Trajectories of Self-Determined Motivation during the Secondary School: A Growth Mixture Analysis

Frédéric Guay[1*+], Alexandre J. S. Morin[2+], David Litalien[1], Joshua L. Howard[3] & William Gilbert[1].

[1]Faculté des sciences de l'éducation, Université Laval, Québec, Canada
[2]Department of Psychology, Concordia University, Quebec, Canada
[3]Monash University, Melbourne, Australia

*Corresponding author:
Frédéric Guay, Ph.D.
Département des fondements et pratiques en éducation
Pavillon des sciences de l'éducation
2320, rue des Bibliothèques
Local 942
Université Laval
Québec (Québec) G1V 0A6
Tél: 418-656-2131 poste 402379
Courriel: Frederic.Guay@fse.ulaval.ca

[+]The first two authors (F.G. & A.J.S.M.) contributed equally to this article and their order was determined at random: Both should thus be considered first authors

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Abstract

Based on an accelerated longitudinal design involving three cohorts of secondary school students followed during three consecutive school years, this study has three main objectives. First, we seek to identify different profiles of students following distinct trajectories of self-determined motivation over the secondary school years. Second, we examine whether different sources of relatedness (father, mother, teachers, peers) predict membership into these motivational trajectory profiles. Third, we look at the consequences of these motivational trajectory profiles in terms of adaptive and maladaptive outcomes. Nine hundred forty-one students (56.1% girls) from three distinct cohorts participated in the first measurement time (309 students initially in Secondary 1, 346 students initially in Secondary 2, 272 students initially in Secondary 3). Results revealed that no generic decline in global levels of self-determined motivation was observed during the secondary school years. Five distinct trajectory profiles in which the proportion of students varied were identified. The many comparisons made between these five profiles indicate few significant differences on sources of relatedness. However, teachers and fathers were important positive predictors of membership into the profiles characterized by higher self-determined trajectories, in addition to having a direct effect on initial levels of self-determined motivation observed within each profile (teachers), and on within-profile increases over time in global levels of self-determined motivation (teachers and fathers). Finally, students in profiles characterized by low self-determined motivation trajectories showed lower levels of adaptive outcomes and higher levels of maladaptive outcomes.

Educational Impact and Implications Statement of the Article

This study suggests that there are distinct subgroups of secondary students defined by how their motivation change over a five-year period. Although most students experience an increase in their motivation over five years, for some students their motivation remains stable and quite low. This last group of students experience low levels of adaptive outcomes (low grades and engagement), but high levels of maladaptive ones (high aggressive and risk behaviors). Moreover, students with high levels of motivation over the five-year period are those who perceive relationships that are more positive with their teachers and fathers. These results suggest that we need to determine ways of improving motivation by focusing on teachers and fathers' relationship quality.

Keywords: Academic Motivation; Self-Determination Continuum; Bifactor-ESEM; Growth Mixture Analyses; Secondary School

Understanding the development of academic motivation during secondary school is an important consideration for educational research (Otis, Grouzet, & Pelletier, 2005). Various trajectories of motivation can be expected among students (e.g., increasing, decreasing, and stable) and identifying why students experience these trajectories could help to inform theory and practice about psychosocial factors responsible for changes in motivation levels. Moreover, these trajectories could lead to different outcomes for students at a developmental period where career choices are particularly salient. Indeed, secondary students having school difficulties (poor grades, social adjustment problems, and low engagement; Otis et al., 2005) stemming from suboptimal motivational trajectories might experience narrower career options that could have long-lasting consequences in their life (job turnover; Colarelli, Dean, & Konstans, 1987). In this study, we investigate self-determined motivation trajectories during secondary school (12 to 16 years old) and the determinants and consequences of these trajectories. Until now, some studies have investigated such trajectories, but relying on a limited number of contextual determinants, weak methodological designs, or suboptimal statistical models. In this regard, there is a need to evaluate different sources of relatedness, namely parents (father and mother), peers, and teachers. Identifying which of these sources of relatedness is more fundamental for the development of optimal motivational trajectories may not only lead to more focused intervention strategies, but also to the refinement of theoretical models focusing on the role of relatedness for human functioning (Baumeister & Leary, 1995). We used self-determination theory (SDT; Ryan & Deci, 2017) to frame the research problem, to propose hypotheses, and to guide the development of our measurement models on motivation. This decision is anchored in the fact that this theory of motivation has been found to be relevant in the prediction of a variety of academic outcomes including achievement, persistence, and engagement (Guay, Ratelle, & Chanal, 2008).

Self-Determination Theory

SDT is a metatheory according to which all humans are expected to be agentic (Ryan & Deci, 2017). Under adequate circumstances, individuals are capable of being proactive and volitional while accomplishing different activities. The extent to which persons are volitional can be captured by various types of regulation underlying their behaviors. According to SDT, these various forms of regulations can be placed along a continuum of self-determination (also referred to as a continuum of relative autonomy) ranging from intrinsic motivation, as the most self-determined regulation, followed by different types of extrinsic motivation and amotivation. Intrinsic motivation is defined as the pleasure and enjoyment individuals experience when performing an activity (Deci, Ryan, & Guay, 2013). The reward is thus in the activity itself. In contrast, extrinsic motivation encompasses contingencies outside the activity itself (Ryan & Deci, 2017). This category of motivation includes three types of regulation that are more or less volitional: identified regulation, introjected regulation, and external regulation. Identified regulation includes behaviors that are performed not because they are pleasurable, but rather because they are important for individuals. When the behavior is introjected, individuals act to avoid negative self-conscious emotions such as guilt and anxiety, or to experience positive emotional states that are based on self-esteem concerns such as approval from others. External regulation is the least self-determined type of motivation. Individuals regulate their behaviors to avoid punishment and threats, or to obtain rewards. Finally, amotivation is defined by a lack of intentionality. Individuals do not see the contingencies behind their behaviors, which are not regulated by either intrinsic or external regulations (Deci & Ryan, 1985).

According to this self-determination continuum, correlations among types of regulation scores are expected to show a simplex-like pattern, with stronger positive correlations between adjacent than distant types (Ryan & Connell, 1989). For example, identified regulation and intrinsic motivation should be more positively correlated than external regulation and intrinsic motivation. Moreover, SDT posits that correlations between types of regulation, antecedents and outcomes should follow the global level of self-determined motivation described by this continuum (Deci & Ryan, 2002). For example, the correlation between intrinsic motivation and academic achievement should be stronger than the correlation between identified regulation and academic achievement. Similarly, the correlation between identified regulation and academic achievement should be stronger than the correlation between introjected regulation and academic achievement.

Based on this continuum, many researchers have claimed that the self-determined quality of motivation is more relevant than its quantity (Ratelle, Guay, Vallerand, Larose, & Senécal, 2007; Vansteenkiste, Sierens, Soenens, Luyckx, & Lens, 2009). However, conceptual issues arise from research testing this proposition, which was mostly done within the confines of confirmatory factor analyses (CFA; Guay, Morin, Litalien, Valois, & Vallerand, 2015) or profile analyses (Ratelle et al., 2007). In past research, motivation factors were usually estimated without prior removal of the variance shared among all items designed to measure the different types of motivation and reflecting this underlying continuum of self-determination. As a result, although items assess various types of regulation, the scores on the same items may also reflect a general factor of self-determination which serves to artificially inflate the correlations among the regulation factors, thus leading to imprecise results in which these two sources of effects are confounded.

Recently, however, researchers have adopted a new approach allowing them to estimate a global factor reflecting participants overarching level of self-determined motivation separately from the unique qualities associated with each specific type of regulations. This bifactor approach has been successfully applied to the study of work motivation (Gillet et al., 2018; Howard, Gagné, Morin, & Forest, 2018), athletic motivation (Gunnell & Gaudreau, 2015), and academic motivation (Litalien et al., 2017), and has generally supported the idea that the main driver of associations with a variety of predictors and outcomes was this global self-determination factor. Conceptually, this global self-determined motivation factor represents an individual's global sense of volition and self-directedness, as distinguished from the regulation subscales which capture the unique qualities of specific regulation motives. For example, whereas identified regulation captures motives relating to the perceived meaningfulness associated with an activity and intrinsic motivation represents the inherent enjoyability and interest of this activity, these subscales also tell us about the overarching degree of volition experienced by an individual for this specific activity. This overarching degree of volition is often referred to as the self-determination continuum within SDT. Traditional measurement models, such as CFA in which each type of regulation is linked to a single factor, conflate this overarching degree of self-determination with the specific characteristics of each unique regulation subscale, therefore obscuring the degree to which covariates are influenced by this overarching level of self-determination relative to the unique characteristics associated with each specific type of regulation. Historically, the degree of self-determination experienced by an individual in relation to an activity has often been estimated through the Relative Autonomy Index (Ryan & Connell, 1989), a complex weighted change score variable combining all forms of regulations in a single manifest score. However, although this index was able to capture participants' relative autonomy, it did so in a way that was severely tainted by measurement error and remained redundant with the specific measures of behavioral regulations (e.g., Chemolli & Gagné, 2014). Through bifactor modeling, we are able to estimate reliably (and therefore able to study) participants' overall degree of self-determination with a non-redundant estimate of the specificity involved in each regulation subscale.

Gillet et al. (2018) reinforce the importance of considering participants' global levels of self-determination in research seeking to better understand the emergence, growth, and outcomes of motivation. In our study, we rely on a similar approach to identify students' developmental trajectories of global self-determined motivation unfolding over the course of the secondary school years. The main advantage of relying on global self-determined academic motivation lies in the fact that it reliably takes into account all of the information related to self-determination contained across items covering all types of regulations, and thereby directly accesses a core aspect of SDT related to participants' location along the continuum of self-determination. Furthermore, previous research conducted in the field of education (Litalien et al., 2017) and management (Howard et al., 2018) also reinforces the importance of considering this global level of self-determined motivation, finding it to be a stronger predictor of outcomes when compared to the remaining specific regulation subscales. In addition, this procedure also has the advantage of reducing the complexity of resulting trajectories, allowing us to achieve a finer grained understanding of the associations between these trajectories, their predictors, and their outcomes.

Longitudinal Trajectories of Self-Determined Motivation during Adolescence

Few studies have systematically looked at the development of self-determined motivation among secondary school students. Specifically, some studies indicate that intrinsic motivation tends to decrease over time throughout the primary and secondary school years (e.g., Gnambs & Hanfstingl, 2016; Leroy & Bressoux, 2016). For example, Gillet, Vallerand, and Lafrenière (2012) observed a decrease in intrinsic motivation between the age of 9 and 15 years old, followed by a slight increase from 15 to 17 years old. They explain this increase by a greater flexibility and autonomy that students might experience in their course choices at this age period. Other types of motivation proposed by SDT have also been shown to decrease over the secondary school years. For example, Otis et al. (2005) demonstrated that all types of extrinsic regulations (identified, introjected, and external) decrease from 8th grade to 10th grade. Thus, students are less motivated toward school in general as they move through the secondary school years. The authors explained these findings by the fact that older students are more engaged in activities such as leisure and work compared with academic ones (Otis et al., 2005). Ratelle, Guay, Larose, and Senécal (2004) observed similar results during the transition from secondary school to college. They noted that most types of regulation showed a decline during the transition, except for intrinsic motivation which increased. However, looking at the heterogeneity of these trajectories, Ratelle et al. (2004) found that introjected and external regulations were very stable among participants, whereas intrinsic and identified regulation trajectories differed across different subpopulations of students, showing an increase for some, and a decrease for others.

Past studies on trajectories of autonomous and controlled motivations are nonetheless characterized by some limitations. With the exception of Ratelle et al. (2004), they adopt a variable-centered approach assuming that the observed trend (e.g., downward trajectory) applies to the entire sample. The possibility that different subpopulations (or profiles) of students may demonstrate distinct trajectories of self-determined motivation varying in intensity is therefore not taken into account. Moreover, most studies have estimated trajectories from scores of several types of motivation rather than examining an overall index of autonomous motivation (Litalien et al., 2017). Although this approach could be useful in some instances, it does not offer the possibility of uncovering different trajectories for a global self-determined motivational construct. In addition, the majority of studies focusing on the development of motivation in primary or secondary school are based on cross-sectional comparison of groups of students varying in age (Corpus, McClintic-Gilbert, & Hayenga, 2009; Gillet et al., 2012; Lepper, Corpus, & Iyengar, 2005; Martinek, Hofmann, & Kipman, 2016). Unfortunately, these studies do not evaluate self-determined motivation over several years, which limits our ability to understand motivational trajectories during the whole secondary school experience.

In this study, we try to overcome these limitations by using (1) an accelerated longitudinal design covering the entire length of secondary school in the Quebec educational system (five years), from Secondary 1 (12 years old; 7th grade) to Secondary 5 (16 years old, 11th grade); (2) a statistical approach that offers the possibility of uncovering different trajectories for different groups of students (Growth Mixture Mode [GMM]; Grimm, Ram, & Estabrook, 2016; Morin et al., 2011) and (3) a global factor of self-determined motivation encompassing all the information embedded in all items (namely the ESEM Bi-factor model; Morin, Arens, & Marsh, 2016). Although the present study would be the first to adopt this approach to study school motivation among a secondary school sample, it is important to acknowledge that a recent study (Gillet et al., 2018) adopted a similar approach to study global self-determination trajectories among a sample of upcoming officers undergoing a nine-month vocational police training program. Results revealed three relatively stable profiles characterized by low, moderate, or high levels of self-determined motivation among officers. However, as noted by the authors, it remains possible for this stability to be a simple artifact of the limited time frame (9 months) and stable context (a single vocational training program), underscoring the need to consider longer periods in studies of self-determined motivation trajectories.

Determinants of Motivational Trajectories

According to SDT, the social context is important for the development of self-determined types of motivation. In this study, we focus on a specific aspect of social context which is relatedness with significant others. Relatedness is considered a basic human need in many theories (see Baumeister & Leary, 1995). Within SDT, relatedness is defined as the basic psychological need to feel connected to others, to love and feel loved, to care and feel cared for (Deci & Ryan, 2000). It is commonly known that different sources of relatedness exist in the ecological system of secondary school students: parents (mother, father), teachers, and peers (Guay, Denault, & Renauld, 2017). These different sources might have more weight on motivational trajectories at different developmental periods. Two different perspectives have been proposed to better understand how these sources of relatedness might predict self-determined motivational trajectories. The first suggests that, as adolescents grow older, they rely less on their father or mother, and more on their peers and teachers (Scholte & Van Aken, 2006). The neo-psychoanalytic and the evolutionary or socio-cognitive perspectives endorse this point of view, positing that increasing independence in adolescence causes closeness to decrease, conflicts to increase, and power to equalize between youth and their parents (De Goede, Branje, & Meeus, 2009). According to this perspective, independence sets the stage for greater self-direction and the possibility to establish new significant relationships, such as those with peers and teachers. The second perspective posits that the process of separation–individuation does not occur at the expense of relatedness with parents (Smollar & Youniss, 1989). According to this perspective, relatedness with parents offers adolescents the opportunity to develop their autonomy and establish new significant relationships with others, such as friends and teachers (Ryan, Stiller, & Lynch, 1994). In other words, relatedness with parents and other sources of relatedness are mutually supportive, an assumption that was recently supported by Ciarrochi, Morin, Sahdra, Litalien, and Parker (2017) who showed that higher levels of social support from peers were generally matched by similar levels of social support from teachers. However, their results also supported the first perspective in showing that levels of peer support did not systematically match those of parent and teacher support.

This theoretical background could lead to different hypotheses regarding the role of each source of relatedness in predicting self-determined motivation. The first perspective would posit that relatedness with parents is less important during adolescence in terms of supporting self-determined motivation whereas the second would suggest that all sources of relatedness are important. However, among studies contrasting the effects of various sources of relatedness on student motivational outcomes, no clear picture has emerged regarding the importance of one source of relatedness over the other. For example, Ryan et al. (1994) reported that adolescents' relatedness with both parents and teachers were significantly associated with intrinsic (see also Learner & Kruger, 1997) and identified regulations toward school, while their relatedness with friends was not. On the other hand, Furrer and Skinner (2003) showed that a sense of relatedness to parents, teachers and peers each predicted students' emotional and behavioral engagement. More recently, Guay et al. (2017) tested, in a cross-lag model, if different sources of relatedness were predictive of self-determined types of academic motivation. Their results indicated that relatedness with parents and friends did not predict self-determined motivation. Only relatedness with teachers and school attachment did (see also Raufelder, Hoferichter, Schneeweiss, & Wood, 2015). Some studies have measured mother and father separately and showed that the absence of support from the father does not constitute a risk factor for developing low self-determined motivation when other sources (mother, teachers and peers) offer some support (Guay, Ratelle, Larose, Vallerand, & Vitaro, 2013). In contrast, other studies have demonstrated that paternal warmth did predict membership into a more desirable self-determined motivation profile over and above maternal warmth (Litalien, Gillet, Gagné, Ratelle, & Morin, 2019). Other studies contrasted only peers and teachers and showed that both sources are important for self-determined motivation (Cox & Ullrich-French, 2010; Gairns, Whipp, & Jackson, 2015). Finally, Gillet et al. (2018) found a positive effect of peer support on self-determined motivation trajectories over the course of a police vocational training program. Unfortunately, their study did not consider the possible additional effects of different sources of social support.

