Self-Determined Profiles of Academic Motivation

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Abstract

This study was designed to investigate academic motivation profiles (and their similarity) among distinct samples of high school students. Anchored in recent developments in Self-Determination Theory, these profiles were estimated while considering both the global and specific nature of academic motivation. The role of fixed mindsets and parenting practices in predicting profile membership, as well as the implications of these profiles for several outcomes, were also investigated. Latent profile analysis revealed five profiles (*Weakly Motivated*, *Moderately Motivated*, *Self-Determined*, *Amotivated*, and *Strongly Motivated*) differing in global and specific motivation levels. Fixed mindset was weakly related to profile membership, perceived parenting practices showed more widespread associations. Most desirable outcomes were linked to the *Self-Determined* and *Strongly Motivated* profiles, and then to the *Moderately Motivated*, *Weakly Motivated*, and *Amotivated* profiles.

Keywords: self-determination theory (SDT); global self-determination; self-reported grades; profiles; life satisfaction; grit; dropout intentions; latent profile analysis (LPA); academic motivation; bifactor exploratory structural equation modeling (bifactor-ESEM)

Finding solutions to underachievement and academic dropout are one of the key priorities for educational institutions around the world (e.g., OECD, 2016). For instance, 7% of U.S. adults (U.S. Department of Education, 2014) and 8.5% of Canadian adults (Statistics Canada, 2010) never obtained a high school diploma. Similar rates have been reported in Europe (European Commission, 2018). These preoccupying statistics highlight the importance of achieving a better understanding of the psychological mechanisms at play in students' achievement, persistence, and motivation. Past research has demonstrated that academic motivation is a key psychological factor at play in influencing school performance and persistence (Ryan & Deci, 2017). Motivation, however, is a complex multifaceted phenomenon that can take various forms, each with their own unique outcome associations (e.g., Guay et al., 2016). Self-determination theory (SDT; Ryan & Deci, 2017) highlights this multidimensional nature of human motivation, while acknowledging that each student's unique motivational profile is likely to encompass a combination of multiple types of motivation (Vallerand, 1997). Taking these multidimensional configurations into account, rather than considering the isolated impact of unique types of motivation, is likely to yield a finer-grained understanding of the role of academic motivation on educational outcomes. Therefore, the present study sought to identify subpopulations (or profiles) of students characterized by different configurations of academic motivation. To establish the generalizability of these profiles, we assess their replicability across two distinct samples of high school students. Finally, to document their construct validity, we consider their associations with theoretically-relevant outcomes (i.e., academic performance, math self-efficacy, grit, dropout, school engagement, and life satisfaction) and predictors (i.e., beliefs about the malleability of intelligence and math abilities, and perceptions of their caregivers' parenting skills).

The Taxonomy of Academic Motivation

SDT (Ryan & Deci, 2017) posits that academic motivation can take multiple forms, organized along a self-determination continuum ranging from the most self-determined types of motivation to the least self-determined ones (Howard et al., 2020). First, *intrinsic motivation* refers to the drive to perform an activity for the enjoyment and pleasure that it procures. *Identified regulation* refers to the drive to perform an activity perceived as personally important and valued. *Introjected regulation* occurs when involvement in the activity is propelled by internal pressures or coercion (e.g., self-worth, shame or guilt). *External regulation* denotes involvement in an activity that is externally driven by a wish to avoid punishments or to obtain rewards. Finally, *amotivation* refers to an absence of intention and a lack of any drive to perform an activity. Intrinsic motivation and identified regulation, forming together one extreme of the self-determination continuum, are referred to as autonomous motivation because they denote an involvement in an activity that is driven by personal choices1. Introjected and external regulations, which are positioned near the opposite end of the continuum of self-determination (before amotivation), are rather described as controlled forms of motivation because they symbolize an involvement that is "controlled" by internal or external factors. SDT acknowledges the unique qualities associated with each of these specific types of motivation while also positioning them along a global self-determination continuum (Deci & Ryan, 1985; Ryan & Deci, 2017). This continuum is often referred to as a global self-determination factor and represents students' global sense of self-directedness and volition (i.e., "I want to" do this activity), where the specificity uniquely associated with each specific regulation refers the reason for this desire (e.g., Howard et al., 2020).

Previous studies have documented that autonomous motivations tended to be related to various desirable academic outcomes, such as self-esteem, wellbeing, academic achievement, persistence, and challenge-seeking (e.g., Guay et al., 2010; see Guay et al., 2008 for an overview). These same studies have also shown controlled motivations to be related to less desirable academic outcomes, such as school dropout, anxiety, and academic dishonesty. Despite their importance, these variable-centered studies make it impossible to consider that people might simultaneously endorse more than one from of

1 SDT also proposes the existence of integrated regulation, falling between intrinsic motivation and identified regulation, and referring to engagement in an activity seen to be self-consistent. Integrated regulation was excluded from the present study for three reasons. (1) Integrated regulation has been theorized to emerge in later phases of development when individuals' identities are more fully formed (e.g., Deci et al., 2013; Ratelle et al., 2007). (2) Scale validation studies often fail to identify integrated regulation as a distinguishable motivational factor (e.g., Gagné et al., 2015; Vallerand et al., 1992). (3) A recent meta-analysis indicated that integrated regulation was difficult to empirically distinguish from identified regulation in education (Howard et al., 2017).

motivation (Vallerand, 1997). Thus, students might go to high school because it is mandatory (i.e., external regulation) but also because they enjoy it (i.e., intrinsic motivation). Likewise, via their focus on separate motivation dimensions considered on their own, these studies are unable to properly disaggregate the effects stemming from participants' global self-determination levels (reflecting their global position on the self-determination continuum; Howard et al., 2018, Litalien et al., 2017) relative to the unique quality of their specific motivation types. Distinguishing these global and specific effects is particularly important given that academic motivation is posited to have a dual global/specific nature and that both components (global and specific) carry valuable information and provide an incomplete picture of human motivation when considered on their own. In practical terms, a study using a traditional operationalization of behavioral regulations might identify positive associations between identified regulation and, for example, academic achievement. However, it is not possible to distinguish if this result is due to the unique characteristics associated with identified regulation (i.e., meaningfulness) or to the effect of global levels of self-determination that are shared across all regulations. This study addresses these limitations by adopting a person-centered perspective, seeking to identify academic motivation profiles of high school students by jointly considering their global levels of self-determined motivation together with their specific levels across each motivation type.

Academic Motivation Profiles

Several investigations have considered the academic motivation configurations that best represented distinct subpopulations of participants within the SDT framework. However, only a few focused specifically on adolescents or high school students. These studies, which form the theoretical basis of the present investigation, are described more extensively in the online supplementary materials (Table S1). Some of these studies have estimated motivational profiles while relying on global indicators of intrinsic/extrinsic or autonomous/controlled motivations, rather than considering motivation at the more specific subscale level. These studies have generally converged on a similar set of profiles (Hayenga & Corpus, 2010; Vansteenkiste et al., 2009; Wormington et al., 2012): (a) high autonomous (HA) and low controlled (LC) (autonomous); (b) HA and high controlled (HC) (strongly motivated); (c) Low autonomous (LA) and HC (controlled); and (d) LA and LC (amotivated).

The remaining studies relied on a more comprehensive set of motivation types as profiles indicators (Liu et al., 2009; Paixao & Gamboa, 2017; Ratelle et al., 2007; Wang et al., 2016, 2017). Interestingly, some of these studies yielded results sharing important similarities with the aforementioned results stemming from studies focusing on a reduced set of more global motivational indicators. Thus, Paixao and Gamboa (2017) revealed profiles matching the HA-LC, LA-HC, and LA-LC configurations. When incorporating amotivation to the analyses as an additional profile indicator, Liu et al. (2009) and Ratelle et al. (2007) found profiles matching the HA-HC configuration but also presenting low amotivation, as well as the LA-HC configuration with high amotivation. Whereas Ratelle et al. (2007) found a third profile presenting moderate motivation across all forms, Liu et al. (2009) found HA-LC and LA-LC profiles, but both also presenting low amotivation. Two final studies have been conducted by Wang and colleagues (Wang et al., 2016, 2017). The first of these studies contrasted solutions estimated from global levels of autonomous and controlled motivation with solutions in which the specific subscales were considered. Results from the first set of analyses revealed profiles matching the HA-HC, HA-LC, and LA-HC configurations, with an additional moderate motivation profile matching the one reported by Ratelle et al. (2007). Although results from their second set of analyses revealed profiles generally matching these configurations, it also revealed important discrepancies in levels of introjected and external across both LA-HC profiles. Even though both profiles were high in external regulations, they respectively presented low and moderate introjected regulation. Their results also revealed completely distinct profiles dominated by internalized forms of regulation (intrinsic, identified, introjected). In a later study, Wang et al. (2017) similarly reported one profile by non-matching levels of external and introjected regulations (coupled with low levels of identified regulation, and intrinsic motivations), another one dominated by external and identified regulations, and two profiles presenting either moderately high to high, or moderately low to low levels across regulations.

Taken together, these studies suggest that some core profiles (i.e., HA-HC, LA-LC, HA-LC, LA-HC, and moderate motivation) emerge with regularity across studies, although this regularity starts to break down in more comprehensive (i.e., relying on a more multidimensional approach to motivation measurement) and precise (i.e., relying on latent profile analysis as opposed to cluster analysis) studies. Furthermore, these studies highlight the value of adopting a complete multidimensional perspective when trying to capture academic motivation configurations among high school students, showing that ignoring specific types of motivation might mask finer-grained shape-related (i.e., qualitative) differences, such as profiles characterized by distinct levels of intrinsic motivation and identified regulations, or of introjected and external regulations. In fact, a common limitation of these studies is their failure to rely on a methodological approach allowing for an adequate disaggregation of participants' global self-determination from the specific quality linked to each motivation type. Statistical research has shown that, when global (self-determination) constructs co-exist with specific ones, failure to consider this multidimensionality results in a lack of theoretical clarity and precision when identifying latent profiles as the role played by each specific form of motivation in profile definition is likely to be masked by participants' global levels of self-determination (Morin, Boudrias et al., 2016, 2017; Morin & Marsh, 2015). Thus, whereas these previous studies are informative, profiles identified in these studies are likely to reflect "level effects" (Morin & Marsh, 2015) where profile definition is dominated by the unexpressed presence of the global self-determination factor. Interestingly, this phenomenon has already been observed in research focused on work motivation profiles (Howard et al., 2016) where profiles systematically tend to display a shape matching the SDT continuum (e.g., high intrinsic, moderately high identified, average introjected, moderately low external, low amotivation). These observations clearly highlight the need for studies, such as the present one, to rely on a more comprehensive operationalization (i.e., multidimensional and global/specific) of academic motivation (see Figure 1 for an illustration of this operationalization). Importantly, despite some commonalities, the variability observed in previous results also showcase the need for replication to ascertain that profiles are not a methodological artifact of a specific sample.

Predictors of Motivational Profiles

In addition to the importance of replication, which is known to be critical to person-centered research (e.g., Meyer & Morin, 2016; Morin, Meyer, et al., 2016), many have highlighted the need to document the theoretical significance (i.e., construct validity) of profiles by investigating their associations with theoretically relevant predictors and outcomes (e.g., Meyer & Morin, 2016). This verification is also important for practical purposes, given that only little information is available to inform intervention regarding predictors of motivation profiles among high school students.

In this study, we consider both contextual (perceived parenting practices) and individual (implicit theories of intelligence and math abilities) predictors. First, we consider students' implicit theories, or individual beliefs, about the malleability of their cognitive attributes (i.e., math abilities and intelligence; Dweck, 2006). Students with fixed mindsets tend to see their intelligence or math abilities as static and impossible to alter through effort. These students believe that academic success depends on having or not having some innate ability, and see little value in exerting efforts to address academic difficulties. Conversely, students with a growth mindset see these attributes as something that can be developed via effort. Previous research has shown that having a fixed mindset predicted the adoption of performance (rather than mastery) goals, negative beliefs regarding the value of effort, helpless-oriented (relative to mastery-oriented) strategies, and negative emotions (e.g., Burnette et al., 2013).

Previous variable-centered studies have shown (1) positive associations between having a fixed mindset and controlled motivations (e.g., Biddle et al., 2003); (2) positive associations between having a growth mindset and autonomous motivations (e.g., Wang et al., 2009); (3) negative associations between having a fixed mindset and autonomous motivations (e.g., Haimovitz et al., 2011), and (4) negative associations between having a growth mindset and controlled motivations (e.g., Renaud-Dubé et al., 2015). Despite this typical distinction between fixed and growth mindsets, many studies simply consider these two mindsets as the opposite end of a continuum represented by high and low scores on a single set of items (O'Conner et al., 2013). The present study followed this approach.

SDT also postulates that the social environment in which individuals evolve greatly affects their motivation (Ryan & Deci, 2017). Although previous research has started to document the role of school-related factors in the prediction of academic motivation profiles, parents are also a key source of complementary influence for youth's motivation (e.g., Ryan & Deci, 2017). This study thus seeks to expand on prior research by considering the role of three key parenting behaviors in the determination of motivational profiles (Skinner et al., 2005): Parental care, autonomy support, and overprotection. Parental *care* involves parental expression of empathy, warmth, and affection (Parker et al., 1979). Parental *autonomy support* refers to valuing children's initiatives as well as encouraging their choices and feelings (Mageau & Vallerand, 2003). Parental *overprotection* refers to controlling and restrictive behaviors whereby pressure is put on children to behave in a certain way (Joussemet et al., 2008).

Need supportive behaviors in general (i.e., behaviors aiming to support psychological needs for relatedness, competence, and autonomy, which encompass care, autonomy support, and a lack of overprotection) have been shown to predict student autonomous motivation (e.g., Niemiec et al., 2006). Focusing on parental behaviors, previous variable-centered research has demonstrated positive associations between autonomy supportive or caring parenting and autonomous types of motivation (e.g., Gillet et al., 2013; Lowe & Dotterer, 2013) as well as non-significant or negative relations between autonomy supportive or caring parenting and controlled forms of motivation (e.g., Chirkov & Ryan, 2001; Dietrich & Salmela-Aro, 2013). In contrast, opposite relations have been noted for overprotection (e.g., Deci et al., 1993; Grolnick & Ryan, 1987). Although no person-centered research has, to our knowledge, looked at the relations between parenting and motivation profiles among high school students, a recent study demonstrated associations between parental warmth perceptions and more intrinsically motivated profiles among university students (Litalien et al., 2019).

Outcomes of Motivational Profiles

Arguably, a key reason for studying academic motivation stems from its established role as a core predictor of achievement, engagement, and dropout intentions. Indeed, previous variable-centered studies have demonstrated that academic performance tends to be positively and moderately associated with autonomous motivations, weakly related or unrelated to controlled motivations, and negatively related to amotivation (Guay et al., 2010; Soenens & Vansteenkiste, 2005). Likewise, previous person-centered research have also tended to demonstrate positive associations between membership into autonomously driven profiles and students' levels of academic performance, although membership into highly motivated profiles (i.e., HA-HC) was also typically found to result in high levels of academic performance (e.g., Ratelle et al., 2007; Vansteenkiste et al., 2009).

Contrasting with academic achievement, school engagement is typically seen as another process variable leading to more desirable achievement outcomes, and yet as an outcome of school motivation (Reeve, 2012). More precisely, school engagement refers to a positive school-related psychological state characterized by absorption (being fully immersed and focused on one's studies), dedication (being highly involved at school), and vigor (displaying high levels mental resilience and energy at school) (Schaufeli et al., 2002). Engaged students are more likely to continue their studies (Archambault et al., 2009), and tend to perform better (Salanova et al., 2003). Variable-centered research has shown positive relations between autonomous motivations and engagement, and smaller or negative relations between controlled motivations and engagement (e.g., Steinmayr et al., 2018).

Like achievement, school dropout is another critical outcome to consider, and has been shown to carry its own set of undesirable consequences (e.g., Thornberry et al., 1985). Studies examining associations between academic motivation and dropout have demonstrated that more autonomous types of motivation tended to predict a lower likelihood of school dropout and dropout intentions (Hardre & Reeve, 2003; Renaud-Dubé et al., 2015). Students who dropped out also tended to display lower levels of autonomous motivation and higher levels of amotivation when compared to students who persisted in their studies (Vallerand et al., 1997).

