Testing associations between global and specific levels of student academic motivation and engagement in the classroom

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Abstract

Using data from 4047 adolescents in three countries, this study was designed to investigate the associations between two important components of the learning process: academic motivation and student engagement. To increase the precision and accuracy of these analyses, preliminary analyses were conducted to identify the optimal measurement structure of both constructs, leading us to retain a bifactor exploratory structural equation modeling representation of academic motivation and of a partial bifactor confirmatory factor analytic representation for student engagement. Our main analyses revealed that academic motivation factors were able to explain almost 66% of the variance in global levels of engagement, and between 5% and 35% of the variance in specific levels of engagement. Finally, mediation analyses supported the role of emotional engagement as a mediator of the association between academic motivation and global and specific behavioral forms of engagement.

Keywords. academic motivation; student engagement; bifactor exploratory structural equation modeling; bifactor confirmatory factor analysis; adolescence.

Academic motivation and student engagement have both been found to be related to a variety of desirable educational outcomes, such as higher academic achievement (Eccles, 2004; Fredericks et al., 2004; Roksa & Whitley, 2017; Steinmayr & Spinath, 2009; Wu, 2019) and more positive developmental trajectories (Lazowski & Hulleman, 2016; Lerner et al., 2011; Reschly & Christenson, 2012; Wigfield & Cambria, 2010), as well as with lower rates of grade retention and dropout (Allen, 1999; Appleton et al., 2008; Finn, 1989; Finn & Rock, 1997; Furlong & Christenson, 2008). Whereas motivation is generally assumed, from a theoretical perspective, to predate engagement (Ainley, 2012; Froiland & Worrell, 2016; Green et al., 2012; Martin et al., 2017; Reeve, 2012; Skinner, Kindermann, Connell, et al., 2009), both motivation and engagement are broad multidimensional constructs whose correct operationalization requires the ability to account for this multidimensional structure and their subdimensions. This complexity, and the variety of approaches used to operationalize both constructs, could potentially explain why research results have typically led to inconsistent conclusions regarding their associations and the practical implications of these associations (Christenson et al., 2012; Martin et al., 2017). This study was designed to test the associations between motivation and engagement by clarifying the multidimensional structure of both constructs and, in doing so, to achieve a more accurate picture of their associations. The study also responds to prior calls for more integrative approaches to motivation and engagement research (Martin, 2007; Reschly & Christenson, 2012).

Definitions of Academic Motivation and Student Engagement

Anchored in the theoretical underpinnings of self-determination theory (SDT; Deci, 1975; Deci & Ryan, 1985), Vallerand et al. (1989, 1992) have defined academic motivation as a multidimensional construct varying in quantity (different global levels of self-determination) and retaining a specific quality captured by its subdimensions (intrinsic motivation, extrinsic motivation and amotivation). Based on this perspective, intrinsic motivation refers to engaging in an activity for the pleasure and satisfaction that it procures, either by allowing students to learn something new, to experience stimulation, or to accomplish something. In contrast, extrinsic motivation refers to engaging in an activity for instrumental reasons (i.e., to obtain a reward). Finally, amotivation refers to a lack of desire, reason, or motive for engaging in the activity. Deci and Ryan (1985) note that extrinsic motivation encompasses various forms of motivation differentiated by the extent to which the perceived instrumentality of the activity is internally or externally driven. At its most extreme, external regulation occurs when involvement in an activity is underpinned by a desire to gain rewards, to avoid punishment, or by social pressure. In contrast, introjected regulation refers to the internalization of these various contingencies, so that activity involvement becomes driven by internal pressures, such as by a desire to avoid negative emotions (such as shame or culpability), to preserve one’s self-esteem, or to achieve a sense of pride. Finally, identified regulation refers to involvement in an activity seen as personally relevant and driven by personally-endorsed values and objectives (such as acceptance, value, importance). Despite acknowledging the unique qualities associated with each of these specific subdimensions of motivation, SDT also positions them along a single self-determination continuum (Deci & Ryan, 1985; Ryan & Deci, 2017), ranging from intrinsic motivation, to identified regulation, to introjected regulation, to external regulation, and finally to amotivation.

Conversely, student engagement refers to students’ active participation in academic, co-curricular, and school-related activities, as well as to their commitment to educational goals and learning (Christenson et al., 2012). Just like motivation, student engagement is generally conceptualized as a multidimensional construct encompassing various subdimensions. However, unlike motivation (at least when seen from the perspective of SDT), there is little agreement on the number and types of subdimensions of student engagement. For instance, Fredericks et al. (2004) and Archambault et al. (2009) differentiate behavioral, emotional and cognitive forms of engagement, whereas Finn and Zimmer (2012) propose to consider academic, social, cognitive and affective forms of engagement. Even more comprehensive, Appleton et al. (2006) identified six subdimensions of engagement encompassing teacher-student relationships, control and relevance of school work, peer support for learning, future aspirations and goals, family support for learning, and extrinsic motivation. Many of these previous conceptualizations, however, confound manifestations of student engagement occurring within the classroom context, with additional aspects of student engagement occurring outside of that critical classroom context (Dierendonck et al., 2020). Given the wide range of conceptualizations found in the literature on student engagement, concept clarification and dimensionality testing of student engagement thus seems to remain a salient research avenue in this specific field of research. In this regard, the present study adopts a recent comprehensive conceptualization of student engagement (Dierendonck et al., 2020) which exclusively focuses on specific subdimensions of behavioral (i.e., effort/attention and boredom/distraction), emotional (i.e., social and learning), and cognitive (i.e., strategies and autoregulation) manifestations of student engagement occurring within the classroom context. Similar to motivation, a global engagement construct can be specified to provide, following Christenson et al.'s (2012) definition, a direct reflective indicator of students' global levels of commitment and persistence towards their academic activities, educational goals, and learning in general, thus encapsulating students' global levels of engaged in their academic activities. From this perspective, and similar to other studies in engagement literature (e.g., Gillet et al., 2020; Olivier et al., 2020; Tóth-Király et al., 2020), students are proposed to experience academic engagement in a more holistic manner as a single overarching dimension. In this conception, the specific engagement dimensions are posited to refer to the presence of students' actions and conduct in class (i.e., behavioral), their affective reactions in class (i.e., emotional), and their non-visible thought processes in class (i.e., cognitive) over and above, as well as independently from, their global engagement tendencies. These specific dimensions also refer to the extent to which behavioral, cognitive and emotional engagement deviates from the global levels of engagement[1].

Academic Motivation and Student Engagement: Relations and Mediation

In the empirical and theoretical research literature, a broad agreement exists to the effect that: (1) motivation and engagement are distinct but related constructs (Christenson et al., 2012; Skinner et al., Kindermann, & Furrer, 2009), (2) motivation is an antecedent to student engagement (Anderman & Patrick, 2012; Reeve, 2012; Schunk & Mullen, 2012; Skinner, Kindermann, Connell et al., 2009; Wigfield & Guthrie, 2010), and (3) the benefits of motivation in terms of achievement are generally expected to occur via student engagement (Ainley, 2012; Green et al., 2012; Martin et al., 2017; Reeve, 2012; Voelkl, 2012). However, very little is known regarding how the global and specific facets of these two constructs relate to one another.

Our first objective is to address this limitation by testing the associations between global and specific facets of academic motivation and engagement. Based on previous research (Dierendonck et al., 2020; Howard et al., 2018; Litalien et al., 2017; Stefansson et al., 2016; Wang et al., 2016), we expect stronger positive associations to occur between global levels of academic motivation and student engagement than among their more specific facets. From a theoretical perspective, students are more likely to display enhanced commitment and persistence toward academic activities (i.e., high global levels of engagement) when they are able to act with a full sense of volition (i.e., high global levels of self-determination) because they find the activity interesting, exciting, and personally valuable, while not feeling obligated to engage in it (Ryan & Deci, 2017). Self-determined students are thus expected to engage with academic activities more globally and intensely.

We also expect some significant and meaningful relations to occur at the more specific level. When considering the effects of specific facets of academic motivation, abundant empirical research (e.g., Cox et al., 2013; Litalien et al., 2017; Liu et al., 2009; Ryan & Deci, 2017) lead us to expect positive associations between specific levels of intrinsic motivation and identified regulation and the positive facets of school engagement (higher levels of effort/attention, positive emotions related to others and to learning, use of cognitive strategies and autoregulation, and lower levels of boredom/distraction), smaller or negative associations between specific levels of introjected and external regulation and these positive facets of engagement, and negative associations between specific levels of amotivation and these positive facets of engagement. These expectations are in line with SDT's theoretical propositions (Ryan & Deci, 2017) suggesting that students driven by interest and enjoyment (intrinsic) or the accepted value and personal importance of learning (identified) are more likely to display enhanced levels of engagement and persistence in an activity. In contrast, being driven toward learning by internal (introjected) or external pressures is less likely to facilitate the development of persistent engagement

[1] As an example, readers could imagine a group of students who actively participate in class (i.e., behavioral), react to the learning process with interest and enjoyment (i.e., emotional) and try different problem-solving strategies (i.e., cognitive). On a global level, these students might be considered to be globally engaged with their academic activities. However, they might also uniquely manifest additional signs of behavioral engagement (e.g., they might try to answer all questions asked by the teacher or perform additional assignments tasks) over and above their global engagement levels.

because students do not have an inherent desire to learn. In contrast, when students are amotivated, they lack any drive and willingness to perform any learning-related activity, in turn decreasing their engagement.

Expected associations between motivation and engagement become slightly more complex when considering how the effects of motivation would differ as a function of the specific emotional, behavioral, and cognitive components of student engagement. In this regard, taking anchor in a wide range of motivational theories (e.g., Deci & Ryan, 1985; Harter, 1978; Pekrun et al., 2002), Skinner et al. (2008) suggested that emotional forms of engagement (interest, enthusiasm) were likely to play a key role in the emergence of other (cognitive and behavioral) forms of engagement. This proposition thus positions emotional forms of engagement as mediators of the effects of various predictors (including motivation) on other facets of student engagement. This proposition is thus important to our understanding of the possible psychological mechanisms underpinning the associations between motivation and engagement, as well as to how motivation carries over to engagement. Likewise, Green et al. (2012) compared three models depicting the associations between academic motivation, emotional engagement (positive attitude towards school), behavioral engagement (class participation, homework completion, absenteeism) and performance. Their results supported the heuristic superiority of a model conceptualizing emotional engagement as a predictor of behavioral engagement rather than as being located as the same level of the predictive sequence. Their results showed that motivation predicted emotional engagement, which in turn predicted behavioral engagement dimensions (i.e., higher levels of class participation and homework completion, and lower levels of absenteeism), which themselves predicted performance. The present study tests this mediation effect.