Overall, while recent studies in social psychology have revealed the incremental value of relatedness experiences (Moller, Deci, & Elliot, 2010), it is impossible to draw a clear conclusion from these results. The question as to whether one source of relatedness is more important than others during adolescence thus remains open. In this work, we go a step further than previous studies by measuring different relatedness sources and by making a distinction between mother and father as relatedness agents. Moreover, we verify how these sources contribute independently to the different motivational trajectories observed.

Consequences of Motivational Trajectories

It is well known that more self-determined types of regulations tend to lead to positive consequences (Ryan & Deci, 2017). In the present study, we focus on two adaptive (academic achievement and engagement) and two negative (risk behaviors and aggressive behaviors) outcomes. Among adaptive outcomes, variable- (e.g., Guay, Ratelle, Roy, & Litalien, 2010) and person- (e.g., Gillet et al., 2018) centered studies showed that self-determined motivation is associated with academic achievement or performance. Previous results also showed that self-determined motivation is positively associated with engagement (Jang, Kim, & Reeve, 2016; Ratelle et al., 2007), and more specifically with behavioral, emotional and cognitive engagement (Skinner, Kindermann, Connell, & Wellborn, 2009; Vansteenkiste, Zhou, Lens, & Soenens, 2005).

In terms of maladaptive outcomes, few studies have focused on the relation between self-determined motivation and students' risk behaviors and direct aggressive behaviors toward their peers and teachers. However, it is possible to assume that students having low global levels of self-determined motivation might be at greater risk of exhibiting these maladaptive behaviors (Björkqvist, Lagerspetz, & Kaukiainen, 1992). Indeed, low global levels of self-determined motivation might lead some students to exhibit aggressive behaviors such as harassing peers and teachers. Specifically, students regulating their behavior by internal or external pressures might want to gain attention from others via disruptive behaviors within the classroom setting. Likewise, a mode of functioning mainly driven by more external forces might lead them to assume that others are similarly driven, and thus to assume that aggression might be an efficient mode of regulating others' behaviors. Moreover, the lack of interest and volition they have regarding the educational tasks might lead them to miss some courses, to not complete homework, and to not listen to teachers (Silva & Matos, 2017).

Goals and Hypotheses

Based on an accelerated longitudinal design which involves three cohorts of students (Secondary 1, 2, and 3) followed during three consecutive school years, this study has three main objectives. First, we examine whether there are different profiles of students following distinct trajectories of self-determined motivation over the secondary school years. To achieve this goal, we use a bi-factor ESEM model to extract the variance shared among motivation items via a global factor providing a direct reflection of SDT underlying continuum of self-determined academic motivation. Second, we examine whether different sources of relatedness (father, mother, teachers, peers) predict membership into these distinct motivational trajectory profiles. Third, we look at the consequences of these motivational trajectory profiles in terms of adaptive and maladaptive outcomes. Five hypotheses emerge from these three goals.

Hypothesis 1. Global levels of self-determined motivation will decline over the secondary years for the entire sample of students. This hypothesis is based on previous findings showing that intrinsic motivation and identified regulation decline over the secondary school years.

Hypothesis 2. Despite this general decline, different profiles of students following quantitatively and qualitatively distinct developmental trajectories of self-determined motivation will be identified. Some of these profiles will show a trajectory corresponding to this generic decreasing trend, whereas others will follow stable or increasing trajectories. We adopt an exploratory approach in regard to the exact number or the shape of the different trajectories as no studies have investigated academic motivation profiles from a global self-determined factor estimated from bifactor-ESEM model over a five-year period. However, in accordance with Gillet et al.'s (2018) results, we expect to identify at least three distinct self-determined motivation trajectories.

Hypothesis 3. Students' sources of relatedness will positively predict their membership into profiles characterized by increasing trajectories of self-determined motivation, and into profiles characterized by high and stable trajectories. Profiles characterized by trajectories evidencing either a decrease in global levels of self-determined motivation, or stably low trajectories, will be characterized by lower scores on the relatedness sources.

Hypothesis 4. In accordance with previous results (Guay et al., 2017; Raufelder et al., 2015), it is expected that relatedness with teachers will be the most important source in the prediction of high and increasing self-determined motivational trajectories.

Hypothesis 5. Students characterized by high and stable self-determined motivation trajectories will display a higher level on the adaptive outcomes (academic achievement and engagement) and a lower level on the maladaptive outcomes (risk behaviors and aggressive behaviors) than students characterized by decreasing or low self-determined motivation trajectories.

This study contributes to existing knowledge in three ways. First, it is the first study to investigate the heterogeneity of global self-determined motivation trajectories across the secondary school years (age 12 to 16). Second, this study focuses on adaptive and maladaptive outcomes stemming from these trajectories, something that has rarely been studied before. Third, this study contrasts different sources of relatedness while taking into account differentiated perceptions for the mother and the father.

Method

Participants and Procedure

In November 2003, we distributed questionnaires in seven secondary schools. Nine hundred forty-one students (56.1% girls) from three distinct cohorts participated in the first measurement time (Time 1; 309 students in Secondary 1, $M_{age} = 12.77$, $SD = .792$; 346 students in Secondary 2, $M_{age} = 13.90$, $SD = .799$; 272 students in Secondary 3, $M_{age} = 14.71$, $SD = .763$). Each cohort was followed for two additional and consecutive school years with a one-year interval between each measurement. Attrition rates were acceptable with 812 and 763 students who completed questionnaires at Time 2 and Time 3, respectively. Most of the participants spoke French (94.8%) as a first language and were born in the Canadian province of Quebec (90.3%). Only a small proportion spoke another language (4.8%) or were born in another Canadian province (4.5%) or country (4.6%). Most participants lived with both parents (58%), but some lived solely with their mother (12.6%) or father (3.6%). Another 8% of the students reported living in shared custody, and 11.2% with their mother and her life partner (other than the biological father). Other possible living status (alone, with friends, with another partner, host family) represented less than 3% of the sample. Participants completed each measure yearly, at three occasions. The number of students in each of the seven schools was: 43, 212, 77, 224, 103, 199, and 83. Thus, we collected data from students in three cohorts at seven different schools for three consecutive school years (3 measurement points).

Measures

Academic Motivation. The original *Academic Motivation Scale* (AMS) includes seven subscales, each containing four items representing a possible reason (or regulation) for engaging in school-related academic activities (Vallerand, Blais, Brière, & Pelletier, 1989; French version). Items are scored on a five-point Likert scale ranging from 1 (*strongly disagree*) to 5 (*strongly agree*). In this study, we retained the following four subscales in our questionnaire: intrinsic motivation for knowledge (α = .895 to .900 across time points; e.g., "Because I experience pleasure and satisfaction while learning new things in this course"), identified regulation (α = .792 to .806; e.g., "Because eventually this course will enable me to enter the job market in a field that I like"), introjected regulation (α = .773 to .843; e.g., "To prove myself that I am able to succeed in this course"), external regulation (α = .722 to .747; e.g., "To have a better salary later on") and amotivation (α = .790 to .855; e.g., "Honestly, I do not really know why"). Numerous studies have supported the factorial, convergent, and divergent validity, and the scale score reliability of the AMS (Vallerand et al., 1989, 1992, 1993; Guay et al., 2015).

Socio-Economic Status. This construct was measured at Time 1 only, using mother education level, father education level, and family income (α = .676).

Sources of relatedness. Relatedness with mothers, fathers, teachers and peers was measured using the French version of the *Interpersonal Relationships Quality Scale* developed by Senécal, Vallerand, and Vallières (1992). This scale includes four items (e.g., "My relations with this person are satisfying", "My relations with this person are trustworthy") which students are asked to answer in reference to each source of relatedness (Mother α = .894 to .923 across time points; Father α = .923 to .943; Teachers α = .857 to .916; Peers α = .806 to .839). Items are scored on a five-point Likert scale ranging from 0 (*strongly disagree*) to 4 (*strongly agree*). The study of Senécal et al. (1992) supported the reliability and validity of scores on this scale. Students were asked to respond to the items targeting teachers while considering all of their teachers during the school year at which they completed the measure. For items targeting peers, students were told to complete them having in mind their complete peers' network.

Academic achievement. A cumulative measure of grades in Language, Humanities, and Sciences was obtained from the official school records. Grades are reported on a 0 to 100 scale in the Quebec education system. To obtain a cumulative measure of academic achievement for a given school year, the school administration simply computed students' grades in various school subjects for the entire school year. Scores on this variable could range from 0 to 100.

Engagement. We assessed students' levels of school engagement using the eight positively worded items (α = .808 to .825 across time points) from the school engagement subscale of *School Failure Tolerence Scale* (SFT; Clifford, 1988). Examples of the positive subscale items include: "I like to ask questions at school because I am learning by asking questions", "If I do not understand something, I ask my teacher to explain it" and "If I have a low grade in a job, I look at my mistakes and I rework the problems on which I had errors".The items are scored on a six-point Likert scale ranging from 1 (*strongly disagree*) to 6 (*strongly agree*). Clifford (1988) results supported the scale score reliability of the SFT.

Risk behaviors and aggressive behaviors. A scale was developed for purposes of this study to assess risk behaviors and aggressive behaviors. Risk behaviors were assessed with five items (α = .662 to .731 across time points; "I missed some courses without any good reasons", "I do my homework-reverse scoring", "I listen to my teachers-reverse scoring", "I take drugs before my classes", "I had the intention to dropout from school"). Aggressive behaviors were assessed with four items (α = .629 to .712; "I tell nasty things to some students", "I tell nasty things to some teachers in front of all classmates", "I make threats to some of my teachers", "I threaten some students to hurt them").

Analyses

Preliminary Analyses

Rather than using scale scores to estimate the growth mixture trajectories and their relations with the predictors and the outcomes, factor scores (estimated in standardized units with $M = 0$, $SD = 1$) were saved from a preliminary measurement models and used as inputs for the main analyses. To ensure comparability in the measures across time waves, these factors scores were saved from longitudinally invariant measurement models (Millsap, 2011). Although factor scores do not explicitly control for measurement errors the way latent variables do, they provide a partial control for measurement errors by giving more weight to more reliable items (Skrondal & Laake, 2001). Furthermore, factors scores are able to preserve the nature of the underlying measurement structure (e.g., measurement invariance) better than scale scores. For a more extensive discussion of the advantages of factor scores in the estimation of person-centered analyses, see Morin, Meyer, Creusier, and Biétry (2016). The measurement models for the motivation variables were estimated using bifactor exploratory structural equation modeling (bifactor-ESEM; Morin, Arens, & Marsh, 2016). This decision is based on recent studies showing that bifactor-ESEM measurement models are naturally suited to measures of academic (Litalien et al., 2017) and work (Howard et al., 2018) motivation based on self-determination theory (SDT: Deci & Ryan, 1985, 2000; Ryan & Deci, 2000). Indeed, these studies showed that bifactor-ESEM provided a way to obtain a direct and precise estimate of the global continuum of self-determination proposed by SDT underlying all motivation ratings (i.e., the global levels of self-determined motivation), which is used here to estimate participants growth trajectories of motivation. In this study, only this global self-determined motivation factor is used in the estimation of the profiles. Details on all measurement models, their longitudinal invariance, as well as correlations and model-based composite reliability estimates are reported in the online supplements.

Growth Mixture Models (GMM)

Analyses were conducted with Mplus 8 (Muthén & Muthén, 2015) robust maximum likelihood estimator (MLR) and Full Information Maximum Likelihood (FIML) to handle missing data (e.g., Enders, 2010; Graham, 2009, 2012). For our main analyses, we combined the data obtained from the three cohorts of students to estimate longitudinal trajectories spanning 5 years of secondary school (ages 12-16 or Secondary 1-5). In this study, 927 students provided a total of 2,502 time-specific ratings (M = 2.70 time-specific ratings per participant), with the majority of participants (N = 751, 81.0%) completing all three time-points, 73 (7.9%) completing two time-points, and only 103 (11.1%) completing a single time-point. Further details on missing data are provided in the online supplements. To avoid converging on a local maxima, analyses were conducted using 10,000 random sets of start values, 1000 iterations, and 500 solutions for final stage optimization (Hipp & Bauer, 2006).

In this study, linear[1] GMM with one to eight latent trajectories of global self-determined motivation were estimated and compared. GMM are built from latent curve models (e.g., Bollen & Curran, 2006), and aim to identify subgroups of participants following distinct longitudinal trajectories (e.g., Grimm et al., 2016; Morin, Maïano et al., 2011). Linear GMM summarize a series of repeated measures by the estimation of random intercepts and slope factors reflecting, respectively, the initial level of the growth trajectories (the loadings of the time-specific measures on this factor are all fixed to 1) and the rate of change over time (the loadings of the time-specific measures on this factor are fixed to values reflecting the passage of time). How to model the passage of time can be challenging in GMM, especially when different time metrics are available such as in this study where time could be modeled as a function of the time of measurement, secondary level (ranging from Secondary 1 to 3 at Time 1), or age (ranging from 12 to 17 at Time 1). Metha and West (2000) showed that relying on uniform time codes when participants differ from one another on another time metric (such as age or grade) is proper when: (1) the regression of the intercept of a latent curve model on the other metric is equal to the slope, and (2) the regression of the slope on the other metric is equal to zero. In this study, preliminary analyses

[1] With a maximum of three time points available per participant, it was not possible to model nonlinearity while also incorporating the cohort sequential nature of this data set (i.e., modeling trajectories as a function of grades).

revealed that neither age nor secondary level could be considered to be negligible when trajectories were measured as a function of time points, but that age could be considered to be negligible when trajectories were modeled as a function of secondary level (whereas the reverse was not true).

For this reason, we estimated GMM as a function of individually-varying time codes defined as a function of secondary levels using an approach first introduced by Grimm and al. (2016) via the Mplus MODEL CONSTRAINT function. This approach made it possible to estimate self-determination trajectories between Secondary 1 (the secondary level of the youngest cohort at Time 1) to Secondary 5 (the secondary level of the oldest cohort at Time 3). To ensure that no information was lost by our decision to estimate trajectories based on secondary level rather than age, age was also incorporated as a predictor in later analyses. In these analyses, the intercept factor was set to reflect self-determined motivation levels in Secondary 1, and the slope factor reflected the amount of linear change (increase or decrease) in self-determined motivation levels associated with each increase of one secondary level. More precisely, the time codes used to reflect the passage of time for students from the first cohort (Secondary 1 at Time 1) were 0 at Time 1 (to locate the intercept of the trajectories in Secondary 1), 1 at Time 2, and 2 at Time 3. For the second cohort matching time codes were respectively 1-2-3 while they were 2-3-4 for the third cohort. In GMM, latent profiles are defined on these latent intercepts and slope factors to obtain subgroup-specific latent trajectories. The mean of these latent factors thus reflects the average level (intercept) and rate of change (slope) observed in each profile, while the variances of these latent factors reflect the level of within-profile inter-individual variability. A more technical presentation of GMM, together with an example of the syntax used to specify individually-varying time codes, are provided in the online supplements.

Current statistical recommendations are that GMM should ideally be estimated while allowing all models parameters (intercepts and slope means, intercept and slope variances and covariances, and time-specific residuals) to be freely estimated in all profiles (Diallo, Morin, & Lu, 2016; Morin, Maïano et al., 2011). However, this recommendation comes with the recognition that this free estimation is not always possible due to the tendency of these more complex models to converge on improper solutions, or not to converge at all (Diallo et al., 2016), which is typically taken to reflect overparameterization and the need to rely on simpler models (e.g., Bauer & Curran, 2003; Chen, Bollen, Paxton, Curran, & Kirby, 2001). This was the case in the present study. In such situations, the recommendation is to implement equality constraints across profiles on model parameters to achieve a more parsimonious representation of growth trajectories (Diallo et al., 2016). In the current study, we relied on the Mplus default which sets the latent variance-covariance matrix to be invariant across latent profiles, while allowing the time-specific residuals to be freely estimated in each profile, but homoscedastic across time points (e.g., Li & Hser, 2011; Tofighi & Enders, 2007). This specification of the residuals is consistent with typical operationalization of growth models estimated in the multilevel framework, unavoidable given our decision to rely on individually-varying time codes, and results in the estimation of profiles which are assumed to provide an equally efficient representation of the repeated measures, while allowing this explanatory power to differ across profiles.

To determine the number of latent trajectory profiles in the data, it is critical to consider the substantive meaning, theoretical conformity, and statistical adequacy of the solution (Bauer & Curran, 2003; Marsh, Lüdtke, Trautwein, & Morin, 2009; Muthén, 2003), as well as statistical indices: (i) The Akaïke Information Criterion (AIC), (ii) the Consistent AIC (CAIC), (iii) the Bayesian Information Criterion (BIC), (iv) the sample-size Adjusted BIC (ABIC), and (v) the Integrated Classification Likelihood BIC (ICL-BIC: A BIC corrected for the model entropy, an indicator of the model classification accuracy)[2]. A lower value on these indicators suggests a better-fitting model. Simulation

[2] Neither the Lo, Mendel and Rubin's (2001) Likelihood Ratio test, nor the Bootstrap Likelihood Ratio Test (BLRT) are available for models with individually-varying time codes.

studies indicate that four of these indicators (CAIC, BIC, ABIC, and ICL-BIC) are particularly effective (e.g., Diallo et al., 2016, 2017; Nylund, Asparouhov, & Muthén, 2007; Peugh & Fan, 2013; Tein, Coxe, & Cham, 2013; Tofighi & Enders, 2008), while the AIC should not be used (we thus only report the AIC for purposes of complete disclosure). A recent simulation study (Diallo et al., 2016) suggests that the BIC and CAIC should be privileged under conditions of high entropy (e.g., ≥ .800), whereas the ABIC and BLRT appear to perform better in conditions of low entropy (e.g., ≤ .500). These tests remain heavily influenced by sample size (Marsh et al., 2009), so that they may keep on decreasing without reaching a minimum. In these cases, they should be graphically presented through "elbow plots" illustrating the gains associated with additional profiles (Morin, Maïano et al., 2011; Morin, 2016). In these plots, the point after which the slope flattens suggests the optimal number of profiles. This elbow plot is presented in Figure S1 of the online supplements.

