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Self-Determination Trajectories during Police Officers' Vocational Training Program: A Growth Mixture Analysis

Nicolas Gillet[1*], Alexandre J. S. Morin[2], Isabelle Huart[13], Dominique Odry[4], Séverine Chevalier[1], Hélène Coillot[1], & Evelyne Fouquereau[1]

[1] Université de Tours, Tours, France
[2] Concordia University, Montréal, Canada
[3] Centre Régional de Formation de la Police Nationale, Saint Cyr sur Loire, France
[4] Ministère de l'Intérieur, Paris, France

Since the first two authors (N.G. & A.J.S.M.) contributed equally to the preparation of this paper, their order of appearance was determined at random: All should be considered first authors.

* Corresponding author
Nicolas Gillet,
Université de Tours,
UFR Arts et Sciences Humaines,
Département de psychologie,
3 rue des Tanneurs, 37041 Tours Cedex 1, France
E-mail: nicolas.gillet@univ-tours.fr

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Abstract

This study examines the evolution of police officers' global self-determination trajectories over the course of a vocational training program. We also examine the effects of mental load, work load, emotional load, and peer support on these trajectories. Moreover, this study documents the implications of these trajectories for a variety of outcomes (positive and negative affect, and performance). A sample of 1676 police officers completed all measures four times over the course of a vocational training. Longitudinal growth mixture analyses (GMA) revealed three distinct trajectories of self-determined motivation for the training (High, Moderate, and Low). Results showed that mental load increased the likelihood of membership into the High profile relative to the Moderate and Low profiles. Similarly, peer support increased the likelihood of membership into the High profile relative to the Moderate profile. In contrast, emotional load increased the likelihood of membership into the Moderate and High profiles relative to the Low profile. Finally, the High profile was associated with the highest levels of positive affect and performance, and the lowest levels of negative affect.

Keywords: Self-determination trajectories; Person-centered approach; Motivation; Police officers; Vocational training.

The ability to transfer abilities acquired during training into the job is a ubiquitous but frequently unmet goal of training initiatives, amounting to billions of dollars lost annually, and resulting in masses of under-skilled workers who fail to apply training content to their job (Roberts, Rogers, Thomas, & Spitzmueller, 2018). For instance, in 2017, organizations based in the United States spent $90.6 billion and an average of 47.6 hours per employee on training and development (Training Magazine, 2017), without even considering vocational training costs occurring before entry into the workforce. Unfortunately, research suggests that only 10% to 13% of those expenditures actually resulted in changed trainee behavior once back on the job (Curry, Caplan, & Knuppel, 1994). Among many, a key mechanism underpinning the failure of training programs is linked to trainees' lack of self-determined motivation during the training process (Bauer, Orvis, Ely, & Surface, 2015). Indeed, numerous studies have shown that trainees characterized by high levels of self-determined motivation are more likely to perceive the learning content of their programs more constructively, to demonstrate higher levels of persistence in acquiring the skill set covered in the program, and to feel more accountable for ensuring their own mastery of the training objectives (Deci & Ryan, 2000; Dysvik & Kuvaas, 2008). For this reason, achieving a clear understanding of the processes involved in the evolution of trainees' self-determined motivation trajectories over the course of training appears to be central to our ability to devise strategies aiming to improve training success.

This consideration is particularly important in the context of vocational training programs which play a key role in ensuring that trainees are realistically prepared for entry into the workforce. Vocational training programs can also easily be adapted to target subsets of participants presenting less desirable motivational trajectories for preventive purposes. In particular, when this training focuses on a profession that can be as stressful and important as policing (Birch & Herrington, 2011; Green, 2004), it becomes critical to maximize the preparation and motivation of upcoming officers. The present study seeks to contribute to a better understanding of training success through the identification of trainees' profiles characterized by distinct longitudinal trajectories of self-determined motivation over the course of a police vocational training program. The adoption of such a longitudinal perspective is, arguably, a key contribution of the present research. Indeed, and despite the fact that motivation is typically conceptualized as a dynamic process (e.g., Ryan & Deci, 2017), the bulk of prior research conducted in the work or educational areas has been cross-sectional, or based on limited longitudinal designs precluding a clear understanding of motivation trajectories occurring at the individual level. In addition, we also consider the effects of mental load, work load, emotional load, and peer support during the course of vocational training as possible determinants of these self-determination trajectories, and investigate the associations between these trajectories and various outcomes (i.e., positive and negative affect, and objective performance).

The present study was also designed as a substantive-methodological synergy (Marsh & Hau, 2007), seeking to illustrate how the reliance on innovative statistical procedures can help us to achieve a more refined understanding of individuals' self-determined motivation trajectories over the course of a vocational training program. As part of this synergistic effort, this study seeks to introduce organizational and vocational researchers to these procedures, and to demonstrate how these procedures can be used to enrich self-determination theory (SDT) research (Deci & Ryan, 2000; Ryan & Deci, 2017). More precisely, these procedures allowed us to achieve a more accurate measurement of trainees' global levels of self-determined motivation (via bifactor exploratory structural equation modeling – B-ESEM) coupled with the application of growth mixture analyses (GMA) to identify trainees characterized by distinct longitudinal trajectories.

Self-Determination Theory

Trainees' motivation represents the energizing/intensity, directing, and maintenance/persistence components of learning behavior in training contexts (Colquitt, LePine, & Noe, 2000). According to SDT (Ryan & Deci, 2017), individuals can be motivated for a variety of reasons. Intrinsic motivation refers to volitional engagement in an activity for the pleasure and satisfaction that it affords. Identified regulation refers to engagement in an activity that serves personally-endorsed values or objectives. Intrinsic motivation and identified regulation are conceptualized as autonomous forms of behavioral regulation. Introjected regulation refers to engagement in an activity driven by internal pressures, such as the avoidance of guilt and shame, or the pursuit of pride. External regulation refers to engagement in an activity that is controlled by external sources, such as rewards, punishments, or constraints. Introjected and external regulations are conceptualized as controlled forms of behavioral regulation. Finally, amotivation refers to the lack of motivation toward the target behavior.

SDT does not conceptualize these types of regulation as mutually exclusive but rather postulates that they can be placed on a continuum according to their level of self-determination. These various types of motivation are proposed to coexist within workers (Gillet, Becker, Lafrenière, Huart, & Fouquereau, 2017; Howard, Gagné, Morin, & Van den Broeck, 2016), and to follow an underlying continuum of self-determination ranging from intrinsic motivation to amotivation (Deci & Ryan, 2000; Howard, Gagné, & Bureau, 2017; Howard, Gagné, Morin, & Forest, 2018). This continuum ranges from the more autonomous forms of regulation to the more controlled forms of regulation. Autonomous motivation characterizes engagement in activities driven by pleasure, volition, and choice, whereas controlled motivation characterizes activity engagement driven by internal or external pressures. More precisely, integrated regulation, identified regulation, introjected regulation, and external regulation fall in sequence between intrinsic motivation and amotivation on this continuum.

So far, research has generally supported the distinctive nature of the various types of behavioral regulation proposed by SDT, as well as their differential predictive validity in relation to a variety of outcome variables (Deci, Olafsen, & Ryan, 2017; Gagné & Deci, 2005; Guay, Ratelle, & Chanal, 2008). However, the continuum hypothesis has recently been challenged. Relying on Rasch analyses, Chemolli and Gagné (2014) failed to find evidence supporting the idea that motivation ratings obtained in the work and education areas could be conceptualized according to a single dimension matching the continuum hypothesis. In contrast, parallel efforts have shown that the free estimation of cross-loadings between the behavioral regulation factors via ESEM (Asparouhov, Muthén, & Morin, 2015; Morin, Marsh, & Nagengast, 2013) resulted in the estimation of factor correlations more closely aligned with the hypothetical continuum structure (Guay, Morin, Litalien, Valois, & Vallerand, 2015; Litalien, Guay, & Morin, 2015). More recently, Howard et al. (2018; in the work area) and Litalien et al. (2017; in the education area) combined these two perspectives through the application of B-ESEM (Morin, Arens, & Marsh, 2016) and provided a reliable, direct, and meaningful assessment of global levels of self-determined motivation, reflecting the SDT theoretical continuum. More specifically B-ESEM made it possible for them to identify a well-defined global factor reflecting the self-determination continuum (with factor loadings ranging from strongly positive for items tapping into more autonomous forms of motivation to moderately negative for amotivation items) co-existing with specific factors reflecting the variance uniquely attributable to each type of behavioral regulation.

Thus, despite the general recognition that a complete assessment of motivation should tap into the different types of behavioral regulation (Gillet, Becker et al., 2017), it has been demonstrated that individuals might experience motivation in a more holistic manner as a single overarching dimension. This global approach seems to be supported by the observation of high correlations among the different forms of motivation (Gillet, Morin, & Reeve, 2017). Moreover, this global level of self-determination is the motivation facet displaying the strongest relation to a variety of predictors and outcome variables (e.g., psychological need satisfaction; achievement; dropout intentions; ill-being; Howard et al., 2018; Litalien et al., 2017). These results underscore the importance of considering global levels of self-determined work motivation in the context of research focusing on the emergence, development, and consequences of human motivation.

Importantly, these results match bulk of prior SDT research showing that individuals' levels of self-determination appear to be positively related to well-being and performance (Gillet, Fouquereau, Vallerand, Abraham, & Colombat, 2018; Gillet, Vallerand, Lafrenière, & Bureau, 2013) and negatively related to maladaptive outcomes (e.g., dropout intentions, burnout, negative affect; Fernet, Austin, & Vallerand, 2012; Gillet, Gagné, Sauvagère, & Fouquereau, 2013). These conclusions appear to hold across settings (e.g., sport, education, work), cultural contexts (Gillet, Fouquereau, Lafrenière, & Huyghebaert, 2016; Jowett et al., 2017), and operationalization of motivation (either as a single score, as higher order autonomous and controlled scores, or as separate behavioral regulation dimensions; Fernet, Chanal, & Guay, 2017; Howard et al., 2016; Koen, Klehe, & van Vianen, 2015). This last observation supports the idea that the reliance on a single score, properly operationalized to reflect global levels of self-determined motivation, might represent a promisingly parsimonious approach to the study of motivation. In the present study, we adopt this new operationalization of self-determined motivation levels advocated by Howard et al. (2018) and Litalien et al. (2017) to consider the evolution of global levels self-determined motivation over the course of a vocational training program. More precisely, these global levels of self-determination can be considered to represent the extent to which trainees perceived their involvement into training activities to be self-determined (autonomously-driven with limited levels of external control) in nature.

Self-Determined Motivation during Vocational Training

A Longitudinal Perspective.

The bulk of research on work or academic motivation has relied on cross-sectional designs or on limited longitudinal designs (i.e., including only two time points), precluding a clear understanding of the developmental trajectories occurring at the individual level (Ployhart & Vandenberg, 2010). More precisely, data collected across two times of measurement can be highly useful when the goal is to assess rank-order stability (stability in the relative position of individuals relative to one another, as assessed by correlations), the absolute magnitude of longitudinal change, cross-lagged relations among constructs, or even stability and change in motivational profiles (e.g., Gillet, Morin, & Reeve, 2017). However, such data is not sufficient to achieve a proper understanding of intra-individual stability and change in the shape of motivation trajectories that best characterize specific individuals (Grimm, Ram, & Estabrook, 2016). For this, more intensive longitudinal research (i.e., including three time points or more) is needed. In particular, more intensive longitudinal research appears to be critical for SDT, which defines motivation as a partly situational construct (e.g., Vallerand, 1997). In other words, motivation is seen as emerging in part from the changing characteristics of the specific life context to which a person is exposed rather than to be an inherently stable characteristic of that person.

In the training context, this dynamic nature of motivation is best reflected in Beier and Kanfer’s (2009) model that depicts the evolution of trainees’ motivation according to three stages. First, it begins with the motivation to enroll in the training program. Then, it follows by the motivation to participate in the learning and training activities during the program itself. Finally, it ends with the motivation to transfer the knowledge and skills acquired during training to their work environments. This three stage sequence makes it clear that motivation is expected to fluctuate to some extent during training. These fluctuations themselves may also vary from one person to another. As such, the ability to study how trainees’ motivation evolves over time, and to be able to consider how this evolution differs across distinct subpopulations of individuals, would provide a rich window of opportunity to study the developmental mechanisms at play in the emergence of relations between motivation and a variety of important predictors and outcomes.

The GMA approach taken in this study is specifically designed to examine how self-determination trajectories of distinct profiles of upcoming police officers evolve over the course of their vocational training. It also aims to document how these distinct trajectories are related to various predictors and outcomes. More precisely, a first objective of the present study is to identify the most typical self-determination trajectories that characterize upcoming police officers over the course of their vocational training (9 months). The decision to focus on a sample of upcoming workers in a vocational training context is based on three distinct considerations. First, there is an almost complete lack of research on the precursors of work motivation. Given the intimate connection between vocational training and entry into the workforce that exists for police officers, many of which (at least in France) have prior experience of military or security work, vocational training appeared to be a natural entry point into the emergence of work motivation. Vocational training is typically when one’s expectations regarding the anticipated nature of one’s chosen profession are first challenged through a comparison with exposure to true job requirements, leading to potentially important changes in motivation levels.

Second, vocational training courses are more typically “self-determined” in nature when compared to the mandatory nature of daily job activities. This context is thus a potentially rich one to achieve a better understanding of the emergence and change in global self-determination levels at the initial stage of one’s career. Third, learning and persistence in vocational training programs are critically important considerations for organizations worldwide. Indeed, vocational training is associated with multiple social, economic, and psychological consequences for the upcoming workers themselves as well as for organizations as a whole (Nilsson, 2010). In particular, the implications of such training programs become even more broadly relevant when the employing organization is the society itself, such as it is typically the case for police organizations. Among the key drivers of learning and persistence, workers’ levels of self-determined motivation appear to represent a particularly important mechanism to consider (Deci et al., 2017). Yet, despite the importance of vocational training in terms of professional, social, and vocational achievement and success, self-determined motivation among trainees has received relatively little attention in prior longitudinal research.

A Person-Centered Perspective on Longitudinal Trajectories.

Vocational training occupies a very unique position in research, being located at the border between educational and organizational research areas. For this reason, despite the lack of longitudinal research conducted in the organizational area focusing on workers' motivation, some guidance can be obtained from a consideration of the few studies conducted in the educational area among younger populations. Thus, longitudinal research conducted on sample of primary and secondary students generally tends to reveal decreasing levels of self-determined motivation (i.e., decreasing levels of autonomous motivation coupled with increasing levels of controlled motivation and amotivaiton) over time (e.g., Leroy & Bressoux, 2016; Maulana, Opdenakker, & Bosker, 2013). However, these levels might increase across the transition into higher education (Kyndt et al., 2015).