Types of motivation are expected to present stronger associations with constructs having the same referent (i.e., academic motivation measured across all subjects should relate most strongly with similarly generic outcomes, such as global levels of achievement, engagement, and dropout intentions) (Guay & Bureau, 2018; Huang, 2012). However, to more broadly document the implications of the academic motivation profiles, we also consider outcomes located at more specific (i.e., math self-efficacy) or generic (grit and life satisfaction) levels. Our interest in mathematics is rooted in the fact that STEM (science, technology, engineering, and mathematics) areas are essential to the development and advancement of technology and countries in general, making it is critical to understand the motivational underpinnings of math-related self-beliefs, themselves associated with broader educational outcomes such as aspirations, achievement or university entry (e.g., Guo et al., 2015). Here, we focus on math self-efficacy, referring to students beliefs about their capabilities in reaching desired domain-specific (i.e., math) objectives (e.g., Bandura, 2006). Generally, past research have tended to report moderately positive associations between self-efficacy and more autonomous types of motivation, weakly positive, or non-significant, associations between self-efficacy and more controlled types of motivation, and negative associations between self-efficacy and amotivation (Austin et al., 2013; Komarraju, 2013; Turner et al., 2009).

Grit, conceptualized as an ability to persevere toward the accomplishment of long-term goals even when facing difficulties (Tang et al., 2019), is an individual characteristic likely to play a role in students' capacity to invest years of sustained efforts in their studies. Research shows that grit predicts higher educational attainment, performance, and retention (Duckworth & Quinn, 2009; Strayhorn, 2014). However, grit is not immutable and needs to be anchored in psychological resources, such as academic motivation, to support persistent interest and effort (Alan et al., 2019). Variable-centered studies have reported inconsistent relations between autonomous motivation and two components of grit: Positive relations with perseverance of effort, and non-significant associations with consistency of interest (Reraki et al., 2015; Steinmayr et al., 2018). Person-centered studies have similarly shown the HA-LC profile to display higher levels of efforts (Vansteenkiste et al., 2009; Wang et al., 2017).

Finally, given that the school context is one of the most important life domain during adolescence, it is reasonable to hypothesize associations between students' school experiences and their life satisfaction. Previous studies conducted in educational contexts have indeed reported positive associations between life satisfaction and autonomous motivations, and between controlled motivations and lower levels of life satisfaction (e.g., Bailey & Phillips, 2016; Ratelle et al., 2005).

The Present Study

This study investigates how distinct types of academic motivation combine within profiles of high school students, while relying on a proper disaggregation of students' global self-determination levels, from the unique quality linked to each specific type of motivation. Based on previous studies, we hypothesized that three to five profiles would be identified (Hypothesis 1), and that a subset of those profiles would match the most commonly occurring configurations reported in previous research (i.e., LA-LC, LA-HC, moderate, HA-LC, HA-HC) (Hypothesis 2). However, given our distinct methodological approach (global self-determination versus specific motivation types), we also hypothesized the identification of additional profiles driven by specific motivation types (Hypothesis 3), but leave as a research question the number and nature of these profiles (Research Question 1).

This study also seeks to document the construct-related validity and replicability of the extracted profiles by considering: (a) the replicability of these profiles across independent samples of high school students, (b) the role of students' malleability mindsets (Sample 1) and parenting perceptions (Sample 2) as predictors of profile membership, and (c) associations between profile membership academic achievement (Samples 1 and 2), engagement (Sample 2), dropout intentions (Sample 2), math self-efficacy (Sample 1), grit (Sample 1), and life satisfaction (Sample 2). Although we hypothesized that the number and nature of the profiles would be replicated across samples (Hypothesis 4), we leave as a research question whether the degree of similarity among profile members and the relative size of the profiles will be replicated (Morin, Meyer, et al., 2016) (Research Question 2). In terms of prediction, we hypothesized that fixed intelligence mindsets (and math to a lesser extent) (Hypothesis 5), as well as parental overprotection (Hypothesis 6), would predict membership into less desirable profiles (i.e., lower global self-determination, or higher specific introjected regulation, external regulation and/or amotivation). Conversely, we hypothesized that autonomy support (Hypothesis 7) and parental care (Hypothesis 8) would predict membership into more desirable profiles (higher global self-determination, or higher specific intrinsic motivation and/or identified regulation). Finally, from an outcomes perspective, we hypothesized that the more desirable profiles would be positively associated with academic performance, math self-efficacy, grit, engagement and life satisfaction, and negatively associated with dropout intentions (Hypothesis 9).

Methods

Participants and Procedures

In Sample 1, students came from one high school (Grammar school) located in the capital of a Hungarian county in April-May 2016. A total of 409 adolescents (62.3% female), aged between 16 and 21 (M = 18.23, SD = 1.32), from different grades (35.7% in Grade 9, 26.2% in Grade 10, 18.1% in Grade 11, and 20.0% in Grade 12) participated. In Sample 2, students came from one high school (Grammar school) from the capital of another Hungarian county in September-November 2017. This sample included 525 students (77.1 % female), aged between 15 and 20 (M = 17.27, SD = 1.21), from different grades (27.1% in Grade 9, 27.9% in Grade 10, 23.0% in Grade 11, and 21.9% in Grade 12).

This study followed the guidelines of the Declaration of Helsinki and was approved by the University Research Ethics Committee. Prior to data gathering, schools (i.e., principals and teachers) were informed about the research aims, and parents received a passive consent information form (i.e., opt-out). All students from both schools were invited to participate (with the exception of those for whom parents refused consent), and received information regarding the questionnaire content and aims of the study beforehand. Participants were also told that their participation was anonymous and voluntary, and that no consequences would follow from their decision to participate or not, or to stop participation. Participants filled out an online questionnaire during classes.

Measures

Questionnaires not validated in Hungarian were developed through standardized translation back-translation methods (e.g., Beaton et al., 2000).

Academic Motivation (Both Samples). Academic motivation was assessed using the Hungarian version (Tóth-Király et al., 2017) of the High School Academic Motivation Scale (AMS; Vallerand et al., 1989). Five factors2 were assessed with four items each: *intrinsic motivation* (e.g., "Because I experience pleasure and satisfaction while learning new things"; $\alpha_{\text{Sample 1}} = .795$, $\alpha_{\text{Sample 2}} = .826$), *identified regulation* (e.g., "Because this will help me make a better choice regarding my career orientation"; $\alpha_{\text{Sample 1}} = .818$, $\alpha_{\text{Sample 2}} = .828$), *introjected regulation* (e.g., "Because I want to show myself that I can succeed in my studies"; $\alpha_{\text{Sample 1}} = .800$, $\alpha_{\text{Sample 2}} = .750$), *external regulation* (e.g., "Because I want to have "the good life later on"; $\alpha_{\text{Sample 1}} = .780$, $\alpha_{\text{Sample 2}} = .800$), and *amotivation* (e.g., "I can't see why I go to school and frankly, I couldn't care less"; $\alpha_{\text{Sample 1}} = .833$, $\alpha_{\text{Sample 2}} = .870$). Items were rated on a seven-point scale (1 = *does not correspond at all*, 7 = *corresponds exactly*).

Academic Performance (Outcome; Both Samples). The measure of academic performance was based on the students' self-reported school grades. In the beginning of the questionnaire, a single item asked them to report their current average grades across all school subjects using a 1 (*fail*) to 5 (*excellent*) scale ($M_{\text{sample1}} = 3.74$, $SD_{\text{sample1}} = 0.73$; $M_{\text{sample2}} = 4.00$, $SD_{\text{sample2}} = 0.72$). High correlations have been reported between self-reported and actual school grades (Noftle & Robins, 2007; for a meta-analysis, see Kuncel et al., 2005).

Mindset (Predictor; Sample 1). Students' beliefs about the malleability of their intelligence (3 items, e.g., "You have a certain amount of intelligence and you really can't do much to change it"; $\alpha = .789$) was measured with the Hungarian version (Orosz et al., 2017) of the Implicit Theories of Intelligence Scale (Dweck et al., 1995). Items were adapted from the same scale to create a second factor assessing math mindset (e.g., "Some people are good at math, others are bad and this is something that you cannot change"; $\alpha = .789$). Items were rated on a six-point scale (1 = *totally disagree*; 6 = *completely agree*).

Parenting (Predictor; Sample 2). Students' perceptions of their parents' practices were measures using the Hungarian (Tóth & Gervai, 1999) version of the Parental Bonding Instrument (PBI; Parker et al., 1979). Items were rated on a four-point scale (1 = *very like this*; 4 = *very unlike this*) and referred to the first 16 years of students' life. Following Xu et al. (2018), we focus on three parenting behaviors: care (12 items, e.g., "Was affectionate to me"; $\alpha = .911$), autonomy (6 items, e.g., "Liked me to make my own decisions"; $\alpha = .803$), and overprotection (7 items, e.g., "Tried to control everything I did"; $\alpha = .772$).

Math Self-Efficacy (Outcome; Sample 1). Four-items (e.g., "In math, I am sure to be able to solve even the most difficult tasks"; $\alpha = .907$) were used to measure math self-efficacy (Marsh et al., 2019). Items were rated on a five-point scale (1 = *not true at all*, 5 = *completely true*).

Grit (Outcome; Sample 1). The Hungarian version (Orosz et al., 2017) of the short Grit Scale (Duckworth & Quinn, 2009) was used to measure students' perseverance of effort (3 items, e.g., "I am diligent"; $\alpha = .732$) and inconsistency of interest (3 items, e.g., "I have been obsessed with a certain idea or project for a short time but later lost interest"; $\alpha = .619$)3. Items were rated on a five-point scale (1 = *very much like me* to 5 = *not like me at all*).

2 Although intrinsic motivation might be divided into three components (Carbonneau et al., 2012), only *intrinsic motivation to know* was considered. First, this type of motivation is the most closely related to SDT's general description of intrinsic motivation. Second, prior studies of adolescents (e.g., Caleon et al., 2015; Tóth-Király et al., 2017) reported correlations between facets of intrinsic motivation high enough to undermine their discriminant validity. This decision is also supported by recent meta-analytic results (Howard et al., 2017).

3 While one additional item is typically included for each of the factors, previous studies (e.g., Arco-Tirado et al., 2018; Karaman et al., 2019; Mullen & Crowe, 2018; Zhong et al., 2018) have shown these additional items to present weak factor loadings. These items were thus excluded from the present study.

School Engagement (Outcome; Sample 2). The Utrecht Work Engagement Scale (Schaufeli et al., 2002) was used to assess school engagement. In this study, references to work were changed to refer to school and studying. This scale covers three dimensions with three items each: vigor (e.g., “At school, I feel bursting with energy”; α = .841), dedication (e.g., “The school inspires me”; α = .881), absorption (e.g., “I am happy when I am studying intensely”; α = .883). Items were rated on a seven-point scale (1 = *never*, 7 = *always*).

Dropout Intentions (Outcome; Sample 2). Dropout intentions were measured with three items (e.g., “I often consider dropping out of school”; α = .835) (Hardre & Reeve, 2003; Vallerand et al., 1997), rated on a seven-point scale (1 = *not at all in agreement*, 7 = *completely in agreement*).

Life Satisfaction (Outcome; Sample 2). The Hungarian version (Martos et al., 2014) of the Satisfaction with Life Scale (Diener et al., 1985) was used to assess students’ level of satisfaction with their lives. Items (5 items, e.g., “If I could live my life over, I would change almost nothing”; α = .862) were rated on a seven-point scale (1 = *strongly disagree*, 7 = *strongly agree*).

Analyses

Preliminary Analyses

Preliminary measurement models were estimated to derive factor scores (in standardized units with *M* = 0 and *SD* = 1 with measurement invariance across samples) for the main analyses. Based on recent evidence (Howard et al., 2018; Litalien et al., 2017) showing that measures of motivation based on SDT are best represented via bifactor-ESEM (Morin, Arens, et al., 2016), we relied on this approach to model academic motivation. Bifactor-ESEM made it possible to estimate a global (G-) factor representing students’ global academic self-determination (defined from all items and a pattern of factor loadings following their position on the SDT motivation continuum), together with specific (S-) motivational factors reflecting the unique quality of each motivation subscale left unexplained by the G-factor. The factor scores generated from these preliminary analyses, reported in the online supplements (Appendix 1), thus allowed us to rely on profile indicators preserving this global/specific nature. A similar approach has been previously used to study motivation profiles in the work area (Fernet et al., 2020; Gillet et al., 2020; Howard et al., 2021; Tóth-Király et al., 2021).

Latent Profile Analyses (LPA)

LPAs were conducted using Mplus 8 (Muthén & Muthén, 2017) and estimated using a robust maximum-likelihood estimator (MLR). In both samples, solutions including one to eight profiles were estimated, with freely estimated means and variances (Diallo et al., 2016; Peugh & Fam, 2013). To ensure convergence on a true maximum likelihood, all models were estimated using 5000 random start values, 1000 iterations, and 200 final optimizations (Hipp & Bauer, 2006).

Profile Similarity

Once the optimal solution was selected in each sample, a multigroup LPA was estimated to conduct multi-sample tests of profile similarity in the following sequence (Morin, Meyer, et al., 2016): (1) *configural* similarity (same number of profiles across samples); (2) *structural* similarity (same within-profile means); (3) *dispersion* similarity (same within-profile variances); and (4) *distributional* similarity (same relative size). Similarity is achieved when two information criteria (i.e., the Bayesian Information Criterion or BIC, the Sample-Size-Adjusted BIC or SSABIC, and the Constant Akaike Information Criterion or CAIC) have a lower value relative to the preceding level of similarity.

Predictors and Outcomes

Predictors were directly incorporated into the most similar profile solution via multinomial logistic regressions to assess associations between the predictors and the profiles. Profile-specific levels of the outcomes were contrasted using a model-based approach (Lanza et al., 2013) executed using the auxiliary DCON function (Asparouhov & Muthén, 2014). These analyses were estimated via the manual three-step approach (Litalien et al., 2019; Morin & Litalien, 2017).

Results

The results pertaining to the selection of the optimal sample-specific LPAs, as well as tests of profile similarity, are described in the online supplements (Appendix 2). Results converged on a highly similar 5-profile solution in both samples, thus supporting configural similarity as well as Hypothesis 1. These solutions were combined in a multi-sample model of configural similarity. Equality constraints were then gradually imposed on the within-profile means (structural), variances (dispersion), and profile sizes (distributional). As shown in the online supplements (Table S11), the sequential imposition of these equality constraints all resulted in lower values on at least two information criteria relative to the previous model, supporting the complete similarity of this solution across samples, providing support for Hypothesis 4 and a response to our Research Question 2. This distributional similarity solution was retained for interpretation (see Figure 2). The exact within-profile means and variances are reported in the online supplements (Table S12).

Profile 1 was the largest (43.5%) and described students with average levels on most motivational factors coupled with moderately high levels of amotivation. This profile was labeled "*Weakly Motivated*" to reflect this combination of average motivation and high amotivation. Profile 2 described 23.4% of the students. These students also presented average levels on most motivation factors. However, they also displayed low levels of amotivation, leading us to label this profile "*Moderately Motivated*". Profile 3 was smaller (4.1%), described students with high global self-determination accompanied by similarly high specific levels of intrinsic motivation, average specific levels of identified regulation, and low specific levels of introjected regulation, external regulation and amotivation. We hereafter refer to this profile as "*Self-Determined*". Profile 4 described 24.9% of the students with low global self-determination, slightly under average specific levels of intrinsic, identified and introjected regulations, slightly over average specific levels of external regulation, and high specific levels of amotivation. This profile was thus labelled "*Amotivated*". Finally, Profile 5 described 4.1% of the students with high global self-determination, slightly under average specific levels of intrinsic and identified regulations, high specific levels of introjected and external regulations, and low specific levels of amotivation. We thus labelled this profile "*Strongly Motivated*". Overall, the identification of these five profiles provided support for our Hypotheses 2 and 3 and a response to our Research Question 1.

Predictors of Profile Membership

Predictors were included in the final solution. Results from these multinomial logistic regressions are reported in Table 1 which provided partial support for Hypothesis 5. Two significant associations were found in Sample 1, showing that a fixed intelligence mindset predicted an increased likelihood of membership into the *Amotivated* compared to the *Moderately* and *Strongly Motivated* profiles. Math mindsets did not predict profile membership.

Associations were more numerous in Sample 2, first showing higher levels of perceived parental care to predict a decreased likelihood of membership into the *Amotivated* profile relative to all others, as well as an increased likelihood of membership into the *Strongly Motivated* profile relative to all others, thus supporting Hypothesis 8. Somewhat unexpectedly, perceived autonomy support from the parents predicted a decreased likelihood of membership into the *Moderately Motivated* profile compared to the *Amotivated* one, thus failing to support Hypothesis 7. Finally, partially supporting Hypothesis 6, perceived parental overprotection predicted a higher likelihood of membership into the *Strongly Motivated* profile relative to all other profiles as well as a higher likelihood of membership into the *Weakly Motivated* profile relative to the *Moderately Motivated* one.

