Running Head: Motivation Profiles

Stability, Change, and Implications of Students' Motivation Profiles: A Latent Transition Analysis

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Abstract

This study examines profiles of University students defined based on the types of behavioral regulation proposed by self-determination theory (SDT), as well as the within-person and within-sample stability in these academic motivation profiles across a two-month period. This study also documents the implications of these profiles for students' engagement, disengagement, and achievement, and investigates the role of self-oriented perfectionism in predicting profile membership. A sample of 504 first-year undergraduates completed all measures twice across a two-month period. Latent profile analysis and latent transition analysis revealed six distinct motivation profiles, which proved identical across measurement points. Membership into the Autonomous, Strongly Motivated, Poorly Motivated, and Controlled profiles was very stable over time, while membership into the Moderately Autonomous and Moderately Unmotivated profiles was moderately stable. Self-oriented perfectionism predicted a higher likelihood of membership into the Autonomous and Strongly Motivated profiles, and a lower likelihood of membership into the Controlled profile. The Autonomous, Strongly Motivated, and Moderately Autonomous profiles were associated with the most positive outcomes, while the Poorly Motivated and Controlled profiles were associated with the most negative outcomes. Of particular interest, the combination of high autonomous motivation and high controlled motivation (Strongly Motivated profile) was associated with positive outcomes, which showed that autonomous motivation was able to buffer even high levels of controlled motivation.

Keywords: Motivation profiles; Self-determination theory; Autonomous and controlled motivations; Undergraduate students; Achievement

According to self-determination theory (SDT; Deci & Ryan, 2008; Ryan & Deci, 2017), students' academic motivation is best represented as a series of distinct, yet complementary, types of behavioral regulation that can co-exist within students to varying degrees and play a role in the emergence of goal-directed behaviors for specific activities. A variety of variable-centered studies have supported the existence of well-differentiated relations between these various types of behavioral regulation and a series of important educational outcomes, ranging from student's well-being to their levels of academic achievement (e.g., Guay, Ratelle, & Chanal, 2008; Ryan & Deci, 2009; Standage, Gillison, Ntoumanis, & Treasure, 2012). However, one may find a positive link between autonomous motivation (i.e., engaging in an activity out of pleasure and/or volition and choice) and well-being in a variable-centered approach without knowing whether a student with high levels of autonomous motivation also reports high levels of controlled motivation (i.e., engaging in an activity for internal or external pressures). Yet, Deci and Ryan (2000) argued that students can endorse different types of motivation in their educational activities (also see Pintrich, 2003).

Attention has recently been paid to how these various forms of behavioral regulation combine and interact with one another within specific individuals across a variety of life settings encompassing education (e.g., Boiché & Stephan, 2014; González, Paoloni, Donolo, & Rinaudo, 2012;), sport (e.g., Gillet, Vallerand, & Paty, 2013; Gillet, Vallerand, & Rosnet, 2009), and work (e.g., Graves, Cullen, Lester, Ruderman, & Gentry, 2015; Van den Broeck, Lens, De Witte, & Van Coillie, 2013). Traditional variable-centered analyses, designed to test how specific variables relate to other variables, on average, in a specific sample of students, are able to systematically test for interactions among predictors (i.e., if the effect of a predictor differs as a function of another variable). However, these traditional approaches are unable to clearly depict the joint effect of variable combinations involving more than two or three interacting predictors. In contrast, person-centered analyses are naturally suited to this form of investigation through their identification of subgroups of participants characterized by distinct configuration on a set of interacting variables (e.g., Howard, Gagné, Morin, & Van den Broeck, 2016b). In accordance with SDT, person-centered analyses make it possible to examine how the different types of motivation combine into motivation profiles, thus providing responses to questions such as: Does a profile characterized by high levels on all forms of motivation relate to the most positive outcomes? Do the different types of behavioral regulation act synergistically to explain all outcomes? More generally, the person-centered approach provides a complementary—yet uniquely informative—perspective on these same research questions, focusing on individual profiles rather than specific relations among variables (Marsh, Lüdtke, Trautwein, & Morin, 2009; Morin & Wang, 2016).

Prior research has already considered the nature of students' profiles of academic motivation based on the SDT framework (e.g., Boiché & Stephan, 2014; Liu, Wang, Tan, Koh, & Ee, 2009; Ratelle, Guay, Vallerand, Larose, & Senécal, 2007; Ullrich-French & Cox, 2009; Wang, Morin, Ryan, & Liu, 2016; Vansteenkiste, Sierens, Soenens, Luyckx, & Lens, 2009). However, although these studies generated new insights into the nature and implications of school motivation, they led to divergent conclusions regarding the importance of autonomous and controlled motivations. For instance, and contrary to theoretical predictions (Deci & Ryan, 2000), outcome levels were found to be identical across motivation profiles characterized by (a) high levels of autonomous and controlled motivations, and (b) high levels of autonomous motivation and low levels of controlled motivation (e.g., Ratelle et al., 2007; Wang et al., 2016).

In the present research, we used a person-centered approach to examine the simultaneous occurrence of different forms of motivation within students. Specifically, the present research extends the literature on University students' motivation profiles by (1) simultaneously considering all types of behavioral regulation proposed by SDT, rather than relying on a reduced number of more global dimensions; (2) using a longitudinal design to address the joint issues of within-person profile stability (the stability in the academic motivation profiles exhibited by specific individuals over the course of a semester) and within-sample profile stability (whether the nature of the academic motivation profiles changes over the course of a semester) (Kam, Morin, Meyer, & Topolnytsky, 2016); (3) assessing the construct validity of the academic motivation profiles through the consideration of determinants and outcomes; (4) considering a wide range of outcomes encompassing engagement (positive affect, effort, interest, critical thinking), disengagement (dropout intentions, boredom, cognitive disorganization), and measures of expected and objective achievement; and (5) relying on state-of-the art latent profile analyses (LPA) and latent transition analyses (LTA) rather than on suboptimal cluster analyses which

have been heavily criticized (see Meyer & Morin, 2016), particularly in the context of longitudinal research involving predictors and outcomes.

Self-Determination Theory

According to SDT (Deci & Ryan, 2008; Ryan & Deci, 2017), students can be motivated for a variety of reasons. First, intrinsic motivation represents the volitional engagement in an activity for the pleasure and satisfaction it affords. Second, identified regulation refers to behavior that serves a personally endorsed value or goal. Intrinsic motivation and identified regulation are conceptualized as autonomous (or self-determined) forms of behavioral regulation. Third, introjected regulation refers to the regulation of behavior out of internally pressuring forces, such as avoidance of guilt and shame, or the pursuit of pride. Fourth, external regulation is characterized by behaviors controlled by external sources (e.g., rewards, punishments, constraints). Introjected and external regulations are conceptualized as controlled forms (i.e., mainly driven by externally-driven forces) of motivation. Finally, amotivation refers to the lack of motivation or intention toward the target behavior. According to SDT, these forms of behavioral regulation are not seen as mutually exclusive, and neither is the distinction between autonomous and controlled forms of motivations conceptualized as a dichotomy. Rather, these various forms of behavioral regulation are proposed to co-exist within individuals and to form a continuum of relative autonomy (or self-determination) ranging from purely intrinsic motivation for inherently pleasurable activities to activities that are driven by purely external forms of inducement (Deci & Ryan, 2000; Ryan & Connell, 1989), although more recent representations position amotivation as the second pole of this continuum (Howard et al., 2016a, 2016b).

As noted above, the differential predictive validity of these various types of behavioral regulation has also been relatively well-documented in relation to a variety of educational outcomes (e.g., Guay et al., 2008; Ryan & Deci, 2009), generally supporting the idea that more autonomous forms of motivation tend to predict more positive outcomes than controlled forms of motivation. For instance, Brunet, Gunnell, Gaudreau, and Sabiston (2015) revealed that autonomous and controlled forms of motivations were respectively positively and negatively associated with academic goal progress. However, research also shows that more controlled forms of motivation are not necessarily accompanied by detrimental outcomes. Indeed, Vallerand et al. (1993) showed that introjected and external regulations toward school activities were positively linked to concentration, positive emotions in the classroom, and performance. It is interesting to note that a particularly interesting perspective on this question comes from emerging person-centered research showing that controlled forms of motivation may positively relate to positive outcomes, but only when it is accompanied by similarly high levels of autonomous motivation (e.g., Graves et al., 2015; Howard et al., 2016b), underscoring the importance of studying behavioral regulations in combination, rather than in isolation.

Motivation Profiles

In contrast to the variable-centered approach that is designed to examine average relations between variables in a specific sample, the person-centered approach involves the identification of homogeneous subgroups of students sharing similar configurations of behavioral regulations (i.e., hereafter referred to as motivation profiles). However, very little person-centered research on students' motivation profiles has so far been conducted in education. In addition, among the few available studies, some have relied on a combination of the behavioral regulation types proposed by SDT and additional components of students' motivation (approach-avoidance goals: Smith, Deemer, Thoman, & Zazworsky, 2014; social achievement goals: Mouratidis & Michou, 2011) making it impossible to identify configurations of behavioral regulations in isolation from these additional dimensions.

Among the relevant studies, which are summarized in the Appendix, most relied on global dimensions of autonomous and controlled motivation, sometimes also considering amotivation, rather than considering all types of behavioral regulation proposed to be important in SDT. Despite some variations, these studies have tended to reveal profiles characterized by high levels of autonomous motivation and low levels of controlled motivation (HA-LC), high levels of autonomous and controlled motivation (HA-HC), low levels of autonomous motivation and high levels of controlled motivation (LA-HC), and low to moderate levels of autonomous and controlled motivation (LA-LC) with results showing levels of amotivation to follow those of controlled motivation, except in the HA-HC profile (Hayenga & Corpus, 2010; Liu et al., 2009; Ratelle et al., 2007; Vansteenkiste et al., 2009).

Although they relied on a cluster analysis of high school students' motivation toward physical education, Boiché, Sarrazin, Grouzet, Pelletier, and Chanal (2008) separately considered students' levels

of intrinsic motivation, identified, introjected, and external regulations. Interestingly, their results highlighted the added value of this distinction by showing differentiated levels of introjected and external regulation in at least two out of the three profiles. Thus, the first profile presented high levels of autonomous motivation, moderate levels of introjected regulation, and low levels of external regulation and amotivation. In contrast, the second profile was characterized by moderate scores on each type of motivation. Still, the third profile presented low levels of autonomous motivation and introjected regulation, and high levels of external regulation and amotivation. Importantly, their results showed that the motivation profile leading to the highest levels of academic performance was characterized by moderate levels of introjected regulation but low levels of external regulation (also see Boiché & Stephan, 2014). Also in the physical education context, Wang et al. (2016), essentially replicated these results in identifying a profile showing well differentiated levels of introjected and external regulation, a distinction that was lost when they considered an alternative solution based only on the two global dimensions of autonomous and controlled motivation.

The first purpose of the present study was thus to identify University students' academic motivation profiles using LPA, while simultaneously considering all facets of academic motivation proposed to be relevant from a SDT perspective (i.e., intrinsic motivation, identified regulation, introjected regulation, external regulation, and amotivation). Due to the scarcity of research using LPA to identify motivation profiles in the educational domain, it is difficult to specify hypotheses about the nature and number of the expected profiles. However, in line with past person-centered research (see Appendix), it was expected that a relatively small number of profiles (i.e., between four and six profiles) would be identified. We also hypothesized that the profiles corresponding to the four routinely configurations would also emerge in the present study: (1) HA-HC, (2) LA-LC, (3) HA-LC, and (4) LA-HC. In accordance with previous research, we also expect amotivation levels to follow levels of controlled forms of motivation (introjected and external regulation), except in the HA-HC profile where we expect to observe low levels of amotivation. Finally, in line with Boiché et al.'s (2008) results, we also expect to identify at least one profile showing diverging levels of introjected and external regulation, but leave as an open research question whether a similarly diverging profile would characterize students' levels of intrinsic motivation and identified regulation.

In order to further extend knowledge in this area and to study the stability of students' motivational profiles over the course of a University semester, we also examined the extent to which the motivation profiles would remain stable over a two-month period. According to Kam et al. (2016), the adoption of a longitudinal perspective makes it possible to assess two types of stability in LPA solutions over the course of the semester: (a) the consistency of profiles over time for specific participants (*within-person stability*); and (2) the stability of the profile structure within a sample (*within-sample stability*). However, to date, studies of motivation profiles have been mostly cross-sectional and have not adequately addressed the important issue of profile stability. Although some studies (e.g., Boiché et al., 2008; Boiché & Stephan, 2014) have previously relied on a prospective design, they did not examine whether students' motivation profiles remained stable or fluctuated over time. Interestingly, Vallerand (1997) hierarchical model of motivation postulates that motivation assessed at the contextual level of generality (e.g., in the educational, sport, or work settings, such as in the present study) should display less stability than global levels of motivation (i.e., individual differences in one's motivational orientations). In addition, prior studies showed that autonomous motivation toward school tends to show important fluctuations over time, while controlled forms of motivation tend to display greater levels of stability (e.g., Corpus, McClintic-Gilbert, & Hayenga, 2009; Gillet, Vallerand, & Lafrenière, 2012). Still, it remains unclear to what extent these variable-centered results might generalize to the person-centered context. For instance, a variable-centered increase in levels of autonomous motivation could easily be translated into: (a) a greater tendency for students to transition toward profiles characterized by higher levels of autonomous motivation (a within-person source of instability); (b) modifications in the nature of profiles so that they become characterized by higher levels of autonomous motivation (a within-sample source of instability); and (c) the increase in the relative size of some profiles characterized by higher levels of autonomous motivation (another form of within-sample source of instability). Thus, we leave as an open research question whether the motivation profiles would remain stable over time, although, based on prior research, we expect greater levels of stability (within-person and within-sample) to be associated with the profiles characterized by higher levels of controlled motivation.

Determinants of Motivation Profiles

Surprisingly, little research to date has been designed to investigate the determinants of motivation profiles in the educational context. For instance, Vansteenkiste et al. (2009) tested the relation between perceived teaching climate (i.e., teacher autonomy support, structure, and involvement) and students' motivation profiles. Their results showed that higher levels of perceived autonomy support, structure, and involvement predicted a higher likelihood of membership into the HA-LC and HA-HC profiles relative to the LA-HC and LA-LC profiles (also see Wang et al. 2016). Liu et al. (2009) also found significant associations between motivation profiles and psychological need satisfaction (competence, relatedness, and autonomy), showing higher levels of need satisfaction to be associated with the HA-HC and HA-LC profiles relative to the LA-HC and LA-LC profiles.

In the present study, we focused on the possible relations between students' levels of self-oriented perfectionism and their likelihood of membership into the various profiles. Self-oriented perfectionism reflects an internal drive to uphold exceedingly high personal standards and a tendency to criticize oneself harshly (Hewitt & Flett, 1991). It also features a sense of self-worth that is contingent on academic success (Jowett, Hill, Hall, & Curran, 2013). Self-oriented perfectionists also tend to approach success through the use of self-referenced criteria and to be driven by a strong striving for perfection and self-improvement (Hewitt & Flett, 1991). It would thus seem logical to expect self-oriented perfectionism to foster both more autonomous forms of motivation (via self-referenced criteria, self-improvement or growth strivings; Harvey et al., 2015; Miquelon, Vallerand, Grouzet, & Cardinal, 2005) and more controlled form of motivation (via harsh self-criticism and always-salient conditions of worth; Jowett et al., 2013). These various considerations suggest that self-oriented perfectionism should be particularly important in the prediction of the likelihood of membership into profiles characterized by a matching level of autonomous and controlled forms of motivations (e.g., HA-HC) relative to the others. Further, self-oriented perfectionism should also be negatively related to profiles characterized by high levels of amotivation, because this internal drive to uphold high standards is closely related to control over outcomes, which is the opposite of amotivation. However, to the best of our knowledge, no study has yet examined the role of self-oriented perfectionism in the prediction of membership into motivation profiles. This study is thus the first to consider the role of self-oriented perfectionism in motivation profiles, aiming to provide a better understanding of the role of individual factors in the determination of students' motivation.

Because demographic characteristics are known to be at least weakly associated with both students' levels of motivation (e.g., Gillet et al., 2009) and perfectionism (e.g., Sastre-Riba, Pérez-Albéniz, & Fonseca-Pedrero, 2016), all relations among motivation, predictors, and outcomes were estimated while controlling for the effects of sex and age. In particular, given that the majority of participants are female (76.8 %) and aged between 17 and 21 years (93.9 %), it appeared important to ascertain that the observed effects were not an artifact of these demographic characteristics.

Outcomes of Motivation Profiles

Despite providing a different perspective on academic motivation from a variable-centered analysis, it is critical to document both the generalizability and meaningfulness (i.e., construct validity) of person-centered analyses (e.g., Morin, 2016; Morin & Wang, 2016). More precisely, it has often been argued that in order to support a substantive interpretation of latent profiles as being meaningful and relevant, it is critical to demonstrate that they show relevant relations with key outcome variables and that they can reliably be replicated across samples or time points (Marsh et al., 2009; Morin, Morizot, Boudrias, & Madore, 2011; Muthén, 2003).