Importantly, all of these studies reported an important level of inter-individual heterogeneity. Part of this heterogeneity could be explained by the presence of subpopulations characterized by distinct longitudinal trajectories that may be important to identify for intervention purposes. Person-centered analyses, such as the longitudinal GMA approach adopted in this study, are specifically designed to assess how the self-determination trajectories of future police officers evolve over the course of their vocational training across distinct profiles of participants (Morin, 2016; Muthén, 2002).

Vocational training is a key component of upcoming employees' occupational socialization, defined as "a process by which an individual acquires the social knowledge and skills necessary to assume an organizational role" (Van Maanen & Schein, 1979, p. 211). Interestingly, the research literature on occupational socialization explicitly recognizes that people are likely to follow very distinct longitudinal trajectories depending on the extent to which the socialization and training process matches or exceeds their expectations, or reveals unexpected aspects of work roles that are less desirable than initially anticipated (e.g., Boswell, Boudreau, Tichy, 2005; Solinger, Van Olffen, & Hofmans, 2013; Weiss, 1978). For instance, some employees may display an initially cautious appraisal of the occupational requirements that become progressively integrated to their identities (referred to as the *Learning to Love* scenario). In contrast, other employees could experience increasing levels of disappointment following an initial level of exuberant enthusiasms (referred to as the *Honeymoon-Hangover* scenario). Finally, a final group of employees might encounter a reality that more closely matched their expectations (referred to as the *Matching* scenarios).

To our knowledge, a single study has relied on person-centered GMA to study motivation in the educational area. In this investigation of 410 students followed annually for two years, Nishimura and Sakurai (2017) identified two distinct longitudinal profiles. The first of those profiles characterized 22.2% of the students presenting decreasing levels of intrinsic motivation and identified regulation. The second profile characterized 77.8% of the students presenting increasing levels of external and introjected regulations. These two profiles apparently matched the aforementioned normative declines observed in self-determination levels (Leroy & Bressoux, 2016; Maulana et al., 2013). Despite the lack of similar research on motivation trajectories conducted in the work area, Solinger et al. (2013) studied trajectories of affective commitment to their organization among a sample of 72 newly hired employees. Affective organizational commitment is a motivational construct referring to autonomously-driven force that binds employees to a course of action relevant to their organization (e.g., Meyer, Becker, & Vandenberghe, 2004). Solinger et al.'s (2013) results, focusing on the first six months of employment, revealed trajectories corresponding to five onboarding socialization scenarios: Learning to Love (16.5%), Honeymoon-Hangover (25%), High Match (34.5%), Moderate Match (12.5%), and Low Match (11.5%).

Unfortunately, despite their ground-breaking nature, these studies present a few critical limitations. First, GMA are computer-intensive and relatively demanding in terms of sample size. This may explain why these authors decided to rely on a suboptimal restricted parameterization of GMA (Diallo, Morin, & Lu, 2016; Morin, Maïano et al., 2011), which may have impacted their results. Second, Nishimura and Sakurai's (2017) attempt to estimate distinct profiles of participants while simultaneously taking into consideration four highly correlated growth processes (rather than a single process at a time, or a global indicator of participants' levels of self-determined motivation). This might have limited their ability to identify more numerous profiles, particularly in light of the sample size requirements of GMA. Finally, and most importantly, Nishimura and Sakurai (2017) failed to demonstrate the construct validity of the extracted profiles through the demonstration of meaningful patterns of associations with theoretically significant covariates (Marsh, Lüdtke, Trautwein, & Morin, 2009; Morin, Morizot, Boudrias, & Madore, 2011). Although Solinger et al. (2013) did consider covariates related to the cognitive underpinning of these scenarios (person-organization fit, psychological contract breaches, and met expectations), it would have been interesting to also consider possible drivers of these trajectories, as well as likely outcomes. The present study addresses these limitations by adopting a less restricted GMA parameterization (see the analysis section for additional details). We also adopted a more parsimonious approach focusing on a single longitudinal process reflecting participants' global levels of self-determination. Finally, we addressed the construct validity of the extracted profiles using a much larger sample of participants.

Due to the rarity and limitations of prior research relying on a person-centered approach to identify motivation trajectories in the educational and work domains, it is difficult to formulate clear expectations regarding the nature of all profiles to be identified in the present study. However, based on the results obtained by Nishimura and Sakurai (2017) and Solinger et al. (2013), we propose the following hypotheses:

Hypothesis 1. Participants' self-determined motivation trajectories will be best represented by two to four profiles.

Hypothesis 2. At least some of those profiles will correspond to the *Learning to Love* (i.e., low levels followed by a progressive increase) or *Honeymoon-Hangover* (i.e., high levels followed by a progressive decrease) scenarios.

Hypothesis 3. A majority of participants will be characterized by profiles corresponding to the *Matching* (stable high, moderate, or low levels) scenarios.

A Construct Validation Perspective

The present study is the first to rely on the specific operationalization of participants' global levels of self-determination in the estimation of longitudinal trajectories. It is also the first to estimate such trajectories in a vocational training context. In person-centered research, best practice recommendations indicate the importance of documenting the criterion-related validity of the extracted trajectory profiles in relation to meaningful external covariates (e.g., Marsh et al., 2009; Morin, Morizot et al., 2011). To this end, a second objective of the present study is to adopt a construct-validation perspective in order to assess the effects of vocational training demands (mental load, work load, and emotional load) and resources (peer support) on these self-determination trajectories. We also investigated the associations between these trajectories and various outcomes (i.e., positive and negative affect, and objective performance). These covariates were selected based on their documented importance in the educational and work contexts, their relevance to SDT, and results from prior research on motivation conducted in the work or educational context (e.g., Gillet, Becker et al., 2017; Gillet, Vallerand et al., 2013).

Vocational Training Demands and Resources.

According to the job demands-resources model (Bakker & Demerouti, 2007), a health impairment process is activated by excessive demands that lead to physical and psychological health problems. Demands refer to those aspects of an activity that require sustained physical and/or psychological effort and are therefore associated with physiological and/or psychological costs. In contrast, resources may help to enhance well-being and reduce ill-being as they contribute to achieving goals, reducing the costs associated with demands, and stimulating personal development. Demands and resources exert their influence through helping to build personal strengths (Xanthopoulou, Bakker, Demerouti, & Schaufeli, 2007), professional development (Evers, van der Heijden, Kreijns, & Vermeulen, 2016), equity (Hu, Schaufeli, & Taris, 2013), recovery experiences (Kinnunen, Feldt, Siltaloppi, & Sonnentag, 2011) or connectedness (Huynh, Xanthopoulou, & Winefield, 2014). Despite the well-documented importance of demands and resources (e.g., Alarcon, 2011; Nahrgang, Morgeson, & Hofmann, 2011), to the best of our knowledge, no person-centered research has examined the effects of demands (e.g., work load, mental load, emotional load) and resources (e.g., peer support) on self-determined motivation trajectories. However, prior variable-centered studies conducted in both the work and education contexts (e.g., Bartholomew et al., 2018; Fernet, Trépanier, Austin, Gagné, & Forest; 2015; Trépanier, Forest, Fernet, & Austin, 2015; Vujčić, Oerlemans, & Bakker, 2017) suggest that demands and resources should predict participants' levels of self-determined motivation. For instance, Fernet et al. (2015) showed that work load was associated with lower levels of self-determined motivation. In contrast, social support is positively related to self-determined motivation (Gillet, Becker et al., 2017). Thus, higher demands should predict a greater likelihood of membership into the profiles characterized by lower levels and/or decreasing levels of global self-determination. In contrast, higher resources should predict a greater likelihood of membership into the profiles characterized by higher levels and/or increasing levels of global self-determination.

However, research has also shown that the effects of job demands on employees might differ according to their hindering or challenging nature (Cavanaugh, Boswell, Roehling, & Boudreau, 2000; Crawford, LePine, & Rich, 2010; LePine, Podsakoff, & LePine, 2005). This distinction has also been found to be relevant to the prediction of self-determined work motivation (Fernet et al., 2015; Vujčić et al., 2017). More specifically, challenge demands are those that generate problem-focused coping activities contributing to the achievement of working goals. Hence, they create opportunities for development and growth, and in turn, lead to positive affective states and outcomes (Cavanaugh et al., 2000). In contrast, hindrance demands refer to obstacles that drain employees' energy. Hindrance demands lead employees to experience reduced control over their work environment and to rely on emotion-focused coping styles, in turn leading to a variety of negative affective states and outcomes (Van den Broeck, De Cuyper, De Witte, & Vansteenkiste, 2010). Vujčić et al. (2017) showed that challenge demands were associated with higher levels of self-determined motivation. In contrast, hindrance demands were negatively related to self-determined motivation. These differential effects of challenge and hindrance demands on self-determination may be explained by the fact that challenges, contrary to hindrances, are positively related to need satisfaction (Olafsen & Halvari, 2017).

In the present study, we rely on measures of mental load (i.e., a cognitive demand that primarily impinges on the brain processes involved in information processing such as working with a lot of precision), work load (i.e., trainees' perceptions of having too much work to do in the time available), and emotional load (i.e., the effort needed to deal with training inherent emotions) as joint indicators of training demands. Peer support (i.e., trainees' perceptions of social support that they receive from their colleagues) was also considered as an indicator of training resources (see Lequeurre, Gillet, Ragot, & Fouquereau, 2013). Based on previous finding related to the job demands-resources model and to the challenge/hindrance distinction, we propose the following hypotheses:

Hypothesis 4. We expect higher perceptions of mental load (controlled for the effects of work load and emotional load) to predict a higher likelihood of membership into profiles characterized by higher and/or increasing levels of global self-determination.

Hypothesis 5. We expect higher perceptions of peer support to predict a higher likelihood of membership into profiles characterized by higher and/or increasing levels of global self-determination.

Hypothesis 6. We expect higher perceptions of work load (controlled for the effects of mental load and emotional load) and emotional load (controlled for the effects of work load and mental load) to predict a higher likelihood of membership into profiles characterized by lower and/or decreasing levels of global self-determination.

Outcomes of the Self-Determination Trajectories.

Finally, in order to better document the likely impact of membership into the various self-determination profiles on training success and participants' outcomes, we also assess the extent to which these profiles will be related to participants' levels of positive and negative affect at the end of the training. Moreover, we examine the associations between trainees' motivation profiles and their objective levels of achievement (as a performance outcome) at the end of the vocational training program. Consistent with SDT predictions (Deci & Ryan, 2000), prior studies have supported the idea that higher levels of self-determination tended to be associated with higher levels of positive affect and lower levels of negative affect (Gillet, Becker et al., 2017; Vujčić et al., 2017), as well as with higher levels of performance (Trépanier et al., 2015; Valero, Hirschi, & Strauss, 2015). In addition, positive affect was selected based on mounting research evidence supporting its key role in achievement (Gillet, Vallerand et al., 2013). Likewise, negative affect was retained based on its role in the prediction of turnover, which is in turn associated with important costs for organizations and educational systems (Kacmar, Andrews, Van Rooy, Steilberg, & Cerrone, 2006). In addition, policing has been widely discussed as a stressful occupation and identified as one of the most demanding occupations worldwide (Duran, Woodhams, & Bishopp, 2018). It thus appeared important to identify the factors potentially contributing to the development of future police officers' well- and ill-being. In line with these empirical results and theoretical considerations, we propose the following hypothesis:

Hypothesis 7. We expect the profiles characterized by higher levels and/or increasing levels of global self-determination to be associated with the most adaptive outcomes, and those characterized by lower and/or decreasing levels of global self-determination to be associated with the least desirable outcomes.

Method

Sample and Procedure

This study relies on a sample of 1676 participants (Mean age = 26.24; *SD* = 3.83; 66.5% male) undergoing a 9-month full-time vocational training program to become police officers. Eighty-eight participants (5.3%) had no previous diploma, 206 already had a previous vocational training certificate (12.3%), 906 already had a previous high school diploma (54.1%), 397 already had a previous university diploma (23.7%), and 79 participants did not indicate their previous education level (4.7%). Participation was voluntary and all future police officers enrolled in this program were invited to complete a self-reported questionnaire 5 (n = 868), 14 (n = 908), 25 (n = 843), and 41 (n = 604) weeks after the beginning of the training period. At each data collection point, members of the research team explained the purpose of the study to the participants. Then, trainees provided informed consent before completing a 15-minute questionnaire in the classroom. Participants were ensured that their responses would be kept confidential and would not impact their grades. They were also asked to provide a personal identification code to allow researchers to match their responses across data collection points.

Measures

Participants were first asked to indicate their age (in years), sex (coded 0 for males and 1 for females), and education level (0-no previous diploma to 3- University diploma). Then, they completed different scales assessing their motivation, perceptions of demands and resources, and affect.

Self-Determined Motivation. Participants completed Gagné et al.'s (2015) Multidimensional Work Motivation Scale, which was slightly adapted to refer to the vocational training context. This questionnaire includes 19 items, all rated on a 7-point scale ranging from 1 (does not correspond at all) to 7 (corresponds very strongly). It assesses six dimensions of motivation: (a) intrinsic motivation (3 items; e.g., "Because I have fun engaging in this training"; α_{t1} = .85; α_{t2} = .87; α_{t3} = .88; α_{t4} = .85), identified regulation (3 items; e.g., "Because putting efforts in this training has personal significance to me"; α_{t1} = .61; α_{t2}= .64; α_{t3}= .69; α_{t4}= .70), introjected regulation (4 items; e.g., "Because I have to prove to myself that I can"; α_{t1} = .64; α_{t2}= .68; α_{t3}= .70; α_{t4}= .69), external-social regulation (3 items; e.g., "Because others will respect me more"; α_{t1} = .70; α_{t2}= .81; α_{t3}= .84; α_{t4} = .86), external-material regulation (3 items; e.g., "Because others will reward me financially only if I put enough effort in this training"; α_{t1} = .48; α_{t2}= .56; α_{t3}= .61; α_{t4} = .63), and amotivation (3 items; e.g., "I do little because I don't think this training is worth putting efforts into"; α_{t1} = .87; α_{t2}= .89; α_{t3}= .91; α_{t4} = .92).

Demands and resources. Mental load (4 items; e.g., "During this training, do you have to give continuous attention to your work?"; α_{t1} = .86; α_{t2}= .88; α_{t3}= .91; α_{t4} = .88), work load (4 items, e.g., "During this training, do you have too much work to do?"; α_{t1} = .78; α_{t2}= .80; α_{t3}= .79; α_{t4} = .82), emotional load (4 items; e.g., "During this training, does your work demand a lot from you emotionally?"; α_{t1} = .75; α_{t2}= .79; α_{t3}= .80; α_{t4} = .83), and peer support (4 items; e.g., "Can you count on your colleagues when you encounter difficulties in this training?"; α_{t1} = .89; α_{t2}= .91; α_{t3}= .95; α_{t4} = .93) were measured with four subscales taken from a comprehensive measure developed and validated by Lequeurre et al. (2013). All items were rated on a 7-point response scale ranging from 1 (never) to 7 (always) and referring to the training context.