Predictors and Outcomes of Profile Membership. Once the optimal number of profiles has been selected, relations between these profiles and a series of predictors and outcomes were investigated. In this study, predictors and outcomes were also specified as invariant factor scores from preliminary measurement models. In order to be able to assess the associations between global self-determined motivation trajectories modeled as a function of secondary level with factor scores reflecting participants' scores on these covariates at a matching secondary level, we relied on a strategy initially proposed by Morin, Maïano et al. (2011). Essentially, factors scores reflecting these covariates were saved from latent curve models (Bollen & Curran, 2006), also estimated as a function of secondary level, to reflect the intercept (level in Secondary 1) and slope (rate of change per increase in secondary level). These preliminary measurement and latent curve models are described in the online supplements. Correlations among all variables can be consulted in Table 1.

A strong assumption of person-centered analyses including predictors and outcomes is that the profiles should remain unaffected by inclusion of the covariates (Diallo et al., 2017; Marsh et al., 2009; Morin, Morizot, Boudrias & Madore, 2011). Observing such a change indicates that the nature of profiles depends on the choice of covariates and calls into question the assumption that the *causal* ordering is from the predictors to the profiles, and from the profiles to the outcomes (Marsh et al., 2009). To ensure that this did not happen, predictors were included to the final solution using the start values from the final retained unconditional GMM (Diallo et al., 2017; Morin, Meyer et al., 2016).

Following the incorporation of predictors into the model, a series of models were contrasted, following recommendations from Diallo et al. (2017) previously implemented in applied research by Morin and colleagues (Morin, Maïano et al., 2011; 2013; Morin, Rodriguez et al., 2012). First, to assess the effects of the intercepts of the predictors' trajectories considered in the present study (relatedness with peers, father, mother, and teacher), we estimated a null effects model in which the effects of these predictors on the probability of membership in all profiles, as well as on the growth factors, were constrained to be zero. Second, a first alternative model was estimated in which the predictors were allowed to predict profile membership through a multinomial logistic regression. Tests were then conducted on additional models in which the predictors were also allowed to influence within-profile variation in the intercepts and slopes of the trajectories (via a multiple regression equation), and in which these effects were allowed to vary from one profile to another. However, before estimating this sequence, we completed preliminary analyses based on the same sequence using only the possible control variables (age, sex, SES) to verify the need to incorporate these controls as additional time-invariant predictors (TIP) in the main predictive models. These analyses supported the need to retain age, but not SES or sex, as a control in the main predictive analyses.

In a second series of models, the same sequence of tests was repeated to assess the effects of the intercepts of the predictors' trajectories considered in the present study (relatedness with peers, father, mother, and teacher). Then, starting with the final model retained in the previous steps, the slopes of the predictors' trajectories were included in the model to verify if changes over time in these predictors could influence students' motivational trajectories over and above their initial effects. For this final set of analyses, we contrasted models in which these slope factors were allowed to predict profile membership and the slope of the motivation trajectories in a manner that was assumed to be identical, or different, across profiles. As recommended by Diallo et al. (2017, also see Morin, Meyer et al., 2016), the relative fit of the alternative models was contrasted using the same information criteria already used in the present study, with a lower value indicating a better fitting model.

Finally, outcomes were contrasted across profiles using a model-based proposed by Lanza, Tan, and Bray (2013) and implemented through the Auxiliary (DCON) function (Asparouhov & Muthén, 2014). This allowed for the comparison of probabilities-based profiles on the outcomes without allowing these outcomes to change the nature of the profiles.

Results

Unconditional Models

The results from the unconditional GMM are reported in the top section of Table 2. While the AIC and ICL-BIC kept on decreasing, all remaining indices converged on a specific solution: 2 profiles for the CAIC, 3 profiles for the BIC and 5-6 profiles for the ABIC. Based on recommendations from Diallo et al. (2016) for models associated with a relatively low levels of entropy, it appears that the information provided by the ABIC should be favored. In addition, the graphical representation of these indices (the matching elbow plot is reported in Figure S1 of the online supplements) reveals that the decrease in the values of ABIC, the AIC, and the ICL-BIC appear to reach a plateau between 4 and 6 profiles. Examination of the 5-profile solution and of the adjacent 4- and 6- profile solutions showed that the 5-profile solution contributed to the addition of a meaningful and well-defined profile (characterized by persistently low levels of self-determined motivation), whereas the sixth profile solution only resulted in the arbitrary division of one of the profiles into two highly similar profiles, one of which was so small as to be meaningless (corresponding only to .2% of the sample). The 5-profile solution was thus retained. This solution is graphically presented in Figure 1, and specific parameter estimates are reported in Table 3. This solution resulted in a moderate to high level of classification accuracy of participants into their most likely profile (see Table S13 of the online supplements), ranging from 57.8% to 73.0% across profiles, consistent with its moderate entropy value (.537). In the interpretation of these results, it is important to keep in mind that these trajectories were estimated on the basis of time-invariant factor scores with a mean of 0 and a standard deviation of 1 on the global self-determination factor at the beginning of the study. Thus, a value of 0 corresponds to the average level of global self-determination in Secondary 1, and other scores are expressed in standard deviation units.

Profiles 1 and 3 are both characterized by initially high global levels of self-determined motivation and a slight increasing tendency over time (corresponding to .135 *SD* units per year for profile 1 and .175 *SD* units for profile 3). Despite this apparent similarity, these two profiles differ from one another at the level of the time-specific residuals, suggesting that smooth trait-like self-determination trajectories are not as efficient at depicting students' corresponding to profile 3 as they are at describing students' corresponding to profile 1. In other words, whereas both profiles are characterized by self-determined motivation trajectories that are, on the average, high and characterized by a slight increase over time, students' corresponding to profile 3 show important state-like deviations (of almost .5 *SD* units on the average) over time from this average trait-like trajectory. In contrast, the levels of self-determined motivation observed among students corresponding to profile 1 appear to be highly stable over time, deviating from this average trajectory by only .089 *SD* units on the average. It is interesting to note that the level of state-like fluctuations observed around the smooth linear trajectory observed in profile 3 seems to correspond to the level observed in the other profiles (ranging from .469 to .792 *SD* units). This suggests that the motivational stability observed in Profile 1, which is also small in comparison to most of the other profiles (5.75% of the participants), is not normative in this sample and reflect a key defining characteristic of this *High-Stable* profile. In contrast, profile 3 is much larger (50.43%), suggesting that a majority of students seem to follow *High* motivational trajectories marked by normative time-specific fluctuations. Supporting the distinctive nature of these profiles, they were both already present in the solution including 3 and 4 profiles.

Profile 2 represents about a fourth of the students (24.26%) characterized by *Moderate* levels of global self-determined motivation that tend to stay that way over the course of the study (i.e., neither the intercept, nor the slope, of these trajectories differed significantly from 0). Likewise, Profile 4 characterized a smaller proportion of students (3.97%) characterized by persistently *Low* global levels of self-determined motivation (the slope of these trajectories did not differ significantly from 0). Finally, Profile 5 characterized 15.58% of the students presenting an *Increasing* trajectory of global self-determined motivation, as illustrated by a slope factor indicating an increase of global self-determined motivation levels of almost .5 *SD* unit per grade. Over the course of the study, this profile thus appeared to switch from the *Low* trajectory from the *Moderate* trajectory.

Predictors

The results from the models with predictors are reported in the middle and lower sections of Table 2. Starting first with the models including the intercepts of the predictors and age, most indices (CAIC, BIC, ABIC, and ICL-BIC) support the model allowing these predictors to simultaneously predict the probability of profile membership and the intercept factors in a profile-invariant manner (Model M11 in Table 2). This model was thus retained as the baseline model to examine the possible effects of the slopes of the predictors' trajectories. These additional results showed that the lowest values for the CAIC, BIC, ABIC, and ICL-BIC were associated with the model in which the slopes of predictor were allowed to predict the slopes of the self-determined motivation trajectories (but not profile membership) in a profile invariant manner (Model M16 in Table 2). In addition, this model also resulted in a lower value on the BIC and ABIC when compared to model M11, and similar levels on the CAIC and ICL-BIC, supporting the value of this model.

Parameter estimates from this final predictive model (M16) are reported in Table 4. A first observation that emerges from these results is that most of the effects of the predictors seem to occur on the growth trajectory factors, with only limited effects on the likelihood of membership into the various profiles. In addition, once the effects of students' relatedness with their peers, father, and teacher are taken into account, no remaining effect was associated with relatedness with their mother. In contrast, students' relatedness with their father in Secondary 1 predicted an increased likelihood of membership into the *High-Stable* versus *Moderate* profiles and increases in relatedness with their father over time also predicted more pronounced increases in self-determined motivation levels over time (slope factor). Students' relatedness with their peers in Secondary 1 predicted an increased likelihood of membership into the *Low* profile relative to the *High* and *Increasing* ones, but also higher levels of self-determined motivation in Secondary 1 over and above this effect on profile membership. Students' relatedness with their teachers in Secondary 1 proved particularly beneficent, being associated with an increased likelihood of membership into the *High-Stable* and *High* profiles relative to the *Increasing* one (which was characterized by low levels of self-determined motivation in secondary1), as well as with higher levels of self-determined motivation in Secondary 1 (intercept factor). Moreover, increases in relatedness with their teachers over time also predicted more pronounced increases in self-determined motivation levels over time. Finally, older students were more likely to correspond to the *Low* profile relative to the *High* and *High-Stable* ones, and to present lower levels of self-determined motivation in Secondary 1.

Outcomes

Results from the comparison of the time-specific outcomes across profiles are reported in Table 5, and profile-specific outcome trajectories are reported in Figure 2. These results reveal that the five profiles are clearly differentiated from one another on the outcomes considered, with a pattern of associations that differs as a function of the outcome. In Secondary 1, grades are highest in the

Increasing profile, followed equally by the *High-Stable* and *Moderate* profiles, then by the *High* profile, and finally by the *Low* profiles. Increases over time in grades are highest in the *High* profile, whereas the *High-Stable* and *Moderate* profiles are characterized by mostly stable grade levels over time and similar longitudinal trajectories. In contrast, the *Low* and *Increasing* profiles are both characterized by decreases (more pronounced in the *Increasing* profile) in grades. Overall, by Secondary 5, grades levels are close to the sample mean in the *High-Stable* (.060 *SD*), *Moderate* (.093 *SD*) and *High* (.017 *SD*) profiles, higher than the sample mean in the *Increasing* (.440 *SD*) profile, and lower than the sample mean in the *Low* (-.912 *SD*) profile.

Levels of school engagement in Secondary 1 were highest in the *Moderate* profile, followed by the *High-Stable* profile, then equally by the *High* and *Increasing* profiles, and finally by the *Low* profile. However, the *Low* profile was characterized by more pronounced increases in levels of engagement over time relative to the other profiles, followed by the *High* profile. Changes over time in engagement levels remained negligible in the *High-Stable* and *Moderate* profile, whereas the *Increasing* profile presented decreasing levels of engagement over time. By Secondary 5, engagement levels were well below the sample mean in the *Increasing* (-.871 SD) profile, close to the sample mean in the *Low* (.099 SD) profile, almost .5 *SD* above the sample mean in the *High* (.404 SD) and *High-Stable* (.467 SD) profiles, and well above the sample mean in the *Moderate* (1.120 SD) profile.

Levels of risk behaviors in Secondary 1 were highest in the *Low* profile, followed equally by the *High-Stable* and *High* profiles, then by the *Moderate* profile, and finally by the *Increasing* profile. Both the *Low* and the *Increasing* profiles are characterized by increases in risk behaviors over time (more pronounced in the *Low* profile), whereas the *High-Stable* and *Moderate* profiles were characterized by negligible changes in risk behaviors over time. In contrast, the *High* profile was characterized by decreases over time in the level of risk behaviors. By Secondary 5, levels of risk behaviors were comparable and below the sample mean in the *High* (-.670 *SD*), *Moderate* (-.321 *SD*), and *Increasing* (-.142 *SD*) profiles, above the sample mean in the *High-Stable* (.397 *SD*) profile, and more than three *SD* above the sample mean in the *Low* profile.

Finally, levels of aggressive behaviors in Secondary 1 were also highest in the *Low* profile, followed equally by the *Increasing* and *High* profiles, then by the *Moderate* profile, and finally by the *High-Stable* profile. Whereas the *Moderate* profile was characterized by negligible changes in aggressive behaviors over time, the remaining profiles presented decreasing levels of aggressive behaviors over time that were the most marked in the *Low* profile, followed by the *Increasing* profile, then by the *High* profile, and finally by the *High-Stable* profile. By Secondary 5, due to these normative decreases in levels of aggressive behaviors, all profiles presented similar levels of aggressive behaviors that were slightly below the sample mean (-.584 *SD* to -.704 *SD*).

Discussion

In contrast with Hypothesis 1, our results revealed that, for the total sample, no generic decline in global levels of self-determined motivation were observed during the secondary school years. In line with Hypothesis 2, we observed five different trajectory profiles in which the proportion of students varied (3.97% *Low*, 5.75% *High-Stable*, 15.58% *Increasing*, 24.26% *Moderate*, and 50.43% *High*). Hypothesis 3 proposed that higher scores on sources of relatedness would positively predict membership into profiles characterized by high and increasing trajectories of self-determined motivation. Over the many comparisons made between the five profiles, very few significant differences were obtained. Hypothesis 4 postulated that relatedness with teachers would be the main predictor of membership into profiles characterized by high and increasing trajectories of self-determined motivation. This assumption was supported because relatedness with teachers and fathers were the most important predictors of membership into the profiles characterized by higher self-determined trajectories. Hypothesis 5 stipulated that students in profiles characterized by higher self-determined motivation trajectories would show higher levels of adaptive outcomes and lower levels of maladaptive outcomes.

Results are mostly in line with this assumption.

Self-Determined Motivation Trajectories: Distinct Profiles

The results regarding motivation trajectories did not confirm our initial expectations regarding a potential decline in self-determined motivation over the secondary school years. In fact, three trajectory profiles were characterized by an increase in self-determined motivation levels, although the amplitude of this increase differed from one profile to another. One of those profile (*High-Stable* profile) was characterized by high self-determination levels that remained relatively stable over the course of the study, whereas another one (*High* profile) was also characterized by generally high self-determination levels that tended to fluctuate over the course of the study. Yet, the third of those profiles (*Increasing* profile) presented a marked increase in self-determined motivation levels over the course of school years, with initially very low levels that reached a moderate level by the end of the secondary 5. The remaining two profiles (*Low* and *Moderate* profiles) were characterized by unchanging low, or moderate, self-determined motivation levels. Thus, none of the five trajectory profiles showed a decrease. This is surprising given the fact that the secondary school context is sometimes perceived as being controlling by the students (Vallerand, Fortier, & Guay, 1997) and that past studies have shown a decrease in some types of self-determined motivation over the secondary school years (Gottfried, Fleming, & Gottfried, 2001; Otis et al., 2005). However, the observation of self-determined motivation trajectories dominated by stability is consistent with the results recently reported by Gillet et al. (2018).

These results allow us to speculate that the secondary school context might nowadays be less controlling than it was before. Indeed, calls for reform were made by several scholars in the 1990s to ensure the creation of secondary school environments that would better support adolescent needs and motivation (Eccles & Roeser, 2009). Since then, pedagogical practices that promote student motivation have attracted the attention of many researchers from different theoretical backgrounds (e.g., Gillies, 2016; Wigfield, Eccles, & Rodriguez, 1998; Guay, Valois, Falardeau, & Lessard, 2016) and it is possible that evidence-based practices stemming from this research are becoming more and more used by teachers both in and outside Canada (Thoonen, Sleegers, Oort, Peetsma, & Geijsel, 2011). Of note, preliminary tests of longitudinal measurement invariance (reported in our online supplements) support this interpretation in showing that this generic increase over time in levels of global self-determined motivation was accompanied by a matching increase in specific levels of intrinsic motivation and decreases in specific levels of amotivation, identified regulation, introjected regulation, and external regulation. However, this interpretation of the results is tentative because we have not measured variables relating to the autonomy supportive or controlling nature of the school context itself, variables that could have been used to conduct time-related comparisons. If our interpretation is correct, autonomy support from teachers should increase over the secondary school years while their tendency to emit controlling behaviors should decrease.

