALL%
c#1-c#2 on TFL_1 ABL_1 SOTA_1 SOET_1 SOEQ_1;
i on TFL_1@0 ABL_1@0  SOTA_1@0  SOET_1@0  SOEQ_1@0 ;
s on TFL_1@0  ABL_1@0  SOTA_1@0  SOET_1@0  SOEQ_1@0 ;
i s | sdt_1@0 sdt_2@.5 sdt_3@1 sdt_4@2;
%c#1%
[I S ];
SDT_1 SDT_2 SDT_3 SDT_4 (r1);
%c#2%
[I S ];
SDT_1 SDT_2 SDT_3 SDT_4 (r2);
%c#3%
[I S ];
 SDT_1 SDT_2 SDT_3 SDT_4 (r3);
[…]
```

Mplus Input to Estimate the 3-Profile Quadratic Growth Mixture Analysis with Time-Invariant Predictors: Effects on Class Membership and the Intercept Factor (Model M17)

```
! Annotations only focus on functions not previously defined.
[…]
%OVERALL%
c#1-c#2 on TFL_1 ABL_1 SOTA_1 SOET_1 SOEQ_1;
i on TFL_1 ABL_1 SOTA_1 SOET_1 SOEQ_1;
s on TFL_1@0  ABL_1@0  SOTA_1@0  SOET_1@0  SOEQ_1@0 ;
i s | sdt_1@0 sdt_2@.5 sdt_3@1 sdt_4@2;
%c#1%
[I S ];
SDT_1 SDT_2 SDT_3 SDT_4 (r1);
%c#2%
[I S ];
SDT_1 SDT_2 SDT_3 SDT_4 (r2);
%c#3%
[I S ];
 SDT_1 SDT_2 SDT_3 SDT_4 (r3);
[…]
```

Mplus Input to Estimate the 3-Profile Quadratic Growth Mixture Analysis with Time-Invariant Predictors: Effects on Class Membership and the Intercept and Slope Factors (Model M18)

```
! Annotations only focus on functions not previously defined.
[…]
%OVERALL%
c#1-c#2 on TFL_1 ABL_1 SOTA_1 SOET_1 SOEQ_1;
i on TFL_1 ABL_1 SOTA_1 SOET_1 SOEQ_1;
s on TFL_1 ABL_1 SOTA_1 SOET_1 SOEQ_1;
i s | sdt_1@0 sdt_2@.5 sdt_3@1 sdt_4@2;
%c#1%
[I S ];
SDT_1 SDT_2 SDT_3 SDT_4 (r1);
%c#2%
[I S ];
SDT_1 SDT_2 SDT_3 SDT_4 (r2);
%c#3%
[I S ];
 SDT_1 SDT_2 SDT_3 SDT_4 (r3);
[…]
```

Mplus Input to Estimate the 3-Profile Quadratic Growth Mixture Analysis with Time-Invariant Predictors: Effects on Class Membership and the Intercept Factor Freely Estimated in All Profiles (Model M19)

```
! Annotations only focus on functions not previously defined.
[…]
%OVERALL%
c#1-c#2 on  TFL_1 ABL_1 SOTA_1 SOET_1 SOEQ_1;
i ON TFL_1 ABL_1 SOTA_1 SOET_1 SOEQ_1;
s on TFL_1@0  ABL_1@0  SOTA_1@0  SOET_1@0  SOEQ_1@0 ;
i s | sdt_1@0 sdt_2@.5 sdt_3@1 sdt_4@2;
%c#1%
[I S ];
SDT_1 SDT_2 SDT_3 SDT_4 (r1);
i ON  TFL_1 ABL_1 SOTA_1 SOET_1 SOEQ_1;
%c#2%
[I S ];
SDT_1 SDT_2 SDT_3 SDT_4 (r2);
i ON  TFL_1 ABL_1 SOTA_1 SOET_1 SOEQ_1;
%c#3%
[I S ];
 SDT_1 SDT_2 SDT_3 SDT_4 (r3);
i ON  TFL_1 ABL_1 SOTA_1 SOET_1 SOEQ_1;
[…]
```

Mplus Input to Estimate the 3-Profile Quadratic Growth Mixture Analysis with Time-Invariant Predictors: Effects on Class Membership and the Intercept and Slope Factors Freely Estimated in All Profiles (Model M20)