Positive and negative affect. Participants' levels of positive (5 items; e.g., "calm"; α_{t1} = .72; α_{t2}= .76; α_{t3}= .81; α_{t4} = .83) and negative (5 items; e.g., "depressed"; α_{t1} = .78; α_{t2} = .80; α_{t3}= .83; α_{t4} = .82) affect during training were assessed with two relevant subscales from the Job-related Affective Well-being Scale (JAWS; Van Katwyk, Fox, Spector, & Kelloway, 2000). Responses were provided on a 5-point scale (1- never to 5- always).

Performance. At the end of the training, official grade transcripts were received from the administrative office of the National Police Academy and used as an objective performance outcome. We rely here on the final global grade obtained at the term of the vocational training program (ranging between 847 and 1300 with *M* = 1125.6 and *SD* = 72.27). This is the result of the compilation of all assessments (over 20 of them) completed by the trainees over the course of the program. They include both theoretical exams (e.g., principles of identity control, intervention in a context of family violence) and practical trials (e.g., athletic, shooting).

Analyses

Model Estimation and Missing Data

All models were estimated using Mplus 8.0's (Muthén & Muthén, 2017) robust Maximum Likelihood (MLR) estimator. These models were estimated with Full Information Maximum Likelihood (FIML; Enders, 2010) procedures to account for the relatively limited amount of missing responses at the item level for participants who completed each time point (.12% to 5.63%). FIML also allowed us to estimate all longitudinal models using the data from all respondents who completed at least one wave of data rather than using a listwise deletion strategy focusing only on those having answered all, or a subset, of time waves (Enders, 2010; Graham, 2009). In total, 1676 participants provided a total of 3223 time-specific ratings (M = 1.92 time-specific ratings per participants).

Preliminary Analyses

Rather than using scale scores (the mean or sum of the items) to estimate the trajectories and their relations with predictors and outcomes, factor scores from preliminary measurement models were used for the analyses. For the motivation and predictors measures, these factor scores were estimated in standardized units at Time 1 with M = 0 and SD = 1, with the remaining time points estimated as deviations from Time 1 in SD units. For the outcome measures, we selected Time 4 as the referent time point to set M = 0 and SD = 1. The measurement models for the motivation measure were estimated using B-ESEM (Morin, Arens, & Marsh, 2016; Morin, Boudrias et al., 2016, 2017). This decision is based on recent studies showing that B-ESEM is naturally suited to measures of work (Howard et al., 2018), academic (Litalien et al., 2017), and sport (Gunnel & Gaudreau, 2015) motivation based on SDT (Deci & Ryan, 2000). These studies showed that B-ESEM provides a way to obtain a direct and precise estimate of the global continuum of self-determination proposed by SDT to underlie all motivation ratings (i.e., the global "quantity" of self-determination). This global levels of self-determination is used here to estimate participants' trajectories. To ensure the comparability of measurement across time waves, factors scores were saved from longitudinally invariant measurement models (Millsap, 2011). Although factor scores do not explicitly control for measurement errors the way latent variables do, they provide a partial control for them (Skrondal & Laake, 2001) by giving more weight to more reliable items (for additional discussions of factor scores, see Morin, Boudrias et al., 2016, 2017; Morin, Meyer, Creusier, & Biétry, 2016). Details on these measurement models and their longitudinal invariance are reported in Appendix 1 of the online supplements. Readers interested in learning more about the estimation of B-ESEM models are referred to Morin, Arens, and Marsh (2016) introduction to these models, which comes with an extensive set of annotated syntax for their estimation. The correlations between all variables (i.e., the factor scores saved from these final measurement models and the single item measure of performance) are reported in Table 1.

Growth Mixture Analyses (GMA)

Quadratic GMA models including one to eight latent trajectories of global self-determination were estimated and compared. GMA are built from latent curve models (Bollen & Curran, 2006) to identify subgroups of participants following distinct longitudinal trajectories (Grimm et al., 2016; Morin, Maïano et al., 2011). Quadratic GMA summarize a series of repeated measures by the estimation of random intercept, linear slopes, and quadratic slope factors reflecting, respectively, the initial level of the growth trajectories, the average rate of change over time, and the presence of curvilinearity in the trajectories. This curvilinear component allows for the detection of u-shape, or inverted u-shape trajectories. Quadratic GMA models are very flexible, allowing for the estimation of trajectories that can be (i) stable (when the linear and quadratic slopes are close to zero and non-significant), (ii) linear (increasing or decreasing in a linear manner, when the quadratic slope is close to zero and non-significant), or (iii) curvilinear (u-shape or inverted u-shape trajectories). Time codes on the slope factors were set to 0 at Time 1 (to allow the intercept factor to reflect global self-determination levels at the initial time point), 2 at Time 2, 5 at Time 3, and 9 at Time 4 to reflect the passage of time (in months, rounded to the closest unit). These time codes were squared on the quadratic slope factor. To avoid converging on a local maxima, all models were estimated using 10,000 random sets of start values, 1,000 iterations, and 500 solutions for final stage optimization (Hipp & Bauer, 2006). A more technical presentation of GMA is provided in Appendix 2 of the online supplements. Readers interested in learning more about the estimation of GMA models are referred to Morin and Litalien (2018) recent introductory chapter, which comes with an extensive set of annotated input files.

Current statistical recommendations are that GMA should, whenever possible, be estimated while allowing all models parameters (intercept and slopes means, intercept and slopes variances and covariances, and time-specific residuals) to be freely estimated in all profiles (Diallo et al., 2016; Morin, Maïano et al., 2011). However, this recommendation comes with the recognition that this free estimation of all parameters is not always possible due to the tendency of these more complex models to converge on improper solutions, or not to converge at all (Diallo et al., 2016). This was the case in the present study. In such situations, the recommendation is to implement equality constraints across profiles on specific parameters to achieve a more parsimonious representation (Diallo et al., 2016). Here, we set the latent variance-covariance matrix to be invariant across profiles, but allowed the time-specific residuals to be freely estimated across profiles.

Predictors and Outcomes of Profile Membership. Once the optimal number of profiles has been selected, relations between these profiles and a series of predictors and outcomes were investigated. These predictors and outcomes were directly included in the model (which is recognized as the most efficient way to assess covariates effects; Meyer & Morin, 2016; Morin & Litalien, 2018) using the start values from the final retained unconditional solution to ensure that the inclusion of these covariates did not change the nature of the profiles (Diallo, Morin, & Lu, 2017; Marsh et al., 2009; Morin, Meyer et al., 2016). For analyses of predictors, a series of alternative models was contrasted, following recommendations from Diallo et al. (2017) implemented in applied research by Morin and colleagues (Morin, Rodriguez, Fallu, Maïano, & Janosz, 2012; Morin, Maïano et al., 2011, 2013).

We first considered models including potential demographic controls assessed at Time 1 (age, sex, and education level) to verify the need to incorporate these controls as additional predictors in further models. First, a null effects model was estimated in which the effects of the controls on the probability of membership in all profiles, as well as on the growth factors, were constrained to be zero. Second, a model was estimated in which the controls were allowed to predict profile membership through a multinomial logistic regression. Additional models were then estimated in which predictors were also allowed to influence (via multiple regression) within-profile variation in the intercepts and slopes of the trajectories, and in which these effects were allowed to vary across profiles. These tests aimed to determine which, if any, of these control variables needed to be retained for the subsequent models.

In a second series of models, the same sequence was repeated to assess the effects of the predictors (mental load, work load, emotional load, and peer support). To ensure a temporal ordering of the predictors relative to the predicted variables (i.e., the latent profiles and latent trajectory factors), we solely considered the Time 1 measures of these predictors.

Outcomes measured at the last time point (Time 4: positive and negative affect, performance) were included to the model. Mean differences across profiles were tested using the multivariate delta method (Raykov & Marcoulides, 2004) implemented via the MODEL CONSTRAINT function.

Supplementary Analyses. Supplementary analyses were conducted to contrast the estimated profiles on the basis of predictors and outcomes assessed at each specific time point (1 to 4). For these analyses, it did not prove possible to incorporate these time-varying covariates directly in the model without changing the nature of the profiles (e.g., Diallo et al., 2017; Marsh et al., 2009). For this reason, we had to rely on a model-based approach proposed by Lanza, Tan, and Bray (2013) and implemented through the Auxiliary (DCON) function (Asparouhov & Muthén, 2014). The same approach was also used to contrast the profiles with one another based on the time specific factor scores obtained on each specific motivation factors in the preliminary B-ESEM measurement models. These factor scores reflect the specific quality of employees' motivation left unexplained by their global self-determination levels (Howard et al., 2018). The results from this last set of more exploratory analyses are reported at the end of the online supplements (Appendix 4).

Results

Unconditional Models

The procedures followed in order to select the optimal GMA solution is fully disclosed in Appendix 3 of the online supplements. This procedure led us to retain the 3-profile solution, thus supporting Hypothesis 1. This solution is graphically presented in Figure 1, and exact parameter estimates are reported in Table S6 of the online supplements. Classification accuracy statistics are reported in Table S7 of the online supplements, and reveal a very high level of accuracy ranging from .857 to .878 across profiles.

In the interpretation of the profiles, it is important to keep in mind that the trajectories were estimated on the basis of time-invariant factor scores with a mean of 0 and a standard deviation of 1 obtained at the first time point in preliminary analyses reported in the online supplements. This means that a value of 0 corresponds to the average level of global self-determination at Time 1, and that deviations from this global mean are directly expressed in *SD* units. This final solution depicts three profiles characterized by generally stable longitudinal trajectories of global self-determination over time associated with very slight linear or curvilinear tendencies. This stability is generally consistent with the *Matching* scenarios expected from Hypothesis 3, but fails to support Hypothesis 2. Profile 1 characterized 47.6% of the participants presenting initial global levels of self-determination corresponding to the sample average, a very slight decreasing tendency over time (corresponding to -.035 *SD* units per month), and a negligible curvilinear tendency (corresponding to .001 *SD* units per month). This *Moderate* profile was also associated with the lowest time-specific residuals across time points (corresponding to average deviation from the estimated trajectory ranging from .084 *SD* units at Time 3 to .205 *SD* units at Time 1).

Profile 2 characterized 29.7% of the participants presenting high initial levels of global self-determination (.558 *SD* units higher than the mean) and a slight increasing tendency (.087 *SD* units per month) coupled with a small negative curvilinear tendency (-.010 *SD* units per month). This *High* profile thus followed a slight inverted U-shape trajectory reaching its highest level by the third measurement point and decreasing thereafter. Profile 3 characterized 22.7% of the participants presenting low initial levels of global self-determination (.604 *SD* units lower than the sample mean) and a slight decreasing tendency (-.135 *SD* units per month) coupled with a small positive curvilinear tendency (.011 *SD* units per month). This *Low* profile thus followed a slight U-shape trajectory reaching its lowest level by the third measurement point and increasing thereafter. It is noteworthy that the *High* and *Low* profiles present similar levels of time-specific residuals. These residuals are two to three times as large as those estimated in the *Moderate* profile (ranging from .327 to .575 *SD* units).

Controls

Once the optimal number of profiles has been selected, we conducted a series of tests aiming to determine whether demographic controls (sex, age, and education level) needed to be retained for subsequent analyses. Results from models incorporating controls are reported at the end of Appendix 3 of the online supplements and support the null effects model. Examination of the detailed parameters estimates from these models supports this conclusion regarding the lack of meaningful associations between the controls and the profiles. Controls were thus excluded from further analyses.

Predictors

The results from the models incorporating the predictors to the final 3-profile model are reported at the end of Appendix 3 of the online supplements. These results support a model in which the predictors have an effect on the likelihood of profile membership, as well as a class-invariant effect on the initial levels of global self-determination. The results from these predictive analyses are reported in Table 2. These results supported Hypothesis 4 by showing that mental load increased participants' likelihood of membership into Profile 2 (*High*) relative to Profiles 1 (*Moderate*) and 3 (*Low*). Similarly, peer support also increased the likelihood of membership into Profile 2 (*High*) relative to 1 (*Moderate*), thus supporting Hypothesis 5. In contrast, emotional load increased the likelihood of membership into Profiles 1 (*Moderate*) and 2 (*High*) relative to 3 (*Low*). Over and above these effects on profile membership, mental load was associated with increases in the initial levels of global self-determination. In contrast, work load was associated with decreases in these initial levels. These results partially supported Hypothesis 6.

***Supplementary Analyses*.** As noted above, supplementary analyses were conducted to consider time-varying associations between the profiles and predictor levels measured at each separate time point. These supplementary results are reported in Table S8 of the online supplements. In contrast with the main results reported above in which predictors were used to statistically predict profile membership through multivariate analyses (in which the effects of each predictor was estimated net of what it shared with the other predictors) also considering their effects on the intercept factor, these supplementary analyses simply assess time-specific associations between predictors and profiles in a univariate manner. These additional results are consistent with the results reported above and show that the highest levels of work load, mental load, emotional load, and peer support were associated, at each time point, with the *High* profile, followed by the *Moderate* profile, and then by the *Low* profile.

Outcomes

The results from the analyses in which associations between the distal outcome measures and the likelihood of profile membership are reported in Table 3. These results supported Hypothesis 7 by showing that, from an outcomes' perspective, the most desirable profile was the *High* profile. This profile presented the highest levels of performance and positive affect at the end of the study, as well as the lowest levels of negative affect. Although statistically-significant differences mainly emerged between the *High* and *Moderate* profiles, the *Low* profile also presented higher levels of negative affect than the *High* profile.

Supplementary Analyses. The results from the supplementary analyses in which the univariate time-specific associations between the profiles and the outcomes measured at each separate time point (positive and negative affect only, performance levels were only assessed at the end of the study) are reported in Table S9 of the online supplements. These results show no differences across profiles in terms of positive affect. In contrast, levels of negative affect were higher in the *High* profile relative to the *Low* profile at Time 2, and in the *Moderate* profile relative to the *High* profile at Time 4. The apparent discrepancies in results obtained as part of these supplementary analyses relative to the main analyses reported here can be explained by a variety of methodological factors, such as: (a) the multivariate nature of the main analyses relative to the univariate nature of the auxiliary analyses; (b) the fact that auxiliary analyses rely on a listwise deletion of participants with missing data on the outcome variables; and (c) the superiority of the direct inclusion approach (Morin & Litalien, 2018).

Discussion

The benefits of more self-determined forms of motivation for a variety of educational and work-related outcomes has been well-established in prior research (Deci et al., 2017; Guay et al., 2008). However, with few exceptions (Nishimura & Sakurai, 2017), prior research has largely ignored the dynamic nature and longitudinal heterogeneity of individual motivation trajectories. The present study was designed to address this limitation via the identification of the self-determined motivation trajectories of upcoming police officers over the course of their vocational training. We also considered the role of vocational training demands (mental load, work load, and emotional load) and resources (peer support) in the prediction of these trajectories. Finally, the relations between these trajectories and training-specific affect and performance at the end of the program were examined.