Outcomes of Profile Membership

The results from the analyses of associations between profile membership and outcomes are reported in Table 2. Several outcome comparisons were significant and supported the construct validity of the profiles. In Sample 1, math self-efficacy was highest in the *Self-Determined* profile, followed by all other profiles among which no statistically significant differences were observed. Perseverance of effort was also highest in the *Self-Determined* profile, followed by the *Strongly Motivated* and *Moderately Motivated* profiles, which did not differ from each other, and then by the *Weakly Motivated* and *Amotivated* profiles, which also did not differ. Inconsistency of interest was the lowest in the *Self-Determined* profile in comparison to all others, which did not statistically differ from each other. Lastly, self-reported grades (Sample 1) were highest in the *Self-Determined* profile in comparison to the *Weakly Motivated*, the *Moderately Motivated* and the *Amotivated* profiles. Grades were also higher in the *Moderately Motivated* profile in comparison to the *Weakly Motivated* profile.

In Sample 2, results are even more clear-cut. All three components of school engagement (vigor, dedication, absorption) were highest in the *Self-Determined* and *Strongly Motivated* profiles (which did not statistically differ from each other), then in the *Moderately Motivated* profile, followed by the *Weakly Motivated* profile, and lastly by the *Amotivated* profile. An opposite pattern of results was observed for dropout intentions which were lowest (and impossible to distinguish) in the *Self-Determined* and *Strongly Motivated* profiles, then in the *Moderately Motivated* profile, followed by the *Weakly Motivated* profile and finally by the *Amotivated* profiles. In terms of life satisfaction, the highest value were equivalently observed in the *Strongly Motivated* and *Self-Determined* profiles, followed by the *Moderately Motivated* profile (which was not distinguishable from the *Self-Determined* profile), then by the *Weakly Motivated* profile, with the lowest levels being observed in the *Amotivated* profile. Self-reported grades (Sample 2) were highest in the *Self-Determined* profile, followed by the *Strongly Motivated*, *Moderately Motivated* and *Weakly Motivated* profiles (which were indistinguishable from one another), and lowest in the *Amotivated* profile. Overall, our outcome-related results provided support for Hypothesis 9.

Discussion

Students rarely endorse a single motive at a time when facing academic activities, but rather tend to be driven by a combination of different motives (Vallerand, 1997). In this two-study investigation, we sought to better understand high school academic motivation by (a) relying on person-centered methods to detect the most common motivational configurations and (b) by investigating how these motivational profiles related to theoretically-relevant predictors and outcomes. In doing so, we relied on a proper disaggregation of students' global self-determined academic motivation levels (i.e., students' global sense of volition and self-directedness) from their unique levels of specific behavioral regulations (Howard et al., 2018; Litalien et al., 2017; Ryan & Deci, 2017). This approach allowed us to address the limitations of previous person-centered investigations, in which this multidimensional nature of academic motivation was generally ignored, by separating shape and level effects (Morin & Marsh, 2015).

Academic Motivation Profiles

Matching our hypotheses, five profiles represented best the academic motivation configurations identified among two distinct samples of high school students. Also matching our hypotheses, these profiles presented similarities with some of the most commonly occurring profiles reported in previous studies, but with some noteworthy distinctions highlighting the value of the more rigorous approach we took in the present study in which global and specific levels of motivation were disaggregated. First, we identified a *Self-Determined* profile, which presented important similarities with the simpler HA-LC profile identified in previous studies (e.g., Liu et al., 2009). Likewise, our *Strongly Motivated* profile presented a high level of similarity with the HA-HC profile reported in numerous previous studies (e.g., Vansteenkiste et al., 2009). However, it is also interesting to note that only a small portion of the students corresponded to these two profiles (4.07% and 4.11%), suggesting that few students could be considered to be highly motivated for school. This observation is consistent with previous reports showing that academic motivation tends to decrease to relatively low levels during the high school period (Otis et al., 2005), and that relatively few students can be characterized as presenting high levels of academic motivation (e.g., Vansteenkiste et al., 2009).

In contrast, more than 90% of the students corresponded to one of the remaining three profiles. These profiles displayed a more precise combination of motivations relative to what previous studies have reported on the basis of more typical operationalizations of academic motivation. More specifically, almost half of the students belonged to the *Weakly Motivated* profile, which shared similarities with the *Moderately Unmotivated* profile reported previously among university students by Gillet et al. (2017). The second largest profile, corresponding to about a fourth of the students, was the *Amotivated* one. This profile presented similarities to the LA-HC profile identified in previous studies as also being characterized by high levels of amotivation (e.g., Ratelle et al., 2007). Finally, the *Moderately Motivated* profile also characterized about a fourth of the students, and seemed to match a configuration previously identified by Wang et al. (2016). These students did not lack motivation to go to school (low amotivation), but did not appear to have any reason to be highly motivated either.

These five profiles highlight the benefits of adopting a more precise operationalization of academic motivation, accounting for students' global levels of self-determination and for the specific qualities of their behavioral regulations. This approach adequately separates shape and level effects that could otherwise taint profile definition by emphasizing quantitative differences (Morin & Marsh, 2015), in turn masking the unique effects of each specific behavioral regulation (i.e., qualitative differences). Indeed, students' global levels of self-determination played a critical role (i.e., being a core defining characteristic) in the definition of at least three profiles in which it was either the indicator showing the highest score (i.e., *Self-Determined)*, the lowest score (i.e., *Amotivated*), or a high score sufficient to balance equally high levels of controlled motivation (i.e., *Strongly Motivated*). The specific behavioral regulations also played a critical role in the definition of the same profiles, whereas specific levels of amotivation levels proved to be critical to the definition of the *Weakly Motivated* and *Moderately*

Motivated profiles. These results suggest that the specific qualities of academic motivation and the global levels of self-determination are equally important. More precisely, our methodological approach has facilitated the separation of students' global sense of volition from the unique qualities of their specific behavioral regulations, revealing some profiles mainly driven by this global level of self-determination across all components, and others primarily driven by a more specific type of academic motivation or by a combination of both. Observing that our results broadly match those from previous studies not relying on a similar approach is highly informative in its own right, and indicates that unique role of each specific motivation might be strong enough to emerge even when relying on methods that do not separate shape from level effects.

Predictors of Academic Motivation Profiles

The present study also sought to document the role of different sets of individual (fixed intelligence and math mindset) and contextual (parental care, autonomy-support, and overprotection) factors in the prediction of profile membership. Regarding the role of students' mindsets, our results partially supported our hypotheses in showing that endorsing a fixed intelligence mindset (but not a fixed math mindset) predicted a higher likelihood of membership into the *Amotivated* profile. This result matches previous research demonstrating that fixed mindsets tend to be positively associated with less self-determined types of motives and lower motivation levels (e.g., Biddle et al., 2003). Indeed, students endorsing a fixed mindset do not believe in the benefits of effort, and tend to be preoccupied with self-protection more than with self-development (Dweck, 2006). These beliefs, in turn, lead them to display less efforts and to become disengaged from schoolwork seen as useless intrinsically and extrinsically (Dweck et al., 1995). This state of disengagement is very close to the construct of amotivation (Legault et al., 2006), and might become more pronounced when facing academic difficulties due to the belief that improvement is not possible (Dweck, 2006).

In contrast, although we did not hypothesize that the endorsement of a fixed math mindset would predict profile membership as strongly as the endorsement of a fixed intelligence mindset due to the non-matching referent of our measure (Guay & Bureau, 2018; Huang, 2012), we did hypothesize this alternative mindset to share some relations with profile membership. Although the lack of effect of endorsing a fixed math mindset could also be due to the slight overlap between the two types of fixed mindsets considered here (i.e., students believing in the fixed nature of intelligence should be more likely to believe in the fixed nature of math abilities, as illustrated by a correlation of .490 in the present study – see Table S9 of the online supplements), it would be interesting to further investigate this unexpected result. Importantly, it would be important to verify the extent to which the present results would generalize to the consideration of a broader set of matching (e.g., math-math or global-global), partially matching (e.g., math-science) and non-matching (e.g., math-English or math-global) referents used to assess both students' mindsets and motivation.

Regarding perceived parenting practices, our results supported the idea that these contextual characteristics played a greater role in the prediction of academic motivation profiles than the more stable individual characteristics captured by the mindset variables. The effects of parental overprotection mostly involved increasing the likelihood of students' membership into the *Strongly Motivated* profile, a result that needs to be interpreted while considering this profile's high specific levels of external and introjected regulation. Indeed, this profile was the only one driven intensively by controlled forms of motivation (while the others were not), thus suggesting that the effects of parental overprotection on student motivation might be specific to controlled motivations.

Research has previously revealed variable-centered associations between parental overprotection and controlled forms of motivation (Deci et al., 1993). These effects seem to be maintained in a person-centered framework in relation to the *Strongly Motivated* profile presenting the highest levels of controlled motivation and seem independent from the specific levels of autonomous motivation and from the global levels of self-determination which are also elevated in this profile. Overprotective parents tend to exert a high level of control over their children by imposing pressures and restrictions (e.g., guilt induction, love withdrawal, invalidation of feelings) in order to compel them to behave in a certain way (Joussemet et al., 2008). Initially external to the children (i.e., external regulation), these pressures might also come to be internalized by exposed children (i.e., introjected regulation) who want to meet these external or self-imposed expectations of their parents, thus coming to display a *Strongly Motivated* profile. Overprotective practices from one's parents might thus only lead to a partial internalization process (i.e., the process of taking in values, behaviors or beliefs from external sources and transforming them to their own; Ryan & Deci, 2017), and be insufficient to lead to a complete, fuller internalization characterized by the emergence of a more purely autonomously driven profile. Indeed, via these controlling practices, students' basic psychological needs for autonomy, competence and relatedness are more likely to be thwarted, which might prevent them from engaging with their studies in a purely autonomous (self-endorsed) way, always leaving them with a strong level of controlled motivation. In addition, and supporting our hypotheses, parental overprotection predicted a higher likelihood of membership into the *Weakly Motivated* profile relative to the *Moderately Motivated* one. This result supports the idea that parental overprotection might lead to increases in amotivation among students with otherwise average academic motivation.

More aligned with our hypotheses, parental care decreased the likelihood of membership in the *Amotivated* profile and increased the likelihood of membership in the *Strongly Motivated* one. Parental care is often characterized by expressing warmth and showing interest in children (e.g., Skinner et al., 2005). This positive form of parenting, when transposed to the academic area, involves the provisions of emotional and behavioral support for students' school-related activities, taking the form of guidance, help, and constructive feedback. These practices are known to be beneficial in terms of helping students to internalize the importance of these activities and the pleasure or interest they experience from them (e.g., Lowe & Dotterer, 2013), thus leading to higher levels of self-determined or autonomous motivation and decreasing their levels of amotivation. The lack of positive association between parental care and the *Self-Determined* profile, however, suggests that the effects of parental care might not be sufficient to result in a pure form of autonomous or self-determined motivations. Rather, these results suggest that parental care seems to lead to a more global increase in all forms of motivation, thus combining interest, pleasure, and importance with some accompanying feelings of internal and external pressure to achieve. For instance, parents might emphasize the importance of pleasure when learning something new (i.e., studying something enjoyable), but also the importance for students to prove to themselves that they are intelligent and capable (i.e., introjected regulation) in order to be able to obtain a well-paying job later on (i.e., external regulation). It is possible that parental care behaviors tap into more general and undifferentiated need supportive behaviors, rather than into any specific form of need supportive behaviors pertaining to autonomy (i.e., the provision of choice and the acknowledgement of students' perspectives), competence (i.e., the provision of encouragement and positive feedback) and relatedness (i.e., the provision of warmth and emotional support). As a result, students might develop a stronger bond with their parents which could lead to them having a stronger desire to succeed in school in order to avoid disappointing them. Clearly, future studies are needed to verify these explanations and to assess their generalizability.

Finally, autonomy-support was only found to predict a higher likelihood of membership into the *Amotivated* profile relative to the *Weakly Motivated* one, thus failing to support our hypotheses. This result is unusual in that variable-centered results have generally found autonomy-support to be associated with more autonomous forms of motivation (e.g., Gillet et al., 2013). Yet, it is also important to consider the fact that the present studies considered all three types of parenting behavior simultaneously, and the observed effects might reflect more the unique nature of autonomy-support net of what it shares with parental overprotection (r = -.493 in the present study, see Table S10 of the online supplements) and care (r = .322); i.e., some form of uncaring or unsupportive allocation of freedom. The specific measure of autonomy-support used in this study might reinforce this possibility. Indeed, whereas SDT describes autonomy-support as an active practice involving the explicit provision of goals, guidance, and feedback (Soenens & Vansteenkiste, 2010), the measure used here rather involves a more passive parenting style akin to a permissive or laissez-faire parental style. This particular style has been characterized by a lack of structure, involvement, and guidance, and has been shown to lead to self-regulatory deficits and amotivation (Piotrowsky et al., 2013).

Outcomes of Academic Motivation Profiles

Our outcome-related results provided clear support for the theoretical importance ascribed to students' global levels of self-determination (Ryan & Deci, 2017). Indeed, more desirable outcome levels (e.g., higher grades, life satisfaction, engagement, and lower dropout intentions) were systematically found to be associated with the *Self-Determined* and *Strongly Motivated* profiles, which presented the highest global levels of academic self-determination. Importantly, with very few exceptions (levels of math self-efficacy in Sample 1 and grades in sample two were higher in the *Self-Determined* profile than in the *Strongly Motivated* one), these two profiles were found to have very similar outcomes implications. This similarity, which was also reported in previous studies (e.g., Ratelle et al., 2007) suggests that high global levels of self-determination might be able to counter the undesirable effects typically associated with more controlled forms of motivation (e.g., Guay et al., 2008) or, alternatively, that controlled forms of motivation may not be as problematic as previously assumed when accompanied by matching levels of self-determination (e.g., Gillet et al., 2017).

The outcomes observed in the remaining three profiles were also mainly aligned with our hypotheses. More precisely, after the *Self-Determined* and the *Strongly Motivated* profiles, the most desirable outcome levels were then observed in the *Moderately Motivated* profile, followed by the *Weakly Motivated*, and then by the *Amotivated* profiles. Amotivated students reported the lowest grades, life satisfaction, perseverance of effort, and school engagement levels, as well as the most pronounced dropout intentions. This result is quite worrisome given that this profile includes almost a fourth of the students. The adverse effects of amotivation and weak motivation levels are well-documented (e.g., Legault et al., 2006), and our study adds to, and supports, this observation.

Strengths, Limitations, and Future Directions

This investigation provided an incremental contribution to the research literature on academic motivation by adopting a more recent operationalization of academic motivation allowing us to separately consider its global and specific components, which were both found to play an important role in the definition of the profiles. The present study also provided replication evidence for the identified motivational profile across two independent samples of high school students, and supported their construct validity by considering a wide range of theoretically-relevant predictors and outcomes. However, the cross-sectional design adopted in this study precludes causal inferences and makes it impossible to investigate the directionality of the observed associations between predictors, profiles, and outcomes. Longitudinal studies are thus needed to better document this directionality, as well as to assess the stability of profile membership and predictors of changes in profile membership over time (Gillet et al., 2017). Both studies reported here included self-reported measures which are prone to a variety of biases, suggesting that future research is needed to verify the extent to which the present results would generalize when using more objective indicators (e.g., observed achievement, actual dropout). Similarly, multi-informant data (e.g., from peers, teachers, or parents) might also be helpful to circumvent the limitations of self-reports. Furthermore, while the Academic Motivation Scale is arguably the most commonly used measure of academic motivation, its introjected regulation factor only incorporates approach (but not avoidance; e.g., Assor et al., 2009) motivations, and is entirely oriented toward the self (versus others; e.g., Ryan & Deci, 2000). As such, it would be interesting for future studies to incorporate these distinctions.

Another limitation stems from our reliance on two convenience samples of Hungarian high school students enrolled in grammar schools (i.e., schools whose mission is to prepare students for higher education). Samples drawn from this type of schools might not be representative of the whole population of Hungarian high school students, which also includes students attending vocational (i.e., preparing students for vocational training) or hybrid (i.e., preparing students for vocational training but allowing them to transition to higher education) schools. This limitation restricts the generalizability of our findings, and highlight the need for future replications conducted among more diversified samples attending different types of schools and recruited within more diversified countries. Finally, even though several predictors were taken into account, future studies would benefit from considering a more diverse set of profile determinants. Following SDT, a next step could be the consideration of basic psychological need fulfillment as an additional predictor of profile membership and as a possible mediator for the effects of need fulfilling parenting and school-related characteristics.