Yet, it should be noted that the nature of the construct that we have used to estimate the trajectory profiles (global levels of self-determined motivation) is different from the one evaluated in other studies (e.g., intrinsic motivation; Gottfried et al., 2001; Otis et al., 2005), which could also be an explanation for the differences between our results and those from previous studies. The global factor reflecting the self-determined motivation continuum was estimated by extracting all self-determined motivation information contained across items corresponding to distinct regulations (intrinsic, identified, introjected, external and amotivation). In this study, loadings on the global factor were all positive for all types of motivation with the exception of amotivation for which loadings were negative. Moreover, positive loadings on the global factor were higher in magnitude for autonomous types of motivation (intrinsic and identified regulations) than for external regulations. However, the loadings' magnitude of the introjected items on the global factor were similar to those of the intrinsic and identified regulation items. Because previous studies on motivational trajectories did not rely on a similar method, any comparison made between their results and the ones obtained here must remain tentative. More precisely, studies usually investigate the overtime changes on each individual types of motivation proposed by SDT, suggesting that global levels of self-determined academic motivation might be more stable over time than specific levels of individual types of regulation. This leaves open the following question: Is the decline in motivation observed in some studies associated with the modeling processes used in those studies or does it really correspond to a "true" decline? Clearly, future studies are needed to better understand the characteristics of motivational trajectories in terms of stability and changes as well as the possible impact of changing educational contexts on these trajectories.

Our results also indicate that more than half of the students presented a highly motivated trajectory (either very stable or showing some time-specific fluctuations over generally high levels) and about a fourth of them presented a trajectory characterized by moderate and stable self-determination levels. Consequently, nearly 80% of the students in this study presented no deficit in self-determined motivation levels. Even more interesting was the observation that students forming the *Increasing* profile (15.6%) started secondary school with very low levels of self-determined motivation (more than one *SD* below the sample mean), and showed a marked increase over time (with .5 *SD* growth at each secondary level until Secondary 5), leaving them with levels matching those of the *Moderate* profile by the end of the study. Although these results are encouraging, this still leaves approximately 4% of the sample to follow persistently low self-determined motivation trajectories. Fortunately, some additional results related to predictors suggest possible ways to nurture more desirable self-determined motivation trajectories in the secondary school years.

One results worth mentioning is that older students were more likely to correspond to the *Low* profile relative to the *High* and *High-Stable* ones, and to present lower global levels of self-determined motivation in Secondary 1. These results could be explained by the fact that older students also have greater difficulties at school. They might have repeated one school year during elementary school, which explains why they were more likely to be in the Low profile. However, this interpretation is speculative given the fact that we do not have gathered information on grade retention.

Sources of Relatedness

As mentioned in the introduction, two perspectives differ regarding the benefits of relatedness in the prediction of self-determined motivation trajectories in adolescence. The first perspective argues that some sources of relatedness are more important than others during this developmental period: parents become less important due to the process of independence while the influence of peers and teachers increases (Scholte & Van Aken, 2006). The second perspective proposes that all sources of relatedness are important for adolescents' motivation and optimal functioning (Smollar & Youniss, 1989). From this second perspective, all sources of relatedness should help to discriminate between the profiles obtained in this study. However, we found little support for the second perspective given that our results showed a lack of effects of relatedness with mothers, and effects of relatedness with fathers, teachers and peers that only allowed us to discriminate a subset of the profiles. However, some additional effects of predictors, or changes in predictors over time, on within profile variation in global self-determination levels were also noted.

For instance, feeling more related to the teachers at the start of the study predicted membership in the *High-stable* and *High* profiles in comparison to the *Increasing* profile. In addition, feelings of being more related to the teachers at the beginning of the study predicted higher initial levels of global self-determined motivation irrespective of profile membership. Likewise, increases in feelings of relatedness with the teachers occurring over time predicted increases over time in global levels of self-determined motivation irrespective of profile membership. In addition, students' feelings of being more related to their father at the beginning of the study were more likely to be in the *High-Stable* profile in comparison to the *Moderate* profile. Furthermore, increases over time in feelings of relatedness with fathers also predicted increases over time in global levels of self-determined motivation irrespective of profile membership. In other words, these results indicate that secondary school students with the higher global levels of self-determined motivation (those in the *High* and *High-stable* profiles) are those who experienced positive relatedness with their father and teachers. Furthermore, increases over time in these two types of relatedness also helped students to experience increases in their global levels of self-determined motivation over time. Although not as widespread as we would have expected, these results associated with the benefits of students' relatedness with their teachers are aligned with our expectations regarding the key role of teachers in the prediction of self-determined motivation levels during adolescence (e.g., Guay et al., 2017; Raufelder et al., 2015). Likewise, the observation that fathers seemed to play a more pronounced role in the prediction of self-determined motivation levels appear to match recent cross-sectional results reported by Litalien et al. (2019). However, our results also suggest that the effects of fathers and teachers could be limited to the differentiation of only a subset of profiles, and to predicting within-profile variations rather than membership into more or less desirable profiles. These results could, in part, be explained by the manner in which we assessed teachers' relatedness and students' motivation. Specifically, we measured these constructs in reference to students' global level of self-determined academic motivation and to their relatedness toward all of their teachers in any given year. If we had rather measured self-determined motivation in relation to a specific school subject (e.g., math) and students' perceptions of relatedness toward the specific teacher associated with that matching subject (e.g., their math's teacher), it might have been possible for this source of relatedness to result in a more widespread prediction of profile membership. Future studies will be needed to verify this possibility.

That being said, the observation that students' relatedness with their mother played no role in the prediction of profile membership or within-profile variation once other sources of relatedness were considered remains surprising when considering past findings showing the role of mothers in the prediction of academic motivation (Duchesne & Larose, 2007; Gonzalez-DeHass, Willems, & Holbein, 2005; Guay et al., 2013). Yet, even though some of these studies (Guay et al., 2013) suggest that the role of fathers in terms of academic motivation might be negligible once mothers are taken into account, they also suggest that the role of fathers might be more pronounced when other critical academic outcomes (e.g., achievement) are considered. These observations thus suggest that mothers and fathers might play different roles, which might also differ as a function of the school subject considered (general academic here and in Litalien et al., 2019; French in Guay et al. 2013). Clearly, future research should be conducted to understand why mothers might become less relevant than fathers as a source of relatedness in the prediction of self-determined motivation in adolescence. Therefore, both qualitative and quantitative studies are needed to understand this peculiar finding and to identify possible alternative explanations.

Finally, and in accordance with our expectations, initial levels of relatedness with peers still predicted higher levels of global self-determined motivation irrespective of profile membership. Yet, and contrary to our expectations, the results also showed that students who feel more related to their peers at the beginning of the study were more likely to be classified in the *Low* profile in comparison to the *High* or *Increasing* profiles. These unexpected findings could suggest that this sense of relatedness could possibly conflate deviant peers associations (i.e., associations with peers who do not value school-related activities) with prosocial peer associations (i.e., peers who do value school-related activities) such that the first component predicts membership into the least desirable profile whereas the second one predicts higher initial levels of self-determined motivation. In the research literature on peer relationships, it is already recognized that peers influence can be both positive or negative, leading to greater similarities among peers over time (i.e., those with less motivated peers tend to become less motivated over time, whereas those with more motivated peers tend to become more motivated over time; Kindermann, 2016; Wentzel & Muenks, 2016). It is also important to keep in mind that the relations identified in the present study are estimated while taking alternative sources of relatedness into account, which means that they reflect the effects of peer relatedness over and above what it shares with teachers and parents' relatedness. Interestingly, although Ciarrochi et al. (2017) reported that social support from teachers, parents, and peers were aligned for a majority of youth among which they lead to desirable outcomes, they also found that students whose main source of support was coming from their peers display a profile that was consistent with the presence of deviant peer associations. Unfortunately, this possibility cannot be examined in the present study.

Outcomes

Several distinctions were observed between profiles at the outcome level. Importantly, between-profile differences in terms of outcomes were observed among all five of the profiles identified in this study, supporting their discriminant validity. As expected, adaptive outcomes levels were generally lowest and maladaptive outcomes levels were generally highest for students corresponding to the *Low* profile. These students started secondary school with relatively low academic achievement levels which showed a slight decrease over the years. They also started with a very low level of engagement, which underwent a substantial increase over time although these levels only reached the sample average by the end of the study (remaining lower than in all other profiles save the *Increasing* one). As these students seem to struggle academically (lower grades), it seems plausible to assume that they had to increase their efforts and engagement in order to succeed when facing increasingly complex academic content over the years. Concerning aggressive behaviors and risk behaviors, the results should be interpreted with caution because items were developed for the purpose of this study. That being said, the levels observed on these two outcomes among students corresponding to the *Low* profile in Secondary 1 were higher than those observed in any other profiles. Interestingly, whereas their levels of risk behaviors increased over the school years, their level of aggressive behaviors decreased substantially to reach those observed in any other profiles by the end of the secondary school years. Indeed, decreasing levels of aggressive behaviors seemed to characterize all profiles, and might be related to the age of the students and to their increasing familiarity with the secondary school environment. Aggressive behaviors toward the peers could be decreasing as older students are more likely to have a more stable social network (Brown & Larson, 2009), and such behaviors tend to display a normative decrease in adolescence (Brame, Nagin, & Tremblay, 2001). In contrast, risk behaviors was also operationalized with items that are more likely to be endorsed among older students (missing courses, taking drugs, having the intention to dropout) (Miller, Naimi, Brewer, & Jones, 2007; Schoeneberger, 2012; Stearns & Glennie, 2006)

Results for the *Increasing* profile are more challenging to interpret. Indeed, students in this group started Secondary 1 with relatively low levels of global self-determined motivation, coupled with very high levels of achievement (one *SD* above the sample mean) but moderately low levels of engagement. Yet, whereas their global levels of self-determined academic motivation increased substantially over the years, both their levels of academic achievement and engagement decreased to a greater extent than in the other profiles. It is noteworthy that their levels of achievement, despite this decrease, remained higher than that observed ones in any other profile by the end of the study, whereas their levels of engagement were then the lowest. One possible explanation for these peculiar findings is that students of this profile may have greater levels of school-related abilities, leading them to feel less intrinsically challenged than they would have liked in Secondary 1. Indeed, even high-achieving middle school students are known to experience a decrease in academic motivation during the transition from elementary school, which could be explained by a lack of correspondence between students' cognitive and emotional needs and the school tasks proposed to them (Eccles & Roeser, 2009). In the following secondary levels, as the complexity of course content increases, so might their intrinsic interest for learning, leading to increases in self-determined motivation. Perhaps as a result of having learned that engagement and efforts were not needed to maintain a level of performance that was higher than that of their peers, their initially low levels of effective engagement with school content may keep on decreasing, together with their achievement levels – while remaining satisfactory throughout the secondary school years. This result is important as it suggests that raising the level of self-determined motivation will not always translate into higher achievement and engagement, especially among already high-achieving students. Finally, and in accordance with the interpretation of these students as generally good students, albeit not overly engaged, their levels of aggressive behaviors and risk behaviors remained generally low throughout the study, albeit risk behaviors levels showed a slight increase which may match the observed decrease in engagement levels.

The *High*, *High-Stable*, and *Moderate* profile are particularly interesting to contrast as they all show a similarly shaped average self-determined motivation trajectory. In fact, when compared to *High-Stable* profile, the self-determined motivation trajectory observed in the *High* profile showed higher levels of time-specific state-like fluctuations over time, whereas the *Moderate* profile showed slightly lower levels of self-determined motivation throughout the study. In this regard, it is interesting to note that whereas both the *High-Stable* and *Moderate* profile displayed a comparable level of achievement close to the sample mean in Secondary 1 which remained stable over the years, the *High* profile presented slightly lower levels of achievement in Secondary 1 which showed a slight increase over the years to reach a level comparable to those of the other two profiles by the end of the study. Likewise, initial levels of engagement were initially high for both the *High-Stable* and *Moderate* profiles, although much higher in the *Moderate* profile, while levels of engagement observed in the *High* profiles matched their levels of achievement (initially lower, and showing a slight increase over the years to match the levels observed in the *High-Stable* profile by the end of the study). Finally, whereas both the *Moderate* and *High-Stable* profile displayed moderately low to moderate levels of risk behaviors and aggressive behaviors that remained at this level throughout the study, students from the *High* profile displayed initially average levels of aggressive behaviors and risk behaviors that both decreased over time. It is noteworthy that this is the only profile that showed a decrease in risk behaviors. Comparing these three profiles thus suggests that they might reflect distinct developmental processes. Whereas both the *High-Stable* and *Moderate* profiles seem to describe well-behaved average achievers, the *Moderate* profile appears to compensate for lower levels of self-determined motivation by higher levels of engagement in order to maintain achievement levels. In contrast, the *High* profile seems to describe students who initially struggled a bit more academically and tended to behave more erratically (risk behaviors) but who, through increased engagement and discipline, managed to improve in terms of performance over time. This struggle is further evidenced by the time-specific fluctuation in self-determined motivation levels that characterized this profile. Interestingly, by the end of the study, the *High* and *High-Stable* profiles were almost impossible to differentiate (apart from the slightly lower level of risk behaviors observed in the *High* profile), suggesting that the different trajectories that define these profiles might be specific to the secondary school year and merge later on. Likewise, by the end of the study, the levels of self-determined motivation observed in the *Increasing* profile seemed to join those observed in the *Moderate* profile. This observation is consistent with the fact that fewer trajectories have been reported by Gillet et al. (2018) during vocational training, suggesting that more diverse motivation profiles observed at younger age might combined into fewer profiles later on.

Overall, our results show that starting secondary school with a low level of global self-determined motivation puts students at risk of experiencing negative outcomes, even if this level of global self-determined motivation increases over the school years. Students will experience more positive outcomes if they are in a motivational trajectory where the level of self-determined motivation is high at the beginning of Secondary 1. These results are troublesome because they might indicate that increasing self-determination will produce benefits for those who are already motivated in a self-determined fashion, a Matthew Effect (Rigney, 2010). Clearly, more research is needed in order to identify conditions under which the effects of motivation interventions will yield the most benefits, and how to adapt these interventions to distinct student profiles. More importantly, more research is also needed to identify the mechanisms underpinning the formation of these distinct self-determined motivation profiles, and the extent to which they will be generalized to other samples and cultures.

Implications for practice

First, teachers should be aware that the opportunity to develop high levels of relatedness with their students helps to nourish students' global levels of self-determined academic motivation. Although students' perceptions of relatedness with teachers could stem from potential cognitive biases that students have (high-achieving students usually tend to perceive their teachers more positively), it appears that behaviors emitted by teachers can also help to foster this perception of relatedness among students. Specifically, teachers' behaviors that foster perceptions of relatedness are those showing a high level of engagement, namely being interested in what students are doing and what they value. Professional development programs teaching teachers how to be involved with students have been shown to support students' intrinsic motivation (Guay et al., 2016). Second, fathers should also be made aware that their degree of involvement might help students to develop higher global levels of self-determined academic motivation. Fathers might foster their children's need for relatedness through positive involvement, which includes both the provision of tangible resources (e.g., time, attention) as well as relationship characteristics (e.g., emotional support, warmth) that provide students with the psychological resources essential for motivation in school (Grolnick & Ryan, 1989).

Strengths and Limitations

This study is characterized by some methodological strengths including an accelerated longitudinal design covering all secondary school years (5) in the Quebec educational system, a large sample size with a low rate of attrition, and a set of sophisticated analyses to test the research hypotheses. However, this study also has some weaknesses. First, most determinants and outcomes (with the exception of achievement scores) were self-reported by students. This means that self-report biased could, to some extent, have played a role in the observed relations. It would be interesting for future research to consider implementing a wider range of observational, cognitive, biological (i.e., stress levels), or informant-reported (teachers, parents, peers) measures in order to better understand the developmental mechanisms at play in these developmental trajectories. Second, we relied on homemade measures to evaluate risk behaviors and aggression, which had slightly lower reliabilities than other measures. More standardized measures would have helped to better understand the associations between the observed trajectories and students' levels of aggressive behaviors and risk behaviors. Third, we did not evaluate trajectories separately for each type of behavioral regulation. Rather, we emphasized students' global levels of self-determined motivation, both for the sake of parsimony, but also based on previous evidence showing that this global score proved to be the core (but not the sole) component of a variety of covariates associations (e.g., Howard et al., 2018; Litalien et al., 2017). Fourth, the number and variety of predictors and outcomes considered in this study was limited, albeit somehow compensated by the estimation of longitudinal trajectories for all of these covariates. For instance, we solely focused on relatedness sources, whereas other determinants of self-determined motivation (e.g., related to the needs for autonomy or competence) could have been considered. For example, the extent to which those relatedness sources provide structure and autonomy support to students could have shown a more complete picture. Further research could also assess learning strategies, well-being, self-regulation, and persistence as motivational trajectories outcomes.

Conclusion

In sum, this research provides insightful results on the development of self-determined motivation over the secondary school years. Notably, it appears that the downward trajectory obtained in other studies is not reproduced in this one. Moreover, being in a stable high trajectory over the secondary school years is probably the best scenario for students' outcomes, although via efforts and engagement, students displaying a less stable trajectory can reach similar levels of performance by the end of the secondary school years. In addition, the results associated with the *Increasing* trajectory suggest that particular attention should be devoted to high-achieving students displaying low levels of motivation and engagement to ensure that the school environment is able to provide them with sufficiently challenging learning experiences. Finally, the role of relatedness sources, although not as widespread as initially expected, reinforce the importance of fathers and teachers as important drivers of self-determined motivation during the secondary school years.