Self-Determination Trajectories

In a recent ground-breaking study, Nishimura and Sakurai (2017) identified two distinct longitudinal profiles which best reflected heterogeneity in early adolescents' trajectories of academic motivation. These two profiles were respectively characterized by increasing and decreasing levels of self-determined motivation. Unfortunately, these authors relied on an unnecessarily complex model (simultaneously considering four types of behavioral regulation rather than a single global score of self-determined motivation) coupled with a restricted parameterization of GMA. This could have impacted their ability to detect a richer, and more diversified, set of profiles. Perhaps more importantly, these authors did not document the criterion-related validity of these profiles. This casts doubts on their theoretical and practical meaningfulness. In the present study, we relied on a more flexible operationalization of GMA to study longitudinal trajectories estimated based on a recently proposed integrative representation of participants' global levels of self-determined motivation (Howard et al., 2018; Litalien et al., 2017).

This approach allowed us to identify that three distinct profiles best represented the longitudinal trajectories of self-determined motivation of upcoming police officers over the course of their vocational training program, thus supporting Hypothesis 1. In support to Hypothesis 3, but failing to support Hypothesis 2, results revealed generally stable longitudinal trajectories. More precisely, about half of the participants presented initially average levels of self-determined motivation showing a very slight decreasing tendency over time (the *Moderate* profile). Roughly a third of the participants presented initially high levels of self-determined motivation, which tended to slightly increase over time up to the 25^{th} week of training (the *High* profile). Finally, about one fifth of the participants came to the training with initially low levels of self-determined motivation, which tended to decrease over time up to the 25^{th} week of training (*Low* profile). For these last two profiles, self-determination levels displayed a more linear trajectory between the 25^{th} week and the end of the training program. These results suggest that motivation changes might be slightly more pronounced at earlier stages of training, and support the idea that global self-determination may fluctuate as a function of contextual factors related to the vocational training context (Bartholomew et al., 2018; Fernet et al., 2012; Vallerand, 1997). However, it is important to keep in mind that the observed fluctuations remained minimal.

These slight changes associated with the first weeks of the training could possibly be explained by the fact that trainees initially discover a new environment to which they have to adapt. In the present study, it is interesting to note that trainees presenting initially high levels of self-determined motivation for entering the training program tended to display slightly increasing trajectories. This suggests that the training context tended to match their positive expectations. In contrast, trainees coming to the program with initially low levels of self-determined motivation tended to display slightly decreasing trajectories over time. This suggests a good match between the training context and their lower expectations. Once the training context becomes more familiar however, these trajectories would become more stable.

This further stabilization occurring within already stable trajectories is well-aligned with the idea that these trajectories reflect the three Matching scenarios (High, Moderate, and Low) from the occupational socialization literature identified by Solinger et al. (2013) as best reflecting the onboarding trajectories of affective commitment characterizing a majority of organizational newcomers. Despite this similarity in results, the occupational socialization literature also suggests the presence of two less frequent additional scenarios that could not be identified in the present study (Boswell et al., 2005; Solinger et al., 2013; Weiss, 1978). These *Learning to Love* and *Honeymoon-Hangover* scenarios are proposed to reflect the presence of a mismatch between participants' expectancies and their new work or training contexts. This mismatch could be positive, when the context exceeds expectations (*Learning to Love*), or negative, when the context is a source of disappointment (*Honeymoon-Hangover*). At least two different interpretations could be used to explain this apparent discrepancy. First, these socialization scenarios were initially proposed to describe the process of entering a new occupation. It is thus possible that the more time-restricted nature of vocational training lends itself to fewer changes over time. For instance, the most disappointed or exuberant trainees could decide to bid their time to see how the true work context would differ from the training context. Future research in which trainees are followed over time into their new occupation would be need to test this interpretation. Still, a second interpretation remains possible whereby the current results could be function of the specific professional (police) and cultural (France) context considered here. In France, most people entering vocational training to enter the police force come from a very similar professional background in the military or security sector. They may thus be already familiar with the specific context that characterizes police work and training, leading to an overestimation of the stability of these longitudinal trajectories. However, information on trainees' background was not available in this study. Future research is thus needed to confirm that this background could predict profile membership. More generally, future research covering a broader range of vocational training programs would be needed to test this second interpretation.

A final noteworthy aspect of these results is the observation that higher levels of state-like deviations (as reflected in the time-specific residuals representing deviations from the model estimated polynomial trajectories) tended to be associated with the more extreme (*High*/*Low*) trajectories of self-determined motivation, rather than with the *Moderate* trajectory. These results are particularly interesting in that they stand in sharp contrast with those obtained in the study of self-concept trajectories. Indeed, they revealed that higher self-concept levels tended to be more stable over time whereas lower self-concept levels tended to fluctuate widely over time (i.e., the self-equilibrium hypothesis; Morin, Maïano et al., 2013, 2017; Mund & Neyer, 2016). As discussed by Morin, Maïano et al. (2013, 2017), such patterns of associations between levels and stability in trajectories analyses can only be revealed by GMA. Clearly, additional research is needed to better understand how two constructs so intimately related (e.g., Leary & Tangney, 2012; Ryan & Deci, 2017; Wigfield & Eccles, 2000) could be associated with such discrepant longitudinal mechanisms at the higher end of the spectrum. Before that however, additional research would be needed to assess the extent to which the current results would generalize to other populations and developmental periods.

Predictors of the Self-Determination Trajectories

Our results showed that the trajectory profiles were independent from individuals' demographic characteristics (sex, age, and education level). More importantly, our results also supported the role of resources and demands associated with the training context in the prediction of these trajectories. In support of Hypothesis 5, we found that perceptions of having access to higher levels of peer support were associated with an increased likelihood of membership into the *High* profile relative to the *Moderate* one. Likewise, in support of Hypothesis 6, we found that work load perceptions were associated with decreases in participants' initial levels of self-determined motivation. These results are in line with prior variable-centered studies (e.g., Bartholomew et al., 2018; Fernet et al. 2015; Trépanier et al., 2015) showing that participants' levels of self-determined motivation tend to be negatively associated with the demands and positively associated with the resources present within their occupational or educational contexts. These findings are also consistent with previous research demonstrating job demands and resources to be significantly linked to psychological need satisfaction (e.g., De Cooman, Stynen, Van den Broeck, Sels, & De Witte, 2013; Van den Broeck, Vansteenkiste, De Witte, & Lens, 2008). These relations may be explained by the fact that demands require considerable energy and thus distract trainees from the satisfaction of their psychological needs. In contrast, job resources may establish conditions of growth and goal achievement, and thereby facilitate psychological need satisfaction. More generally, these results concur with the premises of the job demands-resources model in that perceptions of demands and resources are associated with negative and positive outcomes, respectively (Bakker & Demerouti, 2007).

In alignment with Hypothesis 4 and with the challenge-hindrance stressor framework (Crawford et al., 2010), we found higher perceptions of mental load to be associated with an increased likelihood of membership into the *High* profile relative to the *Moderate* and *Low* ones. These perceptions were also associated with higher initial levels of self-determined motivation. The fact that opposite results were found to be associated with a hindrance type of demand (work load) and with a challenge type of demand (mental load) underscores the importance of distinguishing demands according to whether there are seen as challenges or hindrances. Despite their stressful nature, challenges can also represent powerful motivating forces for employees. In contrast, hindrances more typically serve to decrease motivation through increasing feelings of helplessness and insecurity (e.g., Widmer, Semmer, Kälin, Jacobshagen, & Meier, 2012). Challenges tend to foster global self-determination because they enhance individuals' sense that their work is fun, interesting, and meaningful. For instance, Vujčić et al. (2017) showed that workers exposed to job demands of the challenge type tended to experience higher levels of autonomous motivation, positive affect, and work engagement.

Contrary to our expectations formulated in Hypothesis 6, our results showed that emotional load perceptions increased the likelihood of membership into the *Moderate* and *High* profiles relative to the *Low* one. This result thus suggests that emotional load mainly acted as a challenge demand for these trainees. Although we assumed that emotional load should act as a hindrance demand, it is equally possible that the exact impact of emotional load might depend on the valance of the emotions experienced as part of this load. Indeed, regulating negative emotions is more effortful and taxing than regulating positive emotions (Hülsheger & Schewe, 2011). However, our measure of emotional load did not allow us to assess the valence of these emotions, rather focusing on "emotions" in a general sense. It would be interesting for future research to assess the valence of the emotions experienced as part of this load to more explicitly assess this possibility.

Outside of the challenge-hindrance distinction, it is also important to keep in mind that additional studies have demonstrated positive associations between some forms of job demands and workaholism (e.g., Gillet, Morin, Cougot, & Gagné, 2017; Molino, Bakker, & Ghislieri, 2016; Schaufeli, Bakker, van der Heijden, & Prins, 2009). This observation suggests that at least some of the motivational benefits of job demands, even those of a challenge type, might come at a cost in terms of workaholism. Indeed, the more important the demands, the more trainees may be tempted to invest efforts and energy to meet these demands. This may lead them to experience higher levels of self-determined motivation, work engagement, and workaholism (e.g., Schaufeli, Taris, & van Rhenen, 2008). Clearly, our ability to explain the apparent benefits of mental and emotional load perceptions for trainees' self-determined motivation remains tentative. Future studies designed to assess the relative effects of additional challenge (e.g., job responsibility, job complexity) and hindrance (e.g., role ambiguity, role conflict) demands, as well as the likely mechanisms involved in these effects (e.g., emotional valence, workaholism) are needed. Future research would also benefit from a consideration of the impact of additional contextual (e.g., organizational support, leadership behaviors, social cohesion; Gillet, Gagné et al., 2013) or personal (e.g., need satisfaction, self-concept, engagement; Howard et al., 2018) characteristics on participants' self-determination trajectories.

Outcomes of the Self-Determination Trajectories

Our findings clearly support the practical importance of self-determined motivation trajectories in the prediction of outcomes[1]. In accordance with Hypothesis 7, our results revealed well-differentiated

[1] Following procedures outlined in Morin et al. (2012), we contrasted the percentage of explained variance in outcome levels taken from a simple variable-centered latent curve model (allowing the intercept and slope factors to predict the outcomes) with that of a model in which the probability of profile membership were also allowed to

associations between profile membership and the outcomes considered in this study. Thus, the *High* profile was associated with higher levels of positive affect and performance. This profile was also associated with lower levels of negative affect, relative to the *Moderate* profile. Likewise, the *Low* profile was associated with higher levels of negative affect than the *High* profile. These results support SDT's propositions (Deci & Ryan, 2000) and those from previous research (Gagné & Deci, 2005; Guay et al., 2008) in demonstrating the positive effects of participants' global levels of self-determined motivation. These results also contributed to establishing the meaningfulness (i.e., criterion-related validity) of the trajectory profiles identified in the present study.

Despite these encouraging results, it is also important to keep in mind that the *Moderate* and *Low* profiles did not differ from one another on any of the outcomes considered here. Thus, future studies would be needed to verify the possibility that the benefits of self-determined motivation might be circumscribed to high levels, with only a limited impact being associated with presenting average, versus, low levels of self-determination. Alternatively, the restricted time lag considered in the present study might have made it harder to detect effects emerging over a longer time frame. This time range limited us to the detection of more immediate benefits associated with high levels of self-determination. Importantly, our results are also aligned with those from previous research (Gillet, Becker et al., 2017) in demonstrating that the pattern of associations found between the self-determination trajectories and the outcomes differed as a function of the type of outcomes that was considered. Still, in order to confirm the differential effects of self-determined motivation trajectories on a wider range of outcomes, additional research focusing on markers of cognitive engagement, such as critical thinking, would be particularly informative. Indeed, mounting research evidence supports the role of engagement in training activities as a key determinant of occupational commitment and success that is easier to target for intervention purposes than achievement itself (e.g., Mills & Fullagar, 2017). Similarly, cognitive style (as a key predictor of performance; e.g., Russell, 1997), as well as dropout intentions or objective dropout data (e.g., Frey, Balzer, & Ruppert, 2014; Grønborg, 2015) would also be worth considering.

Limitations and Directions for Future Research

The present study has some limitations. First, we relied on self-report measures, with the exception of observed achievement. Such measures can be impacted by social desirability and self-report biases. We thus encourage researchers to conduct additional research using objective dropout data as well as informant-reported measures of trainees' attitudes and behaviors as ultimate outcomes. Likewise, it would be highly interesting for future research to consider work-related outcomes assessed after the end of the vocational training period once the trainees have started their new occupational roles. Second, it would be informative to look more carefully at the possible impact of the learning context and pedagogical approach used within the context of a greater diversity of vocational training programs, as well as across cultures. This would permit the identification of modifiable levers of improvement for trainees' global levels of self-determination. Third, the motivation trajectories reported here were observed in upcoming police officers over the course of their vocational training. Future research should examine whether the same trajectories emerge in samples from different settings, countries, cultural backgrounds, and developmental periods.

Fourth, the current results are intimately related to the time lag that was considered in this study (Cole & Maxwell, 2003): A 9-month vocational training program. Although slight changes were observed over time, the bulk of evidence from the present study was that global levels of self-determination were quite stable over this time interval. This observation supports the idea that studying changes in motivation requires relatively long time lags and/or major changes in professional lives. Still, it was noteworthy that changes appeared to be slightly more pronounced at the early, rather than late, stages of vocational training. This reinforces the idea that life transitions provide a unique window of opportunity to study developmental changes. In particular, it is possible that relying on a shorter time frame (e.g., daily or weekly diary study: Solinger et al., 2013), especially at the early stages of vocational training, could have allowed us to detect finer-grained fluctuations and associations occurring at the state level. In contrast, relying on a much longer time frame (covering multiple years) could have made it easier to observe associations and changes occurring at a more fundamental trait level. Alternatively,

predict outcome levels. This second model resulted in almost twice as much explanatory power (R^2 increased from an average of 8.7% in the latent curve model to 14% when probabilities of profile membership were taken into account).

both of these alternative time frames might have hidden the currently observed relations. Ultimately, longitudinal evidence remains stronger than cross-sectional research to clarify the directionality of associations. Yet, such evidence needs to be built incrementally from an accumulation of studies focusing on alternative time frames (Gillet, Morin et al., 2018).

Practical Implications

This study is the first to document longitudinal trajectories of participants' global levels of self-determined motivation in a vocational training context, and to assess the determinants and outcomes of these trajectories. Vocational training is known to represent an important life transition accompanied by major changes in individuals' educational, work, and social environments. Indeed, trainees are exposed to new, unfamiliar, and challenging learning situations, and changing social networks (Masdonati, 2010; Skrobanek, Reissig, & Müller, 2011). These changes might greatly impact their feelings of being able to act in a purely self-determined manner, with lasting consequences for their upcoming careers. As such, the present results could have a series of important practical implications.