Practical Implications

Our results also have implications for teachers, parents, and people working in education, especially when we consider the fact that more than two-thirds of the high school students included in this study corresponded to either the *Weakly Motivated* profile or to the *Amotivated* profile. For these students, interventions would be needed to help them transition to more optimal motivational profiles. For amotivated students, teachers can adopt a variety of strategies aiming to help students find reasons to engage in school activities. For example, self-persuasion techniques (Aronson, 1999) in which students need to provide intrinsic reasons for going to school can be used to reduce amotivation and, in turn, contribute to stronger persistence in their academic career. Such techniques can be combined with previously tested motivation intervention strategies seeking to help students develop an interest in academic subjects (e.g., Hulleman & Harackiewicz, 2009). Facilitating the connection and the applicability of the course materials to students' everyday life can also help to promote the relevance and meaningfulness of the material. As mindset intervention studies have already reported positive effects in relation to students' motivation and grades (e.g., Yeager et al., 2016), similar practices could also be used to foster the development of a growth (rather than fixed) intelligence mindset. Goal framing interventions can also be relevant to help students develop their own rationale for learning (Hardre & Reeve, 2003), and connecting this rationale to a long term strategy of goal pursuit (Ryan & Deci, 2017). Goal framing does not only lead to intrinsic motivation, but also to better test performance and persistence (Vansteenkiste et al., 2004). In contrast, *Strongly Motivated* students might benefit more from interventions seeking to minimize the emphasis on internal and external incentives and pressures to encourage the emergence of an even more autonomously-driven desire to learn, which might help to orient these students toward a *Self-Determined* profiles. Finally, both types of practices, seeking to enhance autonomous motivation while also reducing the emphasises on internal and external pressures should prove most useful for students corresponding to the *Moderately Motivated* profile, who seem to need some more convincing about the inherent value of schooling.

One possible way for teachers and parents alike is to foster autonomous motivation is by creating an environment that satisfies students' basic psychological needs for autonomy, relatedness, and competence (Ryan & Deci, 2017). Such need-supportive conditions originate from behaviors and communications seeking to provide autonomy-support (reflecting on the need for autonomy), involvement (reflecting on the need for relatedness), and structure (reflecting on the need for competence) to developing students. Experimental and intervention studies have already been conducted that supported the effectiveness of this approach (e.g., Aelterman et al., 2014). As noted by Deci et al., (1991), achieving intrinsic motivation and internalized values is possible through evoking interest in learning, promoting the value of education, and making sure that students are confident in their abilities. In sum, interventions focusing on these elements might have more beneficial and broad consequences not just throughout one's educational career, but outside its scope as well.

References

Aelterman, N., Vansteenkiste, M., Van den Berghe, L., De Meyer, J., & Haerens, L. (2014). Fostering a need-supportive teaching style: Intervention effects on physical education teachers' beliefs and behaviors. *Journal of Sport & Exercise Psychology*, *36*, 595-609.

Alan, S., Boneva, T., & Ertac, S. (2019). Ever failed, try again, succeed better: Results from a randomized educational intervention. *Quarterly Journal of Economics*, *134*, 1121-1162.

Archambault, I., Janosz, M., Morizot, J., & Pagani, L. (2009). Adolescent behavioral, affective, and cognitive engagement in school. *Journal of School Health*, *79*, 408-415.

Arco-Tirado, J.L., Fernández-Martín, F.D., & Hoyle, R.H. (2018). Development and validation of a Spanish version of the Grit-S scale. *Frontiers in Psychology*, *9*, 96.

Aronson, E. (1999). The power of self-persuasion. *American Psychologist*, *54*, 875-884.

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

Assor, A., Vansteenkiste, M., & Kaplan, A. (2009). Identified vs introjected approach and introjected avoidance motivations in school and in sports. *Journal of Educational Psychology, 101*, 482–497.

Austin, S., Guay, F., Senécal, C., Fernet, C., & Nouwen, A. (2013). Longitudinal testing of a dietary self-care motivational model in adolescents with diabetes. *Journal of Psychosomatic Research, 75*, 153-159.

Bailey, T.H., & Phillips, L.J. (2016). The influence of motivation and adaptation on students' subjective well-being, meaning in life and academic performance. *Higher Education Research & Development*, *35*, 201-216.

Bandura, A. (2006). Guide for constructing self-efficacy scales. In T.Urdan & F. Pajares (Eds.), *Self-efficacy beliefs of adolescents* (pp. 307-337). Greenwich: Information Age.

Beaton, D.E., Bombardier, C., Guillemin, F., & Ferraz, M.B. (2000). Guidelines for the process of cross-cultural adaptation of self-report measures. *Spine*, *25*, 3186-3191.

Biddle, S.J., Wang, C.J., Chatzisarantis, N.L., & Spray, C.M. (2003). Motivation for physical activity in young people: Entity and incremental beliefs about ability. *Journal of Sports Science*, *21*, 973-989.

Burnette, J.L., O'Boyle, E.H., VanEpps, E.M., Pollack, J.M., & Finkel, E.J. (2013). Mind-sets matter: A meta-analytic review of implicit theories and self-regulation. *Psychological Bulletin*, *139*, 655-701.

Caleon, I.S., Wui, M.G.L., Tan, J.P.L., Chiam, C.L., Soon, T.C., & King, R.B. (2015). Cross-cultural

validation of the Academic Motivation Scale: A Singapore investigation. *Child Indicators Research*, *8*, 925-942.
Carbonneau, N., Vallerand, R.J., & Lafrenière, M.A.K. (2012). Toward a tripartite model of intrinsic motivation. *Journal of Personality, 80*, 1147-1178.
Chirkov, V.I., & Ryan, R.M. (2001). Parent and teacher autonomy-support in Russian and US adolescents: Common effects on well-being and academic motivation. *Journal of Cross-Cultural Psychology*, *32*, 618-635.
Deci, E.L., Driver, R.E., Hotchkiss, L., Robbins, R.J., & Wilson, I.M. (1993). The relation of mothers′ controlling vocalizations to children′ s intrinsic motivation. *Journal of Experimental Child Psychology*, *55*, 151-162.
Deci, E.L., & Ryan, R.M. (1985). *Intrinsic motivation and self-determination in human behavior*. New York, NY: Plenum
Deci, E.L., Ryan, R.M., & Guay, F. (2013). Self-determination theory and actualization of human potential. In D. M. McInerney, H.W. Marsh, R.G. Craven, & F. Guay (Eds.), Theory driving research: *New wave perspectives on self-processes and human development* (pp. 109–133). Charlotte, NC: Information Age Publishing Inc.
Deci, E.L., Vallerand, R.J., Pelletier, L.G., & Ryan, R.M. (1991). Motivation and education: The self-determination perspective. *Educational Psychologist*, *26*, 325-346.
Diallo, T.M.O, Morin, A.J.S. & Lu, H. (2016). Impact of misspecifications of the latent variance-covariance and residual matrices on the class enumeration accuracy of growth mixture models. *Structural Equation Modeling*, *23*, 507-531.
Diener, E.D., Emmons, R.A., Larsen, R.J., & Griffin, S. (1985). The satisfaction with life scale. *Journal of Personality Assessment*, *49*, 71-75.
Dietrich, J., & Salmela-Aro, K. (2013). Parental involvement and adolescents' career goal pursuit during the post-school transition. *Journal of Adolescence*, *36*, 121-128.
Duckworth, A.L., & Quinn, P.D. (2009). Development and validation of the Short Grit Scale (GRIT-S). *Journal of Personality Assessment, 91*, 166-174.
Dweck, C.S. (2006). *Mindset: The New Psychology of Success*. New York: Random House.
Dweck, C.S., Chiu, C.Y., & Hong, Y.Y. (1995). Implicit theories and their role in judgments and reactions: A word from two perspectives. *Psychological Inquiry*, *6*, 267-285.
European Commission (2018). *Education and Training Monitor 2018: Country analysis*. <*https://ec.europa.eu/education/sites/education/files/document-library-docs/volume-2-2018-education-and-training-monitor-country-analysis.pdf*>**.**
Fernet, C., Litalien, D., Morin, A.J.S., Austin, S., Gagné, M., Lavoie-Tremblay, M., & Forest, J. (2020). On the temporal stability of work motivation profiles: A latent transition analysis. *European Journal of Work and Organizational Psychology*, 29*, 49-63*.
Gagné, M., Forest, J., Vansteenkiste, M., Crevier-Braud, L., Van den Broeck, A., Aspeli, A.K., ... & Halvari, H. (2015). The multidimensional work motivation scale: Validation evidence in seven languages and nine countries. *European Journal of Work & Organizational Psychology, 24*, 178-196.
Gillet, N., Gagné, M., Sauvagère, S., & Fouquereau, E. (2013). The role of supervisor autonomy support, organizational support, and autonomous and controlled motivation in predicting employees' satisfaction and turnover intentions. *European Journal of Work and Organizational Psychology*, *22*, 450-460.
Gillet, N., Morin, A.J.S, Ndiaye, A., Colombat, P., & Fouquereau, E. (2020). A test of work motivation profile similarity across four distinct samples of employees. *Journal of Occupational and Organizational Psychology*, *93*, 988-1030.
Gillet, N., Morin, A.J.S., & Reeve, J. (2017). Stability, change, and implications of students’ motivation profiles: A latent transition analysis. *Contemporary Educational Psychology, 51*, 222-239.
Grolnick, W.S., & Ryan, R.M. (1987). Autonomy in children's learning: An experimental and individual difference investigation. *Journal of Personality & Social Psychology*, *52*, 890-898.
Guay, F., & Bureau, J.S. (2018). Motivation at school: Differentiation between and within school subjects matters in the prediction of academic achievement. *Contemporary Educational Psychology*, *54*, 42-54.
Guay, F., Lessard, V., & Dubois, P. (2016). How can we create better learning contexts for children? Promoting students’ autonomous motivation as a way to foster enhanced educational outcomes. In

L.W. Chia, J.C.K. Wang, and R.M. Ryan (Eds.), *Building autonomous learners*. Springer.
Guay, F., Ratelle, C.F., & Chanal, J. (2008). Optimal learning in optimal contexts: The role of self-determination in education. *Canadian Psychology*, *49*, 233-240.
Guay, F., Ratelle, C.F., Roy, A., & Litalien, D. (2010). Academic self-concept, autonomous academic motivation, and academic achievement: Mediating and additive effects. *Learning and Individual Differences*, *20*, 644-653.
Guo, J., Marsh, H.W., Parker, P.D., Morin, A.J.S., & Yeung, A.S. (2015). Expectancy-value in mathematics, gender and socioeconomic background as predictors of achievement and aspirations: A multi-cohort study. *Learning and Individual Differences*, *37*, 161-168.
Haimovitz, K., Wormington, S.V., & Corpus, J. (2011). Dangerous mindsets: How beliefs about intelligence predict motivational change. *Learning & Individual Differences*, *21*, 747-752.
Hardre, P.L., & Reeve, J. (2003). A motivational model of rural students' intentions to persist in, versus drop out of, high school. *Journal of Educational Psychology*, *95*, 347-356.
Hayenga, A.O., & Corpus, J.H. (2010). Profiles of intrinsic and extrinsic motivations: A person-centered approach to motivation and achievement. *Motivation & Emotion*, *34*, 371-383.
Hipp, J.R., & Bauer, D.J. (2006). Local solutions in the estimation of growth mixture models. *Psychological Methods, 11*, 36-53.
Howard, J.L., Gagné, M., & Bureau, J.S. (2017). Testing a continuum structure of self-determined motivation: A meta-analysis. *Psychological Bulletin*, *143,* 1346-1377.
Howard, J.L., Gagné, M., & Morin, A.J.S. (2020). Putting the pieces together: Reviewing the structural conceptualization of motivation within SDT. *Motivation & Emotion*, *44,* 846-861.
Howard, J.L., Gagné, M., Morin, A.J.S., & Forest, J. (2018). Using bifactor exploratory structural equation modeling to test for a continuum structure of motivation. *Journal of Management*, *44*, 2638-2664.
Howard, J., Gagné, M., Morin, A.J.S., & Van den Broeck, A. (2016). Motivation profiles at work: A Self-Determination Theory approach. *Journal of Vocational Behavior*, *95-96*, 74-96.
Howard, J.L., Morin, A.J.S., & Gagné, M. (2021). A longitudinal analysis of motivation profiles at work. *Motivation and Emotion*, *45,* 39-59.
Huang, C. (2012). Discriminant and criterion-related validity of achievement goals in predicting academic achievement. *Journal of Educational Psychology*, *104*, 48-73.
Hulleman, C.S., & Harackiewicz, J. M. (2009). Promoting interest and performance in high school science classes. *Science*, *326*, 1410-1412.
Joussemet, M., Landry, R., & Koestner, R. (2008). A self-determination theory perspective on parenting. *Canadian Psychology/Psychologie canadienne*, *49*, 194-200.
Karaman, M.A., Vela, J., Aguilar, A., Saldana, K., & Montenegro, M. (2019). Psychometric properties of US-Spanish versions of the grit and resilience scales with a Latinx population. *International Journal for the Advancement of Counselling*, *41*, 125-136.
Komarraju, M. (2013). Ideal teacher behaviors: Student motivation and self-efficacy predict preferences. *Teaching of Psychology*, *40*, 104-110.
Kuncel, N.R., Credé, M., & Thomas, L.L. (2005). The validity of self-reported grade point averages, class ranks, and test scores: A meta-analysis and review of the literature. *Review of Educational Research*, *75*, 63-82.
Lanza, S.T., Tan, X., & Bray, B.C. (2013). Latent class analysis with distal outcomes: A flexible model-based approach. *Structural Equation Modeling, 20*, 1–26.
Legault, L., Green-Demers, I., & Pelletier, L. (2006). Why do high school students lack motivation in the classroom? Toward an understanding of academic amotivation and the role of social support. *Journal of Educational Psychology*, *98*, 567-582.
Litalien, D., Gillet, N., Gagné, M., Ratelle, C.F., & Morin, A.J.S. (2019). Self-determined motivation profiles among undergraduate students: A robust test of profile similarity as a function of gender and age. *Learning and Individual Differences*, *70,* 39-52.
Litalien, D., Morin, A.J.S., Gagné, M., Vallerand, R.J., Losier, G.F., & Ryan, R.M. (2017). Evidence of a continuum structure of academic self-determination: A two-study test using a bifactor-ESEM representation of academic motivation. *Contemporary Educational Psychology*, *51*, 67-82.
Liu, W.C., Wang, J.C.K., Tan, O.S., Koh, C., & Ee, J. (2009). A self-determination approach to understanding motivation in project work. *Learning & Individual Differences*, *19*, 139-145.
Lowe, K., & Dotterer, A.M. (2013). Parental monitoring, parental warmth, and minority youths'

academic outcomes: Exploring the integrative model of parenting. *Journal of Youth and Adolescence*, *42*, 1413-1425.
Mageau, G.A., & Vallerand, R.J. (2003). The coach–athlete relationship: A motivational model. *Journal of Sports Science*, *21*, 883-904.
Marsh, H.W., Pekrun, R., Parker, P.D., Murayama, K., Guo, J., Dicke, T., & Arens, A.K. (2019). The murky distinction between self-concept and self-efficacy: Beware of lurking jingle-jangle fallacies. *Journal of Educational Psychology*, *111*, 331-353.
Martos, T., Sallay, V., Désfalvi, J., Szabó, T., & Ittzés, A. (2014). Az Élettel való Elégedettség Skála magyar változatának (SWLS-H) pszichometriai jellemzői [Psychometric characteristics of the Hungarian version of the Satisfaction with Life Scale (SWLS-H)]. *Mentálhigiéné és Pszichoszomatika*, *15*, 289-303.
Meyer, J.P., & Morin, A.J.S. (2016). A person-centered approach to commitment research: Theory, research, and methodology. *Journal of Organizational Behavior*, *37*, 584-612.
Morin, A.J.S., Arens, A.K., & Marsh, H.W. (2016). A bifactor exploratory structural equation modeling framework for the identification of distinct sources of construct-relevant psychometric multidimensionality. *Structural Equation Modeling*, *23*, 116-139.
Morin, A.J.S., Boudrias, J.S., Marsh, H.W., Madore, I., & Desrumaux, P. (2016). Further reflections on disentangling shape and level effects in person-centered analyses: An illustration exploring the dimensionality of psychological health. *Structural Equation Modeling*, *23*, 438-454.
Morin, A.J.S., Boudrias, J.S., Marsh, H.W., McInerney, D.M., Dagenais-Desmarais, V., Madore, I., & Litalien, D. (2017). Complementary variable-and person-centered approaches to the dimensionality of psychometric constructs: Application to psychological wellbeing at work. *Journal of Business and Psychology*, *32*, 395-419.
Morin, A.J.S., & Litalien, D. (2017). *Webnote: Longitudinal tests of profile similarity and latent transition analyses*. Montreal, QC: Substantive Methodological Synergy Research Lab *smslabstats.weebly.com/uploads/1/0/0/6/100647486/lta_distributional_similarity_v02.pdf*
Morin, A.J.S., & Marsh, H.W. (2015). Disentangling shape from level effects in person-centered analyses: An illustration based on university teachers' multidimensional profiles of effectiveness. *Structural Equation Modeling*, *22*, 39-59.
Morin, A.J.S., Meyer, J.P., Creusier, J., & Biétry, F. (2016). Multiple-group analysis of similarity in latent profile solutions. *Organizational Research Methods*, *19*, 231-254.
Mullen, P.R., & Crowe, A. (2018). A psychometric investigation of the short grit scale with a sample of school counselors. *Measurement and Evaluation in Counseling and Development*, *51*, 151-162.
Muthén, L.K., & Muthén, B.O. (2017). *Mplus user guide.* Los Angeles, CA: Muthén & Muthén.
Niemiec, C.P., Lynch, M.F., Vansteenkiste, M., Bernstein, J., Deci, E.L., & Ryan, R.M. (2006). The antecedents and consequences of autonomous self-regulation for college: A self-determination theory perspective on socialization. *Journal of Adolescence*, *29*, 761-775.
Noftle, E., & Robins, R. (2007). Personality predictors of academic outcomes: big five correlates of GPA and SAT scores. *Journal of Personality & Social Psychology*, *93*, 116-130.
OECD (2016). *PISA 2015 Results (Volume I): Excellence and Equity in Education*. OECD, Paris
O'Connor, A.J., Nemeth, C.J., & Akutsu, S. (2013). Consequences of beliefs about the malleability of creativity. *Creativity Research Journal*, *25*, 155-162.
Orosz, G., Péter-Szarka, S., Bőthe, B., Tóth-Király, I., & Berger, R. (2017). How not to do a mindset intervention: Learning from a mindset intervention among students with good grades. *Frontiers in Psychology*, *8*, 311.
Otis, N., Grouzet, F.M., & Pelletier, L.G. (2005). Latent motivational change in an academic Setting: A 3-Year longitudinal study. *Journal of Educational Psychology, 97*, 170-183.
Paixão, O., & Gamboa, V. (2017). Motivational Profiles and Career Decision Making of High School Students. *The Career Development Quarterly, 65*, 207-221.
Parker, G., Tupling, H., & Brown, L.B. (1979). A parental bonding instrument. *British Journal of Medical Psychology, 52,* 1-10.
Peugh, J. & Fan, X. (2013). Modeling unobserved heterogeneity using latent profile analysis: A Monte Carlo simulation. *Structural Equation Modeling*, *20*, 616-639.
Piotrowski, J.T., Lapierre, M.A., & Linebarger, D.L. (2013). Investigating correlates of self-regulation in early childhood with a representative sample of English-speaking American families. *Journal of*