Prior research on academic motivation profiles has documented associations between students' profiles and a variety of important educational outcomes. Thus, Ratelle et al. (2007) showed that the HA-HC profile reported the highest scores on school satisfaction, as well as the lowest levels of school anxiety and distraction in class. In addition, their results showed that, among college students, the HA-LC and HA-HC profiles did not differ from one another on their levels of school achievement. In another study, Liu et al. (2009) found that the HA-LC profile tended to present higher levels of positive emotions related to their studies and the greatest levels of perceived learning. In contrast, the LA-HC profile reported the lowest levels of perceived learning. Furthermore, Vansteenkiste et al. (2009) showed that the HA-LC profile tended to present lower levels of school anxiety than the HA-HC profile, although both of these profiles reported even lower levels of school anxiety than the LA-HC profile. Finally, Boiché et al. (2008) showed that the profile characterized by high levels of autonomous motivation,

moderate levels of introjected regulation, and low levels of external regulation and amotivation presented the highest levels of academic performance, followed by the moderately motivated profile, and finally by the profile characterized by low levels of autonomous motivation and introjected regulation, and high levels of external regulation and amotivation.

In sum, consistent with SDT predictions (Deci & Ryan, 2000; Ryan & Deci, 2017), prior studies showed that motivation profiles characterized by high levels of autonomous motivation tended to be associated with the most positive academic outcomes, followed closely by the HA-HC profile. However, past research also leads to divergent conclusions regarding the relative importance of autonomous and controlled forms of behavioral regulation in the prediction of academic outcomes. Thus, and contrary to theoretical predictions, Boiché and Stephan (2014) showed that the HA-LC profile did not significantly differ from the HA-HC profile on cognitive disorganization (a marker of cognitive disengagement; Reeve, 2013). In the work domain, Moran, Diefendorff, Kim, and Liu (2012) found that a HA-HC motivation profile was associated with better supervisor ratings of performance than a profile characterized by high levels of autonomous motivation and introjected regulation, and low levels of external regulation. Howard et al. (2016b) showed similar benefits to be associated to the HA-HC and HA-LC profiles in terms of work performance, job satisfaction, engagement, and burnout. These results suggest that high levels of controlled motivation are not necessarily harmful when they are combined with equally high levels of autonomous motivation.

When we summarize all of the above, it seems that we can expect students' motivation profiles to be differentially related to different aspects of students' achievement and engagement. In terms of achievement, we contrast students' expectations in terms of achievement with their objective levels of achievement at the end of the semester. In terms of engagement, we focus on: (a) positive affect (i.e., the extent to which students feel enthusiastic, active, and alert; Watson, Clark, & Tellegen, 1988) and interest (i.e., the extent to which students find their educational activities inherently pleasurable; McAuley, Duncan, & Tammen, 1989) as positive markers of emotional engagement; (b) effort (i.e., the extent to which students invest their capacities in educational activities; McAuley et al., 1989) as a positive marker of behavioral engagement; and (c) critical thinking (i.e., the extent to which students report applying previous knowledge to new situations to solve problems and reach decisions; Pintrich, Smith, Garcia, & McKeachie, 1993) as a positive marker of cognitive engagement. Indeed, these various components of students' engagement appear critical to consider as key educational outcomes of motivational profiles given mounting research evidence supporting the role of students' engagement as a key determinant of academic success that is easier to target in intervention than achievement itself (e.g., van Rooij, Jansen, & van de Grift, 2017). Based on research evidence reviewed thus far, we thus expect that profiles characterized by high levels of autonomous motivation, regardless of the levels of controlled motivation, would yield the greatest levels of expected and observed achievement (e.g., Ratelle et al., 2007), while profiles characterized by high levels of autonomous motivation but low levels of controlled motivation should yield the greatest levels of engagement (e.g., Liu et al., 2009).

To complement prior research, which has typically tended to focus solely on desirable outcomes, we also considered three negative outcomes of students' motivation profiles. More precisely, we selected three outcomes representing students' emotional (i.e., boredom), cognitive (i.e., disorganization) and behavioral (i.e., dropout intentions) disengagement from their studies. The importance of boredom and disorganization as outcomes stems from research indicating that these dimensions are negatively related to many desirable academic outcomes, including achievement (e.g., Elliot, McGregor, & Gable, 1999; Pekrun, Hall, Goetz, & Perry, 2014). Indeed, boredom reduces cognitive resources, induces motivation to escape from the achievement settings, and impairs the use of proper learning strategies. In addition, disorganized students tend to present more difficulties in establishing and maintaining a structured approach to studying, thus leading to reduced levels of achievement. Dropout intentions were also chosen because they are strongly related to school dropout behavior, which is in turn associated with numerous negative life outcomes such as decreased employment rates, and increased criminal activities (Bjerk, 2012). Based on prior research, we expect profiles characterized by high levels of amotivation and low levels of autonomous motivation, regardless of their levels of controlled motivation, to be associated with higher levels of disengagement (e.g., Liu et al., 2009; Ratelle et al., 2007).

The Present Study

The present study was designed to examine how the different types of behavioral regulation

proposed by SDT (Deci & Ryan, 2000) will combine within different subgroups of University students, as well as the within-person and within–sample stability in these academic motivation profiles across a two-month period. The time interval selected is directly aligned with the nature of sample of University students in order to study the evolution of their motivational profiles over the course of a University semester. In addition, this study is also designed to assess the role of self-oriented perfectionism in the prediction of students' likelihood of membership into the various motivation profiles, while controlling for the effects of age and sex. Finally, to better document the construct validity and practical relevance of studying motivation profiles among University students, we also systematically assess the relations between these motivation profiles and a variety of indicators of students' engagement, disengagement, and achievement.

Method

Participants and Procedure

The sample used in this study included a total of 504 first-year undergraduate psychology students (Mean age = 18.95; *SD* = 2.97), including 117 males and 387 females, enrolled in a French University. Participation was voluntary and participants were invited to complete a self-reported questionnaire two weeks after the beginning of the fall semester. Among these participants, 461 (91.5%) agreed to complete the questionnaire again at Time 2, two months later. At each data collection, we explained the general purpose of the study, participants provided informed consent, and then completed a 20-25 minutes questionnaire in class settings. Participants were ensured that their responses would be kept confidential and would not have any influence on their course grades. They were only required to provide a personal identification code to allow researchers to match their responses at each data collection point. All questionnaires were administered in French and instruments not already available in this language were adapted to French using a standardized back-translation procedure (Hambleton, 2005; van de Vijver & Hambleton, 1996) by a panel of experts.

Measures

Motivation. Participants' academic motivation was assessed with an adapted version of the Academic Self-Regulation Questionnaire (ASRQ; Ryan & Connell, 1989) developed by Vansteenkiste et al. (2009). The ASRQ begins with the sentence stem, "Why are you studying in general? I'm studying…" and includes 16 responses scored using a 7-point Likert-type scale ranging from 1 (does not correspond at all) to 7 (corresponds exactly).The ASRQ assesses four dimensions (4 items each) of students' academic motivation, including intrinsic motivation (e.g., "Because I am highly interested in doing this"; Time 1 α = .89; Time 2 α = .94), identified regulation (e.g., "Because it is personally important to me"; Time 1 α = .82; Time 2 α = .87), introjected regulation (e.g., "Because I want others to think I'm a good student"; Time 1 α = .70; Time 2 α = .83), and external regulation (e.g., "Because I'm supposed to do so"; Time 1 α = .48; Time 2 α = .62). Participants also completed the amotivation subscale (4 items; e.g., "Honestly, I don't know; I really feel that I am wasting my time when studying"; Time 1 α = .84; Time 2 α = .89) of the Academic Motivation Scale (Vallerand, Blais, Brière, & Pelletier, 1989), originally developed in French.

The low level of scale score reliability associated with some subscales from this instrument (i.e., external regulation) is concerning, and suggests the importance of conducting a more extensive examination of the underlying measurement properties of this instrument and to rely on analyses providing at least some degree of control for measurement errors. It is also well documented that alpha represents a suboptimal indicator of reliability, as it relies on a series of problematic assumptions (e.g., that all indicators are equivalent and interchangeable), and is thus more generally considered to represent a lower bound for reliability (for a special issue entirely devoted to this topic, see Sijtsma, 2009). These limitations of alpha have led many researchers to propose alternative measures of reliability, such as McDonald (1970) omega (ω) coefficient which has the advantage of being directly estimated from the parameter estimates obtained from any measurement model. Compared to alpha, ω has the advantage of taking into account the strength of association between the items and the latent factors (λ_i), as well as item-specific measurement errors (δ_{ii}) (e.g., Dunn, Baguley, & Brunsden, 2013; Sijtsma, 2009): $\omega = (\Sigma|\lambda_i|)^2 / ([\Sigma|\lambda_i|]^2 + \Sigma\delta_{ii})$ where λ_i are the factor loadings and δ_{ii} the error variances. An additional advantage of omega is that it provides a direct representation of the classical definition of reliability ($r_{xx'}$) where the total variance (σ^2_{total}) is assumed to be an additive function of the proportion of true score variance (σ^2_{true}) and the proportion of random measurement error (σ^2_{error}) so that $r_{xx'} = \sigma^2_{true}/\sigma^2_{total}$. We address these issues later, in the "Preliminary Analyses" section.

Self-oriented perfectionism (Predictor). The short version of the Multidimensional Perfectionism Scale (Cox, Enns, & Clara, 2002; Hewitt & Flett, 1991) was used to assess participants' levels of self-oriented perfectionism (5 items; e.g., "I am perfectionistic in setting my goals"; Time 1 α = .82; Time 2 α = .85). Responses were provided on a 7-point Likert-type scale ranging from 1 (strongly disagree) to 7 (strongly agree).

Positive affect (Outcome). Participants' level of positive affect in their studies was assessed with the relevant subscale (5 items; e.g., "active", "determined"; Time 1 α = .71; Time 2 α = .79) from the Short Form of the Positive and Negative Affect Schedule (Thompson, 2007; Watson et al., 1988). Responses were made on a 5-point Likert-type scale (1- not at all to 5- very much).

Interest and effort (Outcomes). Participants' level of interest toward their studies was assessed with three items (e.g., "I would describe my classes as very interesting"; Time 1 α = .87; Time 2 α = .92) from the interest/enjoyment subscale of the Intrinsic Motivation Inventory (McAuley et al., 1989). Their level of effort was assessed using three items (e.g., "I put a lot of effort in my classes"; Time 1 α = .83; Time 2 α = .88) from the effort/importance subscale of the same questionnaire. Responses were given on 1 (strongly disagree) to 7 (strongly agree) Likert-type scale.

Boredom (Outcome). Participants' level of boredom related to their studies were assessed with three items (e.g., "In class, I am usually bored"; Time 1 α = .74; Time 2 α = .79) taken from a subscale originally developed by Duda, Fox, Biddle, and Armstrong (1992; see also Leptokaridou, Vlachopoulos, & Papaioannou, 2016). Students' responses were provided on a 7-point Likert-type ranging from 1 (strongly disagree) to 7 (strongly agree).

Disorganization (Outcome). Participants' level of disorganization were measured with three items (e.g., "I often find that I don't know what to study or where to start"; Time 1 α = .79; Time 2 α = .80) taken from a questionnaire initially developed by Elliot et al. (1999). Each item was rated each item on a 7-point Likert-type scale (1- strongly disagree to 7- strongly agree).

Critical thinking (Outcome). Participants' levels of critical thinking was assessed with five items (e.g., "I often find myself questioning things I hear or read in my courses to decide if I find them convincing"; Time 1 α = .77; Time 2 α = .81) taken from the Motivated Strategies for Learning Questionnaire (Pintrich et al., 1993). All items were answered on a 7-point Likert-type scale ranging from 1 (strongly disagree) to 7 (strongly agree).

Dropout intentions (Outcome). Participants' intentions to drop out of their studies were assessed with one item (i.e., "I intend to drop out of University") previously used by Vallerand, Fortier, and Guay (1997) and originally developed in French. Participants were requested to indicate their response on a 7-point Likert-type scale ranging from 1 (strongly disagree) to 7 (strongly agree).

Expected achievement (Outcome). Participants' were asked to report their expected grades (between 0 and 20) at the end of the fall semester on a 0 to 20 scale corresponding to the way class grades were provided in this University.

Observed achievement (Outcome). Grade transcripts were received from the administrative office of the University at the end of the semester. The French grading system uses grades varying between 0 and 20 for each course.

Analyses

Preliminary Analyses

Preliminary factor analyses were conducted to verify the psychometric properties of all measures used in this study. Factor scores (estimated in standardized units with $M = 0$, $SD = 1$) were saved from these preliminary measurement models and used as inputs for the main analyses (for additional details on the advantages of factor scores, see Meyer & Morin, 2016; Morin, Meyer, Creusier, & Biétry, 2016). Details on these preliminary measurement models, their longitudinal invariance, and estimates of composite reliability for all constructs are reported in the online supplements. To ensure that the measures used at both time points remained fully comparable, these factors scores were saved from longitudinally invariant measurement models (Millsap, 2011). Factor scores do not explicitly control for measurement errors the way latent variables do, however they provide a partial control for measurement errors by giving more weight to items presenting lower levels of measurement errors (Skrondal & Laake, 2001), and preserve the underlying nature of the measurement model (e.g., measurement invariance) better than scale scores (Morin et al., 2016). Importantly, the estimates of composite reliability associated with each motivation measure (including external regulation) was entirely satisfactory when assessed based on model-based coefficients of composite reliability well-aligned to the use of factor

scores (ω ranged from .88 to .95). Correlations for all variables (including these factor scores) used in the present research are reported in Table S4 of the online supplements.

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

Models were estimated using Mplus 7.31 (Muthén & Muthén, 2015) robust maximum likelihood estimator (MLR) in conjunction with Full Information Maximum Likelihood (FIML) to handle missing data (Enders, 2010). More precisely, all longitudinal models were estimated using the data from all respondents who completed at least one measurement point (N = 504) rather than a listwise deletion strategy focusing on the subset of participants (N = 461) who answered both time points. To avoid local maximum, all LPA were conducted using 5000 random sets of start values, 1000 iterations, and retained the 200 best solutions for final stage optimization (Hipp & Bauer, 2006; McLachlan & Peel, 2000). These values were increased to 10000, 2000, and 400 for the longitudinal models.

LPA models were first estimated separately at each time point using the five motivation factors as profile indicators in order to ensure that the same number of profiles would be extracted at each time point. For each time point, we examined solutions including 1 to 10 latent profiles in which the means and variances of the motivation factors were freely estimated in all profiles (Diallo, Morin & Lu, 2016a; Morin, Maïano et al., 2011; Peugh & Fan, 2013). To determine the optimal number of profiles in the data, multiple sources of information need to be considered, including the examination of the substantive meaningfulness, theoretical conformity, and statistical adequacy of the solutions (Bauer & Curran, 2003; Marsh et al., 2009; Muthén, 2003). Statistical indices are available to 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) Likelihood Ratio Tests (LMR/aLMR; because these two tests typically yield the same conclusion, we report only the aLMR), and (vi) the Bootstrap Likelihood Ratio Test (BLRT). A lower AIC, CAIC, BIC and ABIC value suggests a better-fitting model. The aLMR and BLRT compare a *k*-class model with a *k-1*-class model. A significant *p* value indicates that the *k-1*-class model should be rejected in favor of a *k*-class model. Simulation studies indicate that four of these indicators (CAIC, BIC, ABIC, and BLRT) are particularly effective (Henson, Reise, & Kim, 2007; Nylund, Asparouhov, & Muthén 2007; Peugh & Fan, 2013; Tein, Coxe, & Cham, 2013; Tofighi & Enders, 2008; Yang, 2006), while 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 (e.g., Diallo, Morin, & Lu, 2016b; Henson et al., 2007; Nylund et al., 2007; Peugh & Fan, 2013; Tofighi & Enders, 2008; Yang, 2006). These indicators will thus be reported in order to ensure a complete disclosure and to allow for comparisons with previous profile analyses reported in this literature, but will not be used to select the optimal number of profiles. It should be noted that these tests remain heavily influenced by sample size (Marsh et al., 2009), so that 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, Maïano 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), but it provides a useful summary of the classification accuracy (0 to 1), with higher values indicating more accuracy.

Once the optimal number of profiles has been selected at each specific time point, we integrated the two retained LPA solutions (one at each time point) into a single longitudinal LPA model allowing for systematic longitudinal tests of profile similarity. These tests were conducted following the sequential strategy proposed by Morin et al. (2016) for tests of profile similarity across multiple groups and recently optimized by Morin and Litalien (2017) for the longitudinal context. The first step examines whether the same number of profiles can be identified at each time point (i.e., *configural* similarity) and corresponds to the previously described time-specific LPA. A longitudinal LPA can then be estimated from a model of *configural* similarity, to which equality constraints are progressively integrated. In the second step, the *structural* similarity of the profiles is verified by including equality constraints across time points on the means of the profile indicators (i.e., the motivation factors) to test whether the profiles retain the same global shape over time. If this form of similarity holds, then the third step tests the *dispersion* similarity of the profiles by including equality constraints across time points on the variances of the profile indicators to verify whether the within-profile variability remains stable across time points.

Fourth, starting from the most similar model from the previous sequence, the *distributional* similarity of the profiles is tested by constraining the class probabilities to equality across time points to ascertain whether the relative size of the profiles remains the same over time. The fit of these models can be compared using the aforementioned information criteria, and Morin et al. (2016) suggest that at least two indices out of the CAIC, BIC, and ABIC should be lower for the more "similar" model for the hypothesis of profile similarity to be supported.

The most similar model from the previous sequence is then converted to a longitudinal LTA model (Collins & Lanza, 2010; Nylund et al., 2007), in order to more systematically investigate within-person stability and transitions in profile membership (Morin & Litalien, 2017). This sequence was then extended to tests of "*predictive*" and "*explanatory*" similarity to investigate whether the associations between the profiles and, respectively, their predictors and outcomes remained the same across time points. Following Morin and Litalien's (2017) recommendations, all LTA were estimated using the manual auxiliary 3-step approach described by Asparouhov and Muthén (2014).