From a practical perspective, our findings suggest that organizations and trainers should seek to increase individuals' global self-determination. Indeed, the *High* profile was found to be associated with the most positive outcomes. They also revealed that challenging types of demands, as well as resources related to social support, associated with the training context tend to foster more desirable global self-determined motivation trajectories. A first implication is thus that organizations and trainers could promote trainees' self-determined motivation by making sure that the training context remains a challenging one. They should also try to avoid adding demands seen as hindering progression. Ensuring that trainees feel supported when facing demands might help them to see them as challenges to be overcome rather than as insurmountable obstacles. Moreover, trainer-focused interventions and support systems should be available to help trainers increase trainees' global levels of self-determination (Hardré & Reeve, 2009). In the existing literature, numerous studies have shown that autonomy-supportive behaviors were positively related to autonomous motivation (e.g., Gillet, Gagné et al., 2013). Thus, having trainers displaying higher levels of autonomy-supportive behaviors could be associated with a greater likelihood of membership into the most desirable profile (*High*). The present results also suggest that it might be useful for practitioners to promote peer support systems in order to increase trainees' global levels of self-determined motivation. In order to foster a climate of support among peers, trainers and organizations may implement informal mentoring activities. They may also help to organize informal social events aiming to encourage the development of stronger social ties (Newman, Thanacoody, & Hui, 2012). Interestingly, Jungert, Van den Broeck, Schreurs, and Osterman (2018) demonstrated the efficacy of a brief intervention (focusing on perspective taking, communication, and collaboration) aiming to train team members to better support the psychological needs for autonomy, competence, and relatedness of their colleagues as a way to improve self-determined motivation levels. Finally and more generally, trainers might promote a supportive culture by providing trainees the resources or materials they need to perform their tasks effectively, by reducing work overload, and by promoting justice and fairness in the way policies are implemented and rewards distributed (Eisenberger & Stinglhamber, 2011).

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Table 1

Correlations between Variables

	1.	2.	3.	4.	5.	6.	7.	8.	9.	10.	11.	12.	13.
1. Global Self-Determination (T1)													
2. Global Self-Determination (T2)	.807*												
3. Global Self-Determination (T3)	.805*	.888*											
4. Global Self-Determination (T4)	.757*	.837*	.847*										
5. Mental Load (T1)	.373*	.381*	.410*	.379*									
6. Work Load (T1)	.212*	.209*	.220*	.216*	.649*								
7. Emotional Load (T1)	.152*	.148*	.151*	.152*	.384*	.829*							
8. Peer Support (T1)	.257*	.264*	.295*	.270*	.543*	.084*	-.126*						
9. Positive Affect (T4)	.028	.022	.001	.012	.002	.036	.035	.020					
10. Negative Affect (T4)	-.039	-.047	-.023	-.033	-.026	-.038	-.024	-.023	-.572*				
11. Performance (T4)	.057	.037	.012	.040	.008	.005	.003	-.020	.123*	-.098*			
12. Age	-.072*	-.045	-.029	-.032	-.018	-.040	-.020	-.027	.051	-.044	.047		
13. Sex	.010	.012	.003	.002	.029	.018	.043	-.069*	.006	-.017	-.010	.007	
14. Education level	-.022	-.021	.007	.009	-.031	-.121*	-.098*	.102*	.016	-.004	.015	.040	-.066*

Note. * $p < .01$; all variables with the exception of performance, age, sex, and education level are estimated from factor scores with a mean of 0 and a standard deviation of 1.

Table 2

Results from the Prediction of the Motivation Trajectories

	Intercept		Profile 1 Vs Profile 3		Profile 2 Vs Profile 3		Profile 1 Vs Profile 2	
Predictor	Coef. (*SE*)	β	Coeff. (*SE*)	OR	Coeff. (*SE*)	OR	Coeff. (*SE*)	OR
Mental load	.282 (.061)**	.385	.279 (.226)	1.322	.869 (.375)*	2.385	-.590 (.241)*	.554
Work load	-.143 (.067)*	-.189	-.291 (.278)	.748	-.340 (.407)	.712	.049 (.257)	1.050
Emotional load	.062 (.056)	.079	.691 (.240)**	1.996	.745 (.342)*	2.106	-.055 (.214)	.946
Peer support	.067 (.040)	.095	.045 (.170)	1.046	.299 (.243)	1.349	-.254 (.118)*	.776

Note. Coef. = unstandardized regression coefficient; β = standardized regression coefficient; OR = odds ratio; predictors are estimated from factor scores with mean of 0 and a standard deviation of 1; * $p \leq .05$; ** $p \leq .01$.

Table 3

Outcomes of the Motivation Trajectories

	Moderate (Profile 1)	High (Profile 2)	Low (Profile 3)	Summary of Statistical
Outcome Level	Mean (CI)	Mean (CI)	Mean (CI)	Significance Testing
Performance	-.128 [-.263; .007]	.124 [-.024; .272]	.043 [-.173; .258]	2 > 1; 2 = 3; 1 = 3
Positive Affect	-.080 [-.153; -.008]	.099 [.006; .192]	-.087 [-.229; .054]	2 > 1; 2 = 3; 1 = 3
Negative Affect	.094 [.020; .169]	-.161 [-.267; -.054]	.063 [-.081; .208]	1 > 2; 3 > 2; 1 = 3

Note. CI = 95% confidence intervals; positive affect and negative affect are estimated from factor scores with mean of 0 and a standard deviation of 1 whereas performance levels were standardized to facilitate interpretations.

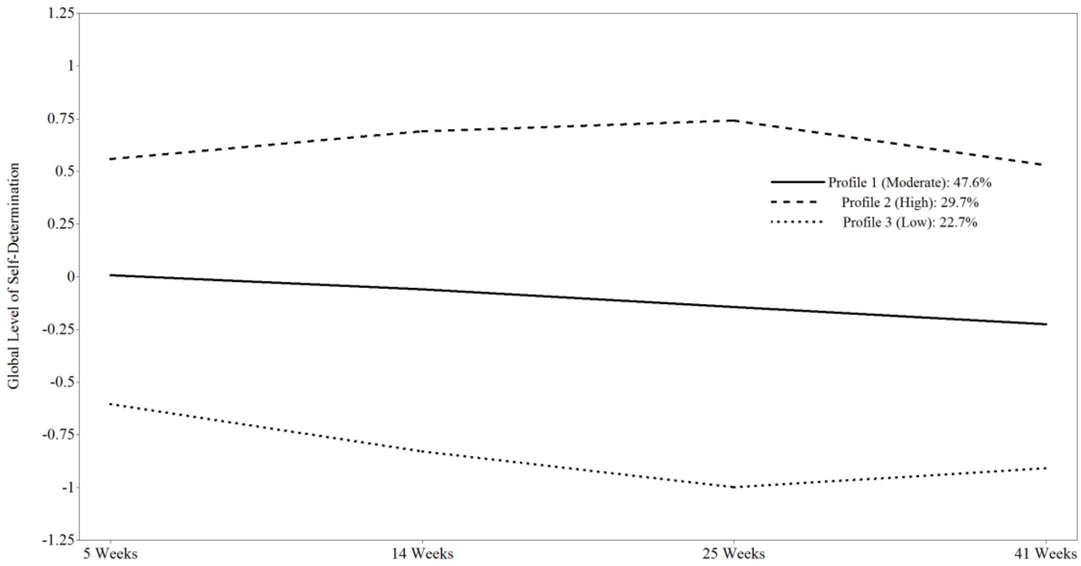

Figure 1. Estimated Growth Trajectories for the Three Self-Determination Profiles.
Note. Trajectories are estimated on the basis of invariant factor scores (*M* = 0 and *SD* = 1 at Time 1) obtained on the global self-determination factor in analyses reported in the online supplements.

Online Supplements for:
Self-Determination Trajectories during Police Officers' Vocational Training Program: A Growth Mixture

Appendix 1. Preliminary Measurement Models

As for models reported in the main manuscript, these preliminary measurement models were estimated using Mplus 8 (Muthén & Muthén, 2017), the robust maximum likelihood (MLR) estimator, and Full Information Maximum Likelihood (FIML; Enders, 2010; Graham, 2009) estimation. 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, and the outcomes. For the motivation measure, a bifactor exploratory structural equation model (bifactor-ESEM; Morin, Arens, & Marsh, 2016; Morin, Arens, Tran, & Caci, 2016; Morin, Boudrias et al., 2016, 2017) including one global factor (G-factor: global quantity of self-determination) and six specific orthogonal factors (S-factors: intrinsic motivation, identified regulation, introjected regulation, external-social regulation, external-material regulation, and amotivation) was estimated based on Howard, Gagné, Morin, and Forest's (2018; also see Litalien et al., 2017) recommendations. However, following Morin and colleagues (Morin, Arens, & Marsh, 2016; Morin, Boudrias et al., 2016, 2017), we started by a systematic comparison of the a priori bifactor-ESEM solution with alternative confirmatory factor analytic (CFA), ESEM, and bifactor-CFA solutions at each separate time point to ascertain the superiority of the bifactor-ESEM solution. The results from these comparisons, which supported the bifactor-ESEM are available upon request.

For the predictors, a CFA approach including four correlated first-order factors (mental load, work load, emotional load, and peer support) was estimated. For the outcomes, a CFA approach including two correlated first-order factors (positive and negative affect) was estimated. 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, 16 factors for the predictors (4 factors x 4 time waves), and 8 factors for the outcomes measures (2 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 two pairs of items presenting parallel wording in the predictor model (e.g., Marsh et al., 2013; Marsh, Scalas, & Nagengast, 2010). The B-ESEM (motivation) models were estimated using confirmatory orthogonal bifactor target rotation, in which all target loadings of items on their a priori factors were freely estimated, and all cross-loadings targeted to be as close to zero as possible (Morin, Arens, & Marsh, 2016).

Before saving the factor scores for our main analyses, we verified that the measurement models operated in the same manner across time waves, through sequential tests of measurement invariance (Millsap, 2011): (1) configural invariance, (2) weak invariance (loadings), (3) strong invariance (loadings and intercepts), (4) strict invariance (loadings, intercepts, and uniquenesses), (5) invariance of the latent variance-covariance matrix (loadings, intercepts, uniquenesses, and latent variances and covariances), and (6) latent means invariance (loadings, intercepts, uniquenesses, latent variances and covariances, and latent means). For the predictor model, an additional step (4b) was included to test the invariance of the correlated uniquenesses included between the two pairs of parallel-worded items.

Given the oversensitivity of the chi-square test (χ^2) to sample size and minor misspecifications (Marsh, Hau, & Grayson, 2005), we relied on goodness-of-fit indices to describe the fit of the models (Hu & Bentler, 1999): The comparative fit index (CFI), the Tucker-Lewis index (TLI), as well as the root mean square error of approximation (RMSEA) and its 90% confidence interval. Values greater than .90 for the CFI and TLI indicate adequate model fit, although values greater than .95 are preferable. Values smaller than .08 or .06 for the RMSEA respectively support acceptable and excellent model fit. Like the chi square, chi square difference tests present a known sensitivity to sample size and minor model misspecifications so that recent studies suggest complementing this information with changes in CFIs and RMSEAs (Chen, 2007; Cheung & Rensvold, 2002) in 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.

The goodness-of-fit results from all longitudinal models are reported in Table S1. These results support the adequacy of the a priori longitudinal measurement models underlying all constructs, with all models of configural invariance being associated CFI/TLI $\geq$ .90 and all RMSEA $\leq$ .06. For the motivation measurement model, the results supported its weak and strong measurement invariance as none of the changes in goodness-of-fit indices exceeded the recommended cut-off scores (ΔCFI/TLI $\leq$ .010; ΔRMSEA $\leq$ .015). However, the model of strict measurement invariance failed to converge (even after increasing the number of iterations and decreasing the convergence criterion), suggesting its failure to uphold strict measurement invariance, an hypothesis that was supported by an examination of the parameter estimates associated with the model of strong invariance. The uniquenesses associated with the model of strong invariance were thus examined, and contrasted using the multivariate delta method (Raykov & Marcoulides, 2004), in order to locate the non-invariant uniquenesses. This examination resulted in the identification of 3 non-invariant item uniquenesses (suggesting slight increases in unreliability over time for three items). Invariance constraints on these uniquenesses were then relaxed, leading to a model of partial strict invariance that was supported by the data. However, the models of invariance of the latent variance-covariances, and latent means, also failed to be supported by the data (ΔCFI/TLI $\geq$ .010). These results revealed a slight increase in within-sample variability of motivation levels over time, and showed that mean levels of global self-determination, intrinsic motivation, and identified regulation tended to slightly decrease over time, while those of introjected regulation, external-social regulation, external-material regulation, and amotivation tended to increase over time. Because the reliance on bifactor-ESEM measurement models makes it impossible to test models of partial invariance at the latent level, we thus retained the model of partial strict invariance to generate the factor scores used in this study. In this model, the scaling of the factors was achieved by fixing the variances and means of the Time 1 factors, respectively, at 1 and 0. This allowed us to estimate motivation levels in standardized units at Time 1, and as deviations from Time 1 levels in standardized units at the following time points.

Turning our attention to the predictor measurement model, the results supported the weak, strong, strict, correlated uniquenesses, and latent variance-covariance across time points (ΔCFI/TLI $\leq$ .010; ΔRMSEA $\leq$ .015). As above, these results failed to support the latent mean invariance of all factors across time points. However, a detailed examination of the parameter estimates and modification indices associated with these various models suggested a model of partial invariance which was supported by the data. In this model, invariance constraints were relaxed on six latent means, revealing that levels of mental load and peer support tended to decrease over time. Factors scores for the main analyses were saved from this model of partial latent mean invariance, in which the means of the non-invariant factors were constrained to be 0 at Time 1 and expressed as deviation from Time 1 levels at the remaining time points. All factor variances were constrained to be 1, and all other latent means were constrained to be 0. 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 models of latent variances, covariances, and means invariance. Indeed, saving factor scores from a model of latent variances and the means invariance (i.e., respectively constrained to take a value of 1 and 0 in all time waves) provides scores that can be readily interpreted in standard deviation units.