```
! Annotations only focus on functions not previously defined.
[…]
%OVERALL%
c#1-c#2 on  TFL_1 ABL_1 SOTA_1 SOET_1 SOEQ_1;
i ON TFL_1 ABL_1 SOTA_1 SOET_1 SOEQ_1;
s on TFL_1 ABL_1 SOTA_1 SOET_1  SOEQ_1;
i s | sdt_1@0 sdt_2@.5 sdt_3@1 sdt_4@2;
%c#1%
[I S ];
SDT_1 SDT_2 SDT_3 SDT_4 (r1);
i ON  TFL_1 ABL_1 SOTA_1 SOET_1 SOEQ_1;
s ON  TFL_1 ABL_1 SOTA_1 SOET_1 SOEQ_1;
%c#2%
[I S ];
SDT_1 SDT_2 SDT_3 SDT_4 (r2);
i ON  TFL_1 ABL_1 SOTA_1 SOET_1 SOEQ_1;
s ON  TFL_1 ABL_1 SOTA_1 SOET_1 SOEQ_1;
%c#3%
[I S ];
 SDT_1 SDT_2 SDT_3 SDT_4 (r3);
i ON  TFL_1 ABL_1 SOTA_1 SOET_1 SOEQ_1;
s ON  TFL_1 ABL_1 SOTA_1 SOET_1 SOEQ_1;
[…]
```

Mplus Input to Estimate the 3-Profile Quadratic Growth Mixture Analysis with Time-Varying Predictors: Null Effects Model (Model M21, built from Model M18)

```
! Annotations only focus on functions not previously defined.
! To ensure stability, the starts values from the final unconditional model (obtained with the SVALUE
! command of the OUTPUT Section) can be used, and the STARTS function set to 0 (STARTS = 0;).
! Predictors need to be added to the USEVARIABLE list.
[…]
Analysis:
TYPE = MIXTURE;
ESTIMATOR = MLR;
process = 3;
STARTS = 10000 500;
STITERATIONS = 1000;
! If there are missing data on the TVP (or TIP), specifying their variance in the %Overall% section
! activates the Full Information Maximum Likelihood function for these covariates, but this needs to
! be accompanied by the following two lines of code in the analysis section:
! algo= integration;
! integration =montecarlo;
MODEL:
%OVERALL%
c#1-c#2 on TFL_1 ABL_1 SOTA_1 SOET_1 SOEQ_1;
i ON TFL_1 ABL_1 SOTA_1 SOET_1 SOEQ_1;
s ON TFL_1 ABL_1 SOTA_1 SOET_1 SOEQ_1;
! The following constrain the effects of the TVP on the time specific measures to be 0.
SDT_1 ON TFL_1@0 ABL_1@0 SOTA_1@0 SOET_1@0 SOEQ_1@0;
SDT_2 ON TFL_2@0 ABL_2@0 SOTA_2@0 SOET_2@0 SOEQ_2@0;
SDT_3 ON TFL_3@0 ABL_3@0 SOTA_3@0 SOET_3@0 SOEQ_3@0;
SDT_4 ON TFL_4@0 ABL_4@0 SOTA_4@0 SOET_4@0 SOEQ_4@0;
! If there are missing data on the TVP (or TIP), specifying their variance in the %Overall% section
! activates the Full Information Maximum Likelihood function for these covariates
!TFL_1 ABL_1 SOTA_1 SOET_1 SOEQ_1 ;
!TFL_2 ABL_2 SOTA_2 SOET_2 SOEQ_2 ;
!TFL_3 ABL_3 SOTA_3 SOET_3 SOEQ_3 ;
!TFL_4 ABL_4 SOTA_4 SOET_4 SOEQ_4 ;
i s | sdt_1@0 sdt_2@.5 sdt_3@1 sdt_4@2;
%c#1%
[I S ];
SDT_1 SDT_2 SDT_3 SDT_4 (r1);
%c#2%
[I S ];
SDT_1 SDT_2 SDT_3 SDT_4 (r2);
%c#3%
[I S ];
 SDT_1 SDT_2 SDT_3 SDT_4 (r3);
[…]
```

Mplus Input to Estimate the 3-Profile Quadratic Growth Mixture Analysis with Time-Varying Predictors: Effects Invariant Across Time and Profiles (Model M22, built from Model M18)