Dimensionality of Academic Motivation and Student Engagement

In order to avoid measurement imprecision and resulting bias in the estimation of associations with other constructs (Asparouhov et al., 2015; Mai et al., 2018; Morin, Arens, & Marsh, 2016), the present study first seeks to identify the optimal way to represent the multidimensional structure of students' ratings of their academic motivation and engagement. More precisely, this preliminary investigation of the factor structure of motivation and engagement relies on the overarching bifactor exploratory structural equation modeling (bifactor-ESEM) framework (Morin, Arens, & Marsh, 2016; Morin, Arens, Tran, et al., 2016). First, this analytic framework makes it possible to account for the multidimensional structure of these two constructs (motivation and engagement) via the extraction of a global component reflecting the globality of each construct (shared across all subdimensions) distinct from a non-redundant estimate of the specificity unique to each subdimension. For instance, this framework makes it possible to obtain a direct and explicit estimate of students' global levels of self-determination or engagement via the estimation of a global factor (G-factor) underpinning responses to all items include in each specific instrument[2]. This G-factor co-exists with specific factors (S-factors) depicting the unique quality associated with each subscale and left unexplained by the G-factor. Furthermore, the bifactor-ESEM framework also makes it possible to account for the fallible nature of the indicators used to assess each construct by allowing cross-loadings to be freely estimated among all factors used to reflect the multidimensional structure of each instrument (Morin et al., 2020). This component thus takes into account the fact that items typically present at least some degree of association with other conceptually-related constructs. Statistical research (Asparouhov et al., 2015; Mai et al., 2018) has shown that this free estimation of cross-loadings tends to result in a more accurate estimate of latent constructs and relations among constructs (relative to CFA), whenever cross-loadings as small as .100 are present in the data, but to remain unbiased in the absence of cross-loadings. Importantly, the reliance

[2] While higher-order and bifactor models both assume the presence of a global construct underlying all indicators, higher-order models rely on an extremely restrictive (and rarely verified) assumption that the ratio of variance explained by the first-order relative to the variance explained by the higher-order factor is constant for all items associated with a single first-order dimension (Gignac, 2016; Part et al., 2020; Perera et al., 2018; Morin et al., 2020). Bifactor models provide a more flexible alternative, not limited by this assumption, and are able to recover true higher-order factor structures (i.e., are mathematically equivalent) when this assumption is met by the data (Jennrich & Bentler, 2011). Moreover, whereas bifactor models allow one to obtain non-redundant G-factors and S-factors, higher-order factors and first-order factors share a conceptual redundancy due to the presence of variance explained by the higher-order factors within the first-order factors, creating confusion when both are simultaneously used in prediction (Morin, Boudrias, et al., 2016, 2017).

on target rotation makes it possible to rely on a theoretically driven definition of the factors, while allowing all cross-loadings to be freely estimated by assigned a target value of zero.

Academic Motivation. SDT researchers have adopted a variety of approaches, each with their own unique pros and cons, in order to test the theoretical structure of the motivation continuum expected to underlie all types of motivation (for a recent review, see Howard et al., 2020). The bifactor-ESEM framework was recently proposed as a way to bridge these various methodological approaches in a way that made it possible to obtain direct estimates of the co-existing global (i.e., a G-factor reflecting a continuum of self-determination) and specific (i.e., a series of S-factors reflecting the unique quality associated with students' ratings of intrinsic motivation, identified regulation, introjected regulation, external regulation, and amotivation) structure of academic (using the *Academic Motivation Scale:* Litalien et al., 2017) and of work (using the *Multidimensional Work Motivation Scale*: Howard et al., 2018) motivations. In these studies, the G-factor was found to perfectly match the SDT continuum hypothesis, being characterized by strong positive loadings from intrinsic motivation items, moderate positive loadings from identified regulation items, smaller positive loadings from introjected regulation items, null or negative loadings from the external regulation items, and stronger negative loadings from the amotivation items. In the present study, we hereafter refer to this G-factor as reflecting students' global levels of self-determination, defined as students' global sense of self-directedness and volition. Both studies also revealed that, although the G-factor was the key driver of associations with a variety of covariates (i.e., vitality, ill-being, achievement, dropout intentions, satisfaction with studies, and need satisfaction in Litalien et al., 2017, and commitment and need satisfaction in Howard et al., 2018), the S-factors were also able to explain additional variance in outcome levels beyond that already explained by the G-factor. However, despite the promising nature of these results, they have yet to be replicated within each of these fields of research. In addition, outcome associations have yet to be examined in relation to other motivational constructs (such as engagement) known to also present a global/specific nature.

Student Engagement. Although it is generally recognized that student engagement, like motivation, can be operationalized using both global and specific components, research into the optimal structure of school engagement still lags behind that of academic motivation, possibly due to the lack of conceptual consensus regarding the optimal conceptualization. However, across conceptualizations, research has often found that a global level of student engagement could be estimated from a series of well-defined specific student engagement dimensions (e.g., Archambault et al., 2009; Lam et al., 2014). More recent studies have rather adopted the more flexible bifactor approach, and found support for the idea that students' ratings of their own engagement typically encompassed co-existing global (i.e., reflecting their global level of engagement across dimensions) and specific (i.e., reflecting the unique quality associated with students' levels of behavioral, emotional, and cognitive engagement over and above the global factor) facets (e.g., Dierendonck et al., 2020; Stefansson et al., 2016; Wang et al., 2016). These studies also found that specific engagement dimensions were able to predict additional variance in academic achievement (Stefansson et al., 2016; Wang et al., 2016), aspirations (Wang et al., 2016) and misconduct (Dierendonck et al., 2020) over and above that already explained by the global engagement factor. Importantly, Dierendonck et al.'s (2020) study relied on the same comprehensive measure of student engagement used in the present study and found that the global engagement factor was able to co-exist with six specific factors reflecting the a priori facets of student behavioral (i.e., effort/attention and boredom/distraction), emotional (i.e., social and learning), and cognitive (i.e., strategies and autoregulation) engagement.

It is important to note that in two of these studies (Dierendonck et al., 2020; Wang et al., 2016), the global factor was found to account for a much larger part of the variance in ratings of the cognitive and behavioral engagement items relative to that of emotional engagement items, suggesting that emotional engagement might represent a component of student engagement distinct from that measured globally across behavioral and cognitive engagement items. Moreover, although these three studies supported the role of global levels of student engagement in the prediction of achievement, aspirations and misconduct, they generally led to discrepant results regarding the exact role of specific engagement dimensions in these predictions, thus mirroring the discrepant results obtained with higher-order factor models (Archambault et al., 2009; Lam et al., 2014). A possible source of explanation for these discrepant results may come from the lack of consideration of cross-loadings in these models, an exclusion which has been statistically shown not only to potentially result in a lack of clarity in terms of construct definition (Asparouhov et al., 2015), but also in the possible inflation of the variance explained by the G-factor in bifactor models (Morin, Arens, & Marsh, 2016; Murray & Johnson, 2013). When we more specifically consider student engagement, no single study has yet implemented a bifactor-ESEM approach to the measurement of engagement and supported the value of incorporating cross-loadings to the model. In the present study, we seek to bridge this measurement gap by contrasting correlated factors and bifactor CFA and ESEM representations of engagement.

The Present Study

To our knowledge, no study has yet examined the associations between motivation and engagement while relying on models allowing for a proper disaggregation of global and specific levels of motivation and engagement. This is the objective of the present study. Based on the available empirical information, we hypothesize that the bifactor-ESEM solution will provide the most accurate representation of students' ratings of academic motivation, and that a bifactor approach (bifactor-CFA or bifactor-ESEM) will provide the most accurate representation of students' ratings of engagement. For ratings of academic motivation, we also expect the G-factor to be associated with a factor loading pattern corresponding to the SDT continuum hypothesis (Howard et al., 2018; Litalien et al., 2017). As for the predictive model, we expect stronger positive associations to occur at the global levels of motivation and engagement than among more specific facets, but also expect some significant and meaningful relations to occur at the more specific level. Given prior studies (Dierendonck et al., 2020; Wang et al., 2016) showing that the general factor of engagement accounted for a large part of the variance of cognitive and behavioral engagement items, but not of emotional engagement items, two alternative predictive models, illustrated in Figure 1, will be contrasted. These models will include, or not, a global factor depending on whether the optimal solution for both constructs follows a bifactor representation. In the first model, no mediation is present, and facets of engagement are all specified as outcomes of motivation facets located at the same position in the a priori motivational dynamic. In the second model, emotional engagement facets are expected to mediate, fully or partially, the effects of motivation facets of behavioral and cognitive engagement facets.

Method

Participants and Procedure

In this study, we rely on data collected in 2017-2018 as part of the FAVAS study funded by the European Union, conducted in three countries (France, Belgium, Luxembourg), among students enrolled in grades 7 to 12 in a total of 19 regular education secondary schools. These schools were recruited based on geographic location in France (Strasbourg district) and Luxembourg (North region). In Belgium, schools from the Wallonia-Brussels Federation were selected with the help of the Center for coordination and management of European programs. This study thus relied on a convenience sample of schools willing to participate in the study. A random selection of classrooms was made within each school to collect data at school level. A total of 4127 students were asked to complete a 50-minute online survey during school hours, in a single testing occasion, within a computer room located in their schools. Standardized instructions were available for administering the questionnaire in each school. The children were briefed on the nature of the questionnaire and on the confidentiality of their answers. Parental and students' consent was obtained from all participants in this study. Table 1 describes the analytic sample of 4047 students used in the present study who responded to the academic motivation and student engagement questionnaires. These students came from each of the 19 schools (with 30 to 520 students per school; M = 213; SD = 146) and from a total of 278 classroom (with 1 to 34 students per classroom; M = 15; SD = 8)

Measures

Items used in the present study were already available in French for the academic motivation scale and in English for the student engagement scale. All items were administered in French in France and Belgium. In Luxembourg, items were administered either in German or in French. In line with the International Testing Commission (ITC) Guidelines for Translating and Adapting Tests (ITC, 2017), adaptation to French (student engagement) or German (both questionnaires) was done using a classical translation-back translation procedure conducted by two of the authors of the present study who are experts in the fields of Psychology, Education, and Sociology, and both native Luxembourgers fluent in German, French and English. The original items were first translated into the target language by one of the authors. A second translator (another co-author of this article) then independently translated these items back to the original language without having seen the original items. Discrepancies between the original and the back-translated version were then examined by both authors. In the few cases where a discrepancy was found to affect the meaning of the items, the discrepancy was resolved by consensus between the two translators and by the consultation of two other bilingual authors when necessary. To ensure that the resulting items were clear, a convenience sample of several German-Speaking and French-speaking secondary school students and teachers were asked to review the questionnaire while commenting on clarity. This verification confirmed that all items were found to be clear and easy to understand by all pilot participants and did not need to be further adjusted for this study.