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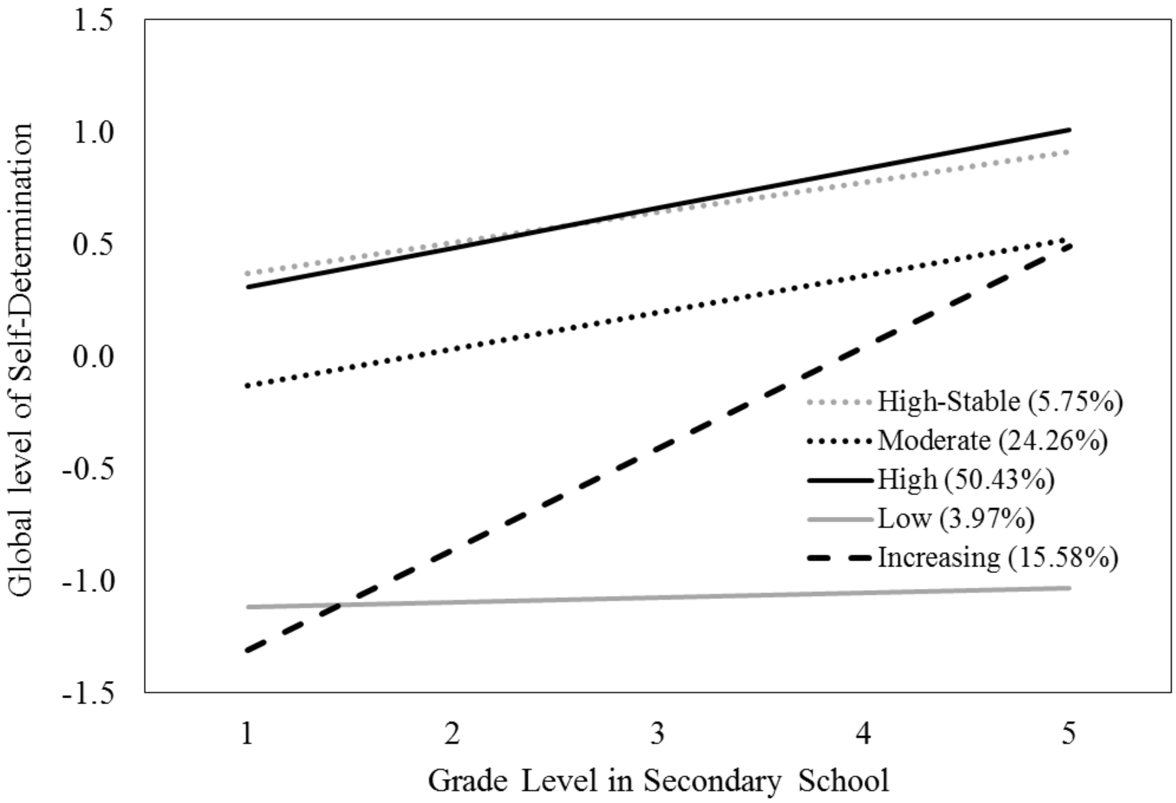

Figure 1

Estimated Growth Trajectories for the Motivation Profiles

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

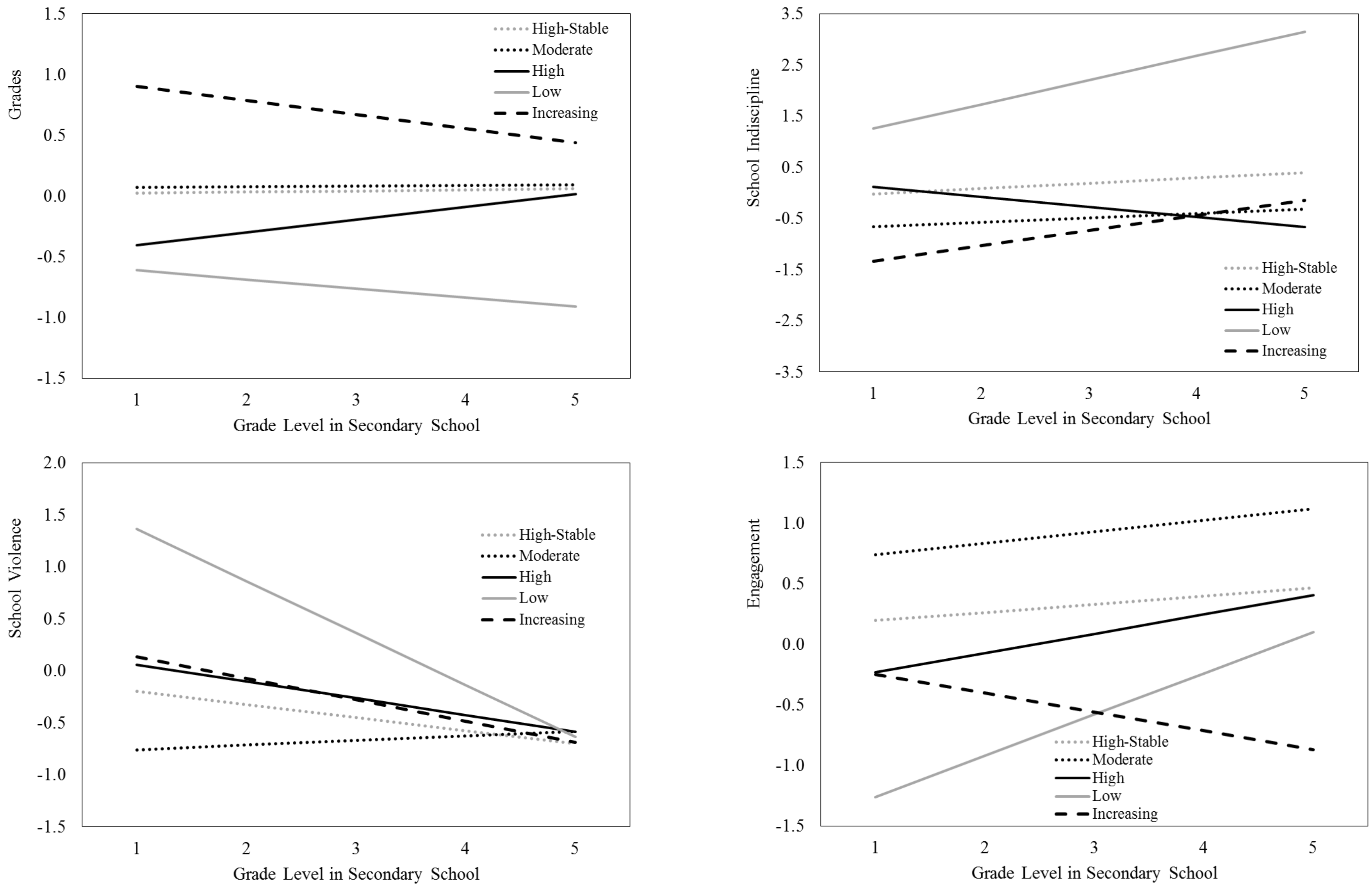

Figure 2
Profile-Specific Outcome Trajectories

Table 1

Correlations Among All Variables Used in the Present Study

	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18	19	20	21
1 SDT_1																					
2 SDT_2	.565**																				
3 SDT_3	.504**	.573**																			
4 Rel. Peer (I)	.242**	.251**	.228**																		
5 Rel. Peer (slo.)	-.223**	-.159**	-.065*	-.583**																	
6 Rel. Father (I)	.251**	.231**	.171**	.522**	-.472**																
7 Rel. Father (slo.)	-.179**	-.078*	.000	-.369**	.644**	-.391**															
8 Rel. Mother (I)	.229**	.207**	.171**	.517**	-.215**	.490**	-.116**														
9 Rel. Mother (slo.)	-.101**	-.072*	.000	-.342**	.494**	-.008	-.101**	-.410**													
10 Rel. Teacher (I)	.434**	.417**	.378**	.543**	-.403**	.581**	-.254**	.628**	-.224**												
11 Rel. Teacher (slo.)	-.304**	-.263**	-.169**	-.364**	.588**	-.514**	.443**	-.682**	.350**	-.753**											
12 Grades (I)	.304**	.277**	.212**	.169**	-.186**	.208**	-.100**	.222**	-.129**	.335**	-.304**										
13 Grades (slo.)	-.246**	-.047	.135**	-.044	.163**	-.112**	.189**	-.143**	.142**	-.141**	.219**	-.534**									
14 Risk behaviors (I)	-.448**	-.368**	-.264**	-.253**	.221**	-.344**	.211**	-.297**	.081*	-.462**	.343**	-.579**	.529**								
15 Risk behaviors (slo.)	.024	-.157**	-.322**	-.060	-.077*	-.039	-.168**	-.013	-.059	-.114**	-.012	-.056	-.604**	-.352**							
16 Aggressive behaviors (I)	-.412**	-.367**	-.283**	-.256**	.176**	-.354**	.171**	-.305**	.059	-.497**	.340**	-.469**	.433**	.823**	-.015						
17 Aggressive behaviors (slo.)	.434**	.322**	.193**	.234**	-.189**	.332**	-.186**	.301**	-.099**	.442**	-.344**	.466**	-.619**	-.696**	.087**	-.908**					
18 Engagement(I)	.545**	.475**	.426**	.336**	-.215**	.387**	-.179**	.388**	-.102**	.548**	-.395**	.534**	-.431**	-.759**	-.035	-.759**	.756**				
19 Engagement (slo.)	-.253**	-.061	.090**	-.057	.124**	-.126**	.177**	-.159**	.112**	-.160**	.200**	-.259**	.903**	.448**	-.522**	.469**	-.656**	-.517**			
20 Age	-.103**	-.133**	-.110**	-.096**	.032	-.129**	.020	-.079*	.019	-.154**	.095**	-.207**	.177**	.227**	-.006	.227**	-.228**	-.216**	.160**		
21 Sexe	-.009	.089**	.065*	.161**	-.030	-.110**	-.033	-.019	-.067*	-.032	.105**	-.039	.110**	-.034	-.062	-.074*	.025	.053	.081*	.051	
22 SES	-.024	.008	-.059	.045	-.272**	.139**	-.025	-.038	-.060	-.010	-.142**	.164**	-.070*	-.076*	.006	-.023	.015	.029	.001	-.049	.004

Note. * p ≤ .05; SDT: Global levels of self-determined motivation; SES: Socio-economic Status; _1 to _3: measurement wave (Time 1 to Time 3); I: Intercepts; S: Slopes.

Table 2

Results from the Growth Mixture Models

Model		LL	#fp	Scaling	AIC	CAIC	BIC	ABIC	ICL-BIC	Entropy
Unconditional Models										
M1	1 profile	-3070.987	6	1.2477	6153.974	6188.966	6182.966	6163.911	Na	Na
M2	2 profile	-3022.321	10	1.3790	6064.643	6122.962	6112.962	6081.203	5278.935	.351
M3	3 profile	-3007.543	14	1.8692	6043.085	6124.733	6110.733	6066.270	4972.147	.441
M4	4 profile	-2997.422	18	1.1984	6030.844	6135.820	6117.820	6060.653	5038.340	.580
M5	5 profile	-2987.106	22	1.1729	6018.211	6146.514	6124.514	6054.644	4742.969	.537
M6	6 profile	-2979.747	26	1.0009	6011.494	6163.125	6137.125	6054.551	4692.089	.565
M7	7 profile	-2973.939	30	0.9378	6007.879	6182.837	6152.837	6057.560	4706.142	.599
M8	8 profile	-2970.417	34	0.9308	6008.833	6207.120	6173.120	6065.139	4264.754	.505
Models with the Intercepts of the Predictors' Trajectories from M5, with Effects of Age on C & I										
M9	Null Effects	-2954.877	16	1.1013	5941.754	6034.926	6018.926	5968.112	4655.285	.543
M10	Effects on C	-2799.169	36	1.1667	5670.338	5879.976	5843.976	5729.645	4641.465	.597
M11	Effects on C, I (Inv.)	-2760.765	41	1.1365	5603.531	5842.286	5801.286	5671.075	4413.773	.535
M12	Effects on C, I, S (Inv.)	-2758.550	46	1.2152	5609.100	5876.972	5830.972	5684.881	4437.492	.533
M13	Effects on C, I (Free)	-2738.926	61	1.2573	5599.852	5955.072	5894.072	5700.344	4590.109	.563
M14	Effects on C, I, S (Free)	-2713.605	86	1.1731	5599.210	6100.013	6014.013	5740.887	4748.840	.576
Models with the Slopes of the Predictors' Trajectories from M11										
M15	Effects on C	-2735.783	57	1.3400	5585.566	5917.493	5860.493	5679.468	4699.757	.611
M16	Effects on S (Inv.)	-2746.266	45	1.2643	5582.532	5844.579	5799.579	5656.665	4424.002	.539
M17	Effects of S (free)	-2731.374	61	1.1764	5584.748	5939.969	5878.969	5685.240	4533.231	.549
M18	Effects on C, S (Inv.)	-2724.567	61	1.5597	5571.134	5926.354	5865.354	5671.626	4618.085	.582
M19	Effects of C, S (free)	-2699.118	77	1.1352	5552.237	6000.630	5923.630	5679.087	4783.781	.618

Note. LL: Model LogLikelihood; #fp: Number of free parameters; AIC: Akaïke Information Criteria; CAIC: Constant AIC; BIC: Bayesian Information Criteria; ABIC: Sample-Size adjusted BIC; na: Not applicable; c: Profile membership; I: Intercept factor; S: Slope factor.

Table 3

Parameters Estimates from the final Unconditional Growth Mixture Model

Parameter	Profile 1 (High-Stable) Estimate (*t*)	Profile 2 (Moderate) Estimate (*t*)	Profile 3 (High) Estimate (*t*)	Profile 4 (Low) Estimate (*t*)	Profile 5 (Increasing) Estimate (*t*)
Intercept Mean	.371 (2.726)**	-.131 (-.796)	.310 (3.621)**	-1.115 (-2.125)*	-1.311 (-5.173)**
Slope Mean	.135 (4.332)**	.163 (.822)	.175 (5.875)**	.021 (.127)	.451 (4.757)**
Intercept Variability ($SD = \sqrt{\sigma}$)	.510 (6.234)**	.510 (6.234)**	.510 (6.234)**	.510 (6.234)**	.510 (6.234)**
Slope Variability ($SD = \sqrt{\sigma}$)	.063 (1.370)	.063 (1.370)	.063 (1.370)	.063 (1.370)	.063 (1.370)
Intercept-Slope Correlation	-.029 (-3.091)**	-.029 (-3.091)**	-.029 (-3.091)**	-.029 (-3.091)**	-.029 (-3.091)**
$SD(\varepsilon_{yi})$	.089 (2.546)*	.792 (7.022)**	.458 (5.030)**	.603 (2.588)**	.469 (6.102)**

Note. t = Estimate / standard error of the estimate (t value are computed from original variance estimate); SD(ε_{yi}) = Standard deviations of the time-specific residuals; We present the square roots of the estimates of variability (trajectory factors, time-specific residuals) so that these results can be interpreted in the same units as the constructs (here, standardized factor scores with a mean of 0 and a *SD* of 1); * $p \leq .05$; ** $p \leq .01$.

Table 4

Results from the Predictive Analyses

	Profile 1 vs 5		Profile 2 vs 5		Profile 3 vs 5		Profile 4 vs 5	
Predictors	Coef. (SE)	OR	Coef. (SE)	OR	Coef. (SE)	OR	Coef. (SE)	OR
Age	-.149 (.388)	.862	-.353 (.424)	.702	-.402 (.371)	.669	.445 (.516)	1.561
Rel. with Peers (Intercept)	.190 (.428)	1.209	.839 (.915)	2.314	.130 (.303)	1.139	1.337 (.601) *	3.809
Rel. with Father (Intercept)	-.057 (.457)	.944	-.721 (.556)	.486	.040 (.435)	1.040	-.838 (.557)	0.433
Rel. with Mother(Intercept)	.255 (.384)	1.290	.474 (.519)	1.606	-.002 (.424)	.998	.431 (.654)	1.539
Rel. with Teacher (Intercept)	.664 (.292)*	1.943	.260 (.778)	1.297	.969 (.374)**	2.634	-.582 (.709)	0.559
	Profile 1 vs 4		Profile 2 vs 4		Profile 3 vs 4		Profile 1 vs 3	
Predictors	Coef. (SE)	OR	Coef. (SE)	OR	Coef. (SE)	OR	Coef. (SE)	OR
Age	-.594 (.300)*	.552	-.799 (.416)	.450	-.847 (.314)**	.429	.253 (.200)	1.288
Rel. with Peers (Intercept)	-1.148 (.602)	.317	-.498 (.995)	.608	-1.207 (.582)*	.299	.059 (.473)	1.061
Rel. with Father (Intercept)	.780 (.543)	2.181	.117 (.653)	1.124	.877 (.515)	2.404	-.097 (.402)	.908
Rel. with Mother(Intercept)	-.176 (.491)	.839	.043 (.526)	1.044	-.433 (.507)	.649	.257 (.203)	1.293
Rel. with Teacher (Intercept)	1.246 (.745)	3.476	.842 (.932)	2.321	1.550 (.842)	4.711	-.305 (.436)	.737
	Profile 2 vs 3		Profile 1 vs 2		Intercept factor			Slope factor
Predictors	Coef. (SE)	OR	Coef. (SE)	OR	Coef. (SE)		Predictors	Coef. (SE)
Age	.049 (.293)	1.050	.204 (.306)	1.226	-.076 (.028)**			
Rel. with Peers (Intercept)	.709 (1.038)	2.032	-.650 (.850)	.522	.118 (.054)*		Rel. with Peers (Slope)	-.072 (.120)
Rel. with Father (Intercept)	-.761 (.555)	.467	.664 (.393)*	1.943	-.077 (.052)		Rel. with Father (Slope)	.168 (.077)*
Rel. with Mother(Intercept)	.475 (.350)	1.608	-.219 (.319)	.803	-.015 (.051)		Rel. with Mother(Slope)	.070 (.058)
Rel. with Teacher (Intercept)	-.709 (.887)	.492	.404 (.652)	1.498	.331 (.049)*		Rel. with Teacher (Slope)	.190 (.095)*

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: *High-Stable*; Profile 2: *Moderate*; Profile 3: *High*; Profile 4: *Low*; Profile 5: *Increasing*.