Predictors and Outcomes of Profile Membership

Multinomial logistic regressions were conducted to test the relations between the predictors (sex, age, and self-oriented perfectionism) and the likelihood of membership into the various profiles. In these analyses, sex and age were allowed to predict profiles estimated at both time points, whereas time-specific measures of self-oriented perfectionism were allowed to predict profile membership at the matching time point. In multinomial logistic regressions each predictor is associated with *k*-1 (with *k* being the number of profiles) regression coefficients related to the comparison of each profile to each possible referent profiles. These regression coefficients represent the effects of the predictors on the log-odds of the outcome (i.e., the pairwise probability of membership in one profile versus another expressed in logarithmic units) that can be expected for a one-unit increase in the predictor. To facilitate interpretations, odds ratios (OR) will also be reported to reflect changes in the likelihood of membership in a target profile versus a comparison profile for each unit increase in the predictor. Three alternative models were contrasted. First, relations between predictors and profile membership were freely estimated across time points, and predictions of Time 2 profile membership were allowed to vary across Time 1 profiles (to test whether the effects of predictors on profile transitions differed across profiles). Second, predictions were freely estimated across time, but not profiles. Finally, the *predictive* similarity of the model was tested by constraining predictions to equality across time points.

Outcomes were also incorporated into the final LTA solution. In these analyses, time-specific measures of the various outcomes (positive affect, interest, effort, boredom, disorganization, critical thinking, dropout intentions and expected achievement) were specified as associated with the profiles estimated at the matching time point, with the exception of observed achievement levels which, because it was only assessed at the end of the study, we specified as associated with Time 2 profiles. We used the MODEL CONSTRAINT command of Mplus to systematically test mean-level differences across pairs of profiles using the multivariate delta method (Kam et al, 2016; Raykov & Marcoulides, 2004). We then proceeded to tests of *explanatory* similarity by constraining the within-profile means of these outcomes to equality across time points.

Results

Latent Profile Solution

The fit indices associated with the LPA estimated at each time point are reported in Table S5 of the online supplements. Examination of these results reveals that, at both time points, all indicators kept on improving with the addition of profiles to the solution, without ever reaching a minimum, with the sole exception of the aLMR (an indicator with a known tendency for under-extraction), which suggested a 3-profile solution at Time 1 and a 4-profile solution at Time 2. We also note that the entropy values are relatively high (.814 to .921) and similar across models and time points. To complement this information, we thus relied on the examination of graphical elbow plots (Morin, Maïano et al., 2011), reported in Figures S1 and S2 of the online supplements. These plots show that the improvement in fit appears to flatten out between 4 and 7 profiles. The examination of these various solutions at both time points showed that these solutions were all fully proper statistically. This examination also revealed moving from a 4- to 5-profile solution, and from a 5- to 6-profile solution both resulted in the addition of a well-defined qualitatively distinct and theoretically meaningful profile to the solution at both time points. However, moving from the 6- to the 7-profile solution simply resulted in the arbitrary division of one of the existing profile into two profiles differing only quantitatively from one another at both

time points. The 6-profile solution was thus retained at each time point, supporting the *configural* similarity of this solution across time points. The fit indices from the final time-specific LPAs and for all longitudinal models are reported in Table 1.

A two time points LPA of *configural* similarity, including 6-profiles per time point, was then estimated. This model was then contrasted to a model of *structural* similarity by constraining the within-profile means on the five motivation factors to be equal across time points. Compared to the model of *configural* similarity, this model resulted in lower values on the CAIC and BIC, thereby supporting the *structural* similarity of this solution across times points. This model was then contrasted to a model of *dispersion* similarity in which the within-profile variance of the motivation factors was constrained to be equal across time points. Compared to the model of *structural* similarity, this LTA resulted in a lower value on of all information criteria, thus supporting the *dispersion* similarity of the solution. Finally, we estimated a model of *distributional* similarity by constraining the size of the latent profiles to be equal across time points. Compared with the model of *dispersion* similarity, this model resulted in lower values on the CAIC, BIC, and ABIC, thus supporting the *distributional* similarity of the solution across time points.

This model of *distributional* similarity is illustrated in Figure 1 and was retained for interpretation and for the next stages (the exact within-profile means are reported in Table S6 of the online supplements). Profile 1 presents high levels of intrinsic motivation and identified regulation, average levels of introjected regulation and external regulation, and low levels of amotivation. This profile was labeled "*Autonomous*" and characterizes 10.0% of the participants. Profile 2 displays moderately high levels on all forms of behavioral regulations (intrinsic motivation, identified regulation, introjected regulation, and external regulation), coupled with average levels of amotivation. This "*Strongly Motivated*" profile is the largest, and characterizes 29.0% of the participants.

Profile 3 presents moderately high levels of intrinsic motivation and identified regulation, coupled with low levels of introjected regulation, external regulation, and amotivation. This "*Moderately Autonomous*" characterizes 16.0% of the participants. In contrast, Profile 4 presents moderately low levels of intrinsic motivation and identified regulation, coupled with close to average levels of introjected regulation and external regulation, and moderately high levels of amotivation. This "*Moderately Unmotivated*" profile is also quite large, characterizing 21.1% of the participants.

Finally, Profiles 5 and 6 are both characterized by high levels of amotivation, and very low levels of intrinsic motivation and identified regulation. However, Profile 5 also displays low levels of introjected regulation and external regulation, whereas Profile 6 presents high levels on these two controlled forms of behavioral regulation. These profiles where thus respectively labelled "*Poorly Motivated*" and "*Controlled*". Profile 5 is the smallest identified in the current study (8.1%), whereas Profile 6 characterizes a slightly larger proportion of participants (15.8%).

Latent Transitions

As noted above, this final model of distributional similarity was then converted to a LTA using the manual auxiliary 3-step approach (Asparouhov & Muthén, 2014; Morin & Litalien, 2017). The transition probabilities from this LTA are reported in Table 2. These results show that membership into Profile 6 (*Controlled*: stability of 95.9%) is the most stable over time. Similarly, membership into Profiles 1 (*Autonomous*: stability of 75.9%), 2 (*Strongly Motivated*: stability of 73.7%) and 5 (*Poorly Motivated*: stability of 70.6%) is also relatively stable over time. In contrast, membership into Profiles 3 (*Moderately Autonomous*: stability of 55.6%), and 4 (*Moderately Unmotivated*: stability of 49.2%) is less stable over time than the other profiles. As such, these results show that profiles characterized by more moderate levels of motivation are also those presenting the lowest levels of stability.

Transitions were rare for participants initially corresponding to Profile 6. When transitions occurred for members of the *Autonomous* (1) profile at Time 1, they mainly involved other relatively autonomous profiles, such as the *Strongly Motivated* (2: 7.6%) or *Moderately Autonomous* (3: 10.6%) profiles. In contrast, when profile membership changed over time for members of the *Strongly Motivated* (2) profile, they involved changes that were both autonomous (*Autonomous*: 9.2%) and controlled (*Moderately Unmotivated*: 8.8%; *Controlled*: 8.2%). However, when they transitioned to another profile, members of the *Poorly Motivated* (5) profile tended to remain associated with profiles located at the lowest end of the SDT continuum (*Moderately Unmotivated*: 13.4%; *Controlled*: 12.2%). Finally, members of both of the least stable profiles displayed an equal combination of autonomous and controlled transitions: (a) members of the *Moderately Autonomous* (3) profile transitioned into the *Strongly Motivated* (2: 19.2%)

and *Moderately Unmotivated* (4: 19.5%) profiles; (b) members of the *Moderately Unmotivated* (4) profile transitioned into the *Strongly Motivated* (2; 17.0%), *Poorly Motivated* (5: 11.1%), and *Controlled* (6: 13.9%) profiles.

Predictors of Profile Membership (Predictive Similarity)

Predictors were then added to this LTA model of *distributional* similarity. We estimated a model in which the effects of the predictors were freely estimated across time points and Time 1 profiles, and contrasted this model with one in which these paths freely estimated across time points only, and then with a model in which these were constrained to be equal across time points and profiles (i.e., *predictive* similarity). As shown in Table 1, the model of *predictive* similarity resulted in the lowest values for all information criteria when compared to the alternative models, thus supporting the *predictive* similarity of the model. The results from the multinomial logistic regression estimated in this model are reported in Table 3.

As expected, very few associations were noted between the likelihood of membership into the various profiles and participants' age and sex. However, supporting the need to control for these variables in this analysis, a few significant associations were observed. Thus, women appeared to be 2.2 to 2.8 times more likely than men to correspond to the *Autonomous* (1), *Strongly Motivated* (2), and *Moderately Autonomous* (3) profiles relative to the *Controlled* (6) profile. Older participants were more likely (about 1.2 times per year) than their younger peers to correspond to the *Autonomous* (1) profile relative to the *Controlled* (6) profile.

Results regarding self-oriented perfectionism show far more extensive associations with the likelihood of membership in the various profiles (see Table 3). More precisely, higher levels of self-oriented perfectionism predicted an increased likelihood of membership into the *Autonomous* (1) and *Strongly Motivated* (2) profiles relative to all other profiles. In addition, it also predicted a decreased likelihood of membership into the *Poorly Motivated* (5) profile relative to all other profiles.

Outcomes of Profile Membership (Explanatory Similarity)

To test for *explanatory* similarity, outcomes were added to the LTA model of *distributional* similarity described earlier. We first estimated a model in which the within-profile levels of outcomes were freely estimated across time points, and contrasted this model to one in which these levels were constrained to equality across time points (i.e., *explanatory* similarity). As shown in Table 1, the model of *explanatory* similarity resulted in the lowest values for all information criteria when compared to the alternative models, thus supporting the *explanatory* similarity of the model. The within-profile means (and 95% confidence intervals) of each outcome are reported in Table 4. Within-profile means of each outcome are also graphically illustrated in Figure 2.

These results clearly support the distinct nature of the profiles. The pattern of associations between profiles and outcomes is also consistent across most outcomes, showing that the most desirable levels of positive affect (higher levels), interest (higher levels), effort (higher levels), critical thinking (higher levels), boredom (lower levels) and dropout intentions (lower levels) were observed in the *Autonomous* (1) profile, followed by the *Strongly Motivated* (2) and *Moderately Autonomous* (3) profiles which could not be distinguished from one another, then by the *Moderately Unmotivated* (4) profile, the *Controlled* (6) profile, and finally the *Poorly Motivated* (5) profile. All of these pairwise comparisons were significant, save for two showing that levels of critical thinking where similar across the *Moderately Unmotivated* (4) and *Controlled* (6) profiles, and that levels of dropout intentions were undistinguishable across the *Autonomous* (1) and *Strongly Motivated* (2) profiles. In addition, levels of boredom also proved to be significantly higher in the *Strongly Motivated* (2) profile relative to the *Moderately Autonomous* (3) profile, confirming the distinct nature of these two profiles.

Expected and observed achievement levels followed a similar ordering across profiles, but fewer significant differences. Expected and observed achievement levels were highest and undistinguishable in Profiles 1 to 3 (*Autonomous*, *Strongly Motivated*, and *Moderately Autonomous*), with the exception of the levels of expected achievement which were significantly higher in the *Autonomous* (1) profile relative to the *Strongly Motivated* (2) profile. The next highest levels for both outcomes were observed in the *Moderately Unmotivated* (4) and *Controlled* (6) profiles, which were similar to one another, followed by the *Poorly Motivated* (5) profile, displaying the lowest levels.

Finally, disorganization was highest in the *Controlled* (6) profile, followed by the *Poorly Motivated* (5), *Moderately Unmotivated* (4), and *Strongly Motivated* (2) profiles which could not be differentiated from one another, then by both the *Autonomous* (1) and *Moderately Autonomous* (3) profiles. In sum,

the key differentiations between disorganization and the other outcomes were that: (1) The least desirable (i.e., highest) levels of disorganization were observed in the *Controlled* profile, rather than in the *Poorly Motivated* profile; (2) the most desirable (i.e., lowest) levels of disorganization were equally observed in the *Autonomous* and *Moderately Autonomous* profiles, rather than in the *Autonomous* and *Strongly Motivated* profiles.

More generally, and consistent with SDT predictions (Deci & Ryan, 2000), our findings confirm that the three profiles with the highest levels of autonomous motivation (i.e., *Autonomous*, *Strongly Motivated*, and *Moderately Autonomous*) were associated with more positive and less negative outcomes than those characterized by lower levels of autonomous motivation (i.e., *Moderately Unmotivated*, *Poorly Motivated*, and *Controlled*). In addition, although autonomous motivation and controlled motivation are typically pitted against one another, the present results suggest that positive outcomes may be associated with high levels of both autonomous motivation and controlled motivation (*Strongly Motivated* profile). It thus appears that the high levels of autonomous motivation displayed in the *Strongly Motivated* profile might have protected profile members against the possible negative effects of controlled motivation.

Discussion

Students' Motivation Profiles: Configuration, Change, and Continuity

The first purpose of the present study was to identify University students' motivation profiles based on their configuration on the different types of behavioral regulation proposed by SDT (Deci & Ryan, 2008). Furthermore, this study was designed to examine the within-person and within-sample stability in these profiles across a two-month period. Our results revealed that six distinct profiles best represented the motivation configurations observed among the current sample of French University students. Three of these profiles corresponded to our expectations and to results obtained in prior studies typically relying on a less extensive set of behavioral regulations (e.g., Boiché et al., 2008; González et al., 2012; Hayenga & Corpus, 2010; Liu et al., 2009; Ratelle et al., 2007; Ullrich-French & Cox, 2009; Vansteenkiste et al., 2009). Specifically, the *Autonomous* profile was characterized by high levels on the autonomous forms of motivation (intrinsic motivation and identified regulation), average levels on the controlled forms of motivation (introjected and external regulations) and low levels of amotivation. In contrast, the *Controlled* profile presented the mirror image of the *Autonomous* profile, and was characterized by high levels of controlled motivation and amotivation, and low levels of autonomous motivation. Finally, the *Strongly Motivated* profile was characterized by moderately high levels on all types of behavioral regulation, and average levels of amotivation.

We also found three additional motivation profiles which, albeit less common, have also been observed in some previous studies (e.g., Boiché et al., 2008; Liu et al., 2009; Ratelle et al., 2007). Thus, the *Moderately Autonomous* and the *Moderately Unmotivated* profiles are both characterized by average levels of autonomous motivation. Thus, students corresponding to the *Moderately Autonomous* profile presented moderately high levels of autonomous motivation coupled with low levels of controlled motivation and amotivation, whereas those corresponding to the *Moderately Unmotivated* profile displayed close to average levels of controlled motivation and amotivation, but low levels of autonomous motivation. Finally, the *Poorly Motivated* profile characterized students with low levels of on all forms of behavioral regulation, and high levels of amotivation.

In is noteworthy that we were able to identify these less common profiles, as well as a total set of six motivation profiles. In contrast, prior research has generally found only three (Boiché et al., 2008; Ratelle et al., 2007), four (González et al., 2012; Liu et al., 2009; Vansteenkiste et al., 2009), or five (Boiché & Stephan, 2014; Ullrich-French & Cox, 2009) profiles. This greater level of precision generally supports the value of relying on a finer-grained representation of academic motivation incorporating specific types of behavioral regulation rather than simply focusing on the two higher-order dimensions of autonomous and controlled motivation. Still, and contrary to our expectations, we did not identify a profile showing diverging levels of introjected and external regulation, or a profile characterized by diverging levels of intrinsic motivation and identified regulation. Although these results are in line with at least some previous research (e.g., Vansteenkiste et al., 2009), they appear to argue against the added value of adopting such a finer-grained representation of academic motivation and rather suggest that the added precision of our results may rather be due to methodological differences (e.g., LPA rather than cluster analyses, and relying on factor scores providing a partial control for measurement errors). Clearly, these divergent conclusions pinpoint the need for additional research

using LPA in order to increase the generalizability of the present findings.

The current study also provides an incremental contribution to the literature by adopting a longitudinal design and addressing the joint issues of within-person stability and within-sample profile stability (Kam et al., 2016). In terms of within-sample stability, our results first revealed that the set of profiles found here fully replicated across measurement occasions, thus supporting the generalizability of our solution across time waves. More precisely, our results revealed the same number of profiles (configural similarity), characterized by the same behavioral regulation configuration (structural similarity), the same level of within-profile variability (dispersion similarity), and the same size (distributional similarity) across time points. However, they also revealed that within-person changes over time in terms of profile membership do occur. More precisely, the results first showed that the six motivation profiles remain moderately to highly stable over a two-month period. Specifically, membership into the *Autonomous*, *Strongly Motivated*, *Poorly Motivated*, and *Controlled* profiles was very stable over time (between 70.6% and 95.9%), while membership into the *Moderately Autonomous*, and *Moderately Unmotivated* profiles was moderately stable over time (between 49.2% and 55.6%). These findings suggest that motivational profiles characterized by moderate levels of motivation tend to be less stable over time, perhaps suggesting that these motivational profiles characterize students whose motivational orientation has not yet crystalized.

In sum, our results support the stability of the profile structure over the course of a University semester. Obviously, this stability may in part reflect the relatively short time interval that was considered here (one semester, versus one or two years). Nevertheless, we also found evidence for a substantial level of within-person changes over time, suggesting that the time interval was indeed sufficient to study change at the individual level. In line with Vallerand's (1997) hierarchical model of motivation, it would be interesting for further research to disentangle which components of motivation (i.e., global, contextual, and situational) present the greatest levels of stability or changes over time. More importantly, future longitudinal investigations are needed to address explanations for, and limits to, profile stability while considering longer time periods and possible changes in the personal and academic lives of the students to more carefully locate determinants of these changes.