Student academic motivation was measured using a shorter version of the AMS (Vallerand et al., 1989) considering only one dimension of intrinsic motivation, as it has been suggested in several studies (e.g., Grouzet et al., 2006; Ratelle et al., 2007). The 20-item instrument covers five dimensions of intrinsic motivation (8 items, α = .882, e.g., *For the pleasure I have in discovering new things never seen before*), extrinsic-identified regulation (3 items, α = .787, e.g., *Because it will allow me to work later on in a field I like*), extrinsic-introjected regulation (3 items, α = .776, e.g., *To prove to myself that I am capable of succeeding in high school*), external regulation (3 items, α = .664, e.g., *To be able to find a good job later on*), and amotivation (3 items, α = .760, e.g., *Honestly, I don't know; I really feel like I'm wasting my time at school*). These dimensions are expected to each form their own S-factor, and all items are also expected to contribute to the definition of a self-determination G-factor matching SDT continuum hypothesis (Litalien et al., 2017). All items were rated using a six-point scale (Totally disagree, Disagree, Rather disagree, Rather agree, Agree, Totally agree). Past research has established the scale score reliability, factor validity, convergent validity, and predictive validity of the short and long forms of the AMS (e.g., Grouzet et al., 2006; Guay et al., 2015; Litalien et al., 2017; Ratelle et al., 2007).

Student engagement was assessed using an 18 items measure developed by Dierendonck et al. (2020) in order to provide a comprehensive coverage of engagement dimensions covered by a series of engagement measures (i.e., Appleton et al., 2006; Skinner et al., 2009; Wang et al., 2011). This measure covers the six dimensions (3 items per dimension) of behavioral engagement: Effort/attention (α = .861, e.g., *When I'm in class, I listen very carefully*), behavioral engagement: boredom/distraction (α = .799, e.g., *I do something else during lessons*), emotional engagement: Social (α = .817, e.g., *I feel well integrated in this class*); emotional engagement: Learning (α = .677, e.g., *When I can't answer a question in class, I feel frustrated*), cognitive engagement: Strategies (α = .727, e.g., *When I am doing schoolwork, I try to understand what these tasks are supposed to teach me*), and cognitive engagement: Autoregulation (α = .758, e.g., *I try to learn from my mistakes*). These dimensions are expected to each form their own S-factor, and all items are also expected to contribute to the definition of global engagement G-factor (Dierendonck et al., 2020). Each item was rated using a six-point Likert scale (Never, Almost never, Sometimes, Often, Quite often, Always). Dierendonck et al. (2020) demonstrated the scale score reliability, factor validity and convergent validity of this measure.

Analyses

Analyses were conducted with the Robust Maximum Likelihood (MLR) estimator implemented in Mplus 8.4 (Muthén & Muthén, 2017). To handle the few missing responses at the item level (from .5 to 5%, M = 2.5%), full information maximum likelihood (FIML) estimation was used (Enders, 2010). The hierarchical nature of the data (students nested in classroom) was taken in account with the Mplus design-based adjustment implemented by the TYPE=COMPLEX function (Asparouhov, 2005).

Four alternative measurement models were estimated separately for academic motivation and student engagement (correlated factors CFA and ESEM, bifactor-CFA and ESEM), see Figure 2 for a schematic illustration. A more extensive presentation of the specification of these models is presented in Appendix 1 of the online supplements. When contrasting these models, we considered model fit information and their parameter estimates, following a sequential strategy advocated by Morin et al (2020) and presented in Appendix 1 of the online supplements.

Once the optimal solution was selected for each measure separately, the final measurement model for academic motivation was combined with the final measurement model for student engagement into three fully latent models designed to assess the associations between these two multidimensional constructs. In Model 1 (see the left-hand side of Figure 1), the academic motivation factors were allowed to predict[3] all of the student engagement factors. This first model was estimated to obtain a first overview of associations between academic motivation and student engagement. In Model 2 and 3, the associations between the academic motivation factors and the behavioral and cognitive (as well as global if the retained model is bifactorial) engagement factors was assumed to be mediated by the emotional engagement factors. In Model 2, this mediation was assumed to be total (as illustrated by the full arrows on the right-hand side of Figure 1). In Model 3, direct paths were added to allow the motivation factors to directly influence the behavioral and cognitive (as well as global if the retained model is bifactorial) engagement factors beyond their effects on the emotional engagement factor (as illustrated by the dotted arrow on the right-hand side of Figure 1). Model 2 and 3 were contrasted to assess the mediation hypothesis, and to assess whether this mediation is total (Model 2) or partial (Model 3). The significance of indirect effects was tested via the calculation of bias-corrected bootstrap (1000 bootstrap samples) 95% confidence intervals (CI) (Cheung & Lau, 2008) and these effects were considered to be statistically significant when the confidence intervals excluded zero.

Model fit was assessed using fit indices and typical interpretation guidelines (Hu & Bentler, 1999; Marsh et al., 2004). More precisely, we report the chi-square statistic, the root mean square error of approximation (RMSEA) with its 90% confidence interval, the comparative fit index (CFI) and the Tucker-Lewis index (TLI). Model fit was considered to be excellent when the RMSEA was below .06, and when the CFI and TLI were above .95. Model fit was considered to be acceptable when the RMSEA was below .08 and CFI and TLI were above .90. Although these indices have never been formally advocated for purposes of comparing alternative measurement specification, we also report the Akaike Information Criterion (AIC), the Consistent AIC (CAIC), the Bayesian Information Criterion (BIC), and the Sample Size Adjusted BIC (SSBIC) upon request from a reviewer. On all of those indices, a lower value indicates better fit. Following Morin et al.'s (2020) recommendations, we report classical model-based omega coefficients (ω) of composite reliability (McDonald, 1970) for all factors, calculated as: $\omega = (\Sigma|\lambda_i|)^2 / ([\Sigma|\lambda_i|]^2 + \Sigma\delta_{ii})$ where λ_i are the standardized factor loadings of the items on the target factor, and δ_{ii} are the error variances of the items.

Results

The Multidimensional Structure of Academic Motivation

The fit of the alternative models is provided in the top section of Table 2. These results, coupled with a detailed examination of the parameter estimates from all of the alternative solutions, led us to retain the bifactor-ESEM solution. Detailed information about model selection and comparison is provided in Appendix 2 of the online supplements. The parameter estimates from this solution are reported in Table 3. The loadings obtained on the G-factor revealed a relatively well-defined global dimension representing participants' global levels of self-determination ($|\lambda|$ = .143 to .780; $M_{|\lambda|}$= .516; ω = .923). Indeed, these loadings were strong and positive for intrinsic motivation items (λ = .557 to .780, M_{λ} = .692), positive and moderate for extrinsic-identified regulation (λ = .490 to .534, M_{λ} = .511) and extrinsic-introjected regulation (λ = .526 to .584, M_{λ} = .557) items and positive but smaller for external regulation items (λ = .241 to .416, M_{λ} = .312), and moderately negative for the amotivation items (λ = -.329 to -.143, M_{λ} = -.217). The extrinsic-introjected regulation (λ = .338 to .576, M_{λ} = .454; ω = .591), extrinsic-identified regulation (λ = .294 to .651, M_{λ} = .446; ω = .604), external regulation (λ = .403 to .654, M_{λ} = .502; ω = .583), and amotivation (λ = .640 to .708, M_{λ} = .678; ω = .744) S-factors were also reasonably well-defined. However, the intrinsic motivation S-factor was not defined as clearly ($|\lambda|$ = .004 to .556; $M_{|\lambda|}$= .174; ω = .368) due to the item loadings on this S-factor decreasing in magnitude and even becoming non-significant for items 4 and 7 in the presence of the G-factor. However, these results simply reflect the fact that the variance included in these intrinsic motivation items were mainly used in defining participants' global levels of self-determination (i.e., the G-factor). For all of these reasons, the best-fitting bifactor-ESEM solution was thus retained for further analyses.

The Multidimensional Structure of Student Engagement

The fit of the alternative models is provided in the bottom section of Table 2. These results, coupled with a detailed examination of the parameter estimates from all of the alternative solutions, led us to retain a partial bifactor-CFA solution in which the emotional engagement items were not used to define

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[3] Here, as well as in the results section, we use the verb "predict" to depict regressions associations whereby scores on one latent variable are used to statistically predict scores on another variable, without assuming causality and directionality.

the engagement G-factor but were rather specified to form an independent correlated factor. This partial bifactor-CFA solution (see Table 2) resulted in an excellent level of model fit according to all indicators, displaying an improvement relative to the initial bifactor-CFA solution (ΔCFI = +.005; ΔTLI = +.005; ΔRMSEA = -.002). Detailed information about model selection and comparison is provided in Appendix 2 of the online supplements. The parameter estimates from this solution are reported in Table 4 and revealed a well-defined G-factor ($|\lambda|$ = .338 to .697; $M_{|\lambda|}$= .551; ω = .848). This G-factor was accompanied by well-defined S-factors for the effort/attention (λ = .311 to .635, M_{λ} = .488; ω = .707) and boredom/distraction (λ = .558 to .728, M_{λ} = .623; ω = .739) components of behavioral engagement, as well as for the strategies (λ = .223 to .561, M_{λ} = .419; ω = .517) and autoregulation (λ = .244 to .662, M_{λ} = .479; ω = .609) components of cognitive engagement. The S-factors reflecting the social (λ = .695 to .841, M_{λ} = .776; ω = .821) and learning (λ = .506 to .790, M_{λ} = .645; ω = .686) components of emotional engagement were also well-defined in this solution, allow us to retain this solution for further analyses.