Child and Family Studies, *22*, 423-436.
Ratelle, C.F., Guay, F., Vallerand, R.J., Larose, S., & Senécal, C. (2007). Autonomous, controlled, and amotivated types of academic motivation: A person-oriented analysis. *Journal of Educational Psychology, 99*, 734-746.
Ratelle, C.F., Senécal, C., Vallerand, R.J., & Provencher, P. (2005). The relationship between school-leisure conflict and educational and mental health indexes: A motivational analysis. *Journal of Applied Social Psychology*, *35*, 1800-1822.
Reeve, J. (2012). A self-determination theory perspective on student engagement. In S.L. Christenson, A.L. Reschly, & C. Wylie (Eds.), *Handbook of research on student engagement*. Springer.
Renaud-Dubé, A., Guay, F., Talbot, D., Taylor, G., & Koestner, R. (2015). The relations between implicit intelligence beliefs, autonomous academic motivation, and school persistence intentions: a mediation model. *Social Psychology of Education*, *18*, 255-272.
Reraki, M., Celik, I., & Saricam, H. (2015). Grit as a mediator of the relationship between motivation and academic achievement. *Ozean Journal of Social Science*, *8*, 19-32.
Ryan, R.M., & Deci, E.L. (2000). Intrinsic and extrinsic motivations: classic definitions and new directions. *Contemporary Educational Psychology*, *25*, 54–56.
Ryan, R.M., & Deci, E.L. (2017). *Self-determination theory. Basic psychological needs in motivation, development, and wellness.* New York, NY: Guilford Press.
Salanova, M., Llorens, S., Cifre, E., Martínez, I.M., & Schaufeli, W.B. (2003). Perceived collective efficacy, subjective well-being and task performance among electronic work groups: An experimental study. *Small Group Research*, *34,* 43-73.
Schaufeli, W.B., Salanova, M., González-Romá, V., & Bakker, A.B. (2002). The measurement of engagement and burnout: A two sample confirmatory factor analytic approach. *Journal of Happiness Studies*, *3*, 71-92.
Skinner, E., Johnson, S., & Snyder, T. (2005). Six dimensions of parenting: A motivational model. *Parenting: Science and Practice*, *5*, 175-235.
Soenens, B., & Vansteenkiste, M. (2005). Antecedents and outcomes of self-determination in 3 domains: The role of parents' and teachers' autonomy support. *Journal of Youth & Adolescence*, *34*, 589-604.
Soenens, B., & Vansteenkiste, M. (2010). A theoretical upgrade of the concept of parental psychological control. *Developmental Review, 30*, 74-99.
Statistics Canada (2010). *Trends in dropout rates and the labour market outcomes of young dropouts*. <***www150.statcan.gc.ca/n1/daily-quotidien/101103/dq101103a-eng.htm***>.
Steinmayr, R., Weidinger, A.F., & Wigfield, A. (2018). Does students' grit predict their school achievement above and beyond their personality, motivation, and engagement? *Contemporary Educational Psychology*, *53*, 106-122.
Strayhorn, T.L. (2014). What role does grit play in the academic success of black male collegians at predominantly white institutions? *Journal of African American Studies*, *18,* 1-10.
Tang, X., Wang, M.T., Guo, J., & Salmela-Aro, K. (2019). Building grit: The longitudinal pathways between mindset, commitment, grit, and academic outcomes. *Journal of Youth & Adolescence*, *48*, 850-863.
Thornberry, T.P., Moore, M., & Christenson, R.L. (1985). The effect of dropping out of high school on subsequent criminal behavior. *Criminology*, *23,* 3-18.
Tóth, I., & Gervai, J. (1999). Szülői bánásmód kérdőív (H-PBI): A Parental Bonding Instrument magyar változata [Perceived Parental Styles: The Hungarian Parental Bonding Instrument]. *Magyar Pszichológiai Szemle*, *54,* 551-566.
Tóth-Király, I., Morin, A.J.S., Bőthe, B., Rigó, A., & Orosz, G. (2021). Toward an Improved Understanding of Work Motivation Profiles. *Applied Psychology: An International Review, 70,* 986-1017.
Tóth-Király, I., Orosz, G., Dombi, E., Jagodics, B., Farkas, D., & Amoura, C. (2017). Cross-cultural comparative examination of the Academic Motivation Scale using exploratory structural equation modeling. *Personality and Individual Differences, 106*, 130-135.
Turner, E.A., Chandler, M., & Heffer, R.W. (2009). The influence of parenting styles, achievement motivation, and self-efficacy on academic performance in college students. *Journal of College Student Development*, *50*, 337-346.
US Department of Education (2014). *The Condition of Education: Status Dropout Rates*. <*https://nces.ed.gov/programs/coe/indicator_coj.asp*>**.**

Vallerand, R.J. (1997). Toward a hierarchical model of intrinsic and extrinsic motivation. *Advances in Experimental Social Psychology*, *29*, 271-360.

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

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

Vallerand, R.J., Pelletier, L.G., Blais, M.R., Briere, N.M., Senecal, C., & Vallieres, E.F. (1992). The academic motivation scale: A measure of intrinsic, extrinsic, and amotivation in education. *Education and Psychological Measurement*, *52*, 1003-1017.

Vansteenkiste, M., Sierens, E., Soenens, B., Luyckx, K., & Lens, W. (2009). Motivational profiles from a self-determination perspective. *Journal of Educational Psycholog*y, *101*, 671-688.

Vansteenkiste, M., Simons, J., Lens, W., Sheldon, K.M., & Deci, E.L. (2004). Motivating learning, performance, and persistence: the synergistic effects of intrinsic goal contents and autonomy-supportive contexts. *Journal of Personality & Social Psychology*, *87*, 246-260.

Wang, J.C.K., Liu, W., Lochbaum, M., & Stevenson, S. (2009). Sport ability beliefs, 2 x 2 achievement goals, and intrinsic motivation: The moderating role of perceived competence in sport and exercise. *Research Quarterly for Exercise and Sport*, *80*, 303-312.

Wang, J.C.K., Liu, W.C., Nie, Y., Chye, Y.L.S., Lim, B.S.C., Liem, G.A., … & Chiu, C.-Y. (2017). Latent profile analysis of students' motivation and outcomes in mathematics. *Heliyon*, *3*, e00308.

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

Wormington, S., Corpus, J., & Anderson, K. (2012). A person-centered investigation of academic motivation and its correlates in high school. *Learning & Individual Differences*, *22*, 429-438.

Xu, M.K., Morin, A.J.S., Marsh, H.W., Richards, M., & Jones, P.B. (2018). Psychometric validation of the parental bonding instrument in a UK population–based sample: Role of gender and association with mental health in mid-late life. *Assessment*, *25*, 716-728.

Yeager, D.S., Romero, C., Paunesku, D., Hulleman, C. S., Schneider, B., Hinojosa, C., ... & Trott, J. (2016). Using design thinking to improve psychological interventions. *Journal of Educational Psychology*, *108*, 374-391.

Zhong, C., Wang, M.C., Shou, Y., Ren, F., Zhang, X., Li, M., & Yang, W. (2018). Assessing construct validity of the Grit-S in Chinese employees. *PloS one*, *13* (12).

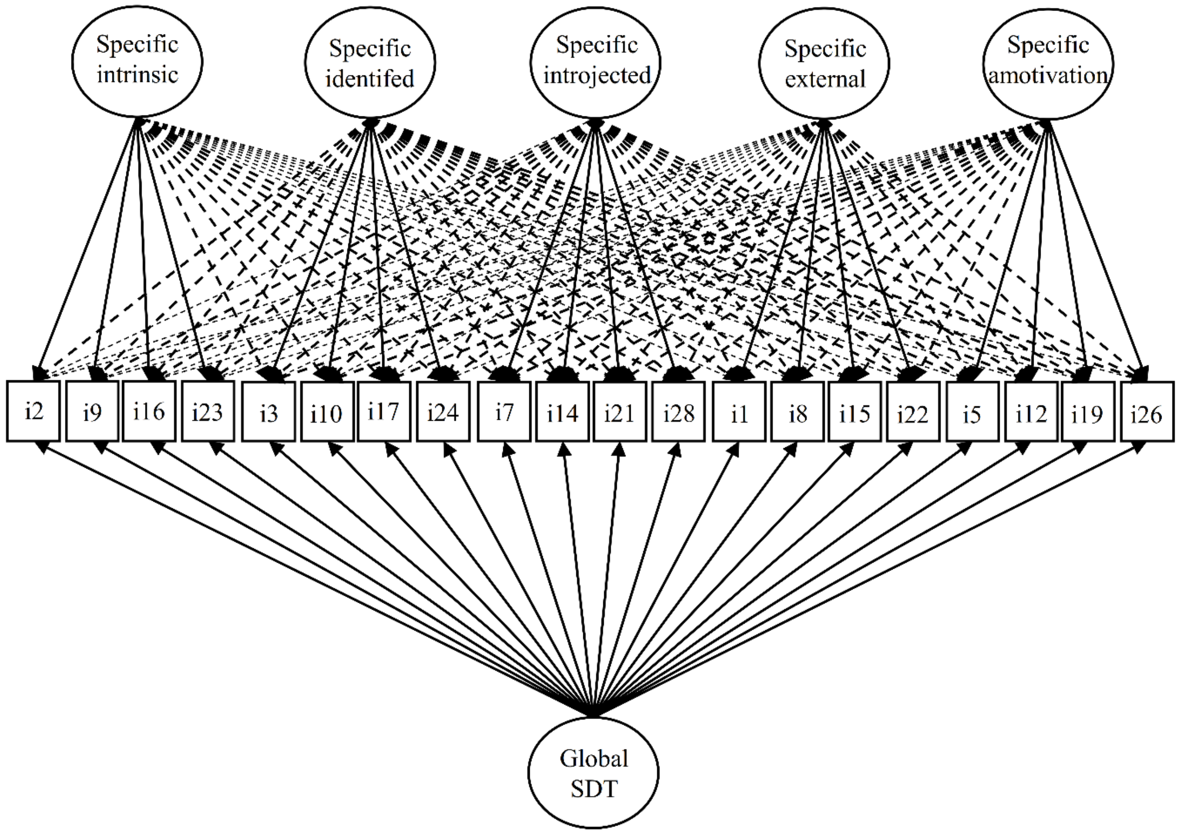

Figure 1
Graphical Illustration of the Comprehensive Operationalization of Academic Motivation via the Bifactor Exploratory Structural Equation Modeling Framework

Note. SDT: self-determination; Circles represent latent factors, squares represent scale items (i.e., 1-28). One-headed full arrows represent factor loadings while one-headed dashed arrows represent cross-loadings.

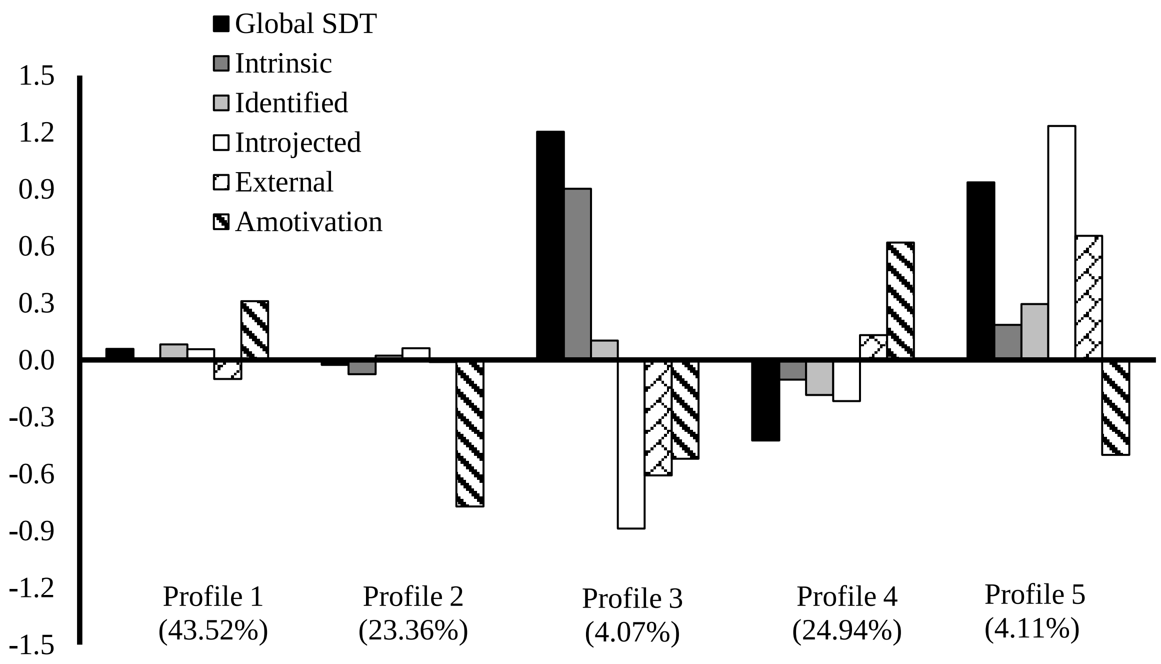

Figure 2
Final 5-Profile Solution

Note. Profile indicators were standardized factor scores (M = 0, SD = 1) derived from preliminary measurement models; SDT: Self-determined motivation; Profile 1: Weakly Motivated; Profile 2: Moderately Motivated; Profile 3: Self-Determined; Profile 4: Amotivated; Profile 5: Strongly Motivated.