Finally, the results supported the weak, but not strong, invariance of the outcomes measurement model. Examination of the parameter estimates of the model of weak invariance and modification indices of the model of strong invariance suggested a model of partial invariance (in which invariance constraints were relaxed on two item intercepts), which was supported by the data. Starting from this model of partial strong invariance, the results supported the model of strict invariance, but not the model of latent variance-covariance invariance due to the fact that the variance of the negative affect factor was slightly lower at Time 1. When equality constraints were relaxed on this factor, the resulting model of partial latent variance-covariance invariance was supported by the data. Starting from this model, the invariance of the latent means also failed to be supported by the data, leading to a final model of partial latent means invariance which was supported by the data. The results from this model showed that levels of negative affect were slightly lower at Time 1 and Time 2, whereas levels of positive affect were slightly higher at Time 1. Factor scores were saved from this model of partial latent mean invariance, in which the means and variance of the non-invariant factors were constrained to be respectively 0 and 1 at Time 4 and expressed as deviation from Time 4 levels at the remaining time points. All other latent means were fixed to 0, and all other latent variances were fixed to 1.

The final parameter and composite reliability (ω; McDonald, 1970[2]) estimates from these

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

measurement models are reported in Tables S2 (motivation), S3 (predictors), and S4 (outcomes), while the correlations between all variables used in the main analyses are reported in Table 1 of the manuscript. The results from the motivation models were fully in line with Howard et al. (2018) and Litalien et al. (2017) in supporting the interpretation of the G-factor as a reliable (ω = .849 to .870 across time points) estimate of global levels of self-determination, with strong positive loadings from the identified regulation ($M_{|\lambda|}$ = .530) and introjected regulation ($M_{|\lambda|}$ = .507) items, moderate positive loadings from the intrinsic motivation items ($M_{|\lambda|}$ = .357: consistent with the interpretation of this factor as assessing self-regulation rather than intrinsic motivation or pleasure), weak loadings from the external-social regulation ($M_{|\lambda|}$ = .295) and external-material regulation ($M_{|\lambda|}$ = .220) items, and negative loadings from the amotivation items (M_{λ} = -.075). Also in accordance with Howard et al. (2018) and Litalien et al. (2017), the results revealed: (a) strongly defined S-factors related to intrinsic motivation ($M_{|\lambda|}$ = .716; ω = .735 to 869), external-social regulation ($M_{|\lambda|}$ = .607; ω = .602 to .714), and amotivation ($M_{|\lambda|}$ = .761; ω = .856 to .925); (b) moderately defined factors related to introjected regulation ($M_{|\lambda|}$ = .376; ω = .597 to .623) and external-material regulation ($M_{|\lambda|}$ = .491; ω = .586 to .621); and (c) a more weakly defined S-Factor related to identified regulation ($M_{|\lambda|}$ = .066; ω = .003 to .028) due to the fact that the items associated with this factor mainly served to define the G-factor. Still, it is important to note that, in latent variable models such as those, scores on the latent variables themselves can be considered to be perfectly controlled for measurement error. Finally, all predictors and outcomes models resulted in factors that were well-defined through high target factor loadings ($M_{|\lambda|}$ = .700), resulting in fully acceptable model-based composite reliability coefficients: (a) mental load ($M_{|\lambda|}$ = .813; ω = .886); (b) work load ($M_{|\lambda|}$ = .704; ω = .798); (c) emotional load ($M_{|\lambda|}$ = .667; ω = .763); (d) peer support ($M_{|\lambda|}$ = .878; ω = .932); (e) positive affect ($M_{|\lambda|}$ = .664; ω = .802); and (f) negative affect ($M_{|\lambda|}$ = .683; ω = .776 at Time 1 and .839 at Times 2-3-4).

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

where $|\lambda_i|$ are the standardized factor loadings associated with a factor in absolute values, and δi, the item uniquenesses. The numerator, where the factor loadings are summed, and then squared, reflects the proportion of the variance 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).

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Table S1

Goodness-of-Fit Statistics of the Preliminary Longitudinal Measurement Models

Description	χ^2 (*df*)	CFI	TLI	RMSEA	90% CI	CM	$\Delta\chi^2$ (*df*)	ΔCFI	ΔTLI	ΔRMSEA
Motivation										
M1. Configural invariance	3390.183 (2051)*	.956	.939	.020	[.019; .021]	-	-	-	-	-
M2. Weak invariance	3673.012 (2303)*	.955	.944	.019	[.018; .020]	M1	317.118 (252)*	-.001	+.005	-.001
M3. Strong invariance	3735.373 (2339)*	.954	.944	.019	[.018; .020]	M2	62.844 (36)*	-.001	.000	.000
M4. Strict invariance	Did not converge									
M5. Partial strict invariance	3918.093 (2393)*	.950	.940	.020	[.018; .021]	M3	130.646 (54)*	-.004	-.004	+.001
M6. Latent variance-covariance invariance	4714.143 (2477)*	.927	.916	.023	[.022; .024]	M5	626.140 (84)*	-.023	-.024	+.003
M7. Latent means invariance	4508.006 (2414)*	.931	.919	.023	[.022; .024]	M5	596.277 (21)*	-.019	-.021	+.003
Predictors										
M1. Configural invariance	3808.048 (1728)*	.925	.912	.027	[.026; .028]	-	-	-	-	-
M2. Weak invariance	3865.231 (1764)*	.924	.913	.027	[.026; .028]	M1	61.428 (36)*	-.001	+.001	.000
M3. Strong invariance	4112.271 (1800)*	.916	.906	.028	[.027; .029]	M2	271.344 (36)*	-.008	-.007	+.001
M4. Strict invariance	4253.342 (1848)*	.913	.905	.028	[.027; .029]	M3	125.227 (48)*	-.003	-.001	.000
M5. Correlated uniquenesses invariance	4259.142 (1854)*	.913	.905	.028	[.027; .029]	M4	11.478 (6)	.000	.000	.000
M6. Latent variance-covariance invariance	4489.569 (1884)*	.906	.900	.029	[.028; .030]	M5	221.395 (30)*	-.007	-.005	+.001
M7. Latent means invariance	4854.448 (1896)*	.893	.886	.031	[.030; .032]	M6	433.725 (12)*	-.013	-.014	+.002
M8. Partial latent means invariance	4604.269 (1890)*	.902	.900	.029	[.030; .031]	M6	120.440 (6)*	-.004	.000	.000
Outcomes										
M1. Configural invariance	1404.330 (652)*	.933	.920	.026	[.025; .028]	-	-	-	-	-
M2. Weak invariance	1458.912 (676)*	.930	.920	.027	[.025; .028]	M1	54.197 (24)*	-.003	.000	+.001
M3. Strong invariance	1703.858 (700)*	.911	.901	.030	[.028; .031]	M2	262.672 (24)*	-.019	-.019	+.003
M4. Partial strong invariance	1570.082 (698)*	.923	.913	.028	[.026; .029]	M2	119.401 (22)*	-007	-.007	+.001
M5. Strict invariance	1652.120 (728)*	.918	.912	.028	[.026; .030]	M4	76.607 (30)*	-.005	-.001	.000
M6. Latent variance-covariance invariance	1811.409 (737)*	.905	.899	.030	[.028; .031]	M5	104.830 (9)*	-.013	-.013	+.002
M7. Partial latent var.-covar. invariance	1734.342 (736)*	.911	.906	.029	[.027; .030]	M5	58.958 (8)*	-.007	-.006	+.001
M8. Latent means invariance	2031.399 (742)*	.885	.880	.032	[.031; .034]	M7	363.828 (6)*	-.026	-.026	+.003
M9. Partial latent means invariance	1772.898 (739)*	.908	.903	.029	[.027; .031]	M7	42.045 (3)*	-.003	-.003	.000

Note. * $p < .01$; χ^2: robust chi-square test of exact fit; *df*: degrees of freedom; CFI: comparative fit index; TLI: Tucker-Lewis index; RMSEA: root mean square error of approximation; 90% CI: 90% confidence interval; CM: comparison model; Δ: change in fit relative to the CM.

Table S2

Standardized Factor Loadings (λ) and Uniquenesses (δ) from the Bifactor-ESEM Solutions (Motivation)

	Time 1								Time 2							
	G	S-IM	S-IDR	S-INR	S-EXRS	S-EXRM	S-AMO		G	S-IM	S-IDR	S-INR	S-EXRS	S-EXRM	S-AMO	
Items	λ	λ	λ	λ	λ	λ	λ	δ	λ	λ	λ	λ	λ	λ	λ	δ
IM																
Item 1	**.364**	**.648**	*-.009*	-.119	-.110	-.114	-.077	.402	**.347**	**.671**	*-.027*	-.122	-.124	-.109	-.127	.368
Item 2	**.402**	**.691**	*.048*	-.074	-.124	-.051	-.059	.331	**.378**	**.705**	.139	-.074	-.137	-.048	-.096	.294
Item 3	**.370**	**.662**	*-.035*	-.085	-.110	-.067	-.161	.375	**.345**	**.669**	-.101	-.085	-.120	-.063	-.259	.327
IDR																
Item 1	**.634**	.159	***.002***	-.153	*-.027*	-.093	-.059	.537	**.626**	.171	***.005***	-.162	*-.031*	-.093	-.100	.528
Item 2	**.472**	.526	***.037***	-.081	-.226	*-.028*	-.067	.436	**.449**	.544	***.108***	-.083	-.253	*-.026*	-.109	.397
Item 3	**.508**	.240	***-.032***	.075	-.124	-.086	-.051	.652	**.495**	.254	***-.096***	.078	-.142	-.084	-.286	.622
INR																
Item 1	**.721**	-.228	*-.032*	***-.098***	.205	*-.017*	*.005*	.376	**.738**	-.253	-.101	***-.107***	.247	*-.018*	*.009*	.397
Item 2	**.683**	*.086*	*.063*	***-.034***	-.102	.060	*.024*	.506	**.673**	*.092*	.192	***-.036***	-119	.060	*.040*	.495
Item 3	**.300**	-.105	*-.012*	**.721**	.185	*.025*	.063	.340	**.265**	-.101	*-.033*	**.682**	.192	*.022*	.096	.267
Item 4	**.350**	-.106	*.002*	**.684**	.057	.140	.057	.373	**.316**	-.105	*.005*	**.663**	.061	.127	.089	.307
EXRS																
Item 1	**.418**	-.118	-.064	*-.071*	**.559**	.054	*.027*	.487	**.396**	-.122	-.188	*-.072*	**.623**	.051	*.043*	.440
Item 2	**.355**	-.084	.044	.129	**.633**	.156	.130	.406	**.313**	-.080	.121	.122	**.657**	.138	.197	.318
Item 3	**.194**	-.095	*.041*	.330	**.607**	.162	.212	.402	**.158**	-.084	.104	.288	**.582**	.133	.297	.269
EXRM																
Item 1	***.068***	-.104	-.033	.102	.271	**.571**	.153	.550	***.060***	-.099	-.089	.097	.281	**.507**	.232	.429
Item 2	**.246**	-.066	.014	*.043*	.068	**.794**	*-.007*	.297	**.244**	-.071	.042	*.046*	.080	**.795**	*-.012*	.295
Item 3	**.346**	*.033*	*.012*	.168	*-.043*	**.171**	*.013*	.820	**.341**	*.035*	*.035*	.177	*-.049*	**.169**	*.021*	.799
AMO																
Item 1	***-.098***	-.259	.074	.128	.288	.094	**.734**	.272	***-.059***	-.170	.139	.083	.205	.057	**.763**	.286
Item 2	***-.139***	-.205	*.023*	.170	.309	.102	**.792**	.176	***-.079***	-.127	.040	.103	.207	.059	**.776**	.216
Item 3	***-.110***	-.203	-.132	.157	.247	.132	**.677**	.368	***-.067***	-.133	-.248	.102	.176	.080	**.705**	.136
ω	.850	.783	.003	.597	.714	.586	.856		.849	.809	.027	.602	.771	.587	.888	

Note. G = global factor estimated as part of a bifactor model; S = specific factor estimated as part of a bifactor model; λ: factor loading; δ: item uniqueness; ω: omega coefficient of model-based composite reliability; IM = intrinsic motivation; IDR = identified regulation; INR = introjected regulation; EXRS = external regulation-social; EXRM = external regulation-material; AMO = amotivation; non-significant parameters ($p \geq .05$) are marked in italics.

Table S2 (Continued)

	Time 3								Time 4							
	G	S-IM	S-IDR	S-INR	S-EXRS	S-EXRM	S-AMO		G	S-IM	S-IDR	S-INR	S-EXRS	S-EXRM	S-AMO	
Items	λ	λ	λ	λ	Λ	λ	λ	δ	λ	λ	λ	λ	λ	λ	λ	δ
IM																
Item 1	**.340**	**.760**	*-.038*	-.124	-.120	-.107	-.146	.300	**.338**	**.741**	*-.025*	-.120	-.122	-.102	-.162	.305
Item 2	**.366**	**.790**	.197	-.075	-.131	-.047	-.109	.235	**.359**	**.760**	.127	-.071	-.132	-.043	-.120	.232
Item 3	**.335**	**.752**	-.142	-.085	-.115	-.061	-.296	.263	**.337**	**.742**	-.095	-.084	-.119	-.059	-.332	.273
IDR																
Item 1	**.644**	.204	***.008***	-.173	*-.031*	-.096	-.122	.477	**.638**	.198	***.005***	-.167	*-.032*	-.091	-.134	.481
Item 2	**.442**	.619	***.155***	-.085	-.246	*-.026*	-.126	.328	**.435**	.598	***.101***	-.081	-.248	*-.024*	-.139	.327
Item 3	**.508**	.302	***-.143***	.084	-.144	-.087	-.104	.560	**.511**	.298	***-.095***	.082	-.149	-.083	-.117	.582
INR																
Item 1	**.788**	-.313	-.157	***-.119***	.260	*-.019*	*.011*	.386	**.789**	-.307	-.104	***-.116***	.267	*-.018*	*.012*	.398
Item 2	**.673**	*.107*	.280	***-.038***	-.117	.060	*.048*	.423	**.681**	*.106*	.187	***-.037***	-.122	.058	*.054*	.445
Item 3	**.255**	-.112	*-.046*	**.685**	.183	*.021*	.109	.211	**.254**	-.110	*-.031*	**.663**	.187	*.020*	.121	.215
Item 4	**.309**	-.118	*.007*	**.675**	.059	.125	.103	.250	**.312**	-.117	*.005*	**.662**	.061	.120	.116	.262
EXRS																
Item 1	**.404**	-.144	-.279	*-.077*	**.628**	.052	*.052*	.391	**.391**	-.136	-.179	*-.072*	**.624**	.048	*.056*	.377
Item 2	**.317**	-.094	.178	.129	**.657**	.141	.236	.279	**.296**	-.086	.110	.117	**.629**	.125	.245	.249
Item 3	**.154**	-.094	.147	.291	**.557**	.130	.340	.216	**.141**	-.085	.090	.260	**.526**	.113	.349	.188
EXRM																
Item 1	***.056***	-.109	-.122	.095	.261	**.480**	.258	.325	***.055***	-.104	-.079	.090	.262	**.445**	.281	.318
Item 2	**.254**	-.086	.064	*.049*	.082	**.829**	*-.015*	.272	**.252**	-.084	.042	*.048*	.083	**.784**	*-.016*	.276
Item 3	**.359**	*.042*	*.054*	.194	*-.051*	**.179**	*.027*	.754	**.354**	*.041*	*.035*	.186	*-.052*	**.168**	*.029*	.755
AMO																
Item 1	***-.056***	-.186	.191	.082	.191	.054	**.848**	.217	***-.051***	-.166	.115	.072	.178	.047	**.861**	.185
Item 2	***-.071***	-.131	.052	.096	.182	.053	**.815**	.147	***-.064***	-.117	.031	.085	.171	.046	**.829**	.125
Item 3	***-.053***	-.123	-.287	.084	.138	.064	**.660**	.073	***-.049***	-.111	-.174	.075	.130	.056	**.677**	.170
ω	.870	.869	.006	.644	.795	.621	.925		.866	.735	.028	.623	.795	.591	.921	

Note. G = global factor estimated as part of a bifactor model; S = specific factor estimated as part of a bifactor model; λ: factor loading; δ: item uniqueness; ω: omega coefficient of model-based composite reliability; IM = intrinsic motivation; IDR = identified regulation; INR = introjected regulation; EXRS = external regulation-social; EXRM = external regulation-material; AMO = amotivation; non-significant parameters ($p \geq .05$) are marked in italics.