Associations between Academic Motivation and Engagement

The retained bifactor-ESEM (for academic motivation) and partial bifactor-CFA (for student engagement) models were combined into a set of predictive models. The results from Model 1 are reported in the top section of Table 5. This model resulted in a satisfactory level of fit to the data (χ^2 = 2340.153; df = 515; $p \leq .01$; CFI = .962; TLI = .948; RMSEA = .030, 95% CI [.028, .031]). When considering the results from this model, it is first noteworthy that the proportion of variance in engagement explained by motivation (R^2) is quite high for participants' global levels of engagement (65.7%), moderate for their specific levels of the cognitive engagement strategies (35.5%) and autoregulation (33.3%) facets, but lower for their specific levels of behavioral engagement effort/attention (16.9%) and boredom/distraction (9.4%) facets, as well as for their levels of emotional engagement social (10.2%) and learning (5.4%) facets.

With respect to individual path coefficients, several results are noteworthy. First, student's global levels of engagement were significantly and positively predicted by their global levels of self-determination (β = .712) as well as by their specific levels of extrinsic-introjected regulation (β = .278), but were negatively predicted by their specific levels of extrinsic-identified regulation (β = -.133) and amotivation (β = -.232). In other words, these results show that the most engaged students tend to be those who display the highest global levels of self-determination and those who study for more introjected reasons. In contrast, students' who study for identified reasons (i.e., ascribing personal importance to school work) over and above their global level of self-determination or who are not motivated for school work, tend to display lower levels of engagement.

Second, specific levels of intrinsic motivation (β = -.167) and of extrinsic-introjected regulation (β = -.335) were both found to predict lower levels of involvement in specific auto-regulatory cognitive engagement. Likewise, specific levels of extrinsic-introjected regulation (β = -.384) also predicted lower levels of involvement in specific cognitive engagement strategies. Thus, students whose academic motivation is influenced by interest and pleasure, or by more introjected reasons, will tend to invest more limited amounts of cognitive efforts in attempts to figure out how to solve learning challenges or difficulties. It is important to note that these effects occur over and above the desirable effects of global levels of self-determination and specific levels of extrinsic-introjected regulation on students' global levels of engagement. In addition, it is noteworthy that none of these specific facets of cognitive engagement seems to be influenced by students' global levels of self-determination.

Third, students' specific levels on the effort/attention facet of behavioral engagement was found to be positively predicted by their levels of extrinsic-identified regulation (β = .144), but negatively predicted by their levels of extrinsic-introjected regulation (β = -.300). In contrast, specific levels on the boredom/distraction facet of behavioral engagement were positively predicted by students' specific levels of extrinsic-introjected regulation (β = .111) and amotivation (β = .155), but negatively predicted by their specific levels of intrinsic motivation (β = -.125). Thus, it appears that students whose motivation is anchored in introjected reasons will tend to invest less efforts during learning activities, while those whose motivation is rather anchored in the personal importance of their studies (identified reasons) will tend to invest more efforts. In contrast, students lacking motivation, or driven by introjected reasons will display higher levels of boredom, whereas those studying for pleasure then will tend to display less boredom. Once again, these effects occur beyond the desirable effects of global levels of self-determination and specific levels of extrinsic-introjected regulation, as well as the negative effects of specific levels of extrinsic-identified regulation and amotivation on students' global levels of engagement. As for cognitive engagement, none of these specific facets of behavioral engagement appears to be influenced by students' global levels of self-determination.

Finally, the social (β = .232) and learning (β = .150) facets of emotional engagement both appeared to be significantly and positively predicted by students' global levels of self-determination. In addition, students' specific levels of intrinsic motivation (β = .116) and extrinsic-identified regulation (β = .065) both positively predicted students' levels of social-emotional engagement, whereas levels of extrinsic-introjected regulation (β = .155) positively predicted their levels of learning-emotional engagement. In contrast, their specific levels of amotivation predicted lower levels of social-emotional engagement (β = -.168), but higher levels of learning-emotional engagement (β = .058). In other words, these students who display the highest global levels of self-determination tend to also be more emotionally engaged in their learning. Moreover, students interested in schoolwork perceived as being personally important (identified regulation) will also be more socially engaged in their learning. In contrast, students studying for mainly introjected reasons tend to be more emotionally concerned by new learnings or learnings difficulties. Finally, students lacking motivation tend to display lower levels of social engagement but higher levels of emotional concerns.

Mediation Analyses

Results from the analyses of mediation first revealed that Model 3 (partial mediation: χ^2 = 2327.535; *df* = 516; $p \leq .01$; CFI = .962; TLI = .948; RMSEA = .029, 95% CI [.028, .031]) was able to achieve a much-improved level of fit to the data when compared to Model 2 (total mediation: χ^2 = 3890.786; *df* = 546; $p \leq .01$; CFI = .930; TLI = .910; RMSEA = .039, 95% CI [.038, .040]). Model 3 was thus retained for interpretation. The results from this model are reported in the bottom section of Table 5 and summarized in Figure 3. When we first consider the direct effects of the academic motivation factors on the student engagement factors, the results from Model 3 entirely replicate those from Model 1, attesting to the stability of these associations.

[Figure 3 near here]

In addition, these results reveal that both forms of emotional engagement (social and learning) predict higher global levels of student engagement (β = .114 and .210, respectively) as well as higher specific levels on the boredom/distraction facet of behavioral engagement (β = .226 and .172, respectively). Thus, students reporting higher levels of social-emotional engagement and tending to be more concerned about learning new material tended to report the highest global level of engagement but also the highest levels of boredom and distraction behaviors. In addition, higher levels of learning-emotional engagement were also associated with lower levels of cognitive engagement across dimensions (β = -.167 for the strategies facet and β = -.156 for the auto-regulation facet). Thus, students reporting greater levels of concerns about learnings new things or learning difficulties tended to report lower levels of specific preventive and corrective cognitive engagement strategies facets. Again, these associations occur beyond the association with global levels of engagement. It is noteworthy that, by allowing emotional engagement facets to also influence the remaining student engagement factors, Model 3 was able to explain more variance in global levels of engagement (+3.2%), specific effort/attention (+4%), specific boredom/distraction (+5.8%) and specific autoregulation (+1.3%).

Altogether, these results suggest 12 indirect (mediated) relations, which were all supported by the estimation of confidence intervals for these indirect effects which excluded the value of 0. First, in addition to its direct positive effect on students' global levels of engagement, students' global levels of self-determination also present a positive indirect relation with students global levels of engagement and with their specific levels of boredom/distraction, as mediated by both specific facets of emotional engagement: (a) global self-determination → social-emotional engagement → global engagement: indirect effect = .048, 95% CI [.007, .333]; (b) global self-determination → social-emotional engagement → boredom/distraction: indirect effect = .057, 95% CI [.033, .166]; (c) global self-determination → learning-emotional engagement → global engagement: indirect effect = .056, 95% CI [.023, .093]; (d) global self-determination → learning-emotional engagement → boredom/distraction: indirect effect = .028, 95% CI [.012, .047]. Second, in addition to its direct negative effect on student specific levels of cognitive-autoregulation engagement, students' global levels of self-determination also present a negative indirect relation with students' specific levels of cognitive-strategies engagement (indirect effect = -.031, 95% CI [-.080, -.002]) and cognitive-autoregulation engagement (indirect effect = -.029, 95% CI [-.063, -.002]) as mediated by learning-emotional engagement.

Turning our attention to the specific facets of academic motivation, in addition to their various direct effects, the results also reveal a variety of indirect effects involving social-emotional engagement: (a) specific intrinsic motivation → social-emotional engagement → global engagement: indirect effect = .026, 95% CI [.005, .198]; (b) specific intrinsic motivation → social-emotional engagement → boredom/distraction: indirect effect = .031, 95% CI [.014, .099]; (c) specific identified regulation → social-emotional engagement → global engagement: indirect effect = .014, 95% CI [.001, .121]; (d) specific identified regulation → social-emotional engagement → boredom/distraction: indirect effect = .017, 95% CI [.004, .060]; (e) specific amotivation → social-emotional engagement → global engagement: indirect effect = -.035, 95% CI [-.280, -.006]; (f) specific amotivation → social-emotional engagement → boredom/distraction: indirect effect = -.042, 95% CI [-.133, -.023].

Discussion

Dimensionality

The present study relied on the bifactor-ESEM psychometric framework (Morin, Arens, & Marsh, 2016; Morin et al., 2020) to investigate the multidimensionality of, and associations between, students' ratings of their academic motivation and school engagement. Our results supported the superiority of a bifactor-ESEM representation of academic motivation, thus highlighting the need to properly disaggregate students' global levels of self-determined motivation (i.e., students' global sense of self-directedness and volition) from the specific quality inherent of each type of behavioral regulation. These results add to the accumulating evidence supporting the value of a bifactor-ESEM representation of motivation measures anchored in the SDT framework across a variety of life domains, including education (Litalien et al., 2017; Howard et al., 2018). Interestingly, factor loadings observed on the global self-determination factor (i.e., students' global sense of self-directedness and volition) identified as part of this model were found to mainly match the SDT's hypothesized continuum structure of motivation, thus lending further support to this hypothesis (e.g., Howard et al., 2017; Ryan & Deci, 2017). Yet, it is important to keep in mind that support for this continuum structure remained imperfect in the present study, as the G-factor loadings obtained for the extrinsic-introjected regulation items were found to be slightly higher than those obtained for the extrinsic-identified regulation items. These findings nevertheless match those previously obtained across two distinct samples of students by Litalien et al. (2017), who also reported lower G-factor loadings for identified regulation (λ = .376 to .493, M_λ = .455) than for introjected regulation (λ = .382 to .599, M_λ = .518). In addition, although most S-factors retained a meaningful level of specificity beyond the variance in item ratings already explained by the G-factor, the intrinsic motivation S-factor retained a more limited amount of specificity. This result, which makes sense from the perspective of SDT (Ryan & Deci, 2017), suggests that students' report of intrinsic motivation mainly serve to define their global levels of self-determined academic motivation (i.e., global sense of self-directedness and volition) and retained only a limited amount of specificity once these global levels are taken into account.