The Role of Self-Oriented Perfectionism in the Prediction of Students' Motivation Profiles

Rather than looking specifically at determinants of changes in profile membership, the present study was designed to investigate the role of a more stable personality characteristic, students' levels of self-oriented perfectionism, in the prediction of profile membership. To date, little research has been conducted in the educational domain to identify personal characteristics that contribute to the development of students' motivation profiles (e.g., Liu et al., 2009; Vansteenkiste et al., 2009). The present results first showed that higher levels of self-oriented perfectionism predicted an increased likelihood of membership in the *Autonomous* and *Strongly Motivated* profiles relative to all other profiles, as well as into all profiles relative to the *Poorly Motivated* one. In other words, self-oriented perfectionism was particularly important to the prediction of membership into profiles characterized by either a high level of autonomous motivation with a moderate level of controlled motivation (*Autonomous*) or an equal combination of both autonomous and controlled motivations (*Strongly Motivated*) but not by high autonomous and low controlled motivations (*Moderately Autonomous*). This result is in line with past studies showing that self-oriented perfectionism fosters autonomous forms of motivation from a reliance on self-reference criteria and growth strivings (Harvey et al., 2015; Miquelon et al., 2005) but also fosters controlled forms of motivation from a sense of self-worth that depends on the ability to achieve success (Gaudreau & Antl, 2008; Stoeber et al., 2013). Taken together, these characteristics of self-oriented perfectionism are aligned with the observation that it plays a key role in the emergence of motivation profiles characterized by high levels of both autonomous and controlled motivations. It is important to keep in mind that these effects appeared to be particularly robust, as they were found to generalize across time points, and to emerge even when controlling for students age and sex.[1]

Affective and Behavioral Outcomes of Students' Motivation Profiles

A final objective of this study was to better document the engagement, disengagement, and achievement implications of membership in the various motivation profiles. In this regard, our results showed that the motivation profiles presented a generally well-differentiated pattern of associations that generalized across measurement points. Specifically, the three profiles characterized by higher levels of autonomous motivation and lower levels of amotivation regardless of the levels of controlled motivation

(*Autonomous*, *Strongly Motivated*, and *Moderately Autonomous*) were found to be associated with the highest levels of expected and observed achievement, the highest levels of behavioral, emotional, and cognitive engagement, and the lowest levels of behavioral, emotional, and cognitive disengagement. Furthermore, the *Autonomous* profile tended to present even more desirable levels on these outcomes relative to the other two profiles, supporting the benefits of very high levels of autonomous motivation. These benefits were reinforced in relation to boredom, an outcome for which levels proved to be lower in the *Moderately Autonomous* profile relative to the *Strongly Motivated* one (two profiles that differed mainly on level of controlled motivation). In contrast and as expected, the two profiles characterized by higher levels of amotivation and lower levels of autonomous motivation regardless of their levels of controlled motivation (*Poorly Motivated* and *Controlled* profiles, followed closely by the *Moderately Unmotivated* profile) were found to be associated with the worst educational outcomes. It is also noteworthy that the *Poorly Motivated* profile presented systematically worst outcomes than did the *Controlled* profile, a finding that suggest that there are at least some advantages to controlled motivation, at least when compared to amotivation.

These results support SDT's propositions (Deci & Ryan, 2000, 2008) in demonstrating the positive effects of autonomous motivation (Tsai, Kunter, Lüdtke, Trautwein, & Ryan, 2008). These results are also in line with prior studies which found that the combination of low levels of autonomous motivation and high levels of amotivation were particularly deleterious in terms of educational outcomes (Liu et al., 2009; Ratelle et al., 2007). However, bearing in mind that introjected and external regulations are located at the controlling end of the self-determination continuum (Deci & Ryan, 2000), one might have anticipated that the *Autonomous* profile would also yield the greatest levels of achievement. This was not the case in the present study as the levels of expected and observed achievement associated with the *Autonomous* (and *Moderately Autonomous*) profiles could not be differentiated from those of the *Strongly Motivated* profile. Indeed, SDT posits controlled motivation as being detrimental for students' achievement and recent studies showed that controlled motivation negatively relates to performance (e.g., Gillet, Vallerand, Lafrenière, & Bureau, 2013).

Of interest, Ratelle et al. (2007) also found that the *Autonomous* and *Strongly Motivated* profiles did not differ from one another on their levels of school achievement. Moreover, in the sport context, Gillet, Berjot, Vallerand, Amoura, and Rosnet (2012; also see Wang et al., 2016) showed that high scores on both autonomous and controlled forms of motivation were accompanied by positive outcomes in terms of achievement albeit detrimental in terms of well-being. More generally, although autonomous and controlled forms of motivation are typically pitted against one another, the present findings suggest that achievement might benefit from the combination of autonomous and controlled motivation. In other words, our results suggest that high levels of controlled motivation are not necessarily harmful for achievement when they are combined with equally high levels of autonomous motivation, though they might be harmful otherwise. These results are also consistent with Amabile's (1993) suggestion that controlled motivation might synergistically combines with autonomous motivation to predict positive outcomes, especially for individuals who also display high levels of autonomous motivation (also see Howard et al., 2016b). In contrast, they are not fully aligned with SDT (Deci & Ryan, 2000), as they indicate that the overall quantity of motivation may be as important in the prediction of achievement as the specific quality (i.e., autonomous) of motivation. However, for the other outcomes, as long as a profile is characterized by higher levels of autonomous than controlled motivation, optimal functioning is promoted. Thus, as demonstrated by Van den Broeck et al. (2013) in the work setting and Ratelle et al. (2007) in the educational context, these findings confirm that the effects of motivational profiles differ as a function of the variables under study.

Indeed, it is important to note that disorganization presented a slightly different pattern of relations with the motivation profiles in the present study. More precisely, levels of disorganization were the highest in the *Controlled* profile, while the lowest levels were observed in the *Autonomous* and *Moderately Autonomous* profiles. In other words, these differences suggest that autonomous motivation appears to be critical to organization, whereas controlled motivation appears to be particularly problematic. These results differ from those previously reported by Boiché and Stephan (2014) who showed no significant differences between the five motivation profiles on this outcome, which could possibly be explained by the fact that the reliance on factor scores in the present study provided us with a better control for measurement errors (Skrondal, & Laake, 2001). It is also possible that the levels of autonomous motivation displayed by students from the present study corresponding to the *Controlled*

profile might have been too low to protect them against the deleterious effects of high levels of introjected regulation, external regulation, and amotivation.

Capacity of Autonomous Motivation to Buffer the Deleterious Effects of Controlled Motivation

To make sense of this overall pattern of findings, it helps to look at how the different types of motivation combined with one another in the composition of the six profiles to predict students' positive and negative educational outcomes (see Figure 2, Table 4). The examination of the *Autonomous* and *Moderately Autonomous* profiles shows that when students were lower in controlled motivation, then higher levels of autonomous motivation translated into more positive educational outcomes in a rather straight-forward manner. The comparison between the *Autonomous*, *Moderately Autonomous*, and *Strongly Motivated* profiles, however, showed that when students were high in autonomous motivation, then high levels of controlled motivation did not necessarily translate into negative educational outcomes, with the exception of slightly higher levels of boredom.

The comparison between the *Poorly Motivated* and *Controlled* profiles tells another interesting story. The educational outcomes associated with the *Poorly Motivated* profile were deeply negative, but those associated with the *Controlled* profile were not as problematic, except for disorganization. For instance, observed achievement was significantly higher for the *Controlled* profile than it was for the *Poorly Motivated* profile. The conclusion is not, however, that controlled motivation was associated with positive outcomes, as the *Controlled* profile was also associated with undesirable outcomes- only less so than the *Poorly Motivated* profile. This is also made clear by a comparison of the *Strongly Motivated* and *Controlled* profiles, as the educational outcomes associated with the *Strongly Motivated* profile were all positive while the educational outcomes associated with the *Controlled* profile were all negative, which shows that what is adaptive was the combination of high levels of autonomous and controlled motivations rather than high levels of controlled motivation itself (e.g., *Controlled* profile).

These comparisons place the spotlight on understanding the positive educational outcomes associated with the *Strongly Motivated* profile. In the end, it appears that controlled motivation is not so bad when it is not the sole driver of students' academic motivation but is accompanied by high level of autonomous motivation. While autonomous motivation is clearly the most adaptive aspect of students' motivation, it may sometimes be necessary for students to self-generate motivation in general in order to maintain or improve their autonomous motivation when facing particularly challenging academic situations or when energy levels start to drop. Such an instance was very nicely illustrated by the results showing that self-oriented perfectionists were apparently able to self-generate a combination of high levels of autonomous motivation (from an internal perceived locus of causality and challenge seeking) and average to high levels of controlled motivation (from an unwillingness to accept failure and extreme self-criticism). It is interesting to speculate about what other individual difference characteristics might also lead to a combination of high levels of both autonomous and controlled forms of motivation such as, perhaps, achievement motivation, goal striving, a promotion mindset, or a possible self. Such a *Strongly Motivated* profile was associated with rather positive academic functioning in the present study, and it therefore suggests the conclusion that high levels of autonomous motivation can buffer against the otherwise negative effects of high levels of controlled motivation, and possibly utilize controlled motivation as a way to maintain persistence in the face of challenge to protect against drops in levels of autonomous motivation. Without such a buffer (*Controlled* profile), student outcomes were very poor.

How autonomous and controlled motivations combine within the composition of a student's motivation profile therefore becomes a crucial concern. It is best, however, not to adopt a variable-centered approach to understanding how the different types of autonomous and controlled motivations interact. As shown in Table S4 of the online supplements, the two types of autonomous motivation were uncorrelated with the two types of controlled motivation (i.e., zero-order correlations were non-significant and near zero). But that does not mean the effects of these two types of motivation were independent from one another, because they clearly did interact in specific profiles in which autonomous motivation protected students against the otherwise negative effects of controlled motivation. This buffering interpretation suggests that autonomous motivation has both its well-known constructive effect on students' educational outcomes, but also a second less-known constructive effect through its role in buffering even high levels of controlled motivation.

Limitations and Directions for Future Research

The present study has some limitations. First, we used self-report measures, with the exception of observed achievement, and such measures can be impacted by social desirability and self-report

biases. We thus encourage researchers to conduct additional research using more objective dropout data as well as informant-reported (e.g., teacher) measures of learning strategies, engagement, and creativity as outcomes. Second, the time interval between the two measurement waves was relatively short (two months), suggesting that the stability of the motivation profiles could be attenuated if considered over a longer time period and incorporating multiple semesters. The present study thus suggests that two months might not be a sufficient time interval for a full consideration of stability and change in profile membership, while still suggesting that at least some changes do occur over such a short period. Future research is clearly needed on this issue.

Third, we only considered one type of perfectionism (i.e., self-oriented perfectionism). It would be interesting for future research to examine the links between other dimensions of perfectionism (socially-prescribed perfectionism, other-oriented perfectionism; Hewitt & Flett, 1991) and students' motivation profiles. Perhaps even more importantly, future research is needed to consider a more diversified set of determinants of students' motivation profiles. For instance, in line with recent studies (Michou, Matos, Gargurevich, Gumus, & Herrera, 2016; van der Kaap-Deeder et al., 2016) showing that motive dispositions (Lang & Fries, 2006) relate to autonomous and controlled forms of motivation, these additional investigations might assess dimensions such as motive to succeed, motive to avoid failure, and even contingent self-esteem. Finally, the motivation profiles reported in the present study were observed only in first-year undergraduate psychology students enrolled in a French University. Future research should examine whether the same profiles emerge in student samples with different academic levels (e.g., primary, secondary, graduate), from different countries, and different cultural backgrounds (e.g., Chan et al., 2015), especially the positive effects of controlled forms of motivation when combined with comparable levels of autonomous motivation. Interestingly, Brunet et al. (2015) also found that the combination of autonomous and controlled types of behavioral regulation yielded positive outcomes in two samples of Canadian University students. This question of how introjected and external regulations affect students' functioning when they are, or are not, combined with matching levels of autonomous motivation clearly warrants further research, both within and across cultures.

Practical Implications

From a practical perspective, our results suggest that teachers should be particularly attentive to students displaying low levels of autonomous motivation coupled with high levels of amotivation as these individuals appear to be at risk for a variety of educational difficulties, such as boredom and dropout intentions. In the existing literature, numerous studies demonstrated that autonomy-supportive teaching behaviors were positively related to autonomous motivation and negatively related to amotivation (e.g., Cheon & Reeve, 2015; Hagger, Sultan, Hardcastle, & Chatzisarantis, 2015; Leptokaridou et al., 2016). In line with these findings, having teachers display higher levels of autonomy-supportive behaviors in the classroom should be associated with a greater likelihood of membership into the most desirable profiles (*Autonomous*, *Moderately Autonomous*, and *Strongly Motivated*). Incorporating autonomy-supportive structure into classes may thus be an important pedagogical consideration. Jang, Reeve, and Halusic (2016) recently tested the educational utility of "teaching in students' preferred ways" as a new autonomy-supportive teaching strategy. Results revealed that students who received a preferred way of teaching (i.e., teachers take their students' perspective and adjust how they deliver a lesson plan so that it aligns with students' preferred ways of teaching) perceived their teacher as more autonomy-supportive and had more positive outcomes. In other words, "teaching in students' preferred ways" represents a way of teaching that may increase students' autonomous motivation and decrease their amotivation.

Footnote

[1] Despite the fact that students' sex and age were simply included as controlled variables in the present study, a few noteworthy results regarding the associations between these demographic characteristics and students' motivation profiles deserve attention. First, women were more likely than men to correspond to the *Autonomous*, *Strongly Motivated*, and *Moderately Autonomous* profiles relative to the *Controlled* one. Second, older students were also more likely than younger students to correspond to the *Autonomous* profile relative to the *Controlled* one. In other words, women and older students are more likely to present a motivation profile characterized by high levels of autonomous motivation. These results are in line with past investigations showing that women tend to display higher levels of autonomous motivation relative to men (Vallerand et al., 1989, 1993) and that age has a positive influence on autonomous motivation (Stynen, Forrier, & Sels, 2014). However, future studies are needed

to further examine age and gender differences in profile composition, as well as the mechanisms involved in the emergence of these differences.

References

Amabile, T. M. (1993). What does a theory of creativity require? *Psychological Inquiry, 4*, 179-181.

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

Bauer, D. J., & Curran, P. J. (2003). Distributional assumptions of growth mixture models over-extraction of latent trajectory classes. *Psychological Methods, 8*, 338-363.

Bjerk, D. (2012). Re-examining the impact of dropping out on criminal and labor outcomes in early adulthood. *Economics of Education Review, 31*, 110-122.

Boiché, J., Sarrazin, P. G., Grouzet, F. M. E., Pelletier, L. G., & Chanal, J. (2008). Students' motivational profiles and achievement outcomes in physical education: A self-determination perspective. *Journal of Educational Psychology, 10*, 688-701.

Boiché, J., & Stephan, Y. (2014). Motivational profiles and achievement: A prospective study testing potential mediators. *Motivation and Emotion, 38*, 79-92.

Brunet, J., Gunnell, K. E., Gaudreau, P., & Sabiston, C. M. (2015). An integrative analytical framework for understanding the effects of autonomous and controlled motivation. *Personality and Individual Differences, 84*, 2-15.

Chan, D. K. C., Yang, S. X., Hamamura, T., Sultan, S., Xing, S., Chatzisarantis, N. L. D., & Hagger, M. S. (2015). In-lecture learning motivation predicts students' motivation, intention, and behaviour for after-lecture learning: Examining the trans-contextual model across universities from UK, China, and Pakistan. *Motivation and Emotion, 39*, 908-925.

Cheon, S. H., & Reeve, J. (2015). A classroom-based intervention to help teachers decrease students' amotivation. *Contemporary Educational Psychology, 40*, 99-111.

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

Corpus, J. H., McClintic-Gilbert, M. S., & Hayenga, A. O. (2009). Within-year changes in children's intrinsic and extrinsic motivational orientations: Contextual predictors and academic outcomes. *Contemporary Educational Psychology, 34*, 154-166.

Cox, B. J., Enns, M. W., & Clara, I. P. (2002). The multidimensional structure of perfectionism in clinically distressed and college student samples. *Psychological Assessment, 14*, 365-373.

Deci, E. L., & Ryan, R. M. (2000). The "what" and "why" of goal pursuits: Human needs and the self-determination of behavior. *Psychological Inquiry, 11*, 227-268.

Deci, E. L., & Ryan, R. M. (2008). Facilitating optimal motivation and psychological well-being across life's domains. *Canadian Psychology, 49*, 14-23.

Diallo, T. M. O, Morin, A. J. S., & Lu, H. (2016a). Impact of misspecifications of the latent variance-covariance and residual matrices on the class enumeration accuracy of growth mixture models. *Structural Equation Modeling, 23*, 507-531.

Diallo, T. M. O, Morin, A. J. S., & Lu, H. (2016b). The impact of total and partial inclusion or exclusion of active and inactive time invariant covariates in growth mixture models. *Psychological Methods.* Advance online publication. doi: 10.1037/met0000084

Duda, J. L., Fox, K. R., Biddle, S. J., & Armstrong, N. (1992). Children's achievement goals and beliefs about success in sport. *British Journal of Educational Psychology, 62*, 313-323.

Dunn, T., Baguley, T., & Brunsden, V. (2014). From alpha to omega: A practical solution to the pervasive problem of internal consistency. *British Journal of Psychology, 105*, 399-412.

Elliot, A. J., McGregor, H. A., & Gable, S. (1999). Achievement goals, study strategies, and exam performance: A mediational analysis. *Journal of Educational Psychology, 91*, 549-563.