Table S3

Fully Invariant Standardized Factor Loadings (λ) and Uniquenesses (δ) from the CFA Solution (Predictors)

Items	Mental load λ	Work load λ	Emotional load λ	Peer support λ	δ
Mental load					
Item 1	.815				.336
Item 2	.780				.391
Item 3	.805				.352
Item 4	.851				.275
Work load					
Item 1		.680			.537
Item 2		.795			.368
Item 3		.682			.534
Item 4		.660			.564
Emotional load					
Item 1			.761		.421
Item 2			.597		.644
Item 3			.663		.561
Item 4			.646		.583
Peer support					
Item 1				.893	.203
Item 2				.943	.110
Item 3				.803	.356
Item 4				.874	.236
ω	.886	.798	.763	.932	

Note. λ: factor loading; δ: item uniqueness; ω: omega coefficient of model-based composite reliability.

Table S4

Standardized Factor Loadings (λ) and Uniquenesses (δ) from the CFA Solution (Outcomes)

	Time 1			Time 2			Time 3			Time 4		
	Pos. aff.	Neg. aff.		Pos. aff.	Neg. aff.		Pos. aff.	Neg. aff.		Pos. aff.	Neg. aff.	
Items	λ	λ	δ	λ	λ	δ	λ	λ	δ	λ	λ	δ
Positive affect												
Item 1	.674		.546	.674		.546	.674		.546	.674		.546
Item 2	.443		.803	.443		.803	.443		.803	.443		.803
Item 3	.793		.371	.793		.371	.793		.371	.793		.371
Item 4	.768		.411	.768		.411	.768		.411	.768		.411
Item 5	.641		.589	.641		.589	.641		.589	.641		.589
Negative affect												
Item 1		.471	.778		.564	.682		.564	.682		.564	.682
Item 2		.824	.322		.880	.225		.880	.225		.880	.225
Item 3		.720	.481		.798	.362		.798	.362		.798	.362
Item 4		.793	.371		.857	.265		.857	.265		.857	.265
Item 5		.331	.890		.409	.833		.409	.833		.409	.833
ω	.802	.776		.802	.839		.802	.839		.802	.839	

Note. λ: factor loading; δ: item uniqueness; ω: omega coefficient of model-based composite reliability.

Appendix 2. A More Technical Presentation of Growth Mixture Analyses (GMA)

GMA aim to represent longitudinal heterogeneity by the identification of subgroups (i.e., profiles) of participants following distinct trajectories. A quadratic 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.

$$y_{it} = \sum_{k=1}^{K} p_k[\alpha_{iyk} + \beta_{1iyk}\lambda_t + \beta_{2iyk}\lambda^2{}_t + \varepsilon_{yitk}] \quad (1)$$

$$\beta_{1iyk} = \mu_{\beta 1yk} + \zeta_{\beta 1yik} \quad (2)$$

$$\beta_{2iyk} = \mu_{\beta 2yk} + \zeta_{\beta 2yik} \quad (3)$$

The *k* subscript indicates that most parameters can be freely estimated across profiles. In this equation, α_{iyk}, β_{1iyk}, and β_{2iyk} respectively represent the random intercept, random linear slope, and random quadratic slope of the trajectory for individual *i* in profile *k*; $\mu_{\alpha yk}$, $\mu_{\beta 1yk}$, and $\mu_{\beta 2yk}$ represent the average intercept, linear slope, and quadratic slope in profile *k;* and $\zeta_{\alpha yik}$, $\zeta_{\beta 1yik}$ and $\zeta_{\beta 2yik}$ represent the variability of the intercept, linear slope, and quadratic slope across cases within profiles. ε_{yitk} represents a diagonal matrix 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 ($\zeta_{\alpha yik}$, $\zeta_{\beta 1yik}$, $\zeta_{\beta 2yik}$) have a mean of zero and a Φ_{yk} variance-covariance matrix:

$$\Phi_{yk} = \begin{bmatrix} \psi_{\alpha\alpha yk} & & \\ \psi_{\alpha\beta 1yk} & \psi_{\beta 1\beta 1yk} & \\ \psi_{\alpha\beta 2yk} & \psi_{\beta 1\beta 2yk} & \psi_{\beta 2\beta 2yk} \end{bmatrix} \quad (4)$$

In these models, Time is represented by λ_t, the factor loading matrix relating the time-specific indicators to the linear slope factor. The estimation of a quadratic slope factor simply involves the squaring o the time codes included in this factor loading matrix. Time is coded to reflect the passage of time and is thus a function of the intervals between measurement points. Given that the current study relies on four measurement points occurring 5, 14, 25, and 41 weeks after the beginning of the training period, we decided to set the intercept at Time 1 [$E(\alpha_{iyk}) = \mu_{y1k}$], and to set the subsequent time codes to reflect the passage of time in months, leading to $\lambda_1 = 0$, $\lambda_2 = 2$, $\lambda_3 = 5$, and $\lambda_4 = 9$. As noted in the main manuscript, the current study relies on a more constrained estimation of GMA through which the latent variance-covariance matrix was specified as invariant across profiles, whereas the residuals were specified as freely estimated across profiles, leading to:

$$y_{it} = \sum_{k=1}^{K} p_k[\alpha_{iyk} + \beta_{1iyk}\lambda_t + \beta_{2iyk}\lambda^2{}_t + \varepsilon_{yitk}] \quad (5)$$

$$\beta_{1iyk} = \mu_{\beta 1yk} + \zeta_{\beta 1yi} \quad (6)$$

$$\beta_{2iyk} = \mu_{\beta 2yk} + \zeta_{\beta 2yi} \quad (7)$$

$$\Phi_y = \begin{bmatrix} \psi_{\alpha\alpha y} & & \\ \psi_{\alpha\beta 1y} & \psi_{\beta 1\beta 1y} & \\ \psi_{\alpha\beta 2y} & \psi_{\beta 1\beta 2y} & \psi_{\beta 2\beta 2y} \end{bmatrix} \tag{8}$$

Appendix 3. Optimal Model Selection

Class Enumeration Process

A challenge in GMA is to determine the number of latent trajectory profiles in the data. Although the substantive meaning, theoretical conformity, and statistical adequacy of the solution are three critical elements to consider in this decision (Bauer & Curran, 2003; Marsh, Lüdtke, Trautwein, & Morin, 2009; Muthén, 2003), statistical indices support this decision (McLachlan & Peel, 2000): (i) the Akaïke Information Criterion (AIC), (ii) the Consistent AIC (CAIC), (iii) the Bayesian Information Criterion (BIC), (iv) the sample-size Adjusted BIC (ABIC), (v) the standard and adjusted Lo, Mendel and Rubin's (2001) LRTs (LMR/aLMR, as these tests typically yield the same conclusions, we only report the aLMR); and (vi) the Bootstrap Likelihood Ratio Test (BLRT). A lower value on the AIC, CAIC, BIC, and ABIC suggests a better-fitting model. The aLMR and BLRT compare a *k*-profile model with a *k-1*-profile model. A significant *p* value indicates that the *k-1*-profile model should be rejected in favor of a *k*-profile model. Simulation studies indicate that four of these indicators (CAIC, BIC, ABIC, and BLRT) are particularly effective (e.g., Diallo, Morin, & Lu, 2016, 2017; Nylund, Asparouhov, & Muthén, 2007; Peugh & Fan, 2013; Tein, Coxe, & Cham, 2013; Tofighi & Enders, 2008). In contrast, the AIC and LMR/ALMR should not be used in the class enumeration process as they respectively tend to over- and under-extract incorrect number of profiles. These indicators will be reported to ensure a complete disclosure, but will not be used to select the optimal number of profiles. These tests remain heavily influenced by sample size (Marsh et al., 2009). Indeed, with sufficiently large samples, they may keep on suggesting the addition of profiles without reaching a minimum. In these cases, information criteria should be graphically presented through "elbow plots" illustrating the gains associated with additional profiles (Morin, 2016; Morin et al., 2011). In these plots, the point after which the slope flattens suggests the optimal number of profiles. Finally, the entropy indicates the precision with which the cases are classified into the various profiles. The entropy should not be used to determine the optimal number of profiles (Lubke & Muthén, 2007). However, summarizes classification accuracy (0 to 1), with higher values indicating more accuracy.

Results: Optimal Number of Profiles

The results from the unconditional GMA models are reported in the top section of Table S5 in these online supplements. The CAIC and BIC reached their lowest point for the 7-profile solution. However, the AIC, ABIC and BLRT keep on suggesting the addition of profiles, and the aLMR supports the 3-profile solution. To complement this information, we thus relied on the examination of an elbow plot, reported in Figure S1 of the online supplements. This plot showed that the improvement in fit flattened between the 2- and 4-profile solutions. The examination of these alternative solutions showed that moving from a 2-profile solution to a 3-profile solution resulted in the addition of a well-defined qualitatively distinct and theoretically meaningful profile. However, moving from a 3-profile solution to a 4-profile solution simply resulted in the arbitrary division of one of the existing profile into two profiles differing only quantitatively from one another (i.e., this solution led to the identification of two very close average trajectory profiles showing only limited change over time). The 3-profile solution was thus retained, supporting Hypothesis 1. However, this solution converged on some improper parameter estimates (i.e., small negative variance estimates for the linear and quadratic slope factors). It suggests potential overparameterization (Bauer & Curran, 2003; Chen, Bollen, Paxton, Curran, & Kirby, 2001) due to the lack of significant within-profile variability on these two growth factors. To achieve proper estimation, these variance estimates (as well as covariances involving these slope factors) were constrained to be zero (Diallo et al., 2016). This constrained model was re-estimated, and converged on a proper solution. Supporting this solution, the CAIC and BIC showed further decreases compared with the model involving the free estimation of these parameters. Classification accuracy statistics are reported in Table S7 and reveal a very high level of accuracy ranging from .857 to .878 across profiles, which is consistent with the entropy value of .699 associated with this solution.

Results: Optimal Predictive Model

As recommended by Diallo et al. (2017; also see Morin, Meyer, Creusier, & Biétry, 2016), the relative fit of the alternative control and predictor models was contrasted using the same information criteria already used in the present study (CAIC, BIC, and ABIC). A lower value indicates a better fit. The results related to the models including the controls are reported in the middle section of Table S5, whereas those related to the models including the predictors are reported in the bottom section of Table S5. These results first support the null effects model for the controls, which resulted in the lowest CAIC, BIC, and ABIC values out of all models considered. For the predictors, the same indicators reached their lowest point for the model in which the predictors had an effect on the likelihood of profile membership, as well as a class-invariant effect on the initial levels of global self-determination.

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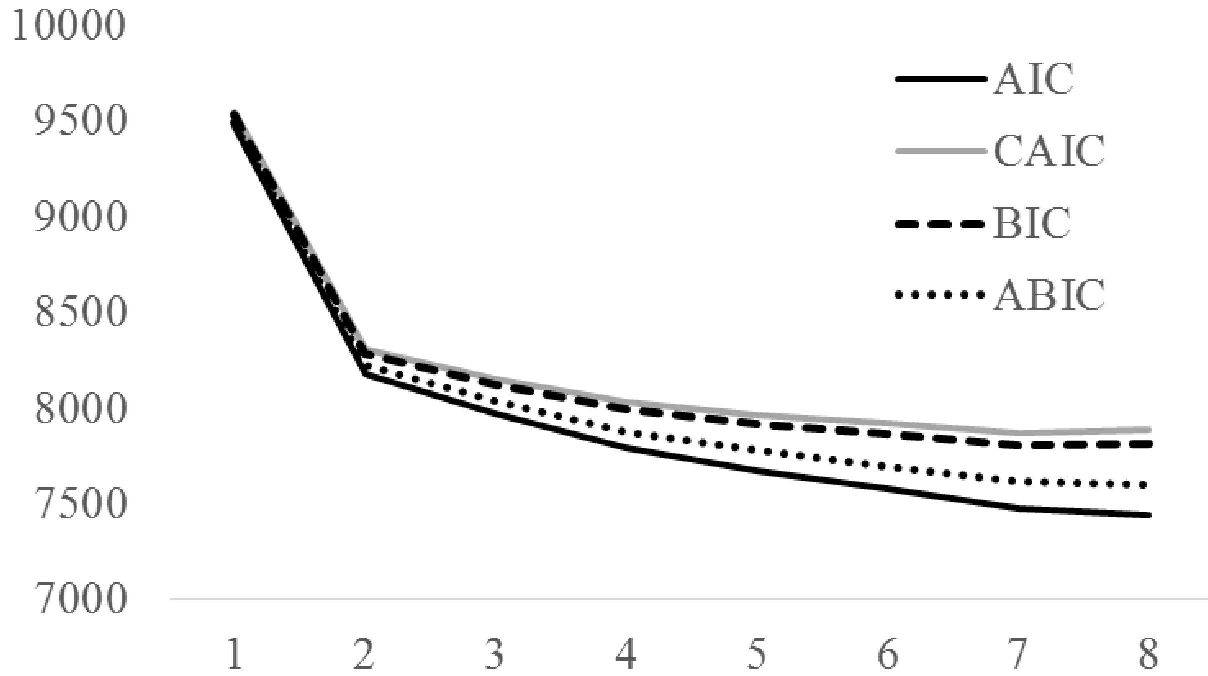

Figure S1
Elbow Plot of the Information Criteria for the Unconditional Growth Mixture Analyses

Table S5

Fit Indices from Alternative Unconditional and Conditional Growth Mixture Analyses