In relation to school engagement, our results rather supported the value of a partial bifactor-CFA representation of school engagement, allowing for a proper disaggregation of students' global levels of school engagement from specific cognitive and behavioral engagement facets. This result thus supports previous research supporting the value of a bifactor representation of school engagement (Dierendonck et al., 2020; Stefansson et al., 2016; Wang et al., 2016). However, in the present study, students' levels of emotional engagement were found to tap into something distinct than the other facets and from the global construct captured as part of the G-factor identified in this bifactor solution. In other words, although the behavioral and cognitive facets of school engagement were found to present a dual global and specific nature (just like motivation ratings), facets of emotional engagement did not, and rather formed distinct components to consider when assessing students' engagement dynamics. This result is aligned with previous reports suggesting that emotional engagement might contribute far less to the definition of global levels of school engagement (the G-factor) relative to the other facets of school engagement (Dierendonck et al., 2020; Wang et al., 2016), as well as with theoretical perspectives attributing a distinct role to emotional engagement relative to other forms of student engagement (Green et al., 2012; Skinner et al., 2008). In addition to providing replication evidence supporting the value of a bifactor representation of student engagement (Dierendonck et al., 2020; Stefansson et al., 2016; Wang et al., 2016), a key contribution of this study stems from this provision of empirical evidence supporting the theoretically-distinct nature of emotional forms of engagement relative to behavioral and cognitive engagement (Green et al., 2012; Skinner et al., 2008)

Furthermore, additional results reported in the online supplements (Appendix 2) supported the robustness of our findings by demonstrating the measurement invariance of responses to both instruments as a function of students' gender, language, and age. Still, these additional results (revealing some differences related to items' uniquenesses) also suggested that some additional fine-tuning might be needed to ensure the complete linguistic equivalence of the student engagement measure across German and French language groups when relying on manifest scale scores. Researchers could also rely on fully latent models when possible, to control for this difference.

Associations between Academic Motivation and Engagement

In terms of associations between academic motivation and engagement, our results first supported our expectation that the most pronounced associations would occur at the level of the G-factors, but also that meaningful associations would happen at the level of the S-factors[4]. Importantly, academic motivation facets were found to explain almost 66% of the variance in the G-factor of engagement, but lower proportions of variance (5% to 35%) in the specific engagement factors.

Turning our attention to more specific effects, global levels of self-determination were also associated with higher specific levels of emotional engagement. Also matching our expectations, once the effects of global levels of self-determination were taken into account, students' specific levels of external regulation were found to share no association with their levels of engagement. Likewise, and also as expected, specific levels of amotivation appeared to share negative associations with students' global levels of school engagement and social-emotional engagement and positive associations with boredom/distraction. However, these specific levels of amotivation also presented an unexpected positive association with students' specific levels of learning-emotional engagement, although this association was relatively small. Similarly, students' specific levels of external-introjected regulation were found to be associated with, as expected, lower levels of cognitive engagement and effort/attention, and higher levels of boredom/distraction. However, these specific levels of external-introjected regulations were also found to be associated with higher global levels of engagement and specific levels of learning-emotional engagement, suggesting that, contrary to our expectations, there seems to be both risks and benefits to the endorsement of introjected instrumental reasons for studying. This result is generally aligned with SDT (Ryan & Deci, 2017) representation of introjected regulation as located close to the middle of the motivation continuum and thus likely to exert both desirable and undesirable effects for students' engagement. More precisely, this study suggests that, despite specific effects on increasing boredom and decreasing efforts and cognitive engagement, the endorsement of introjected instrumental reasons for learning can still help to increase students global and emotional levels of engagement.

The results also showed that specific levels of intrinsic motivation were associated with lower specific levels of boredom/distraction, as well as with higher specific levels of social emotional engagement. As such, when students study for intrinsic reasons, they are more likely to feel happy, safe and well-integrated in their class. They are also less likely to become bored and to do something else during class because they enjoy the study materials (e.g., Pekrun et al., 2014). These results are aligned with SDT (Ryan & Deci, 2017), which positions intrinsic motivation as emerging from the fulfillment of three basic psychological needs (autonomy, competence, and relatedness), themselves known to be associated with higher levels of engagement (Park et al., 2012). These results thus suggest that need fulfillment might exert its positive effect on engagement via the mediating role of motivations. Future studies will be needed to verify these propositions and this particular sequence. In contrast, intrinsically motivated students were less likely to utilize cognitive autoregulation strategies (e.g., bouncing back quickly from bad experiences), possibly because they were less likely to focus on the outcomes associated with their learning (e.g., grades) than on the enjoyment derived from it. This last result

[4] When considering the results pertaining to the specific factors, it is important to note that their interpretation differs from the typical interpretation of correlated factors representations. While factors taken from a correlated factors model reflect the covariance between the items forming a subscale, the specific factors from a bifactor model rather reflect the residual covariance between these items once the covariance between all items has been absorbed by the G-factor. Thus, rather than reflecting the desire to pursue an activity for the pleasure that it procures (intrinsic), or because it matches one's personal value (external-identified), these S-factors might reflect more a form of quest for pure pleasure (specific intrinsic) or the impression of a match between one's values and those conveyed by the activity (specific external-identified), without also capturing the drive component (i.e., the desire to get involved) of the factor taken from a correlated factors model.

replicates prior studies relying on more traditional analytic approaches and highlight the importance of intrinsic motivation for learning (e.g., Cordova & Lepper, 1996; Ryan, Connell, & Plant, 1990; Ryan & Deci, 2013).

In contrast, specific levels of external-identified regulation were associated with higher levels of social emotional engagement and effort/attention, but with lower levels of global school engagement. The positive associations found between specific levels of identified regulation and higher specific levels of social emotional engagement and effort/attention suggest, in line with prior studies (e.g., Jeno et al., 2020), that students perceiving academics as a valuable and important activity might be more likely to exert additional effort, work harder, and become more emotionally invested in their studies. In contrast, and contrary to our expectations, our results revealed negative associations between students' specific levels of identified regulation and their global levels of school engagement. This last result suggests that, once students' global level of self-determination toward school are taken into account, simply perceiving schooling as a valuable activity without the accompanying self-determined drive to pursue this activity might hinder their global levels of engagement. For instance, this situation would apply to students who know that school activities are important, but fail to feel any volitional drive to pursue these activities. As a result, these students might become less engaged toward these otherwise important activities. Clearly, future studies are needed to verify the replicability of these findings, and to better understand the mechanisms at play in this association.

Mediation

Finally, this study assessed Skinner et al.'s (2008) mediation hypothesis according to which the associations between academic motivation and global, behavioral and cognitive facets of school engagement would be mediated by emotional engagement. Adding to accumulating evidence in support of this hypothesis (Green et al., 2012; Skinner et al., 2008), our results also found support for a partial mediational role of emotional engagement. Interestingly, previously identified associations remained unchanged in this new mediational model, supporting their robustness. In addition, this model revealed that levels of emotional engagement were directly related to higher levels of global engagement, as suggested by the mediation hypothesis (Green et al., 2012; Skinner et al., 2008). However, this model surprisingly revealed that, once all direct associations between motivation facets and student engagement are accounted for in the model, emotional engagement levels were also associated with lower levels of cognitive engagement and higher levels of boredom/distraction. This result might also be related to the specific nature of these engagement components as estimated in the partial bifactor model. More precisely, these suggest that, beyond their positive association with global levels of school engagement, high levels of emotional engagement could still be associated with slightly higher levels of boredom/distraction (possibly when course content does not match this emotional drive) and lower levels of cognitive engagement. This later effect seems aligned with the idea that too much emotionality might limit the ability to engage in school activities in a more cognitively-oriented manner. Once again, this result would need to be more extensively explored in future research. Clearly, additional studies will be needed to better document these associations, their possible replicability, and the mechanism underpinning them.

Implications for Future Research and Limitations

The present study has some limitations. Given the manifest differences observed in the operationalization of engagement measures (see for example Green et al., 2012), future research is needed to confirm the replicability of the present results, and their generalizability to alternative representations of academic motivation and student engagement. Importantly, the cross-sectional nature of the present study precludes reaching any conclusion related to the directionality of the observed associations, making it impossible to systematically test our expectation that motivation would predate engagement. Thus, future longitudinal research would be needed to verify that the observed associations really follow the currently hypothesized causal pathways. Longitudinal research would also make it possible to more precisely study continuity and change in longitudinal trajectories of motivation and engagement, and time-structured associations between these two constructs. Perhaps even more importantly, longitudinal research would make it possible to incorporate more contextual measures of the possible family, school, and peer-related determinants of students' motivation and engagement trajectories, as well as some objective outcomes measures of these trajectories related to students' achievement, persistence, and attainment.

The sample of schools and students used in the present study cannot be considered to be representative of the school and student population from these three countries. As a consequence, the generalizability of these results to these countries, and even more importantly beyond these countries, remains uncertain. Future research should thus seek to more systematically assess the generalizability of the present results to other countries, cultural groups, and languages. The convergent and divergent validity of the retained measurement models should be better established using other relevant constructs such as academic achievement, school dropout, and vocational choices using a combination of self-reported, informant-reported, and objective measures. Providing evidence of factor validity and linguistic equivalence for our measures was not a main objective of the present research. For this reason, future research should be designed to more closely investigate the potential use and interpretation of motivation and engagement tests scores for research and practice. These future studies should be guided by a more comprehensive validation framework (i.e., domain description, scoring, generalization, extrapolation, and implications), such as that proposed by Kane (2006, 2013; for an application see Gotch & French, 2020).