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

Gaudreau, P., & Antl, S. (2008). Athletes' broad dimensions of dispositional perfectionism: Examining changes in life satisfaction and the mediating role of sport-related motivation and coping. *Journal of Sport & Exercise Psychology, 30*, 356-382.

Gillet, N., Berjot, S., Vallerand, R. J., Amoura, S., & Rosnet, E. (2012). Examining the motivation-performance relationship in competitive sport: A cluster-analytic approach. *International Journal of Sport Psychology, 43*, 79-102.

Gillet, N., Vallerand, R. J., & Lafrenière, M.-A. (2012). Intrinsic and extrinsic school motivation as a

function of age: Mediating role of autonomy support. *Social Psychology of Education, 15*, 77-95.
Gillet, N., Vallerand, R. J., Lafrenière, M.-A. K., & Bureau, J. S. (2013). The mediating role of positive and negative affect in the situational motivation-performance relationship. *Motivation and Emotion, 37*, 465-479.
Gillet, N., Vallerand, R. J., & Paty, B. (2013). Situational motivational profiles and performance with elite performers. *Journal of Applied Social Psychology, 43*, 1200-1210.
Gillet, N., Vallerand, R. J., & Rosnet, I. (2009). Motivational clusters and performance in a real-life context. *Motivation and Emotion, 33*, 49-62.
González, A., Paoloni, V., Donolo, D., & Rinaudo, C. (2012). Motivational and emotional profiles in university undergraduates: A self-determination theory perspective. *The Spanish Journal of Psychology, 15*, 1069-1080.
Graves, L. M., Cullen, K. L., Lester, H. F., Ruderman, M. N., & Gentry, W. A. (2015). Managerial motivational profiles: Composition, antecedents, and consequences. *Journal of Vocational Behavior, 87*, 32-42.
Guay, F., Ratelle, C. F., & Chanal, J. (2008). Optimal learning in optimal contexts: The role of self-determination in education. *Canadian Psychology, 49*, 233-240.
Hagger, M. S., Sultan, S., Hardcastle, S. J., & Chatzisarantis, N. L. D. (2015). Perceived autonomy support and autonomous motivation toward mathematics activities in educational and out-of-school contexts is related to mathematics homework behavior and attainment. *Contemporary Educational Psychology, 41*, 111-123.
Hambleton, R. K. (2005). Issues, designs, and technical guidelines for adapting tests to languages and cultures. In R. K. Hambleton, P. Merenda, & C. Spielberger (Eds.), *Adapting educational and psychological tests for cross-cultural assessment* (pp. 3-38). Mahwah, NJ: Erlbaum.
Harvey, B., Milyavskaya, M., Hope, N., Powers, T. A., Saffran, M., & Koestner, R. (2015). Affect variation across days of the week: Influences of perfectionism and academic motivation. *Motivation and Emotion, 39*, 521-530.
Hayenga, A. O., & Corpus, J. (2010). Profiles of intrinsic and extrinsic motivations: A person-centered approach to motivation and achievement in middle school. *Motivation and Emotion, 34*, 371-383.
Henson, J. M., Reise, S. P., & Kim, K. H. (2007). Detecting mixtures from structural model differences using latent variable mixture modeling: A comparison of relative model fit statistics. *Structural Equation Modeling, 14*, 202-226.
Hewitt, P. L., & Flett, G. L. (1991). Perfectionism in the self and social contexts: Conceptualization, assessment, and association with psychopathology. *Journal of Personality and Social Psychology, 60*, 456-470.
Hipp, J. R., & Bauer, D. J. (2006). Local solutions in the estimation of growth mixture models. *Psychological Methods, 11*, 36-53.
Howard, J., Gagné, M., Morin, A. J. S., & Forest, J. (2016a). Using bifactor exploratory structural equation modeling to test for a continuum structure of motivation. *Journal of Management*. Advance online publication. doi: 10.1177/0149206316645653
Howard, J., Gagné, M., Morin, A. J. S., & Van den Broeck, A. (2016b). Motivation profiles at work: A self-determination theory approach. *Journal of Vocational Behavior, 95-96*, 74-89.
Jang, H., Reeve, J., & Halusic, M. (2016). A new autonomy-supportive way of teaching that increases conceptual learning: Teaching in students' preferred ways. *Journal of Experimental Education, 84*, 686-701.
Jowett, G. E., Hill, A. P., Hall, H. K., & Curran, T. (2013). Perfectionism and junior athlete burnout: The mediating role of autonomous and controlled motivation. *Sport, Exercise, and Performance Psychology, 2*, 48-61.
Kam, C., Morin, A. J. S., Meyer, J. P., & Topolnytsky, L. (2016). Are commitment profiles stable and predictable? A latent transition analysis. *Journal of Management, 42*, 1462-1490.
Lang, J. W. B., & Fries, S. (2006). A revised 10-item version of the Achievement Motives Scale: Psychometric properties in German-speaking samples. *European Journal of Psychological Assessment, 22*, 216-224.
Leptokaridou, E. T., Vlachopoulos, S. P., & Papaioannou, A. G. (2016). Experimental longitudinal test of the influence of autonomy-supportive teaching on motivation for participation in elementary school physical education. *Educational Psychology, 36*, 1135-1156.

Liu, W., Wang, J., Tan, O., Koh, C., & Ee, J. (2009). A self-determination approach to understanding students' motivation in project work. *Learning and Individual Differences, 19*, 139-145.

Lo, Y., Mendell, N., & Rubin, D. (2001). Testing the number of components in a normal mixture. *Biometrika, 88*, 767-778.

Lubke, G., & Muthén, B. O. (2007). Performance of factor mixture models as a function of model size, covariate effects, and class-specific parameters. *Structural Equation Modeling, 14*, 26-47.

Marsh, H. W., Lüdtke, O., Trautwein, U., & Morin, A. J. S. (2009). Classical latent profile analysis of academic self-concept dimensions: Synergy of person- and variable-centered approaches to theoretical models of self-concept. *Structural Equation Modeling, 16*, 191-225.

McAuley, E., Duncan, T., & Tammen, V. V. (1989). Psychometric properties of the Intrinsic Motivation Inventory in a competitive sport setting: A confirmatory factor analysis. *Research Quarterly for Exercise and Sport, 60*, 48-58.

McDonald, R.P. (1970). Theoretical foundations of principal factor analysis, canonical factor analysis, and alpha factor analysis. *British Journal of Mathematical & Statistical Psychology, 23*, 1-21.

McLachlan, G., & Peel, D. (2000). *Finite mixture models.* New York, NY: Wiley.

Meyer, J. P., & Morin, A. J. S. (2016). A person-centered approach to commitment research: Theory, research, and methodology. *Journal of Organizational Behavior, 37*, 584-612.

Michou, A., Matos, L., Gargurevich, R., Gumus, B., & Herrera, D. (2016). Building on the enriched hierarchical model of achievement motivation: Autonomous and controlling reasons underlying mastery goals. *Psychologica Belgica, 56*, 269-287.

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

Miquelon, P., Vallerand, R. J., Grouzet, F. M. E., & Cardinal, G. (2005). Perfectionism, academic motivation, and psychological adjustment: An integrative model. *Personality and Social Psychology Bulletin, 31*, 913-924.

Moran, C. M., Diefendorff, J. M., Kim, T.-Y., & Liu, Z.-Q. (2012). A profile approach to self-determination theory motivations at work. *Journal of Vocational Behavior, 81*, 354-363.

Morin, A. J. S. (2016). Person-centered research strategies in commitment research. In J. P. Meyer (Ed.), *The handbook of employee commitment* (pp. 490-508). Cheltenham, UK: Edward Elgar.

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

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

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

Morin, A. J. S., Morizot, J., Boudrias, J.-S., & Madore, I. (2011). A multifoci person-centered perspective on workplace affective commitment: A latent profile/factor mixture analysis. *Organizational Research Methods, 14*, 58-90.

Morin, A. J. S., & Wang, C. K. J. (2016). A gentle introduction to mixture modeling using physical fitness performance data. In N. Ntoumanis, & N. Myers (Eds.), *An introduction to intermediate and advanced statistical analyses for sport and exercise scientists* (pp. 195-220). UK: Wiley.

Mouratidis, A., & Michou, A. (2011). Self-determined motivation and social achievement goals in children's emotions. *Educational Psychology, 31*, 67-86.

Muthén, B. O. (2003). Statistical and substantive checking in growth mixture modeling: Comment on Bauer and Curran (2003). *Psychological Methods, 8*, 369-377.

Muthén, L. K., & Muthén, B. (2015). *Mplus user's guide.* Los Angeles, CA: Muthén & Muthén.

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

Pekrun, R., Hall, N. C., Goetz, T., & Perry, R. P. (2014). Boredom and academic achievement: Testing a model of reciprocal causation. *Journal of Educational Psychology, 106*, 696-710.

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

Pintrich, P. R. (2003). A motivational science perspective on the role of student motivation in learning

and teaching contexts. *Journal of Educational Psychology, 95*, 667-686.

Pintrich, P. R., Smith, D. A., Garcia, T., & McKeachie, W. J. (1993). Reliability and predictive validity of the Motivated Strategies for Learning Questionnaire (MSLQ). *Educational and Psychological Measurement, 53*, 801-813.

Ratelle, C. F., Guay, F., Vallerand, R. J., Larose, S., & Senécal, C. (2007). Autonomous, controlled, and amotivated types of academic motivation: A person-oriented analysis. *Journal of Educational Psychology, 99*, 734-746.

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

Reeve, J. (2013). How students create motivationally supportive learning environments for themselves: The concept of agentic engagement. *Journal of Educational Psychology, 105*, 579-595.

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

Ryan, R. M., & Deci, E. L. (2009). Promoting self-determined school engagement: Motivation, learning, and well-being. In K. R. Wenzel, & A. Wigfield (Eds.), *Handbook of motivation at school* (pp. 171-195). New York, NY: Routledge/Taylor & Francis Group.

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

Sastre-Riba, S., Pérez-Albéniz, A., & Fonseca-Pedrero, E. (2016). Assessing perfectionism in children and adolescents: Psychometric properties of the Almost Perfect Scale Revised. *Learning and Individual Differences, 49*, 386-392.

Sijtsma, K. (2009). On the use, misuse, and the very limited usefulness of Cronbach's alpha. *Psychometrika, 74*, 107-120.

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

Smith, J. L., Deemer, E. D., Thoman, D. B., & Zazworsky, L. (2014). Motivation under the microscope: Understanding undergraduate science students' multiple motivations for research. *Motivation and Emotion, 38*, 496-512.

Standage, M., Gillison, F., Ntoumanis, N., & Treasure, D. (2012). Predicting students' physical activity and health-related well-being: A prospective cross-domain investigation of motivation across physical education and exercise settings. *Journal of Sport & Exercise Psychology, 34*, 37-60.

Stoeber, J., Davis, C. R., & Townley, J. (2013). Perfectionism and workaholism in employees: The role of work motivation. *Personality and Individual Differences, 55*, 733-738.

Stynen, D., Forrier, A., & Sels, L. (2014). The relationship between motivation to work and workers' pay flexibility: The moderation of age. *The Career Development International, 19*, 183-203.

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

Thompson, E. R. (2007). Development and validation of an internationally reliable short-form of the Positive and Negative Affect Schedule. *Journal of Cross-Cultural Psychology, 38*, 227-242.

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

Tsai, Y., Kunter, M., Lüdtke, O., Trautwein, U., & Ryan, R. M. (2008). What makes lessons interesting? The role of situational and individual factors in three school subjects. *Journal of Educational Psychology, 100*, 460-472.

Ullrich-French, S., & Cox, A. (2009). Using cluster analysis to examine the combinations of motivation regulations of physical education students. *Journal of Sport & Exercise Psychology, 31*, 358-379.

Vallerand, R. J. (1997). Toward a hierarchical model of intrinsic and extrinsic motivation. In M. Zanna (Ed.), *Advances in experimental social psychology* (pp. 271-360). New York, NY: Academic Press.

Vallerand, R. J., Blais, M. R., Brière, N. M., & Pelletier, L. G. (1989). Construction et validation de l'Échelle de Motivation en Éducation (EME) [Construction and validation of the Motivation toward Education Scale]. *Canadian Journal of Behavioural Science, 21*, 323-349.

Vallerand, R. J., Fortier, M. S., & Guay, F. (1997). Self-determination and persistence in a real-life setting: Toward a motivational model of high school dropout. *Journal of Personality and Social Psychology, 72*, 1161-1176.

Vallerand, R. J., Pelletier, L. G., Blais, M. R., Brière, N. M., Senécal, C., & Vallières, E. F. (1993). On the assessment of intrinsic, extrinsic, and amotivation in education: Evidence on the concurrent and construct validity of the Academic Motivation Scale. *Educational and Psychological Measurement, 53*, 159-172.

van de Vijver, F. J. R., & Hambleton, R. K. (1996). Translating tests: Some practical guidelines. *European Psychologist, 1*, 89-99.

Van den Broeck, A., Lens, W., De Witte, H., & Van Coillie, H. (2013). Unraveling the importance of the quantity and the quality of workers' motivation for well-being: A person-centered perspective. *Journal of Vocational Behavior, 82*, 69-78.

van der Kaap-Deeder, J., Wouters, S., Verschueren, K., Briers, V., Deeren, B., & Vansteenkiste, M. (2016). The pursuit of self-esteem and motivation. *Psychologica Belgica, 56*, 143-168.

van Rooij, E. C. M., Jansen, E. P. W. A., & van de Grift, W. J. C. M. (2017). Secondary school students' engagement profiles and their relationship with academic adjustment and achievement in university. *Learning and Individual Differences, 54*, 9-19.

Vansteenkiste, M., Sierens, E., Soenens, B., Luyckx, K., & Lens, W. (2009). Motivational profiles from a self-determination perspective: The quality of motivation matters. *Journal of Educational Psychology, 101*, 671-688.

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

Watson, D., Clark, L. A., & Tellegen, A. (1988). Development and validation of brief measures of positive and negative affect: The PANAS scales. *Journal of Personality and Social Psychology, 54*, 1063-1070.

Yang, C. (2006). Evaluating latent class analyses in qualitative phenotype identification. *Computational Statistics & Data Analysis, 50*, 1090-1104.

Appendix. Previous Person-Centered Studies of Motivational Profiles

Study	Motivation Variables	Method	Number of Profiles	Labels of the Profiles	Relations with Outcomes
Boiché, Sarrazin, Grouzet, Pelletier, and Chanal (2008)	Motivation toward physical education: Intrinsic motivation (stimulation), intrinsic motivation (knowledge), identified regulation, introjected regulation, external regulation, and amotivation.	Cluster Analysis	3	Self-determined (1), moderate (2), and non self-determined (3).	Performance: 1 > 2 > 3 (Study 1) 2 > 3 and 1 > 2 (Study 2) Grades: 2 > 3 and 1 > 2 (Study 2) Efforts: 2 > 3 and 1 = 2 (Study 2)
Boiché and Stephan (2014)	Motivation toward school: Intrinsic motivation, identified regulation, introjected regulation, external regulation, and amotivation.	Cluster Analysis	5	Additive (1), self-determined (2), moderate (3), low (4), and non self-determined (5).	Deep studying: 1 = 2 = 3 = 4 = 5 Surface studying: 1 = 2 = 3 = 4 = 5 Disorganization: 1 = 2 = 3 = 4 = 5 Class attendance: 1 = 2 = 3 = 4; 4 = 5; 1 = 2 = 3 > 5 Time studying: 1 = 2 = 3 = 4 = 5 Grades: 1 = 3 = 4; 2 = 4 = 5; 2 > 1 = 3; 2 > 4; 5 < 1 = 3
González, Paoloni, Donolo, and Rinaudo (2012)	Motivation toward University: Intrinsic motivation, identified regulation, introjected regulation, external regulation, and amotivation.	Cluster Analysis	4	Low autonomous and controlled (1), controlled (2), high autonomous and controlled (3), and autonomous (4).	Enjoyment: 1 = 2; 1 = 3; 1 < 3; 2 < 3 < 4 Hope: 1 = 2 = 3 < 4 Pride: 1 = 2 < 3 = 4 Anxiety: 1 = 4; 1 = 2 = 3; 2 = 3 > 4; Boredom: 1 = 3 = 4; 1 = 2; 2 > 3 = 4 Hopelessness: 4 < 1 = 2 = 3 Achievement: 1 < 2 < 3 = 4
Hayenga and Corpus (2010)	Intrinsic and extrinsic motivations toward school	Cluster Analysis	4	High quantity (1), good quality (2), poor quality (3), and low quantity (4).	Achievement: 2 > 1 = 2 = 3 (Fall semester) 2 > 1 = 3; 2 = 4 (Spring semester)
Liu, Wang, Tan, Koh, and Ee (2009)	Motivation toward a project: Intrinsic motivation, identified regulation, introjected regulation, external regulation, and amotivation. Psychological needs satisfaction also included	Cluster Analysis	4	Low self-determined/high controlled (1), high self-determined/low Controlled (2), low self-determined/low controlled (3), and high self-determined/high controlled (4)	Enjoyment: 2 > 4 > 3 > 1 Value: 2 > 4 > 3 > 1 Metacognition: 2 > 4 > 3 = 1 Communication: 2 > 4 > 3 = 1 Collaboration: 2 = 4 > 3 = 1 Problem solving skills: 2 = 4 > 3 = 1