Model	LL	#fp	SF	AIC	CAIC	BIC	ABIC	Entropy	aLMR	BLRT
Unconditional Models										
1-Profile	-4719.451	13	2.032	9465.501	9548.883	9535.883	9494.584	Na	Na	Na
2-Profile	-4065.254	21	1.611	8172.509	8307.202	8286.202	8219.489	.607	< .001	< .001
3-Profile	-3953.506	29	1.707	7965.013	8151.018	8122.018	8029.889	.698	< .001	< .001
4-Profile	-3857.739	37	1.406	7789.477	8026.794	7989.794	7872.251	.685	.240	< .001
5-Profile	-3791.453	45	1.312	7672.907	7961.535	7916.535	7773.577	.609	.240	< .001
6-Profile	-3734.221	53	1.368	7574.443	7914.383	7861.383	7693.010	.625	.240	< .001
7-Profile	-3675.940	61	1.380	7473.879	7865.131	7804.131	7610.344	.645	.240	< .001
8-Profile	-3651.665	69	1.489	7441.330	7883.894	7814.894	7595.691	.645	.240	< .001
Final 3-Profile Solution	-3970.496	24	1.546	7988.992	8142.927	8118.927	8042.683	.699	Na	Na
Conditional Models (Demographic Controls)										
Null Effects Model	-3587.237	24	1.473	7222.473	7372.318	7348.318	7272.079	.676	Na	Na
P-> C	-3578.736	30	1.381	7217.472	7404.777	7374.777	7279.478	.677	Na	Na
P-> C and I (INV)	-3576.476	33	1.348	7218.952	7424.988	7391.988	7287.159	.676	Na	Na
P-> C and I (VAR)	-3568.117	39	1.315	7214.234	7457.731	7418.731	7294.843	.676	Na	Na
P-> C and I-S (INV)	-3571.321	36	1.335	7214.642	7439.409	7403.409	7289.050	.673	Na	Na
P-> C and I-S (VAR)	-3558.151	48	1.260	7212.301	7511.99	7463.990	7311.512	.676	Na	Na
P-> C and I-S-Q (INV)	-3570.918	39	1.316	7219.836	7463.333	7424.333	7300.445	.974	Na	Na
P-> C and I-S-Q (VAR)	-3555.343	57	1.237	7224.686	7580.567	7523.567	7342.499	.678	Na	Na
Conditional Models (Predictors)										
Null Effects Model	-3945.853	24	1.540	7939.707	8093.322	8069.322	7993.078	.697	Na	Na
P-> C	-3825.897	32	1.446	7715.793	7920.613	7888.613	7786.955	.718	Na	Na
P-> C and I (INV)	3758.951	36	1.394	7589.902	7816.325	7784.325	7669.959	.706	Na	Na
P-> C and I (VAR)	-3749.327	44	1.368	7586.654	7868.281	7824.281	7684.500	.709	Na	Na
P-> C and I-S (INV)	-3755.756	40	1.394	7591.512	7847.537	7807.537	7680.464	.706	Na	Na
P-> C and I-S (VAR)	-3738.749	56	1.388	7589.498	7947.933	7891.933	7714.030	.710	Na	Na
P-> C and I-S-Q (INV)	-3750.935	44	1.378	7589.869	7871.497	7827.497	7687.716	.706	Na	Na
P-> C and I-S-Q (VAR)	-3725.795	68	1.322	7587.591	8022.833	7954.833	7738.808	.708	Na	Na

Note. LL = model loglikelihood; #fp = number of free parameters; SF = scaling correction factor; AIC = Akaïke information criterion; CAIC = consistent AIC; BIC = Bayesian information criterion; ABIC = sample-size adjusted BIC; aLMR = Lo-Mendel and Rubin’s likelihood ratio test; BLRT = bootstrap likelihood ratio test; NA = not applicable; P -> = the predictors were allowed to influence; C = profile membership; I = intercept; S = linear slope; Q = quadratic slope; INV = prediction invariant across profiles; VAR = prediction varying across profiles.

Table S6

Results from the Final Unconditional Three-Class Growth Mixture Analysis

Parameter	Profile 1 (Moderate) Estimate (*t*)	Profile 2 (High) Estimate (*t*)	Profile 3 (Low) Estimate (*t*)
Intercept mean	.007 (.270)	.558 (13.425)**	-.604 (-8.446)**
Linear slope mean	-.035 (-10.750)**	.087 (6.101)**	-.135 (-7.655)**
Quadratic slope mean	.001 (3.157)**	-.010 (-7.134)**	.011 (6.210)**
Intercept variability ($SD = \sqrt{\sigma}$)	.533 (12.116)**	.533 (12.116)**	.533 (12.116)**
Linear slope variability ($SD = \sqrt{\sigma}$)	0 (Fixed)	0 (Fixed)	0 (Fixed)
Quadratic slope variability ($SD = \sqrt{\sigma}$)	0 (Fixed)	0 (Fixed)	0 (Fixed)
$SD(\varepsilon_{yi1k})$	.205 (7.837)**	.459 (8.178)**	.569 (7.613)**
$SD(\varepsilon_{yi2k})$	.118 (7.085)**	.327 (6.561)**	.447 (3.708)**
$SD(\varepsilon_{yi3k})$	.084 (3.968)**	.383 (5.584)**	.348 (6.532)**
$SD(\varepsilon_{yi4k})$	.170 (9.652)**	.422 (7.064)**	.575 (5.805)**

Note. *t* = estimate / standard error of the estimate (*t* values are computed from original variance estimate and not from their square roots); $SD(\varepsilon_{yit})$ = standard deviations of the time-specific residuals; we present the square roots of the estimates of the variability so that these results can be interpreted units of the motivation factor scores at Time 1 ($M = 0$; $SD = 1$); * $p \leq .05$; ** $p \leq .01$.

Table S7

Classification Accuracy: Classification Probability for Most Likely Profile Membership (Column) as a Function of the Profile Membership (Row)

	Profile 1 (Moderate)	Profile 2 (High)	Profile 3 (Low)
Profile 1 (Moderate)	.878	.076	.046
Profile 2 (High)	.068	.872	.060
Profile 3 (Low)	.060	.083	.857

Table S8

Time-Specific Associations between the Predictors and the Self-Determination Trajectories

Covariate Level	Moderate (Profile 1) Mean (CI)	High (Profile 2) Mean (CI)	Low (Profile 3) Mean (CI)	Summary of Differences
Mental Load				
Time 1	-.104 [-.157; -.051]	.410 [.359; .461]	-.437 [-.515; -.359]	2 > 1 > 3
Time 2	-.391 [-.448; -.334]	.249 [.196; .302]	-.710 [-.794; -.626]	2 > 1 > 3
Time 3	-.570 [-.627; -.513]	.120 [.067; .173]	-.945 [-1.035; -.855]	2 > 1 > 3
Time 4	-.724 [-.775; -.673]	-.136 [-.189; -.083]	-1.061 [-1.141; -.981]	2 > 1 > 3
Work Load				
Time 1	-.057 [-.110; -.004]	.209 [.142; .276]	-.355 [-.429; -.281]	2 > 1 > 3
Time 2	-.059 [-.112; -.006]	.392 [.323; .461]	-.326 [-.399; -.253]	2 > 1 > 3
Time 3	-.029 [-.080; .022]	.485 [.416; .554]	-.301 [-.377; -.225]	2 > 1 > 3
Time 4	-.048 [-.097; .001]	.328 [.265; .391]	-.351 [-.424; -.278]	2 > 1 > 3
Emotional Load				
Time 1	-.028 [-.079; .023]	.104 [.039; .169]	-.328 [-.402; -.254]	2 > 1 > 3
Time 2	-.038 [-.091; .015]	.240 [.171; .309]	-.330 [-.403; -.257]	2 > 1 > 3
Time 3	.008 [-.043; .059]	.388 [.319; .457]	-.278 [-.352; -.204]	2 > 1 > 3
Time 4	-.011 [-.058; .036]	.257 [.194; .320]	-.285 [-.356; -.214]	2 > 1 > 3
Peer Support				
Time 1	-.070 [-.125; -.015]	.286 [.239; .333]	-.254 [-.344; -.164]	2 > 1 > 3
Time 2	-.254 [-.315; -.193]	.209 [.158; .260]	-.411 [-.505; -.317]	2 > 1 > 3
Time 3	-.414 [-.479; -.349]	.077 [.020; .134]	-.647 [-.753; -.541]	2 > 1 > 3
Time 4	-.510 [-.571; -.449]	-.088 [-.145; -.031]	-.725 [-.821; -.629]	2 > 1 > 3

Note. CI = 95% confidence intervals; variables are estimated from factor scores with mean of 0 and a standard deviation of 1 at Time 1.

Table S9

Time-Specific Associations between the Outcomes and the Self-Determination Trajectories

Covariate Level	Moderate (Profile 1) Mean (CI)	High (Profile 2) Mean (CI)	Low (Profile 3) Mean (CI)	Summary of Differences
Positive Affect				
Time 1	.342 [.289; .395]	.299 [.230; .368]	.347 [.271; .423]	1 = 2 = 3
Time 2	.036 [-.019; .091]	.059 [-.010; .128]	.024 [-.056; .104]	1 = 2 = 3
Time 3	-.029 [-.088; .030]	-.025 [-.098; .048]	-.018 [-.102; .066]	1 = 2 = 3
Time 4	-.049 [-.102; .004]	.007 [-.060; .074]	-.032 [-.108; .044]	1 = 2 = 3
Negative Affect				
Time 1	-.558 [-.603; -.513]	-.591 [-.646; -.536]	-.552 [-.617; -.487]	1 = 2 = 3
Time 2	-.190 [-.249; -.131]	-.276 [-.347; -.205]	-.165 [-.251; -.079]	2 > 3; 1 = 2; 1 = 3
Time 3	.022 [-.037; .081]	-.022 [-.095; .051]	.054 [-.032; .140]	1 = 2 = 3
Time 4	.061 [.006; .116]	-.074 [-.139; -.009]	.018 [-.058; .094]	1 > 2; 1 = 3; 2 = 3

Note. CI = 95% confidence intervals; variables are estimated from factor scores with mean of 0 and a standard deviation of 1 at Time 4.

Appendix 4. Specific Motivation Factors: Supplementary Analyses

To further investigate the nature of the estimated growth profiles, we contrasted them on the basis of the time-specific S-factors. Specific levels of identified regulation were not considered in these analyses due to their low level of specificity and composite reliability once participants global levels of self-determination where considered (see Table S2). The results from these comparisons are reported in Table S10. It is important to keep in mind that, according to bifactor specifications, these S-factors were estimated to be uncorrelated with one another and with the G-Factor. Across time points, specific levels of intrinsic motivation were the highest in the *High* profile, followed by the *Moderate* profile, and then by the *Low* profile. Across time points, specific levels of introjected regulation were higher in the *High* profile than in the remaining profiles. However, differences between these remaining profiles changed over time. At Time 1, specific levels of introjected regulation were higher in the *Low* profile relative to the *Moderate* profile. This difference became non-significant at Time 2. Then, at Times 3 and 4, specific levels of introjected regulation were higher in the *Moderate* profile relative to the *Low* profile. Specific levels of external-social and external-material regulations did not differ across profiles at Time 1. However, these two aspects of external regulation showed well-differentiated associations with profile membership at the subsequent time points. At Time 2, specific levels of external-social regulation were the highest in the *Low* profile, followed by the *Moderate* profile, and then by the *High* profile. However, at Time 3, most of these differences disappeared, leaving only a higher level of external-social regulation in the *Low* profile relative to the *High* profile. No differences remained at Time 4. In contrast, specific levels of external-material regulation were higher in the *Moderate* profile than in the *Low* profile at Time 2, and higher in the *High* and *Moderate* profiles relative to the *Low* profile at Times 3 and 4. Finally, across all time points, specific levels of amotivation stayed higher in the *Low* and *Moderate* profiles than in the *High* profile.

Table S10

Time-Specific Associations between the Specific Motivation Factors and the Self-Determination Trajectories

Covariate Level	Moderate (Profile 1) Mean (CI)	High (Profile 2) Mean (CI)	Low (Profile 3) Mean (CI)	Summary of Differences
Intrinsic motivation (specific)				
Time 1	.002 [-.049; .053]	.130 [.067; .193]	-.188 [-.272; -.104]	2 > 1 > 3
Time 2	-.302 [-.359; -.245]	-.141 [-.212; -.070]	-.489 [-.583; -.395]	2 > 1 > 3
Time 3	-.398 [-.443; -.353]	.424 [.351; .497]	-1.625 [-1.739; -1.511]	2 > 1 > 3
Time 4	-.443 [-.482; -.404]	.415 [.342; .488]	-1.541 [-1.639; -1.443]	2 > 1 > 3
Introjected regulation (specific)				
Time 1	-.120 [-.167; -.073]	.204 [.131; .277]	.001 [-.072; .074]	2 > 3 > 1
Time 2	.164 [.111; .217]	.682 [.600; .764]	.101 [.028; .174]	2 > 1 = 3
Time 3	.378 [.329; .427]	1.776 [1.680; 1.872]	-.027 [-.086; .032]	2 > 1 > 3
Time 4	.476 [.421; .531]	.896 [.814; .978]	.340 [.264; .416]	2 > 1 > 3
Ext. social regulation (specific)				
Time 1	-.010 [-.059; .039]	.001 [-.062; .064]	.020 [-.053; .093]	1 = 2 = 3
Time 2	.128 [.065; .191]	.024 [-.052; .100]	.290 [.198; .382]	3 > 1 > 2
Time 3	.317 [.248; .386]	.222 [.138; .306]	.354 [.256; .452]	3 > 2; 1 = 3; 1 = 2
Time 4	.504 [.435; .573]	.541 [.453; .629]	.417 [.319; .515]	1 = 2 = 3
Ext material regulation (specific)				
Time 1	.018 [-.035; .071]	.022 [-.047; .091]	-.067 [-.143; .009]	1 = 2 = 3
Time 2	.168 [.113; .223]	.111 [.042; .180]	.071 [-.007; .149]	1 > 3; 1 = 2; 2 = 3
Time 3	.212 [.153; .271]	.223 [.149; .297]	.085 [.001; .169]	1 = 2 > 3
Time 4	.286 [.231; .341]	.317 [.248; .386]	.121 [.043; .199]	1 = 2 > 3
Amotivation (specific)				
Time 1	.015 [-.038; .068]	-.102 [-.155; -.049]	.102 [.012; .192]	1 = 3 > 2
Time 2	.692 [.588; .796]	.330 [.230; .430]	.688 [.541; .835]	1 = 3 > 2
Time 3	1.227 [1.096; 1.358]	.826 [.689; .963]	1.247 [1.059; 1.435]	1 = 3 > 2
Time 4	1.557 [1.418; 1.696]	1.147 [1.004; 1.290]	1.635 [1.431; 1.839]	1 = 3 > 2

Note. CI = 95% confidence intervals; variables are estimated from factor scores with mean of 0 and a standard deviation of 1 at Time 1.