```
! Annotations only focus on functions not previously defined.
[…]
MODEL:
%OVERALL%
c#1-c#2 on TFL_1 ABL_1 SOTA_1 SOET_1 SOEQ_1;
i ON TFL_1 ABL_1 SOTA_1 SOET_1 SOEQ_1;
s ON TFL_1 ABL_1 SOTA_1 SOET_1 SOEQ_1;
! The labels (r1-r5) constrain the effects to equality across time and profiles.
SDT_1 ON TFL_1 ABL_1 SOTA_1 SOET_1 SOEQ_1 (r1-r5);
SDT_2 ON TFL_2 ABL_2 SOTA_2 SOET_2 SOEQ_2 (r1-r5);
SDT_3 ON TFL_3 ABL_3 SOTA_3 SOET_3 SOEQ_3 (r1-r5);
SDT_4 ON TFL_4 ABL_4 SOTA_4 SOET_4 SOEQ_4 (r1-r5);
!TFL_1 ABL_1 SOTA_1 SOET_1 SOEQ_1 ;
!TFL_2 ABL_2 SOTA_2 SOET_2 SOEQ_2 ;
!TFL_3 ABL_3 SOTA_3 SOET_3 SOEQ_3 ;
!TFL_4 ABL_4 SOTA_4 SOET_4 SOEQ_4 ;
i s | sdt_1@0 sdt_2@.5 sdt_3@1 sdt_4@2;
%c#1%
[I S ];
SDT_1 SDT_2 SDT_3 SDT_4 (r1);
%c#2%
[I S ];
SDT_1 SDT_2 SDT_3 SDT_4 (r2);
%c#3%
[I S ];
 SDT_1 SDT_2 SDT_3 SDT_4 (r3);
[…]
```

Mplus Input to Estimate the 3-Profile Quadratic Growth Mixture Analysis with Time-Varying Predictors: Effects Invariant Across Time and Free Across Profiles (Model M23, built from Model M18)

```
! Annotations only focus on functions not previously defined.
[…]
MODEL:
%OVERALL%
c#1-c#2 on TFL_1 ABL_1 SOTA_1 SOET_1 SOEQ_1;
i ON TFL_1 ABL_1 SOTA_1 SOET_1 SOEQ_1;
s ON TFL_1 ABL_1 SOTA_1 SOET_1 SOEQ_1;
SDT_1 ON TFL_1 ABL_1 SOTA_1 SOET_1 SOEQ_1;
SDT_2 ON TFL_2 ABL_2 SOTA_2 SOET_2 SOEQ_2;
SDT_3 ON TFL_3 ABL_3 SOTA_3 SOET_3 SOEQ_3;
SDT_4 ON TFL_4 ABL_4 SOTA_4 SOET_4 SOEQ_4;
!TFL_1 ABL_1 SOTA_1 SOET_1 SOEQ_1 ;
!TFL_2 ABL_2 SOTA_2 SOET_2 SOEQ_2 ;
!TFL_3 ABL_3 SOTA_3 SOET_3 SOEQ_3 ;
!TFL_4 ABL_4 SOTA_4 SOET_4 SOEQ_4 ;
i s | sdt_1@0 sdt_2@.5 sdt_3@1 sdt_4@2;
%c#1%
[I S ];
SDT_1 SDT_2 SDT_3 SDT_4 (r1);
! The labels (r1-r5) constrain the effects to equality across time. Different labels in each profile allows
! them to be freely estimated in all profiles.
SDT_1 ON TFL_1 ABL_1 SOTA_1 SOET_1 SOEQ_1 (r1-r5);
SDT_2 ON TFL_2 ABL_2 SOTA_2 SOET_2 SOEQ_2 (r1-r5);
SDT_3 ON TFL_3 ABL_3 SOTA_3 SOET_3 SOEQ_3 (r1-r5);
SDT_4 ON TFL_4 ABL_4 SOTA_4 SOET_4 SOEQ_4 (r1-r5);
%c#2%
[I S ];
SDT_1 SDT_2 SDT_3 SDT_4 (r2);
SDT_1 ON TFL_1 ABL_1 SOTA_1 SOET_1 SOEQ_1 (rr1-rr5);
SDT_2 ON TFL_2 ABL_2 SOTA_2 SOET_2 SOEQ_2 (rr1-rr5);
SDT_3 ON TFL_3 ABL_3 SOTA_3 SOET_3 SOEQ_3 (rr1-rr5);
SDT_4 ON TFL_4 ABL_4 SOTA_4 SOET_4 SOEQ_4 (rr1-rr5);
%c#3%
[I S ];
 SDT_1 SDT_2 SDT_3 SDT_4 (r3);
SDT_1 ON TFL_1 ABL_1 SOTA_1 SOET_1 SOEQ_1 (rrr1-rrr5);
SDT_2 ON TFL_2 ABL_2 SOTA_2 SOET_2 SOEQ_2 (rrr1-rrr5);
SDT_3 ON TFL_3 ABL_3 SOTA_3 SOET_3 SOEQ_3 (rrr1-rrr5);
SDT_4 ON TFL_4 ABL_4 SOTA_4 SOET_4 SOEQ_4 (rrr1-rrr5); […]
```

Mplus Input to Estimate the 3-Profile Quadratic Growth Mixture Analysis with Time-Varying Predictors: Effects Free Across Time and Invariant Across Profiles (Model M24, built from Model M18)