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Table 1
Sample Descriptive Statistics (N = 4047)

Variable	N	%
Country		
Country 1 (France)	1011	25.0
Country 2 (Belgium)	1591	39.3
Country 3 (Luxembourg)	1445	35.7
Gender		
Male	2013	49.7
Female	2034	50.3
Age		
14 or under	922	22.8
15 or 16	1330	32.9
17 or over	1790	44.3
Foreign language spoken at home		
Yes	1202	29.8
No	2845	70.2
With grade retention (at least one year)		
Yes	1567	38.9
No	2480	61.1

Table 2

Alternative Measurement Models

Models	*Chi-square*	*df*	*CFI*	*TLI*	*RMSEA [90% CI]*	*AIC*	*CAIC*	*BIC*	*SSBIC*
Academic motivation									
1. Correlated factors CFA	2422.015*	160	.899	.880	.059 [.057; .061]	235683.784	236195.306	236125.306	235902.876
2. Correlated factors ESEM	884.072*	100	.965	.934	.044 [.041; .047]	233587.407	234537.377	234407.377	233994.294
3. Bifactor-CFA	3067.130*	150	.870	.835	.069 [.067; .071]	236449.088	237033.684	236953.684	236699.479
4. Bifactor-ESEM	635.851*	85	.975	.945	.040 [.037; .043]	233208.142	234267.723	234122.723	233661.977
Student Engagement									
5. Correlated factors CFA	948.789*	120	.957	.945	.041 [.039; .044]	222202.209	222706.304	222637.304	222418.052
6. Correlated factors ESEM	189.686*	60	.993	.983	.023 [.019; .027]	221339.616	222282.056	222153.056	221743.150
7. Bifactor-CFA	861.005*	117	.961	.949	.040 [.037; .042]	222087.366	222613.378	222541.378	222312.594
8. Bifactor-ESEM	107.264*	48	.997	.990	.017 [.013; .022]	221254.237	222284.345	222143.345	221695.309
9. Partial Bifactor-CFA	754.740*	112	.966	.954	.038 [.035; .040]	221951.393	222513.935	222436.935	222192.262

Note. * $p \leq .01$; CFA: Confirmatory Factor Analysis. ESEM: Exploratory Structural Equation Model; df: degrees of freedom; CFI: Comparative Fit Index; TLI: Tucker-Lewis Index; RMSEA: Root Mean Square Error of Approximation; CI: Confidence Interval; AIC: Akaike Information Criterion; CAIC: constant AIC; BIC: Bayesian Information Criterion; SSBIC: Sample-Size adjusted BIC.

Table 3

Standardized Factor Loadings (λ) and Uniquenesses (δ) of the Bifactor-CFA and Bifactor-ESEM Solutions: Academic Motivation

Items	G (λ)	S-INT (λ)	S-EID (λ)	S-EIN (λ)	S-ER (λ)	S-A (λ)	δ
1. INT							
Item 1	**.745 (.011)****	**.556 (.088)****	-.055 (.014)**	-.051 (.011)**	-.098 (.016)**	-.043 (.014)**	.119
Item 2	**.557 (.018)****	**.284 (.038)****	-.030 (.020)	.005 (.017)	-.057 (.021)**	.159 (.016)**	.579
Item 3	**.655 (.014)****	**-.070 (.022)****	-.054 (.019)**	.007 (.020)	-.093 (.021)**	.035 (.016)*	.554
Item 4	**.753 (.011)****	**.006 (.020)**	-.096 (.019)**	-.116 (.019)**	.005 (.020)	-.006 (.015)	.410
Item 5	**.780 (.012)****	**-.154 (.019)****	-.103 (.022)**	-.084 (.019)**	.015 (.023)	.034 (.013)**	.348
Item 6	**.749 (.011)****	**-.233 (.046)****	.064 (.028)*	.045 (.019)*	-.129 (.026)**	.016 (.014)	.362
Item 7	**.666 (.012)****	**-.004 (.020)**	-.106 (.029)**	.116 (.019)**	-.021 (.021)	.094 (.014)**	.522
Item 8	**.627 (.013)****	**-.088 (.021)****	.043 (.021)*	.368 (.019)**	-.027 (.022)	.098 (.015)**	.452
ω		.368					
2. EID							
Item 12	**.534 (.013)****	.007 (.017)	**.294 (.028)****	.020 (.020)	.324 (.028)**	-.130 (.016)**	.506
Item 13	**.490 (.015)****	-.055 (.017)**	**.393 (.033)****	-.019 (.020)	.433 (.025)**	-.124 (.015)**	.399
Item 14	**.508 (.014)****	-.029 (.012)*	**.651 (.075)****	.126 (.016)**	.159 (.032)**	-.088 (.014)**	.269
ω			.604				
3. EIN							
Item 9	**.562 (.015)****	-.013 (.021)	-.019 (.036)	**.338 (.028)****	.307 (.025)**	.010 (.015)	.475
Item 10	**.584 (.015)****	-.079 (.019)**	.097 (.020)**	**.448 (.025)****	.058 (.020)**	.053 (.014)**	.436
Item 11	**.526 (.014)****	-.033 (.016)*	.074 (.018)**	**.576 (.022)****	.086 (.019)**	.068 (.013)**	.373
ω				.591			
4. ER							
Item 15	**.280 (.021)****	-.054 (.020)**	.133 (.033)**	.051 (.021)*	**.449 (.036)****	-.018 (.015)	.696
Item 16	**.416 (.016)****	-.036 (.013)**	.308 (.028)**	.079 (.016)**	**.654 (.029)****	-.098 (.012)**	.288
Item 17	**.241 (.019)****	.036 (.024)	.268 (.025)**	.258 (.023)**	**.403 (.028)****	.042 (.017)*	.638
ω					.583		
5. A							
Item 18	**-.329 (.018)****	-.019 (.016)	-.089 (.016)**	-.010 (.016)	-.015 (.018)	**.640 (.017)****	.474
Item 19	**-.143 (.021)****	.001 (.016)	-.090 (.019)**	.033 (.016)*	-.001 (.018)	**.687 (.017)****	.498
Item 20	**-.180 (.020)****	.017 (.013)	-.036 (.018)*	.070 (.015)**	-.064 (.016)**	**.708 (.017)****	.456
ω	.923					.744	

Note. * $p \leq .05$; ** $p \leq .01$; ESEM: Exploratory Structural Equation Model; INT: Intrinsic motivation; EID: Extrinsic-Identified regulation; EIN: Extrinsic-Introjected regulation; ER: External regulation; A: Amotivation; G: Global dimension; S: Specific facet; Target (main) factor loadings are marked in bold.

Table 4

Standardized Factor Loadings (λ) and Uniquenesses (δ) of the Partial Bifactor-CFA Solution: Student Engagement

Items	G (λ)	S (λ)	δ
1. BE			
Item 1	.615 (.021)**	.518 (.028)**	.353
Item 2	.697 (.019)**	.635 (.027)**	.111
Item 3	.691 (.017)**	.311 (.029)**	.425
ω		.707	
2. BB			
Item 4	-.338 (.025)**	.558 (.020)**	.575
Item 5	-.480 (.023)**	.584 (.021)**	.428
Item 6	-.487 (.021)**	.728 (.019)**	.232
ω		.739	
3. ES			
Item 7		.841 (.011)**	.293
Item 8		.793 (.013)**	.371
Item 9		.695 (.015)**	.517
ω		.821	
4. EL			
Item 10		.790 (.021)**	.375
Item 11		.638 (.021)**	.593
Item 12		.506 (.020)**	.744
ω		.686	
5. CS			
Item 13	.535 (.017)**	.223 (.026)**	.664
Item 14	.525 (.019)**	.474 (.029)**	.499
Item 15	.609 (.018)**	.561 (.038)**	.315
ω		.517	
6. CA			
Item 16	.571 (.020)**	.244 (.028)**	.614
Item 17	.497 (.021)**	.662 (.039)**	.315
Item 18	.566 (.019)**	.531 (.034)**	.397
ω	.848	.609	

Note. * $p \leq .05$; ** $p \leq .01$; CFA: Confirmatory Factor Analysis. ESEM: Exploratory Structural Equation Model; BE: Behavioral engagement: Effort/attention; BB: Behavioral engagement: Boredom/distraction; ES: Emotional engagement: Social; EL: Emotional engagement: Learning; CS: Cognitive engagement: Strategies; CA: Cognitive engagement: Autoregulation; G: Global dimension; S: Specific facet.

Table 5

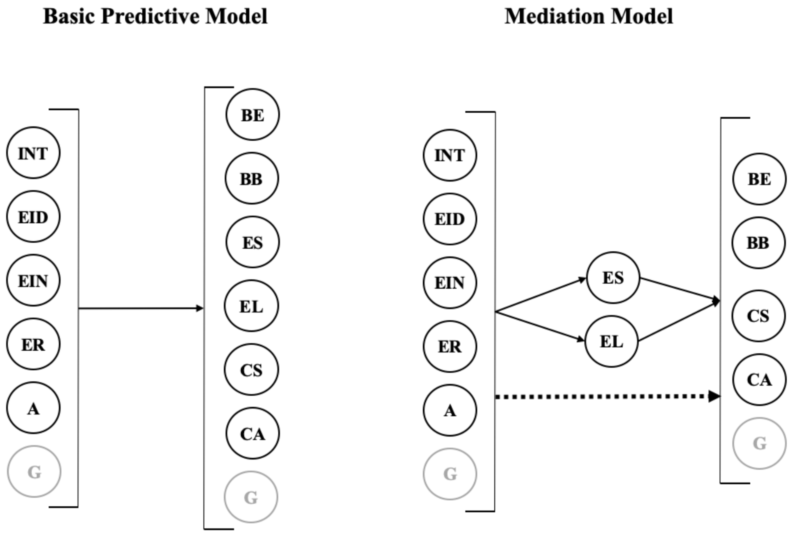
Latent Associations between Academic Motivation and School Engagement

	Academic motivation						Emotional engagement		
	G-factor	Specific-INT	Specific-EID	Specific-EIN	Specific-ER	Specific-A	ES	EL	
Outcomes	β (SE)	β (SE)	β (SE)	β (SE)	β (SE)	β (SE)	β (SE)	β (SE)	R^2
Model 1 – Without mediation									
Engagement G-factor	.712 (.075)**	.014 (.065)	-.133 (.057)*	.278 (.052)**	.011 (.079)	-.232 (.074)**			.657
Specific-BE	-.195 (.193)	.038 (.076)	.144 (.066)*	-.300 (.075)**	-.003 (.092)	-.137 (.103)			.169
Specific-BB	-.167 (.126)	-.125 (.047)**	-.065 (.049)	.111 (.055)*	.098 (.058)	.155 (.058)**			.094
Specific-CS	-.371 (.245)	-.153 (.092)	.174 (.089)	-.384 (.084)**	-.069 (.128)	.105 (.137)			.355
Specific-CA	-.366 (.192)	-.167 (.073)*	.137 (.075)	-.335 (.076)**	.150 (.091)	-.132 (.126)			.333
ES	.232 (.024)**	.116 (.033)**	.065 (.030)*	-.020 (.025)	.039 (.029)	-.168 (.027)**			.102
EL	.150 (.022)**	-.051 (.030)	-.039 (.029)	.155 (.026)**	-.007 (.028)	.058 (.028)*			.054
Model 3 – With mediation									
Engagement G-factor	.642 (.075)**	.007 (.059)	-.130 (.057)*	.242 (.051)**	.015 (.079)	-.224 (.069)**	.114 (.052)*	.210 (.057)**	.689
Specific-BE	-.189 (.185)	.049 (.072)	.151 (.069)*	-.294 (.073)**	-.009 (.097)	-.130 (.098)	-.098 (.071)	-.118 (.060)	.209
Specific-BB	-.174 (.136)	-.148 (.049)**	-.087 (.055)	.118 (.058)*	.097 (.065)	.157 (.061)*	.226 (.054)**	.172 (.039)**	.152
Specific-CS	-.322 (.226)	-.159 (.089)	.159 (.089)	-.344 (.079)**	-.076 (.125)	.110 (.123)	-.016 (.095)	-.167 (.075)*	.353
Specific-CA	-.352 (.175)*	-.189 (.070)**	.118 (.076)	-.301 (.073)**	.137 (.091)	-.106 (.112)	.106 (.088)	-.156 (.063)*	.346
ES	.233 (.024)**	.128 (.035)**	.069 (.031)*	-.021 (.025)	.034 (.029)	-.170 (.027)**	-	-	.106
EL	.149 (.022)**	-.057 (.031)	-.039 (.029)	.155 (.026)	-.006 (.028)	.060 (.028)*	-	-	.055