Table 1

Results from the Multinomial Logistic Regressions Evaluating the Relations between Predictors and Profile Membership across the Two Samples

Sample 1

Outcomes	Weakly Motivated vs. Moderately Motivated		Weakly Motivated vs. Self-Determined		Weakly Motivated vs. Amotivated		Weakly Motivated vs. Strongly Motivated		Moderately Motivated vs. Self-Determined	
	Coeff. (SE)	OR	Coeff. (SE)	OR	Coeff. (SE)	OR	Coeff. (SE)	OR	Coeff. (SE)	OR
Fixed mindset: IQ	.206 (.209)	1.229	.496 (1.151)	1.642	-.478 (.334)	.620	.932 (.499)	2.540	.289 (1.173)	1.335
Fixed mindset: Math	.327 (.197)	1.387	1.911 (1.170)	6.760	-.169 (.319)	.845	.470 (.470)	1.600	1.584 (1.176)	4.874

	Moderately Motivated vs. Amotivated		Moderately Motivated vs. Strongly Motivated		Self-Determined vs. Amotivated		Self-Determined vs. Strongly Motivated		Amotivated vs. Strongly Motivated	
	Coeff. (SE)	OR	Coeff. (SE)	OR	Coeff. (SE)	OR	Coeff. (SE)	OR	Coeff. (SE)	OR
Fixed mindset: IQ	-.684 (.342)*	.505	.726 (.525)	2.067	-.973 (1.199)	.378	.437 (1.204)	1.548	1.410 (.580)*	4.096
Fixed mindset: Math	-.496 (.299)	.609	.143 (.556)	1.154	-2.080 (1.197)	.125	-1.441 (1.279)	.237	.639 (.583)	1.895

Sample 2

Outcomes	Weakly Motivated vs. Moderately Motivated		Weakly Motivated vs. Self-Determined		Weakly Motivated vs. Amotivated		Weakly Motivated vs. Strongly Motivated		Moderately Motivated vs. Self-Determined	
	Coeff. (SE)	OR	Coeff. (SE)	OR	Coeff. (SE)	OR	Coeff. (SE)	OR	Coeff. (SE)	OR
Care	-.385 (.218)	.680	-.659 (.406)	.517	.613 (.291)*	1.846	-2.098 (.568)**	.123	-.274 (.434)	.760
Autonomy-support	.262 (.209)	1.300	-.521 (.397)	.594	-.415 (.287)	.660	.122 (.306)	1.130	-.783 (.413)	.457
Overprotection	.513 (.235)*	1.670	.916 (.547)	2.499	.106 (.270)	1.112	-1.119 (.455)*	.327	.403 (.581)	1.496

	Moderately Motivated vs. Amotivated		Moderately Motivated vs. Strongly Motivated		Self-Determined vs. Amotivated		Self-Determined vs. Strongly Motivated		Amotivated vs. Strongly Motivated	
	Coeff. (SE)	OR	Coeff. (SE)	OR	Coeff. (SE)	OR	Coeff. (SE)	OR	Coeff. (SE)	OR
Care	.998 (.320)**	2.713	-1.713 (.607)**	.180	1.273 (.475)**	3.572	-1.438 (.672)*	.237	-2.711 (.623)**	.066
Autonomy-support	-.677 (.307)*	.508	-.140 (.326)	.869	.106 (.470)	1.112	.643 (.451)	1.902	.537 (.537)	1.711
Overprotection	-.407 (.276)	.666	-1.632 (.483)**	.196	-.810 (.576)	.445	-2.034 (.674)**	.131	-1.224 (.498)*	.294

Note. * $p < .05$; ** $p < .01$; Predictors are standardized factor scores (M = 0, SD = 1); 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; SE: standard error of the coefficient.

Table 2
Outcome Means and Pairwise Comparisons between the Five Profiles

Outcome	Weakly Motivated Mean (SE)	Moderately Motivated Mean (SE)	Self-Determined Mean (SE)	Amotivated Mean (SE)	Strongly Motivated Mean (SE)	Differences between profiles
Sample 1						
Math self-efficacy	-.119 [-.246, .008]	.032 [-.152, .216]	1.123 [.582, 1.664]	.039 [-.141, .219]	.229 [-.194, .652]	1 = 2 = 4 = 5 < 3
Perseverance of effort (grit)	-.004 [-.116, .108]	.203 [.036, .370]	1.023 [.474, 1.572]	-.396 [-.557, -.235]	.515 [.109, .921]	4 < 1 < 2 < 3; 4 < 1 < 5; 2 = 5; 3 = 5
Inconsistency of interest (grit)	.039 [-.073, .151]	.010 [-.151, .171]	-1.053 [-1.725, -.381]	-.066 [-.227, .095]	.248 [-.126, .622]	3 < 1 = 2 = 4 = 5
Self-reported grades	-.290 [-.427, -.153]	-.032 [-.230, .166]	.883 [.303, 1.463]	-.308 [-.504, -.112]	.175 [-.278, .628]	1 < 2 < 3; 4 < 3; 3 = 5; 2 = 4 = 5; 1 = 5; 1 = 4
Sample 2						
Vigor	.080 [-.008, .168]	.417 [.294, .540]	1.021 [.735, 1.307]	-1.106 [-1.222, -.990]	.968 [.637, 1.299]	4 < 1 < 2 < 5 = 3
Dedication	.033 [-.049, .115]	.429 [.317, .541]	1.349 [1.108, 1.590]	-1.140 [-1.256, -1.024]	1.101 [.823, 1.379]	4 < 1 < 2 < 5 = 3
Absorption	.085 [-.003, .173]	.328 [.212, .444]	1.358 [1.109, 1.607]	-1.059 [-1.177, -.941]	1.016 [.734, 1.298]	4 < 1 < 2 < 5 = 3
Dropout intentions	.120 [.453, .727]	-.340 [-.460, -.220]	-.856 [-.995, -.717]	.590 [.453, .727]	-.659 [-.879, -.439]	3 = 5 < 2 < 1 < 4
Life satisfaction	-.136 [-.256, -.016]	.317 [.168, .466]	.580 [.274, .886]	-.358 [-.511, -.205]	.717 [.370, 1.064]	4 < 1 < 2 < 5; 4 < 1 < 2 = 3; 3 = 5
Self-reported grades	.122 [-.005, .249]	.290 [.212, .444]	1.107 [.868, 1.346]	-.159 [-.322, .004]	.323 [-.067, .713]	4 < 1 = 2 = 5 < 3

Note. SE: standard error.

Online Supplements for:

Self-Determined Profiles of Academic Motivation

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

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

Appendix 1.
Preliminary Measurement Models

Motivation Models Specification

A series of preliminary measurement models were estimated in order to verify the psychometric properties of the instruments, as well as to obtain factor scores for use in the main analyses. When compared to manifest scale scores, factor scores provide a way to preserve the nature of the underlying measurement model (e.g., bifactor, invariance) while also providing partial control for measurement error (e.g., Morin, Boudrias et al., 2016; 2017; Morin, Meyer, et al., 2016; Skrondal & Laake, 2001).

Based on recent evidence (Howard et al., 2018; Litalien et al., 2017) showing that measures of motivation based on self-determination theory (SDT; Ryan & Deci, 2017) were best represented via bifactor exploratory structural equation models (bifactor-ESEM; Morin, Arens, et al., 2016; Morin, Arens, Tran, et al., 2016), we relied on this approach to model academic motivation. In the bifactor-ESEM framework, the bifactor component allows one to estimate a global (G-) factor reflecting students' global levels of academic self-determination (defined by all motivation items and a pattern of factor loadings following their position on the SDT motivation continuum), together with specific (S-) motivational factors reflecting the unique quality associated with each motivation subscale (i.e., intrinsic motivation, identified regulation, introjected regulation, external regulation, and amotivation) left unexplained by the G-factor, which should be smaller for the most "self-determined" subscales (i.e., intrinsic and identified) to reflect the fact that the items from these subscales mainly serve to define the G-factor. In contrast, the ESEM component allows one to freely estimate all cross-loadings between the S-factors, which has been previously shown to results in more accurate factor definitions (Asparouhov et al., 2015; Morin et al., 2019).

In order to ascertain the appropriateness of this bifactor-ESEM representation, we followed Morin et al.'s (Morin, Boudrias et al., 2016, 2017; Morin et al., 2019) recommendations and contrasted first-order and bifactor confirmatory factor analytic (CFA) and ESEM solutions. In CFA, items were specified as being only associated with their a priori factors, all cross-loadings were constrained to zero, and factors were allowed to correlate freely. In ESEM, the factors were defined in the same manner as in the CFA, but all cross-loadings were freely estimated, but targeted to be as close to zero as possible through the application of a confirmatory approach to factor rotation (oblique target rotation; Browne, 2001). In bifactor-CFA, all items were associated with one G-factor as well as with their a priori S-factor, cross-loadings were constrained to zero between the S-factors, and factors were specified as orthogonal as per typical bifactor specifications (Morin et al., 2019; Reise, 2012). In bifactor-ESEM, factors were defined as in bifactor-CFA, but cross-loadings were freely estimated between all S-factors, but targeted to be close to zero via orthogonal target rotation. When contrasting CFA and ESEM models, support for the ESEM solutions comes from the observation of equally well-defined factors coupled with reduced estimates of factor correlations (Morin, Boudrias et al., 2016, 2017; Morin et al., 2019). When comparing first-order and bifactor models, support for the bifactor solution would come from the observation of a well-defined G-factor (matching the continuum structure of motivation in the present study: Howard et al., 2018; Litalien et al., 2017) together with at least a subset of well-defined S-factors (Morin, Boudrias et al., 2016, 2017; Morin et al., 2019).

After selection of the optimal solution, to ascertain that we relied on comparable sets of profile indicators (i.e., motivation factor scores) in both samples, tests of measurement invariance were conducted across samples according to the following sequence (Millsap, 2011): (1) configural invariance (same model), (2) weak invariance (equality of loadings), (3) strong invariance (equality of loadings and thresholds), (4) strict invariance (equality of loadings, thresholds, and uniquenesses); (5) invariance of the latent variance-covariance matrix (equality of loadings, thresholds, uniquenesses, and latent variances and covariances); and (6) latent means invariance (equality of loadings, thresholds, uniquenesses, latent variances and covariances, and latent means).

Correlates Models Specification

In Sample 1, the measurement model underpinning the correlates was estimated using a CFA approach including five correlated factors representing math self-efficacy, perseverance of effort, inconsistency of interest, fixed intelligence mindset and fixed math mindset. In this model a priori correlated uniquenesses (CUs) were added between two pairs of self-efficacy items to control for the methodological artefact associated with the parallel wording of these items (Morin et al., 2019). In Sample 2, measurement models underpinning the predictors and the outcomes had to be estimated separately (given their complexity). Following Xu et al. (2018), a three-factor ESEM parameterization was used to represent the predictors (parental care, autonomy-support and overprotection). A priori CUs were included in this model to account for the negative-wording effect between a subset of items belonging to the care factor (Marsh et al., 2010). Finally, outcomes were modeled with a CFA model that included five correlated factors (vigor, dedication, absorption, dropout intentions and life satisfaction).

Model Estimation

Analyses were conducted with Mplus 8 (Muthén & Muthén, 2017) and the weighted least squares mean- and variance-adjusted estimator (WLSMV) which has been found to be superior to maximum-likelihood estimation for ordered-categorical items, particularly when the response categories follow asymmetric thresholds (for a review, see Finney & DiStefano, 2013). In addition, recent studies on the structure of SDT-based motivations measures have also supported the value of WLSMV estimation (Gillet, Morin, & Reeve, 2017; Guay, Morin, Litalien, Valois, & Vallerand, 2015; Litalien, Guay, & Morin, 2015).

Models were evaluated using goodness-of-fit indices (Hu & Bentler, 1999; Marsh et al., 2005): the chi-square test (χ^2), the comparative fit index (CFI), the Tucker-Lewis Index (TLI), and the root mean square error of approximation (RMSEA). CFI and TLI values are typically considered to be adequate or excellent when they are above .90 and .95, respectively. RMSEA values are considered to be adequate or excellent below .08 and .06, respectively. As the chi-square test is known to be oversensitive to minor model misspecifications and sample size (Marsh et al., 2005), it is simply reported for the sake of transparency, but not used in model evaluation. Nested models' comparisons in tests of measurement invariance were based on examination of changes (Δ) in fit indices where a decrease of .010 or higher for CFI and TLI and an increase of at least .015 or higher for RMSEA indicating lack of invariance across samples (Chen, 2007; Cheung & Rensvold, 2002). We finally calculated model-based composite reliability indices (McDonald, 1970) to assess the reliability of the factors (Morin et al., 2019).

Results

Goodness-of-fit indices associated with the preliminary measurement models are reported in Table S2. The results associated with the motivation measurement models estimated in the first sample first show that that ESEM solution provided an increased level of fit to the data when compared to the CFA solution (ΔCFI = +.036, ΔTLI = +.022, ΔRMSEA = -.015). Standardized parameter estimates from both of these solutions are reported in Table S3. These results show that all factors remain generally well-defined (λ = .223-.949, *M* = .634) and reliable (ω =.705 and .898) in the ESEM solution. Although the ESEM solution incorporates multiple statistically significant cross-loadings, most of them remain small enough not to undermine the definition of the factors ($|\lambda|$ = .000-.377, *M* = .103). In fact, only two larger cross-loadings were higher than their target loadings, suggesting that Item 10 (Identified regulation: "Because eventually it will enable me to enter the job market in a field that I like.") might have a stronger correspondence with the external regulation factor, while Item 17 (identified regulation: "Because this will help me make a better choice regarding my career orientation.") might have a stronger correspondence with the introjected regulation factor. More importantly, factor correlations (Table S4) were substantially reduced in ESEM ($|r|$ = .199-.571, M = .424) relative to CFA ($|r|$ = .373-.878, *M* = .608).

The ESEM solution was thus retained, and contrasted with its bifactor counterpart. This solution resulted again in an improved fit to the data (ΔCFI = +.009, ΔTLI = +.010, ΔRMSEA = -.007). It also revealed a reliable (ω = .931) G-factor well-defined by factor loadings matching the SDT continuum from intrinsic (λ = .590-.765, *M* = .676), identified (λ = .495-.670, *M* = .568), introjected (λ = .355-.526, *M* = .468), external (λ = .193-.437, *M* = .320), and amotivation (λ = -.325-.456, *M* = -.385) items. Likewise, S-factors related to introjected regulation (λ = .459-.605, *M* = .539; ω = .754), external regulation (λ = .499-.868, *M* = .668; ω = .834), and amotivation (λ = .602-.813, *M* = .720; ω = .877) were also generally well-defined, whereas those associated with intrinsic motivation (λ = .015-.421, *M* = .275; ω = .444) and identified regulation (λ = .182-.752, *M* = .378; ω = .642) seemed to retain less specificity once the variance explained by the G-factor was taken into account. In this solution, cross-loadings remained similar, yet slightly smaller, than their ESEM counterparts ($|\lambda|$ = .003-.484, *M* = .113) and revealed that the high cross loading reported to be associated with Item 17 in the ESEM solution simply reflected the fact that this item provides a better representation of the G-factor (λ = .670) than of its S-factor ($\lambda = .182$), while problem associated with Item 10 remained. Altogether, these results support the value of the bifactor-ESEM solution.

In Sample 2, goodness-of-fit results and parameter estimates supported the same conclusions regarding the superiority of the bifactor-ESEM solution. However, to more precisely assess the extent to which results from this solution were replicated across samples, tests of measurement invariance were realized on this solution. The results from these tests, reported in the bottom section of Table S2, supported the complete measurement invariance of this solution (ΔCFI/TLI $\leq .010$, ΔRMSEA $\leq .015$). The final parameter estimates from the model of latent mean invariance are reported in Table S5 and generally match those described above for the bifactor-ESEM solution obtained in Sample 1.

Turning our attention to the correlates, the measurement model estimated in both samples had good fit to the data (see Table S2). Standardized parameter estimates from these models are reported in Tables S6 (Sample 1), S7 (Sample 2: predictors) and S8 (Sample 2: outcomes). All factors were well-defined by their target loadings and resulted in satisfactory estimates of reliability ($\omega = .761$ to $.949$). Factor scores were saved from these measurement models for the main analyses. Correlations among all factor scores are reported in Table S9 for Sample 1 and Table S10 for Sample 2.

Appendix 2.
Selecting the Optimal Number of Profiles

Model Comparison

Selection of the optimal number of profiles was guided by the theoretical meaningfulness and statistical adequacy (e.g., the absence of negative variance estimates) of the extracted profiles (Marsh et al., 2009; Muthén, 2003). This decision was also informed by a variety of statistical indicators, including the Akaike Information Criterion (AIC), the Bayesian Information Criterion (BIC), the Constant AIC (CAIC), the Sample-Size-Adjusted BIC (SSABIC), the adjusted Lo-Mendell-Rubin (aLMR) likelihood ratio test, and the Bootstrap Likelihood Ratio Test (BLRT). Lower AIC, BIC, CAIC and SSABIC values suggests a better fitting solution, while non-significant aLMR and BLRT suggest the superiority of a model including one less profile. We also report the model entropy, which provides useful information about classification accuracy, although it should not be directly used to guide the selection of the optimal solution (Lubke & Muthén, 2007).