Study	Motivation Variables	Method	Number of Profiles	Labels of the Profiles	Relations with Outcomes
Ratelle, Guay, Vallerand, Larose, and Senécal (2007)	Motivation for pursuing studies: Intrinsic motivation, identified regulation, introjected regulation, external regulation, and amotivation	Cluster Analysis	3	Studies 1 and 2: Controlled (1), moderate autonomous-controlled (2), and high autonomous-controlled (3). Study 3: Low autonomous-controlled (1), truly autonomous (2), and high autonomous-controlled (3).	Anxiety in school: 1 = 2 > 3 (Study 1) Distraction in class: 1 > 2 > 3 (Study 1) Satisfaction at school: 1 < 2 < 3 (Study 1) School dropout: 1 > 2 > 3 (Study 1) Achievement: 1 < 2 = 3 (Study 2) Absenteeism: 1 < 2 = 3 (Study 2) Achievement-fall: 1 < 2 = 3 (Study 3) Achievement-winter: 1 < 2 = 3 (Study 3) Dropout: 1 > 3 > 2 (Study 3)
Wang, Morin, Ryan, and Liu (2016)	Motivation toward physical education. Option 1: Intrinsic motivation, identified regulation, introjected regulation, and external regulation. Option 2: Autonomous motivation and controlled motivation.	Latent Profile Analysis	5	Option 1: Moderate controlled (1), autonomous (2), internalized (3), strong controlled (4), moderate (5). Option 2: High (1), marked autonomous (2), moderate autonomous (3), moderate (4), controlled (5)	Option 1 only: Perceived competence: 3 > 2 > 5 > 1 > 4 Intentions to be physically active: 2 = 3 > 5 > 1 = 4
Ullrich-French and Cox (2009)	Motivation toward physical education: Intrinsic motivation, identified regulation, introjected regulation, and external regulation.	Cluster Analysis	5	Average (1), motivated (2), self-determined (3), low motivation (4), and external (5).	Enjoyment: 2 = 3 > 1 = 4 > 5 Worry: 1 = 2 = 4 = 5; 2 = 3 = 4 = 5; 1 > 3 Effort: 2 = 3 > 1 = 4 > 5 Value: 2 = 3 > 1 = 4 > 5 Physical activity: 1 = 2 = 3; 1 = 3 = 4 = 5; 2 > 4 = 5
Vansteenkiste, Sierens, Soenens, Luyckx, and Lens (2009)	Study 1: Overall academic motivation: Autonomous motivation and controlled motivation. Study 2: Motivation for one particular course: Autonomous motivation and controlled motivation.	Cluster Analysis	4	Good quality motivation (1), high quantity motivation (2), poor quality motivation (3), and low quantity motivation (4).	Cognitive processing: 1 = 2 > 3 = 4 (both) Test anxiety: 1 = 4 < 2 = 3 (Study 1); 1 < 2 < 3; 1 = 4; 2 = 4 (Study 2) Time/environment use: 1 = 2 > 3 = 4 (both) Meta-cognition: 1 = 2 > 3 = 4 (both) Effort regulation: 1 = 2 > 3 = 4 (Study 1) 1 = 2; 2 = 4; 1 > 4 > 3 (Study 2) Procrastination: 1 < 2 < 4 < 3 (Study 1) 1 = 2; 2 = 4; 1 > 4 > 3 (Study 2) Grade point average: 1 > 2 > 3 = 4 (Study 1) Cheating behavior: 1 = 2 < 3 = 4 (Study 1) Cheating attitude: 1 < 2 < 3 = 4 (Study 1)

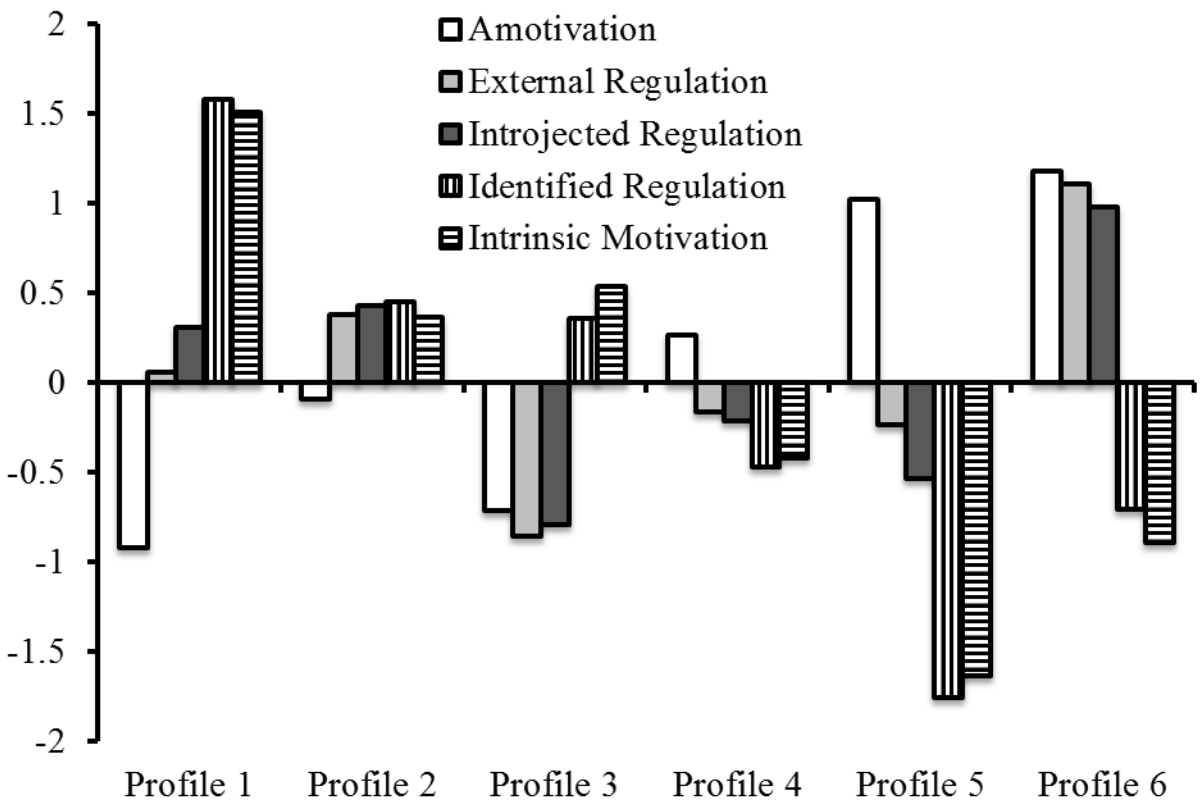

Figure 1. Final 6-profile solution found in this study at both time points.
Note. The profile indicators are estimated from factor scores with mean of 0 and a standard deviation of 1; Profile 1: Autonomous; Profile 2: Strongly Motivated; Profile 3: Moderately Autonomous; Profile 4: Moderately Unmotivated; Profile 5: Poorly Motivated; Profile 6: Controlled.

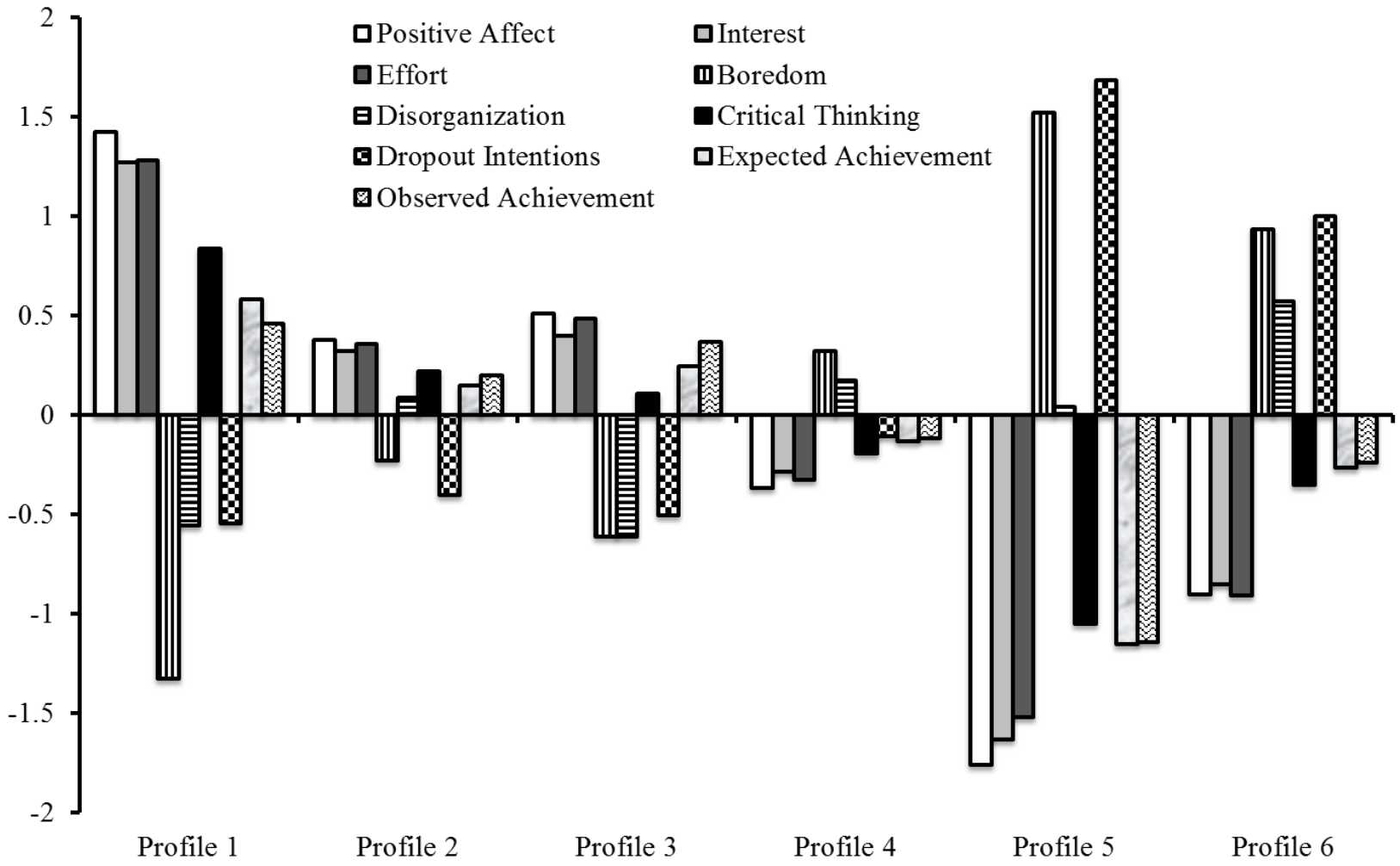

Figure 2. Outcome levels (equal across time) in the final 6-profile solution.
Note. Indicators of positive affect, interest, effort, boredom, disorganization, and critical thinking are estimated from factor scores with mean of 0 and a standard deviation of 1; other indicators have been standardized for this figure; Profile 1: Autonomous; Profile 2: Strongly Motivated; Profile 3: Moderately Autonomous; Profile 4: Moderately Unmotivated; Profile 5: Poorly Motivated; Profile 6: Controlled.

Table 1

Results from the Latent Profile Analyses and Latent Transition Analyses

Model	LL	#fp	Scaling	AIC	CAIC	BIC	ABIC	Entropy
Final Latent Profile Analyses								
Time 1 (*N*=504)	-2213.248	65	1.114	4556.496	4895.964	4830.964	4624.648	.901
Time 2 (*N*=461)	-2182.733	65	1.118	4495.466	4829.136	4764.136	4557.844	.909
Longitudinal Latent Profile Analyses								
Configural Similarity	-4395.981	130	1.1156	9051.962	9730.897	9600.897	9188.265	.868
Structural Similarity	-4452.283	100	1.5022	9104.565	9626.823	9526.823	9209.414	.857
Dispersion Similarity	-4465.009	70	1.4886	9070.019	9435.599	9365.599	9143.412	.854
Distributional Similarity	-4471.966	65	1.5900	9073.932	9413.399	9348.399	9142.083	.854
Latent Transition Analysis	-1382.086	35	0.7714	2834.171	3016.961	2981.961	2870.868	.844
Predictive Similarity								
Profile-Specific Free Relations with Predictors	-1227.957	155	0.5228	2765.914	3561.59	3406.590	2914.663	.882
Free Relations with Predictors	-1266.290	65	0.8224	2662.580	2996.251	2931.251	2724.959	.870
Equal Relations with Predictors	-1276.509	50	0.8991	2653.018	2909.688	2859.688	2701.001	.864
Explanatory Similarity								
Free Relations with Outcomes	-11804.281	154	1.2566	23916.562	24720.839	24566.839	24078.029	.878
Equal Relations with Outcomes	-11666.466	106	1.4538	23544.931	24098.524	23992.524	23656.070	.881

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

Table 2

Transitions Probabilities for the Final Latent Transition Analysis

	Transition Probabilities to Time 2 Profiles					
	Profile 1	Profile 2	Profile 3	Profile 4	Profile 5	Profile 6
Time 1						
Profile 1	.759	.076	.106	.010	.000	.049
Profile 2	.092	.737	.000	.088	.002	.082
Profile 3	.057	.192	.556	.195	.000	.000
Profile 4	.000	.170	.086	.492	.111	.139
Profile 5	.000	.014	.025	.134	.706	.122
Profile 6	.000	.010	.000	.026	.005	.959

Note. Profile 1: Autonomous; Profile 2: Strongly Motivated; Profile 3: Moderately Autonomous; Profile 4: Moderately Unmotivated; Profile 5: Poorly Motivated; Profile 6: Controlled.

Table 3

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

	Profile 1 vs. Profile 6		Profile 2 vs. Profile 6		Profile 3 vs. Profile 6		Profile 4 vs. Profile 6		Profile 5 vs. Profile 6	
	Coef. (SE)	OR	Coef. (SE)	OR	Coef. (SE)	OR	Coef. (SE)	OR	Coef. (SE)	OR
Perfectionism	.792 (.214)**	2.207	.560 (.159)**	1.750	.152 (.173)	1.165	.028 (.164)	1.029	-.457 (.223)*	0.633
Sex	.922 (.411)*	2.516	.815 (.317)**	2.260	1.033 (.368)**	2.810	.546 (.333)	1.726	.605 (.425)	1.831
Age	.192 (.092)*	1.212	.152 (.092)	1.164	.139 (.087)	1.149	.123 (.113)	1.131	.059 (.106)	1.061
	Profile 1 vs. Profile 5		Profile 2 vs. Profile 5		Profile 3 vs. Profile 5		Profile 4 vs. Profile 5		Profile 1 vs. Profile 4	
	Coef. (SE)	OR	Coef. (SE)	OR	Coef. (SE)	OR	Coef. (SE)	OR	Coef. (SE)	OR
Perfectionism	1.249 (.258)**	3.487	1.017 (.210)**	2.765	.610 (.212)**	1.840	.486 (.200)*	1.625	.763 (.193)**	2.145
Sex	.317 (.495)	1.374	.210 (.413)	1.234	.428 (.439)	1.534	-.059 (.419)	0.943	.377 (.392)	1.457
Age	.133 (.082)	1.142	.092 (.081)	1.097	.080 (.073)	1.083	.064 (.102)	1.066	.069 (.105)	1.071
	Profile 2 vs. Profile 4		Profile 3 vs. Profile 4		Profile 1 vs. Profile 3		Profile 2 vs. Profile 3		Profile 1 vs. Profile 2	
	Coef. (SE)	OR	Coef. (SE)	OR	Coef. (SE)	OR	Coef. (SE)	OR	Coef. (SE)	OR
Perfectionism	.531 (.129)**	1.701	.124 (.135)	1.132	.639 (.195)**	1.895	.407 (.137)**	1.503	.232 (.179)	1.261
Sex	.269 (.291)	1.309	.487 (.332)	1.628	-.111 (.419)	0.895	-.218 (.328)	0.804	.107 (.367)	1.113
Age	.028 (.108)	1.029	.016 (.092)	1.016	.053 (.032)	1.054	.013 (.030)	1.013	.040 (.028)	1.041

Note. * $p < .05$; ** $p < .01$; SE: Standard Error of the coefficient; OR: Odds Ratio. The coefficients and OR reflects the effects of the predictors on the likelihood of membership into the first listed profile relative to the second listed profile. Profile 1: Autonomous; Profile 2: Strongly Motivated; Profile 3: Moderately Autonomous; Profile 4: Moderately Unmotivated; Profile 5: Poorly Motivated; Profile 6: Controlled.