Table 5

Associations between Profile Membership and the Outcomes

	Profile 1 (High-Stable)		Profile 2 (Moderate)		Profile 3 (High)		Profile 4 (Low)		Profile 5 (Increasing)		Significant Differences
	M	CI	*M*	CI	*M*	CI	*M*	CI	*M*	CI	
Grades (Intercept)	.024	[-.184; .232]	.069	[-.009; .147]	-.403	[-.509; -.297]	-.612	[-.728; -.496]	.904	[.804; 1.004]	4 < 3 < 1 = 2 < 5
Grades (Slope)	.009	[-.009; .027]	.006	[.000; .012]	.105	[.091; .119]	-.075	[-.097; -.053]	-.116	[-.130; -.102]	5 < 4 < 1 = 2 < 3
Risk behaviors (Intercept)	-.023	[-.160; .114]	-.661	[-.712; -.610]	.118	[.049; .187]	1.255	[1.043; 1.467]	-1.334	[-1.414; -1.254]	5 < 2 < 1 = 3 < 4
Risk behaviors (Slope)	.105	[.062; .148]	.085	[.069; .101]	-.197	[-.226; -.168]	.474	[.343; .605]	.298	[.267; .329]	3 < 1 = 2 < 5 < 4
Aggressive behaviors (Intercept)	-.200	[-.329; -.071]	-.760	[-.791; -.729]	.059	[-.015; .133]	1.362	[1.125; 1.599]	.133	[.025; .241]	1 < 2 < 3 = 5 < 4
Aggressive behaviors (Slope)	-.126	[-.157; -.095]	.044	[.032; .056]	-.162	[-.174; -.150]	-.500	[-.541; -.459]	-.206	[-.233; -.179]	4 < 5 < 3 < 1 < 2
Engagement (Intercept)	.195	[.056; .334]	.740	[.691; .789]	-.232	[-.308; -.156]	-1.261	[-1.447; -1.075]	-.250	[-.338; -.162]	4 < 3 = 5 < 1 < 2
Engagement (Slope)	.068	[.043; .093]	.095	[.085; .105]	.159	[.130; .188]	.340	[.305; .375]	-.155	[-.175; -.135]	5 < 1 = 2 < 3 < 4

Note. M: Mean; CI: 95% confidence interval.

Online Supplements :

Preliminary Measurement Models

Preliminary measurement models were estimated using Mplus 8 (Muthén & Muthén, 2017), the robust maximum likelihood (MLR) estimator. Full Information Maximum Likelihood (FIML; Enders, 2010; Graham, 2009, 2012) estimation was used to handle missing time points (our of 927 participants, 751 completed all three time points, 73 completed two time points, and 103 completed a single time point), missing responses for participants who completed each time point (Time 1: 0 to 6%, *M* = .99%; Time 2: 0 to 8.7%, *M* = .79%; Time 3: 0 to 6.9%, *M* = .65%), and missing school grade information (15.4% to 24.2% across time points, *M* = 18.46%). Due to the complexity of the longitudinal models underlying all constructs assessed here, these analyses were conducted separately for the motivation variables, the predictors (SES, relationships with peers, a relationship with the father, relationship with the mother, and relationships with teachers), and the outcomes. Given the known oversensitivity of the chi-square test of exact fit (χ^2) to sample size and minor model misspecifications, we relied on sample-size independent goodness-of-fit indices to describe the fit of the alternative models (Hu & Bentler, 1999; Marsh, Hau, & Grayson, 2005): the comparative fit index (CFI), the Tucker-Lewis index (TLI), as well as the root mean square error of approximation (RMSEA) and its 90% confidence interval. Values greater than .90 for the CFI and TLI indicate adequate model fit, although values greater than .95 are preferable. Values smaller than .08 or .06 for the RMSEA respectively support acceptable and excellent model fit. Like the chi square, chi square difference tests present a known sensitivity to sample size and minor model misspecifications so that recent studies suggest complementing this information with changes in CFIs and RMSEAs (Chen, 2007; Cheung & Rensvold, 2002) in the context of tests of measurement invariance. A ΔCFI of .010 or less and a ΔRMSEA of .015 or less between a more restricted model and the previous one supports the invariance hypothesis. For all models, we report composite reliability coefficients 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, and δi, the item uniquenesses.

Motivation

For the motivation measure, we adopted the bifactor exploratory structural equation model (bifactor-ESEM; Morin, Arens, & Marsh, 2016) recently proposed by Litalien et al. (2017; also see Howard, Gagné, Morin, & Forest 2018) in order to achieve a direct and precise estimate of the global continuum of self-determination proposed by SDT to underlie all motivation ratings (i.e., the global level of self-determined motivation) properly disaggregated from the specificity remaining at the subscale level. This model included one global factor (G-factor: global level of self-determined motivation) and five specific orthogonal factors (S-factors: intrinsic motivation, identified regulation, introjected regulation, external regulation, and amotivation) and was estimated using an orthogonal bifactor target rotation, allowing us to define each factor in a confirmatory manner while including cross-loadings "targeted" to be as close to zero as possible (Morin, Arens, & Marsh, 2016; Reise, Moore, & Maydeu-Olivares, 2011).

Following recommendations from Morin and colleagues (Morin, Arens, & Marsh, 2016; Morin, Boudrias et al., 2016, 2017), we started by a systematic comparison of the a priori bifactor-ESEM solution with alternative confirmatory factor analytic (CFA), ESEM, and bifactor-CFA solutions at each separate time points to ascertain the superiority of the bifactor-ESEM solution. The goodness of fit of all of these alternative models are reported in Table S1, while the parameter estimates from all alternative solutions are reported in Tables S2 to S8. The results from these comparisons systematically supported the superiority of the bifactor-ESEM solution, which generally resulted in the highest level of fit to the data according to most indices. In addition, the CFA versus ESEM comparisons revealed main factors that were generally well-defined by strong factor loadings in both solutions, multiple small yet non-negligible cross-loadings in the ESEM solution, as well as reduced factor correlations in the ESEM ($|r|$ = .019 to .625, $M_{|r|}$ = .385) relative to CFA (($|r|$ = .002 to .714, $M_{|r|}$ = .458) solution (Asparouhov, Muthén, & Morin, 2015; Morin, Myers, & Lee, 2018). These results thus supported the need to incorporate cross-loadings to the solution. Then, the ESEM solution was compared to our a priori bifactor-ESEM solution, which revealed slightly reduced cross-loadings, a G-factor defined in accordance with the SDT continuum hypothesis (with negative loadings from the amotivation items, small loadings from the external regulation items, and stronger increasing loadings from the introjected regulation, identified regulation, and intrinsic motivation items), and well-defined S-factors. Because these results are fully aligned with those obtained by Litalien et al. (2017) and Howard et al. (2018), the bifactor-ESEM solution was retained as our final solution. The G-factor from this solution, which is used in the main manuscript to assess the longitudinal self-determination trajectories, was also associated with a satisfactory level of composite reliability in these analyses (ω = .887 to .920).

Before saving the factor scores for our main analyses, we verified that this bifactor-ESEM measurement model operated in the same manner across time waves, through sequential tests of measurement invariance (Millsap, 2011): (1) configural invariance, (2) weak invariance (loadings), (3) strong invariance (loadings and intercepts), (4) strict invariance (loadings, intercepts, and uniquenesses); (5) invariance of the latent variance-covariance matrix (loadings, intercepts, uniquenesses, and latent variances and covariances); (6) latent means invariance (loadings, intercepts, uniquenesses, latent variances and covariances, and latent means). The longitudinal model used to assess longitudinal invariance included a total of 18 factors ([1 G-factor + 5 S-factors] x 3 time waves). 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, Abduljabbar et al., 2013).

The results from these tests are reported in Table S9 and supported the configural, weak and strong invariance of the motivation measure. However, strict invariance was not supported by the data, as shown by a substantial decrease in model fit. The modification indices associated with this failed model of strict invariance, as well as the parameter estimates associated with the model of strong invariance suggested that this lack of invariance was mainly due to six item uniquenesses which tended to be slightly higher at Time 1. Invariance constraints were thus relaxed for these six specific uniquenesses, leading to a model of partial strict invariance. From that model, the model of invariance of the variance-covariance matrix was, but only barely, supported by the data. Given the impossibility to test for partial invariance of the latent variance-covariance in bifactor-ESEM, this model was retained. The next model of latent mean invariance was rejected, leading us to save factor scores from the main analyses from the model of latent variance-covariance invariance. Examination of the latent means associated with this final model revealed that the lack of latent mean invariance was due, in part, to an average increase in participants global levels of self-determined motivation of approximately .5 SD occurring between Time 1 and Time 2. This increase was accompanied by a matching increase of about .35 SD in specific levels of intrinsic motivation, and a matching decrease of about .20 SD in specific levels of amotivation occurring between Time 1 and Time 2. In contrast, specific levels of identified, introjected, and external regulation showed a slight decrease of .30 to .40 SD occurring over the whole duration of the study.

Predictors and Controls

The measurement model underlying the predictors and controls included a total of five correlated CFA factors (control: SES; Predictors: relationships with peers, a relationship with the father, relationship with the mother, and relationships with teachers) per measurement point, leading to a 15-factor longitudinal model. 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, Abduljabbar et al., 2013). Likewise, a priori correlated uniquenesses were also included to account for the parallel wording of the items used to assess the quality of students' relationships with their peers, father, mother, and teacher (e.g., Marsh, Abduljabbar et al., 2013). One additional step was included to test for the invariance of these correlated uniquenesses over time. As shown in Table S9, this longitudinal measurement model was able to achieve a fully satisfactory level of fit to the data across time points, and appeared to be completely invariant across time waves. Parameter estimates from this final model are reported in Table S10, and further support its adequacy by revealing well-defined factors all characterized by satisfactory estimates of composite reliability (ω = .680 for the SES factor to .940 for the relationships with father factor).

As noted in the main manuscript, students' self-determination trajectories were estimated as a function of grade level (ranging from grade 7 to grade 11). For this reason, it made no sense to save time-specific factor scores for the predictor variables to assess their associations with self-determined motivation trajectories given that each time-specific set of factor scores on the predictors would conflate results from students across three grade levels. In order to achieve grade specific information on the predictor variables, we extended a strategy initially proposed by Morin, Maïano et al. (2011) which involves the estimation of latent curve trajectories for each predictor variable (Bollen & Curran, 2006). These trajectories were estimated in a single multivariate model, specified as fully latent from the model of strict measurement invariance described above (i.e., the estimation of latent curve models requires the estimation of time specific means and variances, precluding the reliance on the models of latent variance-covariance, or latent mean invariance), and involved the estimation of linear trajectories defined as a function of grade levels using an approach proposed by Grimm, Ram and Estabrook (2016) and implemented via the Mplus' MODEL CONSTRAINT function. Because only three time points were available, it was not possible to model non-linear trajectories. Factors scores reflecting the initial level in grade seven (intercept) and rate of change over time (slope) in predictors trajectories were saved from this model. It should be noted that because these trajectories are estimated from time-specific latent factors estimated in standardized units as deviation from the first time point, the intercept factors had to be set to have a mean of 0 and a SD of 1 so that the slope factors can be directly interpreted in SD units as deviation from Grade 7 scores. The results from this multivariate model are reported in Table S12. These results show that students' relationships with their peers and their teachers tended to slightly increase over time, a tendency that was more pronounced for students with initially lower levels on these variables. In contrasts, students' relationships with their father and mother appeared to be quite stable over time.

Outcomes

The outcome measurement model included a total of four correlated CFA factors (grades, school risk behaviors, aggressive behaviors aggressive behaviorsand engagement) per measurement point, leading to a 12-factor longitudinal model. 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, Abduljabbar et al., 2013). Likewise, a priori correlated uniquenesses were also included to account for the reversed wording of two of the risk behaviors items at each time point (Marsh, Scalas, & Nagengast, 2010). One additional step was included to test for the invariance of these correlated uniquenesses over time. As shown in Table

S9, this longitudinal measurement model was able to achieve a satisfactory level of fit to the data across time points. Although results supported the weak invariance of this model, as well as the invariance of the correlated uniquenesses, they failed to support its strong, strict, latent variance-covariance, and latent mean invariance. These observation lead us to explore, and retain, models of partial invariance in which invariance constraints were relaxed on 5 item intercepts, 11 item uniquenesses, on a total of four variances and covariances involving the aggressive behaviors aggressive behaviorsand engagement factors at Time 1, and on a total of 7 latent means. Latent mean differences observed in the final retained model of partial mean invariance revealed that average levels of aggressive behaviors aggressive behaviorstended to decrease over time (by about .4 SD between Time 1 and Time 2, and .2 SD between Time 2 and Time 3), whereas average levels of engagement increase of about .33 SD between Time 1 and Time 2. Parameter estimates from this final model are reported in Table S11, and reveal well-defined factors all characterized by satisfactory estimates of composite reliability (ω = .669 for the risk behaviors factor at Time 1 to .827 for the engagement factor at Time 1).

Starting from this most invariant measurement model, we adopted a latent curve modeling strategy similar to that used for the predictors in order to obtained factors scores reflecting the initial level in Grade 7 (intercept) and rate of change over time (slope) in outcome trajectories. The results from this multivariate model are reported in Table S12. These results show that students' levels of risk behaviors and engagement tended to slightly increase over time, a tendency that was more pronounced for students with initially lower levels of engagement. In contrast, students' grades appeared to be quite stable over time, despite the fact that students with initially lower grades were more likely to display a slight increase over time. Finally, students' levels of aggressive behaviors aggressive behaviorstended to decrease over time, a tendency that was more pronounced for students with initially higher levels of aggressive behaviorsaggressive behaviors.

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A More Technical Presentation of Latent Curve Models and Growth Mixture Analyses (GMA)

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

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

$$\beta_{iyk} = \mu_{\beta yk} + \zeta_{\beta yik} \tag{2}$$

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

$$\Phi_{yk} = \begin{bmatrix} \psi_{\alpha\alpha yk} & \\ \psi_{\alpha\beta yk} & \psi_{\beta\beta yk} \end{bmatrix} \tag{3}$$

In these models, Time is represented by λ_{it}, the factor loading matrix relating the time-specific indicators to the linear slope factor. Time is coded to reflect the passage of time and is typically estimated as constant across participants (without the *i* subscript). However, the present studies seeks to model longitudinal trajectories as a function of students' grade levels, which differs across students within each specific measurement point and where thus allowed to vary across participants. The current study relies on three equally spaced measurement points, with one year intervals, and the youngest students were enrolled in Grade 7 at Time 1. We thus decided to set the intercept in Grade 7 [$E(\alpha_{iyk}) = \mu_{y7k}$], and to set the subsequent time codes to reflect the passage of time in years. As noted in the main manuscript, the current study relies on a more constrained estimation of GMA through which the latent variance-covariance matrix was specified as invariant across profiles, whereas the residuals were specified as homoscedastic but freely estimated across profiles. The homoscedasticity of the residuals was made necessary by the nature of the time specifications used in the present study, which would have made it unrealistic to freely estimate residuals across time points, knowing that each time point encompassed multiple grade levels. This specification thus led to:

$$y_{it} = \sum_{k=1}^{K} p_k[\alpha_{iyk} + \beta_{1iyk}\lambda_{it} + \varepsilon_{yik}] \tag{4}$$

$$\beta_{iyk} = \mu_{\beta yk} + \zeta_{\beta yi} \tag{5}$$

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

In Mplus, this specification would be achieved by the following syntax for a 2-profile GMA (annotations are in greyscale and should be taken out):

```
!!! This first section identifies the data set.
Data:
File is DATMOT2.csv;
!!! the NAMES function identifies the variables included in the data set, in order of appearance.
Variable:
Names = id G1 G2 G3 nscol;
!!! the USEVARIABLE function identifies the variables included in the model.
Usevariable = G1 G2 G3;
!!! the CONSTRAINT function identifies the variables which included the time information.
!!! Here, nscol identifies the grade level of the student, with the intercept set to correspond to grade 7
!!! 0 = grade 7, 1 = grade 8, 2 = Grade 9.
CONSTRAINT = nscol;
!!! the IDVAR function identifies the unique identifier of each participant.
IDVAR = ID;
!!! the MISSING function identifies the code used to identify missing data.
missing is all (-99);
!!! the CLASSES function identifies the number of latent profiles that are requested.
CLASSES = c(2);
!!! Here, the ANALYSIS section requests the estimation of a mixture model, relying on MLR estimation,
!!! 3 processors, 10000 random starts (500 retained for final optimization), and 1000 iterations.
ANALYSIS:
TYPE = MIXTURE;
ESTIMATOR = MLR;
Process = 3;
Starts = 10000 500; STITERATIONS = 1000;
!!! The MODEL %OVERALL% section describes the basic model.
!!! I refers to the intercept factor (average level for the time code corresponding to 0).
!!! S refers to the slope factor, were the time codes are identified by parameter labels (L1) (L2) (L3)
!!! G1 G2 G3 are the repeated measures. The meanstructure is used to estimate the intercept
!!! and slope [I S ] by fixing the time specific intercepts to 0 [G1@0 G2@0 G3@0]
!!! I S refers to the growth factor variance, I WITH S to their correlation, and G1 G2 G3 to the residuals
MODEL:
%OVERALL%
I BY G1@1 G2@1 G3@1;
S BY G1* (L1)
   G2  (L2)
   G3  (L3);
[G1@0 G2@0 G3@0];
I S ; [I S ]; I WITH S ;
G1 G2 G3;
!!! The class specific sections % c#1% %c#2%  are used to specify which parameters are freely estimated
```

```
!!!! across profiles. Here the intercept and slope means [I S ] and the residuals G1 G2 G3 although these
!!!! are constrained to equality across time period by using a label (r1) (r2) that differs across profiles.
%c#1%
[I S ];
G1 G2 G3 (r1);
%c#2%
[I S ];
G1 G2 G3 (r2);
!!! This section is used to defined the time codes to be used in the model estimation.
!!! The time code corresponding to L1 is based on students' grade levels defined as above.
!!! This is then increased by one each subsequent year of the study.
MODEL CONSTRAINT:
L1 = nscol2;
L2 = nscol2 + 1;
L3 = nscol2 + 2;
OUTPUT:
STDYX SAMPSTAT CINTERVAL RESIDUAL svalues TECH1 TECH7 TECH11 TECH14;
```