Simulation studies have demonstrated the usefulness of the CAIC, BIC, SSABIC, and BLRT, but not that of the AIC and aLMR, as reliable indicators of the optimal number of profiles (e.g., Diallo et al., 2016, 2017; Peugh & Fan, 2013). Furthermore, Diallo et al. (2016) showed that the BIC and CAIC were particularly useful when the classification accuracy of the model was high (i.e., entropy ≥ .800), whereas the SSABIC and BLRT were more useful when the classification accuracy was low (i.e., ≤ .600). For the sake of full disclosure and comparability with prior studies, we report all indicators and put more emphasis on CAIC/BIC or SSABIC/BLRT depending on the classification accuracy. However, all of these indicators are heavily impacted by sample size and often keep on improving with the addition of profiles to the solution (Marsh et al., 2009). In these situations, indicators should be graphically presented as "elbow plots" where the point after which the slope flattens suggests that the optimal number of profiles have been reached and that the contribution of additional profiles becomes negligible (Morin et al., 2011).

Results

The results from the solutions including different numbers of profiles are reported in Table S11 and graphically displayed in Figure S1 of the online supplements. Generally, entropy values remained in the low-to-moderate range across solutions (.564 and .791 in Sample 1; .563 and .800 in Sample 2), suggesting that more attention should be attributed to the SSABIC and BLRT. Indeed, although the BIC and CAIC reached their lowest point around 2-3 profiles in both samples, the SSABIC (and AIC) kept on decreasing with the inclusion of additional profiles without reaching a minimum. However, examination of the elbow plots reported in Figure S1 shows that this decrease becomes negligible between 4 and 6 profiles in Sample 1 and around 5 profiles in Sample 2. Finally, the BLRT seems to support a 4-profile solution in Sample 1 and a 7-profile solution in Sample 2. On this basis, solutions including 4 to 6 profiles were more carefully examined across samples. This inspection revealed that all solutions were statistically proper and similar across samples, and that increasing the number of latent profiles resulted in theoretically meaningful, distinct and interpretable profiles up to the 5-profile solution in both samples. Conversely, adding a sixth (or seventh) profile to the solution simply led to the arbitrary division of one profile into two smaller ones with similar shapes. The 5-profile solution was thus retained in both samples, thus supporting its configural similarity.

References used in the online supplementary document

Asparouhov, T., Muthén, B., & Morin, A.J.S. (2015). Bayesian Structural equation modeling with cross-loadings and residual covariances: Comments on Stromeyer et al. *Journal of Management*, *41*, 1561-1577.

Browne, M. (2001) An overview of analytic rotation in exploratory factor analysis. *Multivariate Behavioral Research, 36*, 111-150.

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

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

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

Diallo, T.M.O, Morin, A.J.S. & Lu, H. (2017). The impact of total and partial inclusion or exclusion of active and inactive time invariant covariates in growth mixture models. *Psychological Methods*, *22*, 166-190.

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

Gillet, N., Morin, A.J.S., & Reeve, J. (2017). Stability, change, and implications of students' motivation profiles: A latent transition analysis. *Contemporary Educational Psychology*, *51*, 222-239.

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

Howard, J.L., Gagné, M., Morin, A.J.S., & Forest, J. (2018). Using bifactor exploratory structural equation modeling to test for a continuum structure of motivation. *Journal of Management*, *44*, 2638-2664.

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

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

Litalien, D., Morin, A.J.S., Gagné, M., Vallerand, R.J., Losier, G.F., & Ryan, R.M. (2017). Evidence of a continuum structure of academic self-determination: A two-study test using a bifactor-ESEM representation of academic motivation. *Contemporary Educational Psychology*, *51*, 67-82.

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

Marsh, H.W., Lüdtke, O., Trautwein, U., & Morin, A.J.S. (2009). Classical Latent Profile Analysis of Academic Self-Concept Dimensions: Synergy of Person- and Variable-Centered Approaches to Theoretical Models of Self-Concept. *Structural Equation Modeling*, *16*, 191-225.

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

Marsh, H.W., Scalas, L.F., & Nagengast, B. (2010). Longitudinal tests of competing factor structures for the Rosenberg Self-Esteem Scale: Traits, ephemeral artifacts, and stable response styles. *Psychological Assessment, 22*, 366–381.

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

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

Morin, A.J.S., Arens, A., & Marsh, H. (2016). A bifactor exploratory structural equation modeling framework for the identification of distinct sources of construct-relevant psychometric multidimensionality. *Structural Equation Modeling*, *23*, 116-139.

Morin, A.J.S., Arens, K., Tran, A., & Caci, H. (2016). Exploring sources of construct-relevant multidimensionality in psychiatric measurement: A tutorial and illustration using the Composite Scale of Morningness. *International Journal of Methods in Psychiatric Research*, *25*, 277-288.

Morin, A.J.S., Boudrias, J.-S., Marsh, H.W., Madore, I., & Desrumeaux, P. (2016). Further reflections on disentengling shape and level effects in person-centered analyses: An illustration exploring the dimensionality of psychological health. *Structural Equation Modeling, 23*, 438-454.

Morin, A.J.S., Boudrias, J.-S., Marsh, H.W., McInerney, D.M., Dagenais-Desmarais, V., Madore, I., & Litalien, D. (2017). Complementary variable- and person-centered approaches to the dimensionality of psychometric constructs: Application to psychological wellbeing at work. *Journal of Business and Psychology, 32*, 395-419.

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

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

Morin, A.J.S., Myers, N.D., & Lee, S. (2019). Modern factor analytic techniques: Bifactor models, exploratory structural equation modeling (ESEM) and bifactor-ESEM. In G. Tenenbaum & R. C. Eklund (Eds.), *Handbook of sport psychology* (4th ed.). New York, NY: Wiley.

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

Muthén, L.K., & Muthén, B.O. (2017). *Mplus User's Guide. Eighth Edition.* Los Angeles, CA: Muthén & Muthén.

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

Reise, S. P. (2012). The rediscovery of bifactor measurement models. *Multivariate Behavioral Research, 47*(5), 667-696.

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

Skrondal, A., & Laake, P. (2001). Regression among factor scores. *Psychometrika*, *66*, 563-575.

Xu, M.K., Morin, A.J.S., Marsh, H.W., Richards, M., & Jones, P.B. (2018). Psychometric Validation of the Parental Bonding Instrument in a UK Population–Based Sample: Role of Gender and Association with Mental Health in Mid-Late Life. *Assessment, 25*, 716-728.

Table S1

Previous Person-Centered Studies on Academic Motivational Profiles Involving Adolescent/High School Samples†

Study	Participants	Profile factors	Method	#	Profile characteristics/names
Hayenga & Corpus (2010)	*N* = 343	Intrinsic motivation Extrinsic motivation	CA	4	(1) High autonomous-low controlled (HA-LC) (2) High autonomous-high controlled (HA-HC) (3) Low autonomous-high controlled (LA-HC) (4) Low autonomous-low controlled (LA-LC)
Liu et al. (2009)	*N* = 767	Intrinsic motivation Identified regulation Introjected regulation External regulation Amotivation	CA	4	(1) HA-HC with low amotivation (2) HA-LC with low amotivation (3) LA-HC with high amotivation (4) LA-LC with low amotivation
Paixao & Gamboa (2017)	*N* = 396	Intrinsic motivation Identified regulation Introjected regulation Environmental exploration Self-exploration	CA	3	(1) Self-determined (~HA-LC) (2) Externally regulated (~LA-HC) (3) Non-self-determined (~LA-LC)
Ratelle et al. (2007)	*N* = 4498	Intrinsic motivation Identified regulation Introjected regulation External regulation Amotivation	CA	3	(1) LA-HC with high amotivation (2) Moderate autonomous-moderate controlled-moderate amotivation (3) HA-HC with low amotivation
Vansteenkiste et al. (2009)	*N* = 887	Autonomous motivation Controlled motivation	CA	4	(1) High autonomous-low controlled (HA-LC) (2) High autonomous-high controlled (HA-HC) (3) Low autonomous-high controlled (LA-HC) (4) Low autonomous-low controlled (LA-LC)
Wang et al. (2016): Analysis 1	*N* = 3220	Autonomous motivation Controlled motivation	LPA	5	(1) High motivation (HA-HC) (2) Marked autonomous motivation (HA-LC) (3) Moderate autonomous motivation (HA-LC)

Study	Participants	Profile factors	Method	#	Profile characteristics/names
					(4) Moderate motivation (5) Controlled motivation (LA-HC)
Wang et al. (2016): Analysis 2	*N* = 3220	Intrinsic motivation Identified regulation Introjected regulation External regulation	LPA	5	(1) Moderate controlled motivation (LA-HC) (2) Autonomous motivation (HA-LC) (3) Internalized regulation (4) Strong controlled motivation (LA-HC) (5) Moderate motivation
Wang et al. (2017)	*N* = 1151	Intrinsic motivation Identified regulation Introjected regulation External regulation	LPA	4	(1) Moderate external, low introjected, low autonomous (2) High external and identified, low intrinsic, moderate introjected (3) High identified and intrinsic, moderately high introjected, and moderate external (4) Low identified and intrinsic, moderately low external and introjected.
Wormington et al. (2012)	*N* = 1066	Intrinsic motivation Introjected regulation external regulation	CA	4	(1) High autonomous-low controlled (HA-LC) (2) High autonomous-high controlled (HA-HC) (3) Low autonomous-high controlled (LA-HC) (4) Low autonomous-low controlled (LA-LC)

Note. † Literature search performed in July 2018; N: sample size; CA: cluster analysis; LPA: latent profile analysis; #: number of profiles identified in the study.

Table S2

Goodness-of-Fit Statistics for the Estimated Models in Sample 1 and Sample 2

	χ^2	df	CFI	TLI	RMSEA (90% CI)	$\Delta\chi^2$	Δdf	ΔCFI	ΔTLI	ΔRMSEA
Sample 1										
Motivation: Five-factor CFA	710.799*	160	.935	.923	.092 (.085, .099)					
Motivation: Five-factor ESEM	345.097*	100	.971	.945	.077 (.069, .086)					
Motivation: Bifactor CFA	698.532*	150	.936	.919	.095 (.088, .102)					
Motivation: Bifactor ESEM	256.051*	85	.980	.955	.070 (.060, .080)					
Correlates	326.398*	92	.969	.960	.079 (.070, .089)					
Sample 2										
Motivation: Five-factor CFA	950.027*	160	.931	.918	.097 (.091, .103)					
Motivation: Five factor ESEM	297.711*	100	.983	.967	.061 (.053, .069)					
Motivation: Bifactor CFA	796.415*	150	.944	.929	.091 (.084, .097)					
Motivation: Bifactor ESEM	215.601*	85	.989	.975	.054 (.045, .063)					
Predictors CFA	1185.365*	257	.924	.911	.083 (.078, .088)					
Predictors ESEM	448.924*	213	.981	.973	.046 (.040, .052)					
Outcomes	277.217*	109	.989	.986	.054 (.046, .062)					
Tests of Measurement Invariance (Motivation)										
Configural invariance	492.593*	170	.984	.964	.064 (.054, .070)					
Weak invariance	519.392*	254	.987	.980	.047 (.041, .053)	149.553*	84	+.003	+.016	-.017
Strong invariance	620.513*	348	.986	.985	.041 (.036, .046)	169.882*	94	-.001	+.005	-.006
Strict invariance	653.844*	368	.986	.985	.041 (.036, .046)	51.180*	20	.000	.000	.000
Latent variance-covariance invariance	565.000*	389	.991	.991	.031 (.025, .037)	40.076*	21	+.005	+.006	-.010
Latent mean invariance	643.841*	395	.988	.988	.037 (.032, .042)	32.357*	6	-.003	-.003	+.006

Note. * p < .05; ** p < .01; CFA: Confirmatory factor analysis; ESEM: Exploratory structural equation modeling; χ^2: Robust chi-square test of exact fit; df: Degrees of freedom; CFI: Comparative fit index; TLI: Tucker-Lewis index; RMSEA: Root mean square error of approximation; 90% CI: 90% confidence interval of the RMSEA.

Table S3

Standardized Parameter Estimates from the Six-Factor CFA and ESEM Solutions for the Academic Motivation Scale in Sample 1

	CFA		ESEM					
	Factor (λ)	δ	Intrinsic (λ)	Identified (λ)	Introjected (λ)	External (λ)	Amotivation (λ)	δ
Intrinsic motivation								
Item 2	**.713****	.492	**.590****	.290**	.047	-.140**	.029	.400
Item 9	**.800****	.360	**.713****	.114*	.082	-.068	-.051	.305
Item 16	**.769****	.409	**.773****	-.108*	.077	.085*	-.106**	.328
Item 23	**.737****	.456	**.341****	-.051	.284**	.197**	-.123**	.539
ω	.841		.788					
Identified motivation								
Item 3	**.707****	.500	.006	**.877****	.032	-.090*	-.034	.224
Item 10	**.740****	.452	.081	**.295****	.067	.470**	-.049	.430
Item 17	**.760****	.422	.202**	**.223****	.283**	.182**	-.086*	.446
Item 24	**.784****	.386	.045	**.469****	.082	.218**	-.217**	.357
ω	.836			.705				
Introjected motivation								
Item 7	**.742****	.449	-.120**	.080	**.851****	-.029	.003	.327
Item 14	**.725****	.475	.377**	.086	**.446****	-.060	.064	.458
Item 21	**.684****	.533	.232**	.180**	**.400****	.056	.120**	.542
Item 28	**.824****	.321	.074	-.007	**.708****	.062	-.094**	.327
ω	.833				.778			
External motivation								
Item 1	**.527****	.723	-.081	.077	.079	**.529****	.073	.672
Item 8	**.858****	.265	-.173**	.129*	.265**	**.587****	-.116**	.303
Item 15	**.778****	.395	.239**	.056	-.173**	**.822****	.026	.330
Item 22	**.826****	.318	-.054	.114*	.010	**.819****	-.002	.251
ω	.840					.830		
Amotivation								
Item 5	**.735****	.460	-.066	-.272**	.102	.104*	**.604****	.478
Item 12	**.727****	.471	-.009	.021	.085	-.025	**.792****	.412
Item19	**.914****	.165	-.071*	.054	.000	.042	**.949****	.126
Item 26	**.917****	.160	.046	-.007	-.061	-.007	**.891****	.179
ω	.896						.898	

Note. * $p < .05$; ** $p < .01$; CFA: Confirmatory factor analysis; ESEM: Exploratory structural equation modeling; λ: Factor loading; δ: Item uniqueness; ω: model-based omega composite reliability based on McDonald (1970); Target factor loadings are in bold.

Table S4

Latent Factor Correlations from the Five-Factor CFA (below the diagonal) and ESEM (above the diagonal) Solutions for the Academic Motivation Scale in Sample 1

	Intrinsic	Identified	Introjected	External	Amotivation
Intrinsic motivation	—	.554**	.547**	.199**	-.294**
Identified regulation	.793**	—	.571**	.404**	-.458**
Introjected regulation	.802**	.817**	—	.547**	-.346**
External regulation	.436**	.793**	.639**	—	-.320**
Amotivation	-.443**	-.603**	-.380**	-.373**	—

Note. * $p < .05$; ** $p < .01$; CFA: Confirmatory factor analysis; ESEM: Exploratory structural equation modeling.

Table S5

Final Standardized Parameter Estimates from the Bifactor-ESEM Measurement Model (Latent Mean Invariance)

	SDT (λ)	Intrinsic (λ)	Identified (λ)	Introjected (λ)	External (λ)	Amotivation (λ)	δ
Intrinsic motivation							
Item 2	**.577****	**.463****	.126**	.177**	-.067*	-.154**	.377
Item 9	**.621****	**.499****	.135**	.192**	-.070**	-.167**	.277
Item 16	**.589****	**.439****	.064	.163**	.037	-.161**	.403
Item 23	**.551****	**.204****	.154**	.172**	.268**	-.208**	.487
ω		.625					
Identified motivation							
Item 3	**.451****	.069**	**.720****	.171**	.063*	-.246**	.179
Item 10	**.304****	.147**	**.363****	.172**	.493**	-.144**	.461
Item 17	**.508****	.135**	**.369****	.211**	.280**	-.213**	.420
Item 24	**.559****	.019	**.395****	.154**	.305**	-.300**	.325
ω			.711				
Introjected motivation							
Item 7	**.162****	.133**	.175**	**.836****	.238**	-.109**	.158
Item 14	**.595****	.095*	.104*	**.348****	.086*	-.083**	.491
Item 21	**.562****	-.042	.032	**.329****	.235**	.000	.518
Item 28	**.415****	.041	.106*	**.586****	.313**	-.169**	.345
ω				.744			
External motivation							
Item 1	**-.074**	.135**	.108**	.193**	**.558****	.006	.616
Item 8	**.064****	.180**	.208**	.250**	**.733****	-.187**	.285
Item 15	**.272****	.066	.160**	.131**	**.667****	-.112**	.421
Item 22	**.225****	-.102**	.051*	.133**	**.887****	-.104**	.121
ω					.849		
Amotivation							
Item 5	**-.297****	.004	-.200**	-.067*	.029	**.675****	.411
Item 12	**-.132****	-.016	-.110**	.025	-.079**	**.774****	.364
Item 19	**-.281****	-.081**	-.074*	-.078**	-.057*	**.866****	.150
Item 26	**-.238****	-.034	-.088**	-.055*	-.129**	**.892****	.118
ω	.890					.908	

Note. * $p < .05$; ** $p < .01$; ESEM: Exploratory structural equation modeling; λ: Factor loading; δ: Item uniqueness; ω: model-based omega composite reliability based on McDonald (1970); Target factor loadings are in bold.