Note. * p < .05; ** p < .01; β: Standardized regression coefficient; SE: standard error of the coefficient INT: Intrinsic motivation. EID: Extrinsic-Identified regulation; EIN: Extrinsic-Introjected regulation; ER: External regulation; A: Amotivation; BE: Behavioral engagement: Effort/attention; BB: Behavioral engagement: Boredom/distraction; ES: Emotional engagement: Social; EL: Emotional engagement: Learning; CS: Cognitive engagement: Strategies; CA: Cognitive engagement: Autoregulation.

Figure 1

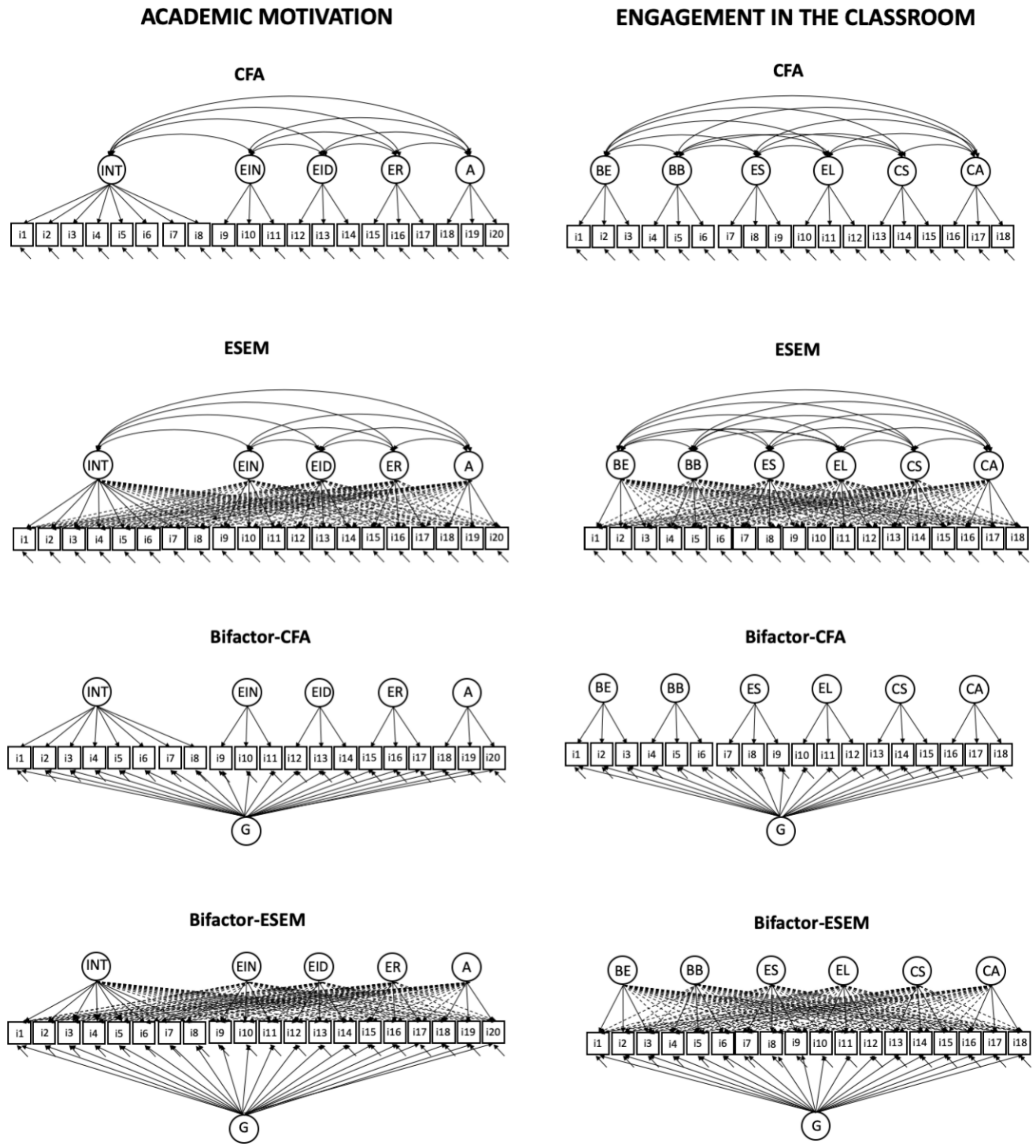
Schematic Representation of the Potential Predictive Models of Academic Motivation Predicting Engagement in the Classroom



Note. G: Global factor; INT: Intrinsic motivation; EIN: Extrinsic-identified regulation; EID: Extrinsic-introjected regulation. ER: External regulation. A: Amotivation. BE: Behavioral engagement: Effort/attention; BB: Behavioral engagement: Boredom/distraction; ES: Emotional engagement: Social; EL: Emotional engagement: Learning; CS: Cognitive engagement: Strategies; CA: Cognitive engagement: Autoregulation.

Figure 2

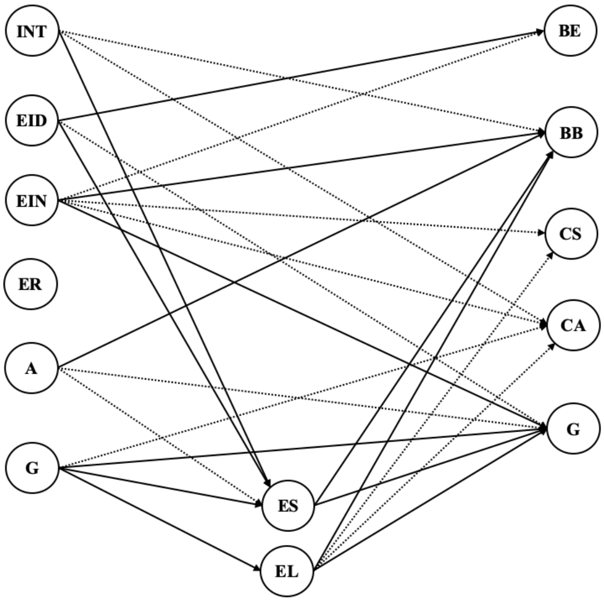
Alternative Measurement Models of Academic Motivation and Engagement in the Classroom



Note. CFA: Confirmatory Factor Analysis. ESEM: Exploratory Structural Equation Model; G: Global factor; INT: Intrinsic motivation; EIN: Extrinsic-identified regulation; EID: Extrinsic-introjected regulation. ER: External regulation. A: Amotivation. BE: Behavioral engagement: Effort/attention; BB: Behavioral engagement: Boredom/distraction; ES: Emotional engagement: Social; EL: Emotional engagement: Learning; CS: Cognitive engagement: Strategies; CA: Cognitive engagement: Autoregulation.

Figure 3

Result Summary from the Final Predictive Model (Partial Mediation)



Note. Only statistically significant paths are shown ($p \leq .05$); positive paths are represented by full arrows whereas negative paths are represented by dotted-arrows; G: Global factor; INT: Intrinsic motivation; EIN: Extrinsic-identified regulation; EID: Extrinsic-introjected regulation. ER: External regulation. A: Amotivation. BE: Behavioral engagement: Effort/attention; BB: Behavioral engagement: Boredom/distraction; ES: Emotional engagement: Social; EL: Emotional engagement: Learning; CS: Cognitive engagement: Strategies; CA: Cognitive engagement: Autoregulation.

Online Supplements for:

Testing associations between global and specific levels of student academic motivation and engagement in the classroom

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
Specification and Estimation of the Alternative Measurement Models for Academic Motivation and Student Engagement

To examine the structure of students' ratings of their academic motivation and engagement, four alternative measurement structures, illustrated in Figure 2 in the manuscript, were separately contrasted for both constructs. In the first of those structures (first row in Figure 2), motivation and engagement ratings were represented using a correlated factors Confirmatory Factor Analytic (CFA) model. In this model, each motivation and engagement facet will be depicted by its own independent factor, each of these factors will be defined uniquely by its a priori indicators, and no cross-loading will be allowed between items and the other factors. The second structure (second row in Figure 2) will rely on a correlated factors Exploratory Structural Equation Modeling (ESEM) model. In this model, each factor will be defined by their a priori indicators, as in the correlated factors CFA solution, but all cross-loadings to be freely estimated between items and non-target factors. This solution will be estimated using a confirmatory approach to rotation (i.e., target rotation), which allows for the a priori specification of the main indicators of each construct, and for the free estimations of cross-loadings "targeted" to be as close to zero as possible (Asparouhov & Muthén, 2009; Morin et al., 2020).

The third structure (third row on Figure 2) will rely on a bifactor-CFA model. In this model, ratings will be used to simultaneously define one global factor (defined by all academic motivation or student engagement) items and by one of several specific factors corresponding to the a priori subscales of the instruments. In bifactor specifications, all factors are assumed to be orthogonal in order to achieve a clear partition of the total observed covariance among the items into one global dimension (G-factor) underlying all the items, and specific facets (S-factors) explaining the residual covariance not explained by the global dimension (Morin et al., 2020). In this solution, the S-factors are defined in the same manner as in the correlated factors CFA solution. Finally, the fourth structure (fourth row on Figure 2) will rely on a bifactor-ESEM model. In this model, factors will be defined as in the bifactor-CFA solution, but all cross-loadings will be freely-estimated between the items and non-target S-factors. This specification will be accomplished via the application of an orthogonal bifactor-target rotation, in which these cross-loadings are "targeted" to be as close to zero as possible.