Table S1

Fit Statistics of the Time-Specific Preliminary Measurement Models

	χ^2	df	#fp	RMSEA	90% CI	CFI	TLI
Time 1							
CFA	671.776*	160	70	.058	.054; .063	.924	.910
Bifactor-CFA	787.182*	150	80	.067	.063; .072	.905	.880
ESEM	341.875*	100	130	.051	.045; .057	.964	.932
Bifactor-ESEM	268.848*	85	145	.048	.042; .054	.973	.939
Time 2							
CFA	431.714*	160	70	.045	.040; .050	.950	.940
Bifactor-CFA	507.320*	150	80	.054	.048; .059	.934	.916
ESEM	221.656*	100	130	.038	.032; .045	.978	.957
Bifactor-ESEM	158.276*	85	145	.032	.024; .040	.986	.970
Time 3							
CFA	535.421*	160	70	.055	.050; .060	.936	.924
Bifactor-CFA	673.615*	150	80	.067	.062; .072	.910	.886
ESEM	269.144*	100	130	.047	.040; .053	.971	.945
Bifactor-ESEM	171.199*	85	145	.036	.028; .044	.985	.967
Predictors (CFA)							
Time 1	127.689*	118	91	.009	.000; .019	.999	.998
Time 2	104.971*	74	78	.022	.011; .032	.994	.991
Time 3	154.483*	74	78	.037	.029; .046	.986	.978
Outcomes (CFA)							
Time 1	478.677*	163	67	.045	.041; .050	.922	.909
Time 2	470.179*	163	67	.048	.043; .053	.898	.881
Time 3	543.318*	163	67	.055	.050; .060	.869	.847

Note. * p < .01; CFA: confirmatory factor analyses; ESEM: exploratory structural equation modeling; χ^2: robust chi-square test of exact fit; #fp: Number of free parameters; *df*: degrees of freedom; CFI: comparative fit index; TLI: Tucker-Lewis index; RMSEA: root mean square error of approximation; 90% CI: 90% confidence interval.

Table S2

Standardized Factor Loadings (λ) and Uniquenesses (δ) from the Motivation CFA and ESEM measurement models (Time 1)

	CFA						ESEM					
Items	F1 λ	F2 λ	F3 λ	F4 λ	F5 λ	δ	F1 λ	F2 λ	F3 λ	F4 λ	F5 λ	δ
Amotivation												
Item 1	**.713**					.491	**.615**	.063	-*.017*	-*.101*	-*.105*	.483
Item 2	**.672**					.548	**.684**	-*.009*	.099	-*.072*	*.035*	.524
Item 3	**.850**					.278	**.817**	*.022*	-*.078*	-*.002*	-*.019*	.288
Item 4	**.836**					.302	**.897**	-*.035*	-*.003*	*.057*	*.051*	.266
External Regulation												
Item 1		**.441**				.805	.193	**.297**	*.012*	.246	-*.082*	.778
Item 2		**.673**				.547	-.139	**.574**	*.018*	.167	-*.002*	.495
Item 3		**.668**				.554	*.048*	**.782**	-*.036*	-*.130*	.097	.482
Item 4		**.796**				.366	*.005*	**.749**	*.093*	*.006*	-*.064*	.374
Introjected Regulation												
Item 1			**.664**			.559	*.063*	*.044*	**.686**	*.130*	-*.142*	.514
Item 2			**.748**			.440	*.021*	-*.003*	**.527**	*.041*	*.278*	.436
Item 3			**.788**			.379	-*.009*	.098	**.743**	-*.096*	*.072*	.376
Item 4			**.844**			.288	-.065	-*.046*	**.920**	-*.009*	-*.058*	.239
Identified Regulation												
Item 1				**.714**		.490	-*.001*	-*.121*	*.041*	**.757**	*.067*	.419
Item 2				**.630**		.603	-*.030*	*.164*	-*.114*	**.627**	*.016*	.530
Item 3				**.739**		.453	-*.087*	*.060*	*.091*	**.594**	*.019*	.466
Item 4				**.736**		.459	-*.070*	.156	.133	**.421**	*.130*	.492
Intrinsic Motivation												
Item 1					**.761**	.421	-*.072*	*.014*	-*.096*	*.024*	**.803**	.375
Item 2					**.837**	.300	*.012*	*.013*	*.001*	*.008*	**.853**	.269
Item 3					**.840**	.295	*.018*	*.045*	*.084*	-*.005*	**.781**	.302
Item 4					**.861**	.259	-*.006*	-*.069*	.144	*.148*	**.671**	.283
ω	.853	.745	.848	.799	.895		.853	.730	.841	.751	.887	

Notes. CFA: Confirmatory factor analysis; ESEM: Exploratory Structural Equation Modeling; F: factor; ω: omega coefficient of composite reliability. Target loadings are marked in bold. Non-statistically significant parameters ($p \geq .05$) are marked in italics.

Table S3

Standardized Factor Loadings (λ) and Uniquenesses (δ) from the Motivation CFA and ESEM measurement models (Time 2)

	CFA						ESEM					
Items	F1 λ	F2 λ	F3 λ	F4 λ	F5 λ	δ	F1 λ	F2 λ	F3 λ	F4 λ	F5 λ	δ
Amotivation												
Item 1	**.749**					.439	**.730**	-.067	*.003*	*.010*	-*.052*	.428
Item 2	**.544**					.704	**.550**	*.048*	*.067*	-*.015*	-*.028*	.683
Item 3	**.819**					.329	**.788**	*.032*	-*.051*	-*.056*	*.021*	.341
Item 4	**.805**					.353	**.821**	*.012*	-*.055*	-*.055*	.096	.346
External Regulation												
Item 1		**.473**				.776	.186	**.321**	.138	.198	-.213	.724
Item 2		**.750**				.438	-*.035*	**.618**	*.041*	.136	-*.026*	.488
Item 3		**.675**				.545	.059	**.586**	*.110*	-*.017*	*.047*	.568
Item 4		**.831**				.309	-.060	**.998**	-.114	-*.068*	*.043*	.163
Introjected Regulation												
Item 1			**.531**			.718	.076	*.050*	**.542**	*.104*	-.115	.673
Item 2			**.739**			.454	-*.027*	-.050	**.671**	*.017*	.124	.459
Item 3			**.695**			.517	-.077	.152	**.697**	-.210	*.041*	.467
Item 4			**.792**			.372	-*.023*	-*.086*	**.789**	*.090*	*.005*	.360
Identified Regulation												
Item 1				**.705**		.503	-*.093*	-*.015*	*.001*	**.593**	.122	.496
Item 2				**.721**		.481	-*.022*	*.024*	-*.062*	**.848**	-*.055*	.347
Item 3				**.724**		.476	-*.074*	*.098*	*.043*	**.520**	.126	.496
Item 4				**.719**		.483	-*.027*	*.114*	.137	**.426**	.163	.510
Intrinsic Motivation												
Item 1					**.777**	.397	-*.034*	-*.006*	*.017*	-*.041*	**.787**	.376
Item 2					**.848**	.281	*.014*	-*.005*	*.032*	*.081*	**.784**	.290
Item 3					**.834**	.304	*.017*	*.006*	-*.005*	*.060*	**.816**	.292
Item 4					**.870**	.243	*.004*	*.006*	*.072*	.104	**.762**	.249
ω	.823	.783	.787	.809	.900		.823	.766	.788	.755	.891	

Notes. CFA: Confirmatory factor analysis; ESEM: Exploratory Structural Equation Modeling; F: factor; ω: omega coefficient of composite reliability. Target loadings are marked in bold. Non-statistically significant parameters ($p \geq .05$) are marked in italics.

Table S4

Standardized Factor Loadings (λ) and Uniquenesses (δ) from the Motivation CFA and ESEM measurement models (Time 3)

	CFA						ESEM					
Items	F1 λ	F2 λ	F3 λ	F4 λ	F5 λ	δ	F1 λ	F2 λ	F3 λ	F4 λ	F5 λ	δ
Amotivation												
Item 1	**.796**					.367	**.732**	-*.027*	-*.020*	-*.062*	-*.048*	.365
Item 2	**.660**					.564	**.701**	-*.033*	*.001*	*.034*	*.020*	.544
Item 3	**.857**					.265	**.822**	*.049*	-*.028*	-*.061*	*.014*	.274
Item 4	**.825**					.320	**.831**	*.035*	-*.027*	-*.023*	*.040*	.314
External Regulation												
Item 1		**.433**				.813	.221	**.313**	.148	*.103*	-*.123*	.764
Item 2		**.723**				.477	-*.007*	**.621**	*.017*	*.161*	-*.022*	.487
Item 3		**.721**				.481	*.032*	**.623**	.129	.019	-*.011*	.502
Item 4		**.842**				.292	-.068	**.892**	-*.020*	-*.007*	*.009*	.220
Introjected Regulation												
Item 1			**.540**			.708	*.073*	*.028*	**.646**	*.066*	-.195	.613
Item 2			**.711**			.494	*.019*	-*.013*	**.582**	*.063*	.174	.498
Item 3			**.783**			.388	-.108	.223	**.631**	-.175	.160	.400
Item 4			**.795**			.368	-*.057*	-.096	**.855**	*.052*	-*.027*	.307
Identified Regulation												
Item 1				**.721**		.480	-*.023*	-.142	-*.012*	**.869**	-*.044*	.368
Item 2				**.688**		.527	-*.069*	.281	-.125	**.555**	*.052*	.478
Item 3				**.757**		.427	-*.063*	*.012*	*.039*	**.607**	*.112*	.451
Item 4				**.712**		.493	*.002*	*.112*	.144	**.502**	*.091*	.501
Intrinsic Motivation												
Item 1					**.786**	.382	-*.060*	-*.091*	*.009*	*.056*	**.728**	.374
Item 2					**.880**	.226	*.019*	*.031*	-*.045*	*.006*	**.912**	.208
Item 3					**.818**	.331	*.027*	-*.035*	*.073*	*.030*	**.779**	.331
Item 4					**.837**	.299	*.009*	*.015*	*.070*	*.077*	**.754**	.300
ω	.867	.782	.803	.811	.899		.864	.752	.802	.781	.892	

Notes. CFA: Confirmatory factor analysis; ESEM: Exploratory Structural Equation Modeling; F: factor; ω: omega coefficient of composite reliability. Target loadings are marked in bold. Non-statistically significant parameters ($p \geq .05$) are marked in italics.

Table S4

Correlations from the Time-Specific Motivation CFA (Under the Diagonal) and ESEM (Above the Diagonal) Measurement Models

Items	Amotivation	External	Introjected	Identified	Intrinsic
Time 1					
Amotivation		.036	-.191**	-.424**	-.370**
External	-.002		.485**	.522**	.121*
Introjected	-.242**	.537**		.536**	.625**
Identified	-.486**	.611**	.652**		.519**
Intrinsic	-.407**	.206**	.700**	.654**	
Time 2					
Amotivation		-.019	-.190**	-.405**	-.498**
External	-.074		.582**	.470**	.177**
Introjected	-.279**	.589**		.525**	.530**
Identified	-.521**	.547**	.636**		.560**
Intrinsic	-.513**	.248**	.619**	.714**	
Time 3					
Amotivation		-.023	-.140**	-.531**	-.444**
External	-.081		.515**	.462**	.082
Introjected	-.241**	.585**		.494**	.472**
Identified	-.590**	.563**	.593**		.589**
Intrinsic	-.472**	.147*	.559**	.662**	

Note. * $p < .05$; ** $p < .01$.

Table S6

Standardized Factor Loadings (λ) and Uniquenesses (δ) from the Motivation bifactor-CFA and bifactor-ESEM measurement models (Time 1)

	Bifactor-CFA							Bifactor-ESEM						
Items	SF1 λ	SF2 λ	SF3 λ	SF4 λ	SF5 λ	Global λ	δ	SF1 λ	SF2 λ	SF3 λ	SF4 λ	SF5 λ	Global λ	δ
Amotivation														
Item 1	**.580**					**-.407**	.498	**.579**	*.044*	*-.037*	*-.078*	*-.116*	**-.361**	.472
Item 2	**.643**					**-.221**	.538	**.610**	*.003*	.098	*-.041*	*.050*	**-.258**	.520
Item 3	**.736**					**-.414**	.287	**.739**	*.031*	*-.051*	*.003*	*-.011*	**-.405**	.289
Item 4	**.807**					**-.297**	.261	**.810**	*-.023*	*.011*	*.053*	*.038*	**-.320**	.267
External Regulation														
Item 1		**.397**				**.158**	.817	.147	**.314**	*.067*	.204	*.030*	***.086***	.754
Item 2		**.501**				**.461**	.537	-.126	**.536**	*.024*	.116	*.005*	**.394**	.493
Item 3		**.638**				**.271**	.519	.052	**.714**	*-.020*	-.107	*.052*	**.248**	.482
Item 4		**.720**				**.359**	.353	*.031*	**.672**	*.034*	*-.012*	*-.094*	**.341**	.372
Introjected Regulation														
Item 1			**.443**			**.509**	.544	*.030*	*.066*	**.532**	.102	*-.030*	**.424**	.476
Item 2			**.258**			**.701**	.442	*.028*	*-.018*	**.351**	*.009*	*.149*	**.633**	.436
Item 3			**.443**			**.635**	.401	*.014*	*.064*	**.472**	*-.103*	*-.017*	**.619**	.376
Item 4			**.565**			**.676**	.224	*-.044*	*-.051*	**.592**	*-.040*	*-.078*	**.664**	.246
Identified Regulation														
Item 1				**.392**		**.612**	.472	*-.009*	-.102	*.059*	**.602**	*.080*	**.499**	.392
Item 2				**.500**		**.459**	.540	*-.019*	.161	*-.102*	**.450**	*-.011*	**.432**	.539
Item 3				**.433**		**.614**	.436	*-.011*	*-.006*	*-.045*	**.437**	-.149	**.631**	.403
Item 4				**.251**		**.673**	.484	*-.053*	.136	*.081*	**.305**	*.058*	**.575**	.493
Intrinsic Motivation														
Item 1					**.536**	**.575**	.383	*-.099*	*.046*	*-.013*	*.012*	**.625**	**.544**	.307
Item 2					**.572**	**.648**	.253	*.005*	*.003*	*.026*	*-.005*	**.565**	**.649**	.256
Item 3					**.459**	**.690**	.313	.080	*-.023*	*-.052*	*-.075*	***.346***	**.785**	.256
Item 4					**.414**	**.737**	.286	*.053*	-.128	*.000*	*.055*	**.287**	**.798**	.250
ω	.828	.696	.645	.562	.761			.829	.704	.712	.638	.757	.920	

Notes. CFA: Confirmatory factor analysis; ESEM: Exploratory Structural Equation Modeling; SF: specific factor; ω: omega coefficient of composite reliability. Because of the partial strict invariance of the model, some standardized parameters differ across time waves. Target loadings are marked in bold. Non-statistically significant parameters (p ≥ .05) are marked in italics.