Table S6

Standardized Parameter Estimates for the Covariates Measurement Model in Study 1

Items	SEFF (λ)	PERS (λ)	INTE (λ)	MS-IQ (λ)	MS-MA (λ)	δ
Self-efficacy						
Item 1	.905**					.181
Item 2	.854**					.271
Item 3	.904**					.184
Item 4	.936**					.124
ω	.945					
Persistence						
Item 1		.761**				.658
Item 2		.705**				.421
Item 3		.799**				.419
ω		.774				
Consistency of interest						
Item 1			.585**			.481
Item 2			.762**			.503
Item 3			.720**			.361
ω			.761			
Fixed IQ mindset						
Item 1				.688**		.526
Item 2				.866**		.250
Item 3				.810**		.344
ω				.833		
Fixed math mindset						
Item 1					-.814**	.337
Item 2					.736**	.459
Item 3					.797**	.364
ω					.826	

Note. * p < .05; ** p < .01; CFA: Confirmatory factor analysis; ESEM: Exploratory structural equation modeling; SEFF: Self efficacy; PERS: persistence; CONS: consistency of interest; λ: Factor loading; δ: Item uniqueness; ω: model-based omega composite reliability based on McDonald (1970); Target factor loadings are in bold.

Table S7

Standardized Parameter Estimates for the Predictors Measurement Model in Study 2

	Confirmatory factor analysis				Exploratory structural equation modeling			
	Care (λ)	Autonomy-support (λ)	Overprotection (λ)	δ	Care (λ)	Autonomy-support (λ)	Overprotection (λ)	δ
Care								
Item 1	.845**			.286	**.882****	.125**	.154**	.251
Item 2	-.570**			.675	**-.507****	.031	.126*	.681
Item 4	-.824**			.483	**-.820****	.006	.005	.328
Item 5	.855**			.322	**.857****	-.065*	-.059	.249
Item 6	.722**			.269	**.769****	.191**	.222**	.421
Item 11	.688**			.479	**.792****	-.005	.155**	.460
Item 12	.820**			.368	**.878****	.062	.137**	.288
Item 14	-.781**			.695	**-.499****	-.006	.416**	.388
Item 16	-.801**			.327	**-.656****	.032	.264**	.364
Item 17	.804**			.732	**.815****	-.035	-.017	.340
Item 18	-.722**			.526	**-.765****	.081	-.007	.451
Item 24	-.772**			.328	**-.725****	.111**	.174**	.385
ω	.939**				.946			
Autonomy-support								
Item 3		.719**		.443	.148**	**.632****	-.042	.492
Item 7		.795**		.390	.258**	**.489****	-.172**	.478
Item 15		.889**		.209	.236**	**.574****	-.214**	.340
Item 21		.763**		.359	-.087**	**.902****	-.012	.219
Item 22		.659**		.353	-.132**	**.850****	.050	.356
Item 25		.428**		.479	.033	**.404****	-.048	.808
ω		.890**				.846		
Overprotection								
Item 8			.553**	.847	-.016	.041	**.637****	.605
Item 9			.821**	.458	-.159**	-.295**	**.487****	.434
Item 10			.517**	.418	.170**	-.244**	**.551****	.606
Item 13			.746**	.565	-.028	-.121**	**.702****	.402
Item 19			.391**	.644	-.165**	.020	**.279****	.860
Item 20			.736**	.404	-.232**	.048	**.608****	.479
Item 23			.597**	.816	.105**	-.139**	**.658****	.531
ω			.821**				.797	

Note. * $p < .05$; ** $p < .01$; λ: Factor loading; δ: Item uniqueness; ω: model-based omega composite reliability based on McDonald (1970); Target factor loadings are in bold.

Table S8

Standardized Parameter Estimates for the Outcomes Measurement Model in Study 2

	VIG (λ)	DED (λ)	ABS (λ)	DROP (λ)	LS (λ)	δ
Vigor						
Item 1	.888**					.211
Item 2	.929**					.137
Item 5	.732**					.150
ω	.929					
Dedication						
Item 3		.922**				.183
Item 4		.904**				.464
Item 7		.783**				.275
ω		.881				
Absorption						
Item 6			.851**			.387
Item 8			.881**			.224
Item 9			.901**			.188
ω			.897			
Dropout intentions						
Item 1				.856**		.267
Item 2				.815**		.336
Item 3				-.898**		.194
ω				.892		
Life satisfaction						
Item 1					.763**	.417
Item 2					.717**	.486
Item 3					.911**	.170
Item 4					.808**	.347
Item 5					.714**	.490
ω					.889	

Note. * $p < .05$; ** $p < .01$; CFA: Confirmatory factor analysis; VIG: vigor factor of engagement; DED: dedication factor of engagement; ABS: absorption factor of engagement; DROP: dropout intentions; LS: life satisfaction; λ: Factor loading; δ: Item uniqueness; ω: model-based omega composite reliability based on McDonald (1970).

Table S9

Correlations Between the Variables Used in Sample 1 of This Study

	1	2	3	4	5	6	7	8	9	10	11
1. Global SDT	—										
2. Intrinsic	.000	—									
3. Identified	.000	.000	—								
4. Introjected	.000	.000	.000	—							
5. External	.000	.000	.000	.000	—						
6. Amotivation	.000	.000	.000	.000	.000	—					
7. Fixed mindset: IQ	-.162**	.050	-.053	-.013	-.174**	.308**	—				
8. Fixed mindset: Math	-.211**	-.108*	-.048	.034	-.042	.278**	.490**	—			
9. Math self-efficacy	.218**	.133**	.077	-.066	-.065	-.050	-.030	-.562**	—		
10. Perseverance of effort	.269**	.180**	.019	.118*	.078	-.153**	-.212**	-.239**	.333**	—	
11. Inconsistency of interest	.066	-.006	.050	.107*	.001	.058	.116*	.068	.039	-.206**	—
12. Self-reported grades	.205**	.219**	.096	.033	.188**	-.081	-.151**	-.182**	.286**	.353**	-.034

Note. * $p < .05$; ** $p < .01$; SDT: self-determined motivation.

Table S10

Correlations Between the Variables Used in Sample 2 of This Study

	1	2	3	4	5	6	7	8	9	10	11	12	13	14
1. Global SDT	—													
2. Intrinsic	.000	—												
3. Identified	.000	.000	—											
4. Introjected	.000	.000	.000	—										
5. External	.000	.000	.000	.000	—									
6. Amotivation	.000	.000	.000	.000	.000	—								
7. Care	.226**	.105*	.114**	.059	.104*	-.320**	—							
8. Autonomy-support	.034	.162**	-.060	-.026	-.054	.027	.322**	—						
9. Overprotection	-.014	-.124**	.038	.117**	-.017	.246**	-.490**	-.493**	—					
10. Vigor	.548**	.221**	.261**	.122**	.034	-.388**	.344**	.050	-.127**	—				
11. Dedication	.689**	.308**	.305**	.151**	.029	-.462**	.366**	.043	-.118**	.796**	—			
12. Absorption	.644**	.318**	.206**	.122**	-.026	-.411**	.306**	.016	-.093*	.731**	.896	—		
13. Dropout intentions	-.354**	-.163**	-.193**	-.097*	-.196**	.430**	-.260**	.018	.105*	-.381**	-.531**	-.452**	—	
14. Life satisfaction	.279**	.153**	.102*	.125**	.148**	-.298**	.563**	.240**	-.313**	.510**	.442**	.371**	-.266**	—
15. Self-reported grades	.185**	.169**	.100*	-.074	.047	-.194**	.143**	.071	-.078	-.167**	.279**	.266**	-.228**	.167**

Note. * $p < .05$; ** $p < .01$; SDT: self-determined motivation.

Table S11

Fit Statistics for Latent Profile Analyses and Tests of Profile Similarity

Model	LL	fp	Scaling	AIC	CAIC	BIC	SSABIC	Entropy	aLMR	BLRT
Latent profile analysis – Sample 1										
1 Profile	-2810.221	12	1.034	5644.441	5704.606	5692.606	5654.528	NA	NA	NA
2 Profiles	-2755.784	25	1.080	5561.569	5686.912	5661.912	5582.582	.711	.005	< .001
3 Profiles	-2723.050	38	1.032	5522.101	5712.622	5674.622	5554.041	.564	.054	< .001
4 Profiles	-2696.203	51	1.069	5494.405	5750.105	5699.105	5537.273	.660	.186	.030
5 Profiles	-2673.706	64	1.096	5475.413	5796.290	5732.290	5529.207	.712	.363	.077
6 Profiles	-2653.560	77	1.079	5461.119	5847.175	5770.175	5525.841	.743	.435	.060
7 Profiles	-2631.481	90	1.091	5442.963	5894.197	5804.197	5518.611	.755	.271	.040
8 Profiles	-2610.980	103	1.094	5427.961	5944.373	5841.373	5514.536	.791	.686	.022
Latent profile analysis – Sample 2										
1 Profile	-3950.247	12	1.016	7924.494	7987.655	7975.655	7937.564	NA	NA	NA
2 Profiles	-3870.907	25	1.112	7791.814	7923.399	7898.399	7819.043	.700	.001	< .001
3 Profiles	-3828.593	38	1.008	7733.187	7933.196	7895.196	7774.574	.563	.001	< .001
4 Profiles	-3799.897	51	0.921	7701.795	7970.228	7919.228	7757.341	.800	.031	.013
5 Profiles	-3770.161	64	1.034	7668.322	8005.179	7941.179	7738.027	.682	.065	< .001
6 Profiles	-3746.277	77	1.034	7646.554	8051.836	7974.836	7730.418	.703	.241	.020
7 Profiles	-3725.976	90	1.357	7631.952	8105.658	8015.658	7729.975	.756	.734	< .001
8 Profiles	-3707.180	103	1.126	7620.361	8162.491	8059.491	7732.543	.778	.435	.177
Tests of Profile Similarity										
Configural similarity	-7087.869	129	1.056	14433.737	15187.030	15058.030	14648.337	.785	NA	NA
Structural similarity	-7132.109	99	1.002	14462.217	15040.326	14941.326	14626.910	.763	NA	NA
Dispersion similarity	-7163.690	69	1.101	14465.381	14868.304	14799.304	14580.166	.776	NA	NA
Distributional similarity	-7174.882	65	1.117	14479.764	14859.329	14794.329	14587.895	.776	NA	NA

Note. LL: loglikelihood; fp: number of free parameters; AIC: Akaike Information Criterion; CAIC: constant AIC; BIC: Bayesian Information Criterion; SSABIC: Sample-Size Adjusted BIC; aLMR: p-value associated with the adjusted Lo-Mendell-Rubin likelihood ratio test; BLRT: Bootstrap Likelihood Ratio Test; NA: Not Applicable.

Table S12

Exact Within-Profile Means, Variances and 95% Confidence Intervals [95% CI] from the Final Five-Profile Solution (Distributional Similarity)

	Weakly Motivated	Moderately Motivated	Self-Determined	Amotivated	Strongly Motivated 5
	Mean [95% CI]	Mean [95% CI]	Mean [95% CI]	Mean [95% CI]	Mean [95% CI]
Global SDT	.058 [-.049, .165]	-.025 [-.406, .355]	1.203 [.560, 1.845]	-.425 [-.661, -.189]	.936 [.693, 1.179]
Intrinsic	.007 [-.083, .098]	-.075 [-.357, .206]	.902 [.371, 1.434]	-.103 [-.283, .078]	.186 [-.113, .486]
Identified	.083 [-.018, .185]	.023 [-.146, .192]	.103 [-.225, .432]	-.185 [-.364, -.005]	.295 [-.069, .659]
Introjected	.057 [-.044, .158]	.062 [-.093, .217]	-.889 [-2.725, .946]	-.216 [-.426, -.007]	1.234 [1.151, 1.,316]
External	-.100 [-.217, .017]	-.010 [-.176, .153]	-.608 [-1.637, .421]	.132 [-.061, .324]	.654 [.264, 1.043]
Amotivation	.311 [.168, .453]	-.772 [-.833, -.711]	-.520 [-.839, -.202]	.619 [.413, .825]	-.500 [-.666, -.334]
	Variance [95% CI]	Variance [95% CI]	Variance [95% CI]	Variance [95% CI]	Variance [95% CI]
Global SDT	.359 [.281, .437]	.571 [.246, .896]	.493 [.142, .844]	1.055 [.767, 1.343]	.218 [.057, .378]
Intrinsic	.281 [.208, .354]	.395 [.241, .550]	.321 [.037, .606]	.985 [.675, 1.294]	.386 [.087, .686]
Identified	.486 [.376, .596]	.584 [.443, .726]	.555 [-.013, 1.123]	.886 [.695, 1.078]	.377 [.085, .670]
Introjected	.398 [.295, .502]	.636 [.477, .796]	.631 [-.580, 1.841]	1.010 [.854, 1.167]	.017 [.002, .031]
External	.528 [.426, .630]	.740 [.602, .878]	1.139 [.149, 2.128]	1.048 [.864, 1.232]	.401 [.137, .664]
Amotivation	.372 [.302, .442]	.030 [.017, .044]	.077 [.020, .134]	.762 [.566, .958]	.092 [.038, .145]

Note. SDT: Self-determined motivation; CI: Confidence interval; Factors were estimated from factor scores with a mean of 0 and a standard deviation of 1.

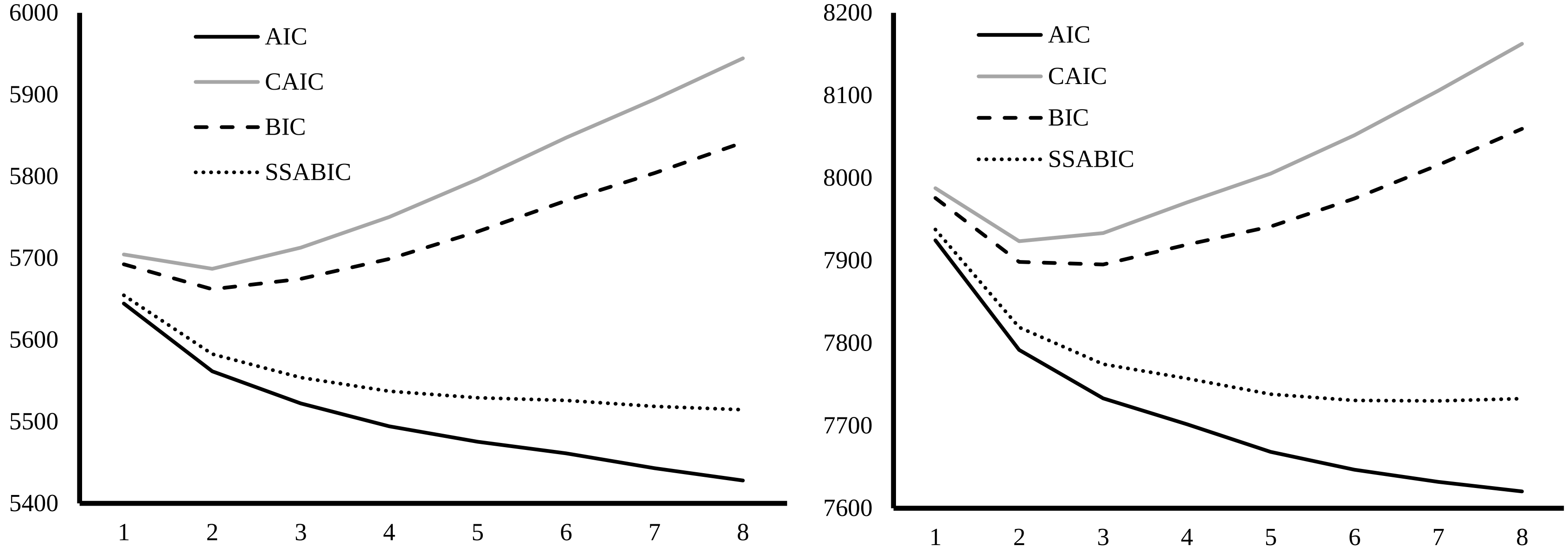

Figure S1

Elbow plot for the information criteria used in class enumeration for Sample 1 (Left) and Sample 2 (Right)

Note. AIC: Akaike Information Criterion; BIC: Bayesian Information Criterion; CAIC: Consistent AIC; SSABIC: Sample-Size-Adjusted BIC.