```
! Annotations only focus on functions not previously defined.
[…]
MODEL:
%OVERALL%
c#1-c#2 on TFL_1 ABL_1 SOTA_1 SOET_1 SOEQ_1;
i ON TFL_1 ABL_1 SOTA_1 SOET_1 SOEQ_1;
s ON TFL_1 ABL_1 SOTA_1 SOET_1 SOEQ_1;
! By default, these relations are invariant across profiles.
SDT_1 ON TFL_1 ABL_1 SOTA_1 SOET_1 SOEQ_1;
SDT_2 ON TFL_2 ABL_2 SOTA_2 SOET_2 SOEQ_2;
SDT_3 ON TFL_3 ABL_3 SOTA_3 SOET_3 SOEQ_3;
SDT_4 ON TFL_4 ABL_4 SOTA_4 SOET_4 SOEQ_4;
!TFL_1 ABL_1 SOTA_1 SOET_1 SOEQ_1 ;
!TFL_2 ABL_2 SOTA_2 SOET_2 SOEQ_2 ;
!TFL_3 ABL_3 SOTA_3 SOET_3 SOEQ_3 ;
!TFL_4 ABL_4 SOTA_4 SOET_4 SOEQ_4 ;
i s | sdt_1@0 sdt_2@.5 sdt_3@1 sdt_4@2;
%c#1%
[I S ];
SDT_1 SDT_2 SDT_3 SDT_4 (r1);
%c#2%
[I S ];
SDT_1 SDT_2 SDT_3 SDT_4 (r2);
%c#3%
[I S ];
 SDT_1 SDT_2 SDT_3 SDT_4 (r3);
[…]
```

Mplus Input to Estimate the 3-Profile Quadratic Growth Mixture Analysis with Time-Varying Predictors: Effects Free Across Time and Profiles (Model M25, built from Model M18)