Table S7

Standardized Factor Loadings (λ) and Uniquenesses (δ) from the Motivation bifactor-CFA and bifactor-ESEM measurement models (Time 2)

	Bifactor-CFA							Bifactor-ESEM						
Items	SF1 λ	SF2 λ	SF3 λ	SF4 λ	SF5 λ	Global λ	δ	SF1 λ	SF2 λ	SF3 λ	SF4 λ	SF5 λ	Global λ	δ
Amotivation														
Item 1	**.609**					**-.432**	.442	**.578**	*-.028*	*.026*	*.009*	*.010*	**-.503**	.420
Item 2	**.493**					**-.238**	.701	**.401**	.112	*.080*	*-.047*	*.077*	**-.369**	.657
Item 3	**.680**					**-.446**	.339	**.720**	*-.015*	*-.046*	*.006*	*-.064*	**-.388**	.314
Item 4	**.711**					**-.401**	.334	**.712**	*-.011*	*-.045*	*-.013*	*.024*	**-.392**	.347
External Regulation														
Item 1		**.462**				**.121**	.772	*.069*	**.404**	.149	.128	*-.021*	***-.130***	.655
Item 2		**.601**				**.437**	.448	-.070	**.648**	*.030*	*.081*	*.052*	**.209**	.460
Item 3		**.563**				**.354**	.558	.066	**.551**	*.083*	*-.015*	*.012*	**.249**	.570
Item 4		**.755**				**.404**	.266	*-.007*	**.924**	-.120	*-.058*	*-.037*	**.349**	.157
Introjected Regulation														
Item 1			**.411**			**.344**	.713	*-.020*	.132	**.503**	*.044*	*.048*	***.085***	.610
Item 2			**.431**			**.591**	.464	*.007*	*-.068*	**.560**	*.034*	*.056*	**.470**	.461
Item 3			**.539**			**.466**	.493	*.016*	*.055*	**.613**	-.150	-.113	**.510**	.395
Item 4			**.514**			**.609**	.364	*-.027*	*-.056*	**.660**	.079	*.033*	**.408**	.372
Identified Regulation														
Item 1				**.232**		**.643**	.533	*-.078*	*-.010*	*-.005*	**.527**	*.092*	**.388**	.493
Item 2				**.756**		**.583**	.088	*-.003*	*.019*	*-.056*	**.758**	*-.066*	**.346**	.363
Item 3				**.226**		**.669**	.501	*-.029*	*.065*	*.019*	**.485**	*.039*	**.455**	.491
Item 4				**.122**		**.707**	.485	*.058*	*.033*	.093	**.447**	*-.004*	**.527**	.476
Intrinsic Motivation														
Item 1					**.553**	**.571**	.368	-.057	*.025*	*-.002*	-.106	**.654**	**.503**	.359
Item 2					**.539**	**.659**	.275	*-.007*	*.019*	*.009*	*.009*	**.640**	**.550**	.275
Item 3					**.516**	**.658**	.301	*.030*	*-.012*	*-.031*	*.027*	**.591**	**.598**	.297
Item 4					**.442**	**.745**	.250	.058	*-.047*	*.029*	.096	**.501**	**.679**	.238
ω	.774	.735	.638	.526	.779	.921		.770	.776	.748	.729	.830	.887	

Notes. CFA: Confirmatory factor analysis; ESEM: Exploratory Structural Equation Modeling; SF: specific factor; ω: omega coefficient of composite reliability. Because of the partial strict invariance of the model, some standardized parameters differ across time waves. Target loadings are marked in bold. Non-statistically significant parameters ($p \geq .05$) are marked in italics.

Table S8

Standardized Factor Loadings (λ) and Uniquenesses (δ) from the Motivation bifactor-CFA and bifactor-ESEM measurement models (Time 3)

	Bifactor-CFA							Bifactor-ESEM						
Items	SF1 λ	SF2 λ	SF3 λ	SF4 λ	SF5 λ	Global λ	δ	SF1 λ	SF2 λ	SF3 λ	SF4 λ	SF5 λ	Global λ	δ
Amotivation														
Item 1	**.608**					**-.513**	.367	**.634**	*.019*	*.006*	*-.033*	*-.011*	**-.460**	.361
Item 2	**.578**					**-.333**	.556	**.616**	*-.008*	*.018*	*.040*	*.019*	**-.312**	.542
Item 3	**.724**					**-.457**	.267	**.762**	*.012*	*-.037*	*-.039*	*-.041*	**-.351**	.259
Item 4	**.714**					**-.424**	.310	**.735**	*.045*	*-.023*	*-.020*	*.021*	**-.357**	.320
External Regulation														
Item 1		**.466**				**.068**	.778	*.112*	**.462**	.203	*.086*	*.068*	***-.051***	.618
Item 2		**.586**				**.422**	.479	*-.013*	**.584**	*.015*	.101	*-.002*	**.372**	.475
Item 3		**.617**				**.368**	.484	*.066*	**.506**	*.071*	*-.002*	*-.072*	**.410**	.504
Item 4		**.722**				**.444**	.282	*-.014*	**.738**	*-.066*	*-.039*	-.069	**.506**	.212
Introjected Regulation														
Item 1			**.534**			**.256**	.650	*.001*	*.132*	**.608**	*.057*	*-.054*	***.170***	.516
Item 2			**.428**			**.554**	.510	*.061*	*-.085*	**.431**	*.033*	*.056*	**.569**	.482
Item 3			**.534**			**.534**	.430	*-.056*	.139	**.467**	-.162	*.059*	**.590**	.391
Item 4			**.629**			**.543**	.310	*-.044*	*-.074*	**.653**	*.022*	*-.018*	**.526**	.331
Identified Regulation														
Item 1				**.599**		**.636**	.236	*-.055*	*-.063*	*.003*	**.630**	*.016*	**.445**	.383
Item 2				**.243**		**.613**	.565	*-.073*	.285	-.109	**.396**	*.062*	**.468**	.477
Item 3				**.159**		**.739**	.429	*.005*	*-.084*	*-.013*	**.480**	*-.016*	**.620**	.408
Item 4				**.079**		**.716**	.481	*.052*	*.020*	*.084*	**.387**	*-.020*	**.604**	.477
Intrinsic Motivation														
Item 1					**.607**	**.510**	.372	-.106	*.027*	*.023*	*.009*	**.689**	**.400**	.320
Item 2					**.674**	**.596**	.191	*.006*	*.056*	*-.042*	*-.025*	**.744**	**.541**	.196
Item 3					**.551**	**.592**	.346	*.061*	-.091	*.022*	*.009*	**.545**	**.589**	.329
Item 4					**.506**	**.660**	.308	.059	*-.067*	*.007*	*.036*	**.507**	**.661**	.284
ω	.821	.739	.704	.405	.818	.923		.836	.744	.730	.673	.845	.911	

Notes. CFA: Confirmatory factor analysis; ESEM: Exploratory Structural Equation Modeling; SF: specific factor; ω: omega coefficient of composite reliability. Because of the partial strict invariance of the model, some standardized parameters differ across time waves. Target loadings are marked in bold. Non-statistically significant parameters ($p \geq .05$) are marked in italics.

Table S9

Longitudinal Measurement Invariance

	χ^2	df	CFI	TLI	RMSEA	90% CI	$\Delta\chi^2$	Δdf	ΔCFI	ΔTLI	ΔRMSEA
Motivation											
M1. Configural Invariance	1777.965*	1287	.978	.970	.020	.018; .022					
M2. Weak Invariance	1994.422*	1455	.976	.971	.020	.018; .022	219.982*	168	-.002	+.001	.000
M3. Strong Invariance	2082.586*	1483	.973	.968	.021	.019; .023	95.581*	28	-.003	-.003	+.001
M4. Strict Invariance	2783.586*	1523	.944	.935	.030	.028; .031	468.780*	40	-.029	-.033	+.009
M5. Partial Strict Invariance	2305.208*	1517	.965	.959	.023	.021; .025	159.502*	34	-.008	-.009	+.002
M6. Latent Var.-Covar. Invariance	2576.142*	1559	.955	.949	.026	.024; .028	232.126*	42	-.010	-.010	+.003
M7. Latent Means Invariance	2905.770*	1571	.941	.934	.030	.028; .032	404.011*	12	-.014	-.015	+.004
Predictors											
M8. Configural Invariance	1279.174*	1026	.989	.987	.016	.013; .019					
M9. Weak Invariance	1350.128*	1050	.987	.985	.017	.014; .020	67.877*	24	-.002	-.002	.001
M10. Strong Invariance	1460.692*	1074	.984	.981	.019	.017; .022	123.868*	24	-.003	-.004	.002
M11. Strict Invariance	1643.188*	1106	.977	.974	.022	.020; .025	131.049*	32	-.007	-.007	.003
M12. Correlated Uniqu. Invariance	1713.760*	1154	.976	.974	.022	.020; .025	70.708	48	-.001	.000	.000
M13. Latent Var.-Covar. Invariance	1935.545*	1174	.968	.965	.026	.024; .028	184.295*	20	-.008	-.009	.004
M14. Latent Means Invariance	2098.639*	1182	.961	.958	.028	.026; .030	202.849*	8	-.007	-.007	.002
Outcomes											
M15. Configural Invariance	2771.736*	1581	.915	.905	.028	.026; .030					
M16. Weak Invariance	2861.398*	1613	.911	.902	.029	.027; .030	79.133*	32	-.004	-.003	+.001
M17. Strong Invariance	3107.946*	1645	.896	.888	.031	.029; .032	282.734*	32	-.015	-.014	+.002
M18. Partial Strong Invariance	2933.035*	1640	.908	.901	.029	.027; .031	75.897*	27	-.003	-.001	.000
M19. Strict Invariance	3602.769*	1680	.863	.855	.035	.033; .036	366.773*	40	-.045	-.046	+.006
M20. Partial Strict Invariance	3020.235*	1669	.904	.900	.029	.028; .031	71.558*	29	-.004	-.001	.000
M21. Correlated Uniqu. Invariance	3030.637*	1671	.903	.900	.029	.028; .031	8.208	2	-.001	.000	.000
M22. Latent Var.-Covar. Invariance	3187.987*	1691	.893	.888	.031	.029; .032	122.144*	20	-.010	-.012	+.002
M23. Partial Latent Var.-Covar. Invariance	3079.977*	1687	.901	.900	.029	.028; .031	28.599	16	-.002	.000	.000
M24. Latent Means Invariance	3213.897*	1695	.892	.887	.031	.029; .032	215.770*	8	-.009	-.013	+.001
M25. Partial Latent Means Invariance	3079.977*	1692	.901	.900	.029	.028; .031	24.718*	5	.000	.000	.000

Note. * $p < .01$; χ^2: Scaled chi-square test of exact fit; #fp: Number of free parameters; *df*: degrees of freedom; CFI: comparative fit index; TLI: Tucker-Lewis index; RMSEA: root mean square error of approximation; 90% CI: 90% confidence interval for the RMSEA; Δ: change in fit relative to the preceding model; scaled chi square difference tests where calculated using using the Satorra-Bentler correction (Satorra, 2000).

Table S10

Standardized Factor Loadings (λ), Uniquenesses (δ), and Correlations from the Final Predictor Measurement Model (M14)

Items	λ	λ	λ	λ	λ	δ
SES						
Education (Mother)	.636					.595
Education (Father)	.659					.565
Income	.637					.594
Relationships with peers						
Item 1		.763				.418
Item 2		.798				.363
Item 3		.735				.460
Item 4		.696				.516
Relationship with father						
Item 1			.897			.195
Item 2			.899			.192
Item 3			.906			.180
Item 4			.868			.246
Relationship with mother						
Item 1				.879		.227
Item 2				.867		.248
Item 3				.862		.257
Item 4				.818		.331
Relationship with teacher						
Item 1					.844	.288
Item 2					.842	.291
Item 3					.856	.267
Item 4					.792	.372
ω	.680	.836	.940	.917	.901	
Correlations	SES	Peer	Father	Mother	Teacher	
1. SES						
2. Relationships with peers	*.010*					
3. Relationship with father	*.089*	.245				
4. Relationships with mother	-*.021*	.283	.426			
5. Relationships with teacher	-*.007*	.294	.306	.248		

Notes. ω: omega coefficient of composite reliability. Because of the complete invariance of the measurement model, all parameters are identical across time waves. Non-statistically significant parameters ($p \geq .05$) are marked in italics.

Table S11

Standardized Factor Loadings (λ), Uniquenesses (δ), and Correlations from the Final Outcomes Measurement Model (M25)

Items	λ_{t1}	δ_{t1}	λ_{t2}	δ_{t2}	λ_{t3}	δ_{t3}
Grades						
Language	.675	.544	.675	.544	.675	.544
Humanities	.673	.546	.673	.546	.673	.546
Sciences	.701	.508	.701	.508	.701	.508
ω	.724		.724		.724	
risk behaviors						
Item 1	.569	.676	.569	.676	.569	.676
Item 2	.611	.627	.611	.627	.611	.627
Item 3	.490	.760	.546	.702	.546	.702
Item 4	.529	.720	.596	.644	.529	.720
Item 5	.561	.686	.561	.686	.561	.686
ω	.687		.714		.699	
Aggressive behaviors						
Item 1	.676	.543	.534	.714	.534	.714
Item 2	.796	.367	.671	.549	.671	.549
Item 3	.510	.740	.556	.691	.556	.691
Item 4	.557	.689	.553	.695	.632	.601
ω	.734		.669		.691	
Engagement						
Item 1	.522	.728	.515	.735	.515	.735
Item 2	.628	.605	.647	.582	.647	.582
Item 3	.449	.799	.462	.787	.462	.787
Item 4	.512	.738	.532	.717	.532	.717
Item 5	.557	.690	.488	.761	.555	.693
Item 6	.769	.409	.708	.498	.708	.498
Item 7	.708	.499	.641	.589	.641	.589
Item 8	.723	.478	.742	.450	.742	.450
ω	.827		.814		.820	

	Time 1			Time 2			Time 3		
Correlations	1.	2.	3.	1.	2.	3.	1.	2.	3.
1. Grades	-								
2. Risk behaviors	-.513	-		-.513			-0.513		
3. Aggressive behaviors	-.213	.744	-	-.309	.649		-0.309	0.649	
4. Engagement	.316	-.592	-.359	.379	-.709	-.366	0.379	-0.709	-0.366

Notes. ω: omega coefficient of composite reliability. Because of the partial invariance (strong, strict, variance-covariance, means) of the model, some standardized parameters estimates differ across time waves. All parameters are statistically significant at $p \leq .05$.

Table S12

Results from the Preliminary Latent Curve Models (Predictors and Outcomes)

Trajectory	Intercept Mean	Variance	Slope Mean (s.e.)	Variance (s.e.)	Intercept-Slope Covariance (s.e.)
Predictors					
Relationships with peers	0	1	.142 (.019)**	.094 (.019)**	-.206 (.035)**
Relationship with father	0	1	-.021 (.020)	.028 (.026)	-.054 (.057)
Relationship with mother	0	1	-.015 (.025)	-.039 (.053)	.104 (.116)
Relationship with teacher	0	1	.212 (.021)**	.026 (.018)	-.121 (.036)**
Outcomes					
Grades	0	1	.013 (.016)	.020 (.016)	-.072 (.033)*
Risk behaviors	0	1	.082 (.031)**	.067 (.025)**	-.039 (.071)
Aggressive behaviors	0	1	-.167 (.017)**	.026 (.022)	-.162 (.041)**
Engagement	0	1	.090 (.019)**	.062 (.018)**	-.129 (.038)**

Notes. * $p < .05$; ** $p < .01$.

Table S13
Classification Accuracy: Average Probability of Membership into Each Latent Profile (Column) as a Function of the Most Likely Profile Membership (Row).

	Profile 1	Profile 2	Profile 3	Profile 4	Profile 5
Profile 1	.578	.045	.346	0	.031
Profile 2	0	.661	.190	.037	.112
Profile 3	.034	.172	.730	.002	.063
Profile 4	0	.151	.004	.723	.122
Profile 5	.005	.223	.122	.063	.587

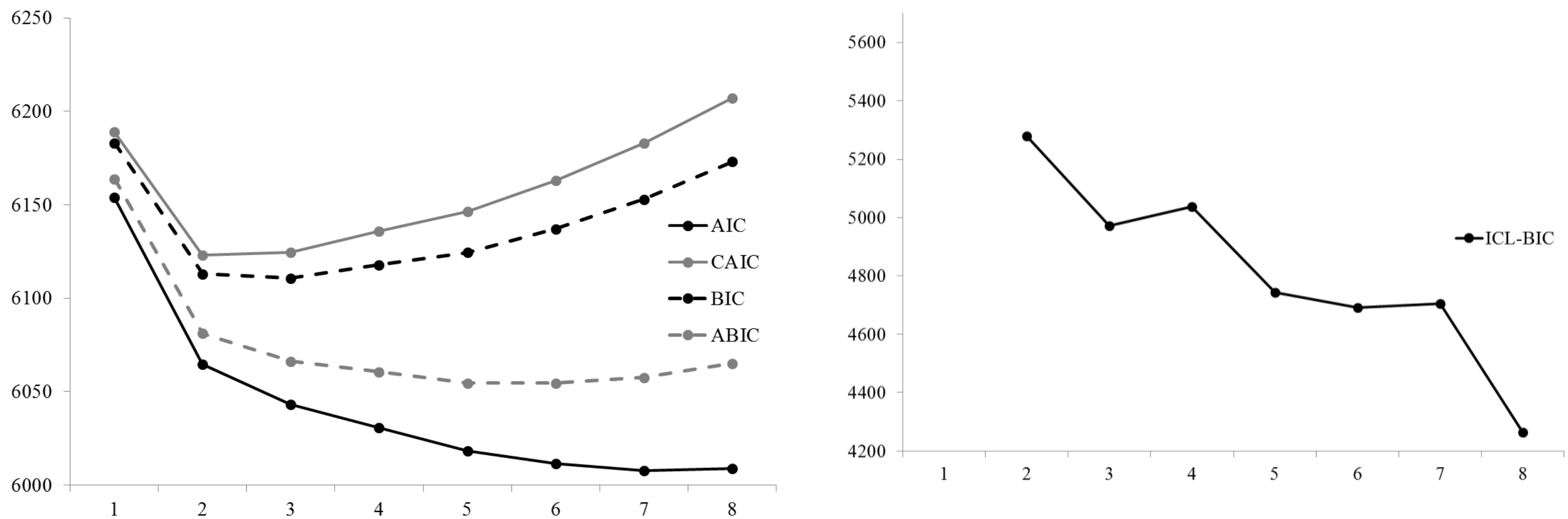

Figure S1
Elbow Plot of the Value of the Information Criteria for Solutions Including Different Number of Latent Profiles