Table 4

Associations between Profile Membership and the Outcomes (Equal Across Time)

	Profile 1 M [CI]	Profile 2 M [CI]	Profile 3 M [CI]	Profile 4 M [CI]	Profile 5 M [CI]	Profile 6 M [CI]	Summary of Significant Differences
Positive Affect	1.420 [1.208; 1.632]	.379 [.168; .589]	.509 [.374; .645]	-.368 [-.479; -.258]	-1.763 [-2.034; -1.492]	-.904 [-1.033; -.776]	1 > 2 = 3 > 4 > 6 > 5
Interest	1.271 [1.053; 1.488]	.318 [.108; .528]	0.399 [.237; .562]	-.289 [-.382; -.195]	-1.632 [-1.894; -1.370]	-.851 [-1.019; -.683]	1 > 2 = 3 > 4 > 6 > 5
Effort	1.278 [1.090; 1.465]	.357 [.127; .587]	.486 [.311; .661]	-.326 [-.450; -.202]	-1.521 [-1.746; -1.297]	-.911 [-1.058; -.764]	1 > 2 = 3 > 4 > 6 > 5
Boredom	-1.327 [-1.594; -1.060]	-.228 [-.456; .000]	-.615 [-.760; -.470]	.322 [.214; .431]	1.519 [1.278; 1.760]	.932 [.796; 1.069]	5 > 6 > 4 > 2 > 3 > 1
Disorganization	-.559 [-.804; -.313]	.085 [-.120; .290]	-.614 [-.835; -.393]	.172 [.001; .343]	.042 [-.225; .308]	.568 [.358; .778]	6 > 2 = 4 = 5 > 1 = 3
Critical Thinking	.836 [.577; 1.095]	.218 [.039; .398]	.106 [-.042; .254]	-.193 [-.380; -.005]	-1.053 [-1.368; -0.738]	-.354 [-.610; -.097]	1 > 2 = 3 > 4 = 6 > 5
Dropout Intentions	1.128 [1.007; 1.249]	1.368 [1.228; 1.508]	1.195 [1.060; 1.331]	1.869 [1.609; 2.130]	4.894 [4.216; 5.572]	3.736 [3.106; 4.365]	5 > 6 > 4 > 2 = 3; 2 > 1; 5 > 6 > 4 > 1 = 3
Expected Achievement	12.120 [11.735; 12.505]	11.456 [11.184; 11.728]	11.606 [11.221; 11.991]	11.030 [10.791; 11.268]	9.483 [8.805; 10.162]	10.828 [10.461; 11.196]	2 = 3 > 4 = 6 > 5; 1 > 2 1 = 3 > 4 = 6 > 5
Observed Achievement	11.568 [10.895; 12.242]	10.923 [10.407; 11.439]	11.337 [10.755; 11.918]	10.160 [9.660; 10.661]	7.659 [6.505; 8.812]	9.857 [9.266; 10.447]	1 = 2 = 3 > 4 = 6 > 5

Note. M: Mean; CI: 95% Confidence Interval. Indicators of positive affect, interest, effort, boredom, disorganization, and critical thinking are estimated from factor scores with mean of 0 and a standard deviation of 1. Profile 1: Autonomous; Profile 2: Strongly Motivated; Profile 3: Moderately Autonomous; Profile 4: Moderately Unmotivated; Profile 5: Poorly Motivated; Profile 6: Controlled.

Online Supplemental Materials for:

Stability and Change in Students' Motivation Profiles: A Latent Transition Analysis

Preliminary Measurement Models

Preliminary measurement models were estimated using Mplus 7.31 (Muthén & Muthén, 2015). Due to the complexity of the longitudinal measurement models underlying all constructs assessed in the present study, these preliminary analyses were conducted separately for the motivation variables and the covariates (predictors and outcomes).

For the motivation measure, a confirmatory factor analytic model (CFA) including five a priori correlated factors (intrinsic motivation, identified regulation, introjected regulation, external regulation, and amotivation) was first estimated at each separated time points. All factors were specified as defined by their a priori indicators, with no cross-loadings or correlated uniquenesses. A longitudinal model was then estimated across both time points and included a total of 10 correlated factors (5 a priori factors x two time points) for the motivation measure. All factors were freely allowed to correlate across and within time points. A priori correlated uniquenesses between matching indicators of the factors utilized at the different time-points were included in the longitudinal models (e.g., Marsh et al., 2013). A similar set of CFA models were estimated for the latent covariates (predictors and outcomes estimated with more than one indicator), including a total of 8 correlated factors at each time points (self-oriented perfectionism, anxiety, positive affect, interest, effort, boredom, disorganization, and critical thinking), and a priori correlated uniquenesses among matching indicators utilized at the different time-points.

All of these measurement models were estimated with the robust weighted least square estimator (WLSMV). The choice to rely on WLSMV estimation is linked to the fact that this estimator is more suited to the ordered-categorical nature of the Likert scales used in the present study than traditional maximum likelihood (ML) estimation or robust alternatives (MLR) (Finney & DiStefano, 2013), especially when the response categories follow asymmetric thresholds (as is the case for all measures used in this study). In these conditions, WLSMV estimation has been found to outperform ML/MLR (Bandalos, 2014; Beauducel & Herzberg, 2006; Finney & DiStefano, 2013; Flora & Curran, 2004; Lubke & Muthén, 2004; Rhemtulla, Brosseau-Liard, & Savalei, 2012). Recent studies conducted on motivational data have also documented the advantages of relying on a WLSMV estimator (Guay, Morin, Litalien, & Valois, 2015; Litalien, Guay, & Morin, 2015).

We verified that the measurement models operated in the same manner across time points through tests of measurement invariance (Millsap, 2011; Morin et al., 2011): (1) configural invariance, (2) weak invariance (loadings), (3) strong invariance (loadings and thresholds), (4) strict invariance (loadings, thresholds, and uniquenesses), (5) invariance of the latent variances-covariances (loadings, thresholds, uniquenesses, and latent variances-covariances), and (6) latent means invariance (loadings, thresholds, uniquenesses, latent variances-covariances, and latent means). Given the known oversensitivity of the chi-square test of exact fit (χ^2) to sample size and minor model misspecifications (e.g., Marsh, Hau, & Grayson, 2005), we relied on sample-size independent goodness-of-fit indices to describe the fit of the alternative models (Hu & Bentler, 1999; Yu, 2002): the comparative fit index (CFI), the Tucker-Lewis index (TLI), as well as the root mean square error of approximation (RMSEA) and its 90% confidence interval. Values greater than .90 for the CFI and TLI indicate adequate model fit, although values greater than .95 are preferable. Values smaller than .08 or .06 for the RMSEA respectively support acceptable and excellent model fit. Like the chi square, chi square difference tests present a known sensitivity to sample size and minor model misspecifications so that recent studies suggest complementing this information with changes in CFI and RMSEA (Chen, 2007; Cheung & Rensvold, 2002) in the context of tests of measurement invariance. A ΔCFI/TLI of .010 or less and a ΔRMSEA of .015 or less between a more restricted model and the previous one supports the invariance hypothesis. Composite reliability coefficients associated with each of the a priori factors are calculated from the model standardized parameters using McDonald (1970) omega (ω) coefficient:

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

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

Longitudinal CFAs were estimated using the data from all respondents who completed at least one measurement point (N = 504) rather than a listwise deletion strategy focusing on the subset of

participants (N = 461) having answered both time points (Enders, 2010; Graham, 2009). To account for missing responses, models were estimated based on the full available information, based on algorithms implemented in Mplus for WLSMV (Asparouhov & Muthén, 2010). This approach thus provided a relatively efficient way of handling the limited number of missing responses on subsets of items at specific time-points (participants who completed each specific time point left on average 0.8% of missing responses at Time 1 and 0.5% of missing responses at Time 2). This procedure allows missing data to be conditional on all observed and latent variables included in the model, which includes the constructs themselves at the previous time point in this study. Still, a key limitation of WLSMV estimation, when compared to ML/MLR, is the reliance on a slightly less efficient way of handling missing data (Asparouhov & Muthén, 2010). For this reason, factor scores saved from the most invariant of these models were not used to impute missing responses at Time 2 for participants who only completed the Time 1 questionnaire given that the MLR estimator used to estimate the main models used in the present study is more efficient to handle missing time points (Enders, 2010; Graham, 2009). This procedure has comparable efficacy to multiple imputation, while being more efficient (Enders, 2010; Jeličič, Phelps, & Lerner, 2009; Larsen, 2011).

The goodness-of-fit results from all models are reported in Table S1. These results support the adequacy of the a priori longitudinal measurement models (with all CFI/TLI ≥ .95 and all RMSEA ≤ .06 for the motivation models; and all CFI/TLI ≥ .90 and all RMSEA ≤ .08 for the covariates models), as well as their complete measurement invariance across time points as none of the changed in goodness-of-fit indices exceeded the recommended cut-off scores (ΔCFI ≤ .010; ΔTLI ≤ .010; ΔRMSEA ≤ .015). To ensure that the latent profiles estimated at each time point were based on fully comparable measures of motivation, the factor scores used in main analyses were saved from the models of complete measurement invariance (loadings, thresholds, uniquenesses, latent variance-covariance, and latent means). Although only strict measurement invariance is required to ensure that measurement of the constructs remains equivalent across time points for models based on factor scores (e.g., Millsap, 2011), there are advantages to saving factors scores from a model of complete measurement invariance for use in latent profile analyses. Indeed, saving factor scores based on a measurement model in which both the latent variances and the latent means are invariant (i.e., respectively constrained to take a value of 1 and 0 in all time points) provides scores on profile indicators that can be readily interpreted as deviation from the grand mean expressed in standard deviation units. The observation of latent mean invariance across time point for the various measures indicates that, on the average, the sample is neither characterized by increases or decreases in levels of motivation or covariates over time.

The final parameter estimates from this measurement model, together with reliability information are reported in Table S2 for the motivation model, and Table S3 for the covariates model, while the correlations between all variables used in the main analyses (i.e., the factor scores saved from these final measurement models) are reported in the main manuscript. Generally, all factors were well-defined through high factor loadings (|λ|), resulting in fully acceptable model-based composite reliability coefficient, ranging from ω = .793 to .953.

References used in this supplement

Asparouhov, T., & Muthén, B. O. (2010). *Weighted least square estimation with missing data*. www.statmodel.com/download/GstrucMissingRevision.pdf

Bandalos, D. L. (2014). Relative performance of categorical diagonally weighted least squares and robust maximum likelihood estimation. *Structural Equation Modeling, 21*, 102-116.

Beauducel, A., & Herzberg, P. Y. (2006). On the performance of maximum likelihood versus means and variance adjusted weighted least squares estimation in CFA. *Structural Equation Modeling, 13*, 186-203.

Chen, F. F. (2007). Sensitivity of goodness of fit indexes to lack of measurement. *Structural Equation Modeling, 14*, 464-504.

Cheung, G. W., & Rensvold, R. B. (2002). Evaluating goodness-of fit indexes for testing measurement invariance. *Structural Equation Modeling, 9*, 233-255.

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

Finney, S. J., & DiStefano, C. (2013). Non-normal and categorical data in structural equation modeling. In G. R. Hancock & R. O. Mueller (Eds), *Structural equation modeling: A second course, 2nd edition* (pp. 439-492). Greenwich, CO: IAP.

Flora, D. B., & Curran, P. J. (2006). An empirical evaluation of alternative methods of estimation for

confirmatory factor analysis with ordinal data. *Psychological Methods, 9,* 466-491.

Graham, J. W. (2009). Missing data analysis: Making it work in the real world. *Annual Review of Psychology, 60,* 549-576.

Guay, F., Morin, A. J. S., Litalien, D., Valois, P., & Vallerand, R. J. (2015). Application of exploratory structural equation modeling to evaluate the academic motivation scale. *Journal of Experimental Education, 83,* 51-82.

Hu, L.-T., & Bentler, P. M. (1999). Cutoff criteria for fit indexes in covariance structure analysis: Conventional criteria versus new alternatives. *Structural Equation Modeling, 6,* 1-55.

Jeličič, H., Phelps, E., & Lerner, R.M. (2009). Missing data methods in longitudinal studies: The persistence of bad practices. *Developmental Psychology, 45,* 1195-1199.

Larsen, R. (2011). Missing data imputation versus full information maximum likelihood with second level dependencies. *Structural Equation Modeling, 18,* 649-662.

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

Lubke, G., & Muthén, B. (2004). Applying multigroup confirmatory factor models for continuous outcomes to Likert scale data complicates meaningful group comparisons. *Structural Equation Modeling, 11,* 514-534.

Marsh, H. W., Abduljabbar, A. S., Abu-Hilal, M., Morin, A. J. S., Abdelfattah, F., Leung, K. C., Xu, M. K., Nagengast, B., & Parker, P. (2013). Factor structure, discriminant and convergent validity of TIMSS math and science motivation measures: A comparison of USA and Saudi Arabia. *Journal of Educational Psychology, 105,* 108-128.

Marsh, H. W., Hau, K., & Grayson, D. (2005). Goodness of fit in structural equation models. In A. Maydeu-Olivares & J.J. McArdle (Eds.), *Contemporary psychometrics: A festschrift for Roderick P. McDonald* (pp. 275-340). Mahwah, NJ: Erlbaum.

McDonald, R. P. (1970). Theoretical foundations of principal factor analysis, canonical factor analysis, and alpha factor analysis. *British Journal of Mathematical & Statistical Psychology, 23,* 1-21.

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

Morin, A. J. S., Moullec, G., Maïano, C., Layet, L., Just. J.-L., & Ninot, G. (2011). Psychometric properties of the Center for Epidemiologic Studies Depression Scale (CES-D) in French clinical and non-clinical adults. *Epidemiology and Public Health, 59,* 327-340.

Muthén, L. K., & Muthén, B. O. (2016). *Mplus user's guide*. Los Angeles, CA: Muthén & Muthén.

Rhemtulla, M., Brosseau-Liard, P. É., & Savalei, V. (2012). When can categorical variables be treated as continuous? A comparison of robust continuous and categorical SEM estimation methods under suboptimal conditions. *Psychological Methods, 17,* 354-373.

Yu, C. Y. (2002). *Evaluating cutoff criteria of model fit indices for latent variable models with binary and continuous outcomes*. Los Angeles, CA: University of California.

Table S1

Goodness-of-Fit Statistics of the Preliminary Measurement Models

Description	χ^2 (*df*)	CFI	TLI	RMSEA	90% CI	MD $\Delta\chi^2$ (*df*)	ΔCFI	ΔTLI	ΔRMSEA
Motivation Measurement Models									
Time 1 (N = 504)	455.005 (160)*	.977	.972	.060	[.054; .067]	-	-	-	-
Time 2 (N = 461)	511.153 (160)*	.986	.984	.069	[.062; .076]	-	-	-	-
Longitudinal configural invariance (N = 504)	1301.422 (675)*	.983	.980	.043	[.039; .046]	-	-	-	-
Longitudinal weak invariance	1320.242 (690)*	.982	.980	.043	[.039; .046]	21.336 (15)	-.001	.000	.000
Longitudinal strong invariance	1415.457 (784)*	.982	.983	.040	[.037; .043]	115.543 (94)	.000	+.003	-.003
Longitudinal strict invariance	1552.388 (804)*	.979	.980	.043	[.040; .046]	158.221 (20)*	-.003	-.003	+.003
Longitudinal latent variance-covariance invariance	1693.254 (819)*	.976	.977	.046	[.043; .049]	92.183 (15)*	-.003	-.003	+.003
Longitudinal latent means Invariance	1865.253 (824)*	.971	.973	.050	[.047; .053]	103.432 (5)*	-.005	-.004	+.004
Covariates Measurement Models									
Time 1 (N = 504)	944.336 (303)*	.941	.931	.065	[.060; .070]	-	-	-	-
Time 2 (N = 461)	890.812 (303)*	.968	.962	.065	[.060; .070]	-	-	-	-
Longitudinal configural invariance (N = 504)	2511.075 (1259)*	.955	.949	.044	[.042; .047]	-	-	-	-
Longitudinal weak invariance	2524.758(1279)*	.955	.950	.044	[.041; .046]	30.582 (20)	.000	+.001	.000
Longitudinal strong invariance	2765.878 (1395)*	.951	.950	.044	[.042; .047]	392.635 (116)*	-.004	.000	.000
Longitudinal strict invariance	2796.558 (1422)*	.951	.951	.044	[.041; .046]	88.750 (27)*	.000	+.001	.000
Longitudinal latent variance-covariance invariance	2897.718 (1450)*	.948	.949	.045	[.042; .047]	117.808 (28)*	-.003	-.002	+.001
Longitudinal latent means Invariance	3071.081 (1457)*	.942	.943	.047	[.045; .049]	131.565 (7)*	-.006	-.006	+.002

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

Table S2

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

Items	Factor 1 λ	Factor 2 λ	Factor 3 λ	Factor 4 λ	Factor 5 λ	δ
1. Intrinsic						
Item 1	.916					.161
Item 2	.916					.162
Item 3	.856					.267
Item 4	.900					.190
ω	.943					
2. Identified						
Item 1		.632				.601
Item 2		.871				.242
Item 3		.848				.282
Item 4		.904				.182
ω		.890				
3. Introjected						
Item 1			.721			.481
Item 2			.896			.197
Item 3			.921			.152
Item 4			.743			.449
ω			.894			
4. External						
Item 1				.594		.648
Item 2				.921		.151
Item 3				.922		.150
Item 4				.759		.423
ω				.882		
5. Amotivation						
Item 1					.914	.165
Item 2					.831	.309
Item 3					.934	.128
Item 4					.970	.058
ω					.953	

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

Table S3

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

Items	Factor 1 λ	Factor 2 λ	Factor 3 λ	Factor 4 λ	Factor 5 λ	Factor 6 λ	Factor 7 λ	δ
1. Positive Affect								
Item 1	.737							.457
Item 2	.443							.804
Item 3	.812							.340
Item 4	.667							.555
Item 5	.610							.627
ω	.793							
2. Perfectionism								
Item 1		.767						.411
Item 2		.766						.413
Item 3		.780						.391
Item 4		.752						.434
Item 5		.642						.588
ω		.860						
3. Interest								
Item 1			.945					.107
Item 2			.943					.112
Item 3			.848					.280
ω			.938					
4. Effort								
Item 1				.800				.359
Item 2				.866				.251
Item 3				.904				.184
ω				.893				
5. Boredom								
Item 1					.625			.610
Item 2					.833			.307
Item 3					.825			.320
ω					.808			
6. Disorganization								
Item 1						.731		.466
Item 2						.766		.413
Item 3						.861		.260
ω						.830		
7. Critical Thinking								
Item 1							.605	.634
Item 2							.786	.383
Item 3							.748	.440
Item 4							.751	.436
Item 5							.630	.604
ω							.832	