```
! Annotations only focus on functions not previously defined.
[…]
MODEL:
%OVERALL%
c#1-c#2 on TFL_1 ABL_1 SOTA_1 SOET_1 SOEQ_1;
i ON TFL_1 ABL_1 SOTA_1 SOET_1 SOEQ_1;
s ON TFL_1 ABL_1 SOTA_1 SOET_1 SOEQ_1;
SDT_1 ON TFL_1 ABL_1 SOTA_1 SOET_1 SOEQ_1;
SDT_2 ON TFL_2 ABL_2 SOTA_2 SOET_2 SOEQ_2;
SDT_3 ON TFL_3 ABL_3 SOTA_3 SOET_3 SOEQ_3;
SDT_4 ON TFL_4 ABL_4 SOTA_4 SOET_4 SOEQ_4;
!TFL_1 ABL_1 SOTA_1 SOET_1 SOEQ_1 ;
!TFL_2 ABL_2 SOTA_2 SOET_2 SOEQ_2 ;
!TFL_3 ABL_3 SOTA_3 SOET_3 SOEQ_3 ;
!TFL_4 ABL_4 SOTA_4 SOET_4 SOEQ_4 ;
i s | sdt_1@0 sdt_2@.5 sdt_3@1 sdt_4@2;
%c#1%
[I S ];
SDT_1 SDT_2 SDT_3 SDT_4 (r1);
! To request the free estimation of these relations in all profiles:
SDT_1 ON TFL_1 ABL_1 SOTA_1 SOET_1 SOEQ_1;
SDT_2 ON TFL_2 ABL_2 SOTA_2 SOET_2 SOEQ_2;
SDT_3 ON TFL_3 ABL_3 SOTA_3 SOET_3 SOEQ_3;
SDT_4 ON TFL_4 ABL_4 SOTA_4 SOET_4 SOEQ_4;
%c#2%
[I S ];
SDT_1 SDT_2 SDT_3 SDT_4 (r2);
SDT_1 ON TFL_1 ABL_1 SOTA_1 SOET_1 SOEQ_1;
SDT_2 ON TFL_2 ABL_2 SOTA_2 SOET_2 SOEQ_2;
SDT_3 ON TFL_3 ABL_3 SOTA_3 SOET_3 SOEQ_3;
SDT_4 ON TFL_4 ABL_4 SOTA_4 SOET_4 SOEQ_4;
%c#3%
[I S ];
 SDT_1 SDT_2 SDT_3 SDT_4 (r3);
SDT_1 ON TFL_1 ABL_1 SOTA_1 SOET_1 SOEQ_1;
SDT_2 ON TFL_2 ABL_2 SOTA_2 SOET_2 SOEQ_2;
SDT_3 ON TFL_3 ABL_3 SOTA_3 SOET_3 SOEQ_3;
SDT_4 ON TFL_4 ABL_4 SOTA_4 SOET_4 SOEQ_4;
[…]
```

Mplus Input to Estimate the 3-Profile Quadratic Growth Mixture Analysis with Time-Varying Outcomes Using the Auxiliary (BCH) Function

```
DATA: FILE IS Data.dat;
NAMES = ID Age Sex Emp Sched Ten
SDT_1 SDT_2 SDT_3 SDT_4
ACP_1 CCP_1 ACE_1 CCE_1 IQE_1 IQP_1
ACP_2 CCP_2 ACE_2 CCE_2 IQE_2 IQP_2
ACP_3 CCP_3 ACE_3 CCE_3 IQE_3 IQP_3
ACP_4 CCP_4 ACE_4 CCE_4 IQE_4 IQP_4
TFL_1 ABL_1 TFL_2 ABL_2 TFL_3 ABL_3 TFL_4 ABL_4
SOTA_1 SOET_1 SOEQ_1 SOTA_2 SOET_2 SOEQ_2
SOTA_3 SOET_3 SOEQ_3 SOTA_4 SOET_4 SOEQ_4 ;
USEVARIABLES = SDT_1 SDT_2 SDT_3 SDT_4;
MISSING ARE ALL (-999);
IDVARIABLE = ID;
CLASSES = c (3);
! Outcomes are specified using the Auxiliary function, with the type (BCH) in parenthesis.
Auxiliary = ACP_1 (bch) ACP_2 (bch) ACP_3 (bch) ACP_4 (bch)
CCP_1 (bch) CCP_2 (bch) CCP_3 (bch) CCP_4 (bch)
ACE_1 (bch) ACE_2 (bch) ACE_3 (bch) ACE_4 (bch)
CCE_1 (bch) CCE_2 (bch) CCE_3 (bch) CCE_4 (bch)
IQE_1 (bch) IQE_2 (bch) IQE_3 (bch) IQE_4 (bch)
IQP_1 (bch) IQP_2 (bch) IQP_3 (bch) IQP_4 (bch);
! To ensure stability, the starts values from the final unconditional model (obtained with the SVALUE
! command of the OUTPUT Section) can be used, and the STARTS function set to 0 (STARTS = 0;).
ANALYSIS:
type = mixture; estimator = MLR;
Process = 3; STARTS = 10000 500; STITERATIONs = 1000;
[…]
MODEL:
%OVERALL%
I S  | SDT_1@0 SDT_2@.5  SDT_3@1 SDT_4@2;
%c#1%
[I S ];
SDT_1 SDT_2 SDT_3 SDT_4 (r1);
%c#2%
[I S ];
SDT_1 SDT_2 SDT_3 SDT_4 (r2);
%c#3%
[I S ];
SDT_1 SDT_2 SDT_3 SDT_4 (r3);
[…]
```