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

Table S4

Correlations between Variables Used in the Present Study

Variable	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15
1. Sex	—														
2. Age	-.095*	—													
3. Intrinsic Motivation (T1)	.051	.120*	—												
4. Identified Regulation (T1)	.062	.158**	.910**	—											
5. Introjected Regulation (T1)	-.051	-.016	-.037	.090	—										
6. External Regulation (T1)	-.078	.015	-.162**	.016	.813**	—									
7. Amotivation (T1)	-.067	-.088	-.725**	-.682**	.369**	.475**	—								
8. Self-Oriented Perfectionism (T1)	-.027	.043	.237**	.277**	.173**	.145**	-.155**	—							
9. Positive Affect (T1)	.103*	.174**	.702**	.660**	-.110*	-.151**	-.649**	.396**	—						
10. Interest (T1)	.084	.140**	.711**	.596**	-.083	-.154**	-.576**	.169**	.782**	—					
11. Effort (T1)	.167**	.147**	.601**	.556**	-.099*	-.123*	-.571**	.408**	.870**	.701**	—				
12. Boredom (T1)	-.112*	-.149**	-.600**	-.533**	.184**	.246**	.644**	-.191**	-.862**	-.743**	-.746**	—			
13. Disorganization (T1)	.024	-.062	-.136**	-.107*	.286**	.278**	.349**	-.100*	-.314**	-.109*	-.338**	.388**	—		
14. Critical Thinking (T1)	-.187**	.088	.342**	.339**	-.013	.007	-.214**	.284**	.499**	.355**	.316**	-.313**	-.220**	—	
15. Dropout Intentions (T1)	-.004	-.076	-.578**	-.574**	.062	.124*	.600**	-.115*	-.499**	-.419**	-.417**	.504**	.181**	-.149**	—
16. Expected Achievement (T1)	-.112*	.086	.335**	.328**	.027	-.007	-.283**	.259**	.363**	.215**	.246**	-.284**	-.181**	.289**	-.298**
17. Intrinsic Motivation (T2)	.025	.146**	.821**	.726**	-.017	-.060	-.669**	.228**	.692**	.692**	.597**	-.621**	-.163**	.326**	-.545**
18. Identified Regulation (T2)	.025	.188**	.760**	.806**	.058	.080	-.640**	.261**	.664**	.594**	.553**	-.563**	-.124*	.344**	-.545**
19. Introjected Regulation (T2)	-.040	-.049	-.041	.078	.815**	.719**	.300**	.157**	-.089	-.053	-.102*	.157**	.310**	-.035	.050
20. External Regulation (T2)	-069	-.037	-.206**	-.066	.667**	.840**	.475**	.099*	-.212**	-.196**	-.188**	.297**	.322**	-.038	.175**
21. Amotivation (T2)	-.063	-.108*	-.579**	-.584**	.287**	.295**	.849**	-.154**	-.598**	-.506**	-.539**	.600**	.352**	-.197**	.528**
22. Self-Oriented Perfectionism (T2)	-.049	.063	.204**	.243**	.185**	.169**	-.148**	.866**	.370**	.159**	.378**	-.183**	-.057	.227**	-.090
23. Positive Affect (T2)	.085	.190**	.628**	.591**	-.052	-.073	-.584**	.316**	.870**	.697**	.776**	-.790**	-.251**	.403**	-.462**
24. Interest (T2)	.073	.146**	.623**	.540**	-.003	-.043	-.519**	.176**	.694**	.784**	.600**	-.667**	-.074	.265**	-.407**
25. Effort (T2)	.149**	.168**	.525**	.509**	-.048	-.045	-.496**	.292**	.751**	.551**	.805**	-.669**	-.243**	.228**	-.405**
26. Boredom (T2)	-.099*	-.147**	-.512**	-.465**	.105*	.137**	.565**	-.170**	-.719**	-.608**	-.653**	.855**	.309**	-.193**	.448**
27. Disorganization (T2)	.020	-.070	-.137**	-.134**	.230**	.209**	.334**	-.093	-.287**	-.096*	-.286**	.340**	.877**	-.175**	.174**
28. Critical Thinking (T2)	-.210**	.134**	.353**	.351**	-.014	.027	-.243**	.273**	.500**	.358**	.311**	-.356**	-.217**	.882**	-.194**
29. Dropout Intentions (T2)	.023	-.087	-.420**	-.447**	-.020	.023	.501**	-.076	-.385**	-.319**	-.342**	.393**	.166**	-.089	.641**
30. Expected Achievement (T2)	-.116*	.093	.338**	.360**	.036	.014	-.317**	.274**	.367**	.211**	.264**	-.282**	-.177**	.234**	-.306**
31. Observed Achievement	.103*	-.001	.256**	.228**	.014	-.067	-.229**	.105*	.289**	.208**	.193**	-.274**	-.070	.128**	-.271**

Table S4 (Continued)

	16	17	18	19	20	21	22	23	24	25	26	27	28	29	30
16. Expected Achievement (T1)	–														
17. Intrinsic Motivation (T2)	.313**	–													
18. Identified Regulation (T2)	.315**	.919**	–												
19. Introjected Regulation (T2)	.025	-.020	.113*	–											
20. External Regulation (T2)	-.046	-.240**	-.067	.822**	–										
21. Amotivation (T2)	-.265**	-.760**	-.721**	.316**	.512**	–									
22. Self-Oriented Perfectionism (T2)	.251**	.256**	.297**	.196**	.128**	-.180**	–								
23. Positive Affect (T2)	.341**	.768**	.727**	-.059	-.212**	-.665**	.370**	–							
24. Interest (T2)	.224**	.773**	.681**	.006	-.172**	-.597**	.207**	.833**	–						
25. Effort (T2)	.222**	.656**	.628**	-.073	-.187**	-.591**	.384**	.879**	.752**	–					
26. Boredom (T2)	-.270**	-.674**	-.611**	.119*	.276**	.659**	-.202**	-.890**	-.788**	-.780**	–				
27. Disorganization (T2)	-.179**	-.216**	-.189**	.282**	.308**	.405**	-.101*	-.331**	-.139**	-.338**	.420**	–			
28. Critical Thinking (T2)	.320**	.433**	.448**	-.049	-.068	-.301**	.288**	.545**	.413**	.390**	-.390**	-.273**	–		
29. Dropout Intentions (T2)	-.191**	-.564**	-.548**	.006	.191**	.628**	-.059	-.502**	-.462**	-.449**	.516**	.257**	-.197**	–	
30. Expected Achievement (T2)	.747**	.359**	.368**	-.002	-.095*	-.361**	.250**	.379**	.280**	.284**	-.310**	-.201**	.275**	-.316**	–
31. Observed Achievement	.326**	.304**	.256**	.008	-.133**	-.276**	.088	.326**	.281**	.218**	-.308**	-.090	.164**	-.322**	.367**

Note. T1: Time 1; T2: Time 2; For all types of motivation, self-oriented perfectionism, positive affect, interest, effort, boredom, disorganization, and critical thinking, scores are factor scores from preliminary models with a mean of 0 and standard deviation of 1. * $p < .05$; ** $p < .01$.

Table S5

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

Model	LL	#fp	Scaling	AIC	CAIC	BIC	ABIC	Entropy	aLMR	BLRT
Time 1 (N = 504)										
1 Profile	-3072.797	10	0.973	6165.595	6217.821	6207.821	6176.080	Na	Na	Na
2 Profiles	-2751.153	21	1.088	5544.306	5653.980	5632.980	5566.324	.814	< .001	< .001
3 Profiles	-2560.311	32	1.171	5184.622	5351.744	5319.744	5218.173	.846	< .001	< .001
4 Profiles	-2421.645	43	1.697	4929.289	5153.860	5110.860	4974.374	.845	.569	< .001
5 Profiles	-2309.315	54	1.096	4726.630	5008.649	4954.649	4783.248	.892	< .001	< .001
6 Profiles	-2213.248	65	1.114	4556.496	4895.964	4830.964	4624.648	.901	.062	< .001
7 Profiles	-2140.941	76	1.344	4433.881	4830.797	4754.797	4513.566	.896	.608	< .001
8 Profiles	-2080.877	87	1.204	4335.755	4790.119	4703.119	4426.973	.897	.239	< .001
9 Profiles	-2028.589	98	1.076	4253.179	4764.991	4666.991	4355.930	.904	.015	< .001
10 Profiles	-1981.059	109	1.180	4180.118	4749.379	4640.379	4294.403	.902	.650	< .001
Time 2 (N = 461)										
1 Profile	-3033.266	10	0.933	6086.532	6137.866	6127.866	6096.128	Na	Na	Na
2 Profiles	-2712.371	21	1.071	5466.741	5574.543	5553.543	5486.894	.828	< .001	< .001
3 Profiles	-2521.391	32	1.216	5106.781	5271.050	5239.050	5137.491	.878	.005	< .001
4 Profiles	-2369.511	43	1.249	4825.023	5045.759	5002.759	4866.289	.892	.011	< .001
5 Profiles	-2277.128	54	1.333	4662.256	4939.460	4885.460	4714.078	.891	.227	< .001
6 Profiles	-2182.733	65	1.118	4495.466	4829.136	4764.136	4557.844	.909	.048	< .001
7 Profiles	-2100.607	76	1.122	4353.214	4743.352	4667.352	4426.149	.914	.047	< .001
8 Profiles	-2032.855	87	1.143	4239.709	4686.315	4599.315	4323.201	.921	.095	< .001
9 Profiles	-1979.053	98	1.112	4154.105	4657.178	4559.178	4248.153	.918	.093	< .001
10 Profiles	-1931.877	109	1.103	4081.755	4641.295	4532.295	4186.359	.915	.151	< .001

Note. LL: model loglikelihood; #fp: number of free parameters; scaling: scaling correction factor associated with robust maximum likelihood estimates; AIC: Akaïke information criteria; CAIC: constant AIC; BIC: Bayesian information criteria; ABIC: sample size adjusted BIC; aLMR: adjusted Lo-Mendel-Rubin likelihood ratio test; BLRT: bootstrap likelihood ratio test.

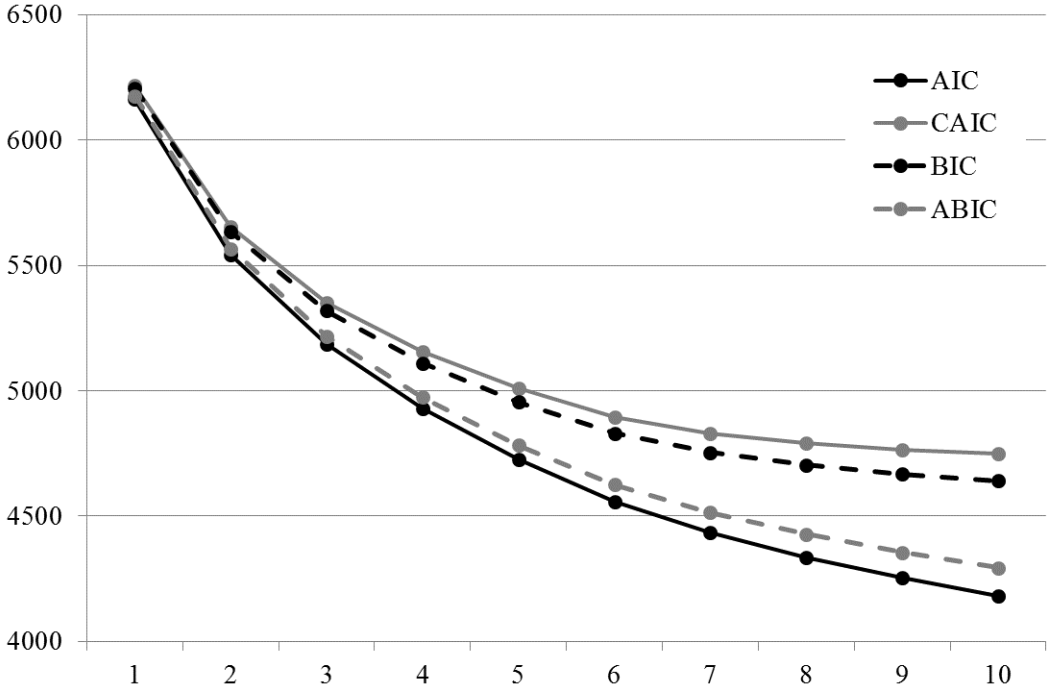

Figure S1
Elbow Plot of the Value of the Information Criteria for Solutions Including Different Number of Latent Profiles (Time 1)

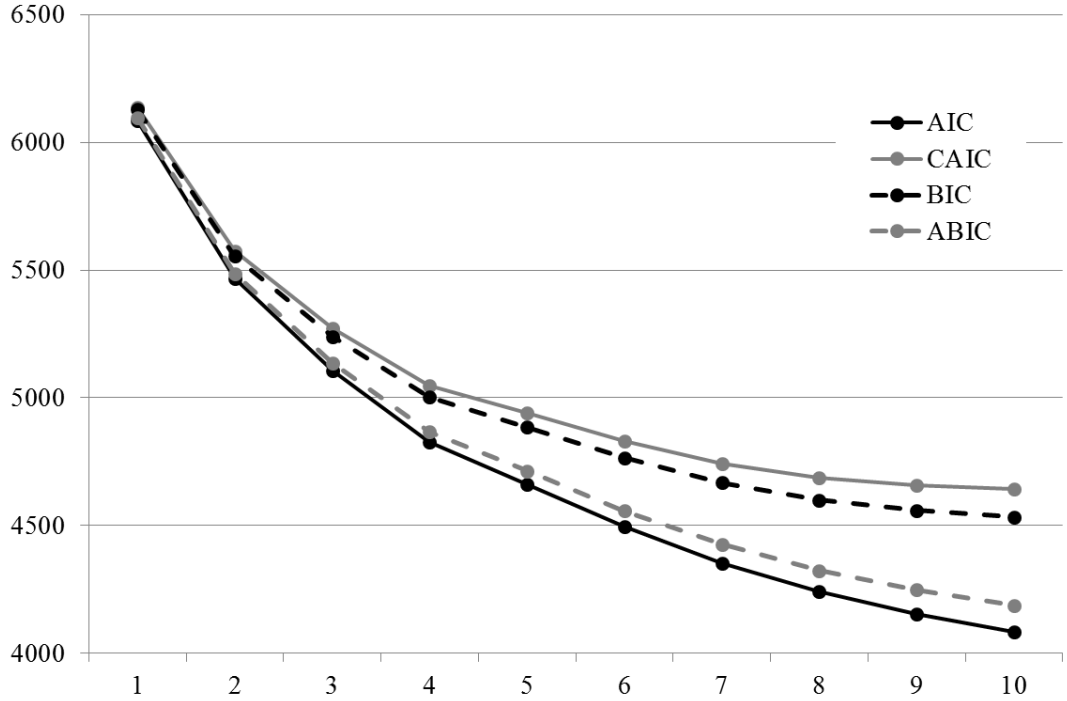

Figure S2
Elbow Plot of the Value of the Information Criteria for Solutions Including Different Number of Latent Profiles (Time 2)

Table S6

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

	Profile 1 Mean [CI]	Profile 2 Mean [CI]	Profile 3 Mean [CI]	Profile 4 Mean [CI]	Profile 5 Mean [CI]	Profile 6 Mean [CI]
Amotivation	-.928 [-1.106; -.750]	-.094 [-.231; .044]	-.714 [-.804; -.624]	.263 [.126; .400]	1.017 [.756; 1.278]	1.173 [.968; 1.377]
External Regulation	.054 [-.211; .319]	.374 [.247; .502]	-.857 [-.973; -.740]	-.167 [-.496; .162]	-.241 [-.476; -.006]	1.108 [.904; 1.313]
Introjected Regulation	.305 [.031; .580]	.423 [.301; .546]	-.794 [-.909; -.679]	-.219 [-.577; .140]	-.536 [-.709; -.364]	.976 [.771; 1.181]
Identified Regulation	1.575 [1.391; 1.759]	.445 [.304; .587]	.357 [.190; .523]	-.475 [-.648; -.301]	-1.758 [-2.054; -1.462]	-.713 [-.872; -.554]
Intrinsic Motivation	1.505 [1.373; 1.637]	.361 [.240; .481]	.530 [.370; .690]	-.422 [-.566; -.277]	-1.639 [-1.992; -1.287]	-.898 [-1.098; -.698]
	Variance [CI]	Variance [CI]	Variance [CI]	Variance [CI]	Variance [CI]	Variance [CI]
Amotivation	.296 [.124; .469]	.219 [.154; .284]	.089 [.059; .119]	.200 [.162; .239]	.457 [.315; .600]	.289 [.209; .369]
External Regulation	.690 [.503; .877]	.337 [.250; .424]	.073 [.034; .112]	.212 [.125; .299]	.331 [.209; .452]	.356 [.263; .448]
Introjected Regulation	.813 [.634; .992]	.319 [.249; .389]	.060 [.024; .097]	.278 [.174; .383]	.207 [.115; .299]	.400 [.280; .520]
Identified Regulation	.110 [.040; .180]	.157 [.113; .201]	.205 [.146; .264]	.104 [.063; .145]	.256 [.148; .365]	.211 [.153; .269]
Intrinsic Motivation	.083 [.049; .117]	.130 [.095; .165]	.215 [.159; .271]	.115 [.077; .152]	.364 [.196; .533]	.248 [.172; .324]

Note. CI = 95% Confidence Interval. The profile indicators are estimated from factor scores with mean of 0 and a standard deviation of 1. Profile 1: Autonomous; Profile 2: Strongly Motivated; Profile 3: Moderately Autonomous; Profile 4: Moderately Unmotivated; Profile 5: Poorly Motivated; Profile 6: Controlled.