As noted by Morin and colleagues (e.g., Morin, Boudrias et al., 2016, 2017; Morin et al., 2020), because each of the four alternative models (CFA, ESEM, bifactor-CFA, bifactor-ESEM) is able to absorb misfit due to unmodelled components (e.g., unmodelled cross-loading can result in inflated factor correlations or in inflated loadings on the G-factor), model comparisons has to incorporate a consideration of model fit, but also need to be anchored in a detailed examination of parameter estimates. More precisely, as suggested by Morin et al. (2020), we started this comparison by an examination of the correlated factors CFA and ESEM solutions. In this comparison, in addition to model fit and the identification of factors well-defined by strong target loadings, the focus is put on cross-loadings and factor correlations. More precisely, this comparison supports the ESEM solution when multiple cross-loadings are observed (although the presence of multiple cross-loadings might also reflect the need to incorporate a G-factor), and when a discrepant pattern of factor correlations is noted by the correlated factors CFA and ESEM solution (Asparouhov et al., 2015; Morin et al., 2020). Once the optimal correlated factors CFA or ESEM solution has been retained, this solution can be contrasted with its bifactor counterpart. In addition to model fit examination, this comparison will support the bifactor representation when it results in a well-defined global factor, in at least some well-defined S-factors and, in the case of ESEM, when cross-loadings are reduced in the bifactor-ESEM solution relative to the correlated factors ESEM solution.

Appendix 2
Results from the Measurement Models

Academic Motivation

The fit of the alternative models (CFA, ESEM, bifactor-CFA, bifactor-ESEM) is provided in Table 2 of the main manuscript. For academic motivation, the correlated factors CFA and bifactor-CFA solutions both failed to achieve an acceptable level of fit according to the CFI and TLI (< .900). In contrast, the correlated factors ESEM and bifactor-ESEM solutions both demonstrated excellent fit according to the CFI and RMSEA, and acceptable fit according to the TLI. Among these two models, the bifactor-ESEM model demonstrated a higher level of fit to the data than the correlated factors ESEM solution (ΔCFI = +.010; ΔTLI = +.011; ΔRMSEA = -.004), a conclusion that is supported by the information criteria, which are all lower for the bifactor-ESEM solution relative to all alternative solutions. However, model selection should not be based solely on model fit but also on the inspection and comparison of parameter estimates (Morin et al., 2020). Latent correlations estimated from the correlated factors CFA and ESEM solutions are reported in Table S1, whereas parameter estimates from the solutions retained for comparison are reported in Tables S2 and S3.

Turning first our attention to the correlated factors CFA and ESEM solutions, it is interesting to note that, whereas the correlated factors CFA solution resulted in well-defined factors for all motivation facets (intrinsic: λ = .561 to .769, M_λ = .690; identified: λ = .719 to .774, M_λ = .744; introjected: λ = .722 to .751, M_λ = .733, external: λ = .541 to .841, M_λ = .652; amotivation: λ = .687 to .736, M_λ = .714), the correlated factors ESEM solution resulted in some slightly weaker target loadings (intrinsic: λ = .344 to .927, M_λ = .669; identified: λ = .200 to .340, M_λ = .200; introjected: λ = .392 to .743, M_λ = .576, external: λ = .392 to .620, M_λ = .493; amotivation: λ = .714 to .755, M_λ = .739), due in part to the presence of substantial cross-loadings between extrinsic-identified regulation and external regulation, some of which were higher than the target loadings. However, factor correlations were considerably reduced in the correlated factors ESEM solution ($|r|$ = .096 to .554, $M_{|r|}$ = .283) relative to the correlated factors CFA solution ($|r|$ = .170 to .889, $M_{|r|}$ = .513). Thus, goodness-of-fit information, the observation of noteworthy cross-loadings, and factor correlations all converge in supporting the correlated factors ESEM solution. This solution was thus contrasted with its bifactor counterpart. This second comparison revealed cross-loadings that were generally smaller in the bifactor-ESEM solution ($|\lambda|$ = .001 to .433; $M_{|\lambda|}$= .081) when compared to the correlated factors ESEM solution ($|\lambda|$ = .002 to .504; $M_{|\lambda|}$ = .119), suggesting that higher ESEM cross-loadings might have reflected the presence of an unmodeled G-factor. The detailed description of the bifactor-ESEM solution is reported in the Results section of the manuscript.

Student Engagement

The fit of the alternative models is provided in the bottom section of Table 2 of the main manuscript. These results show that both the correlated factors CFA and bifactor CFA solutions presented an excellent fit to the data according to the CFI and RMSEA, and an acceptable fit to the data according to the TLI. In contrast, the fit of the correlated factors ESEM and bifactor-ESEM solutions was excellent according to all fit indices, and higher than that of their CFA counterparts. Among these four models, the bifactor-ESEM model demonstrated a higher level of fit to the data according to all indices (including the AIC, BIC, and SSBIC), although this level of improvement remained minimal when compared to the correlated factors ESEM solution (ΔCFI = +.004; ΔTLI = +.007; ΔRMSEA = -.006). However, model selection should not be based solely on model fit but also on the inspection and comparison of parameter estimates (Morin et al., 2020). Latent correlations from the correlated factors CFA and ESEM solutions are reported in Table S1, whereas parameter estimates from the solutions retained for comparisons are reported in Tables S4 and S5.

Turning first our attention to the correlated factors solutions, both the correlated factors CFA (effort/attention: λ = .747 to .916, M_λ = .826; boredom/distraction: λ = .652 to .859, M_λ = .760; social: λ = .695 to .842, M_λ = .777; learning: λ = .506 to .780, M_λ = .645; strategies: λ = .580 to .799, M_λ = .696; autoregulation: λ = .606 to .807, M_λ = .723) and correlated factors ESEM (effort/attention: λ = .616 to .988, M_λ = .809; boredom/distraction: λ = .656 to .885, M_λ = .758; social: λ = .712 to .827, M_λ = .777; learning: λ = .514 to .784, M_λ = .648; strategies: λ = .457 to .843, M_λ = .673; autoregulation: λ = .462 to .848, M_λ = .695) solutions resulted in well-defined factors for all facets of student engagement. This similarity of results could be due, in part, to the fact that most of the cross-loadings estimated as part of the correlated factors ESEM solution remained very small ($|\lambda|$ = 0 to .137; $M_{|\lambda|}$= .033). In fact, only four of these cross-loadings were found to be equal to, or higher than, .100 (out of 90 cross-loadings) and none were higher than the target loadings. In addition, examination of the factor correlations revealed that these were equivalent in the correlated factors CFA ($|r|$ = .036 to .650, $M_{|r|}$ = .286) and correlated factors ESEM ($|r|$ = .032 to .618, $M_{|r|}$ = .282) solutions. This similarity of results coupled with the lack of cross-loadings associated with the correlated factors ESEM solution strongly suggests that the more parsimonious correlated factors CFA solution should be retained. This solution was thus contrasted with its bifactor counterpart.

It is interesting to note that the definition of the bifactor-CFA factors was highly similar to those of the bifactor-ESEM solution, which also resulted in similarly negligible cross-loadings, reinforcing our decision to retain the more parsimonious bifactor-CFA solution. Examination of the bifactor-CFA solution first revealed a G-factor ($|\lambda|$ = .077 to .684, M_{λ} = .429; ω = .885) that was well-defined by items from all behavioral engagement ($|\lambda|$ = .297 to .684; $M_{|\lambda|}$= .531) and cognitive engagement (λ = .528 to .623, M_{λ} = .570) items, but more weakly defined by the emotional engagement items (λ = .077 to .286, M_{λ} = .188). While these emotional engagement items do contribute to the student engagement G-factor, this contribution (as apparent by the size of the target loadings on the G-factor) appears to be, at best, negligible. This observation suggests that these items might in fact decrease the definition and precision of the G-factor. The fact that all emotional engagement target loadings are below .300 (when most common guidelines for the interpretations of meaningful main loadings suggest that these should be at least .400), suggests that these items tap into something relative distinct than what is assessed by the cognitive and behavioral engagement items, and thus should not be used to define the global engagement factor. This observation led us to estimate a partial bifactor-CFA solution in which items related to emotional engagement were not used in the definition of the G-factor. More details about this partial bifactor-CFA solution are reported in the Results section of the manuscript.

Appendix 3
Tests of Measurement Invariance

Once the optimal solution was selected for each measure separately we proceeded to verify the generalizability (i.e., measurement invariance) of these solutions across languages (French/German), age groups (14 years old or under, 15 or 16 years old, 17 years old or over) and gender (Male/Female) in the following sequence (Millsap, 2011): configural invariance (same factor structure), weak invariance (equal factor loadings), strong invariance (equal factor loadings and intercepts), strict invariance (equal factor loadings, intercepts and uniquenesses), invariance of the latent variance/covariance matrix (equal factor loadings, intercepts, uniquenesses, latent variances and latent covariances), and latent mean invariance (equal factor loadings, intercepts, uniquenesses, latent variances, latent covariances and latent means).

In the context of these comparisons, in addition to reporting Satorra-Bentler scaled chi-square difference tests (Satorra, 2000), we consider changes in goodness-of fit indices (ΔRMSEA, ΔCFI and ΔTLI). More precisely, measurement invariance is supported as long as the imposition of equality constraint does not result in a decrease in CFI/TLI greater than .010, or in increases in RMSEA values greater than .015 when compared to the previous model in the sequence (Chen, 2007; Cheung & Rensvold, 2002; Marsh et al., 2009).

Results from these tests for the bifactor-ESEM academic motivation solution are reported in Table S6 of these online supplements. Matchings tests of measurement invariance conducted on the bifactor-CFA student engagement solution are reported in Table S7 of these online supplements. These results are generally consistent across measures and comparisons in supporting most layers of measurement invariance, as almost none of the comparisons resulted in a change in model fit exceeding the recommended guidelines (ΔCFI/TLI ≤ -.010 and ΔRMSEA ≤ +.015). In fact, the sole exception to this generic conclusion is related to the strict invariance of the bifactor-CFA solution for student engagement, which was not supported across linguistic groups, leading us to pursue a solution of partial invariance. This solution of strict partial invariance was supported by the data, and showed that the lack of strict invariance was limited to a single effort/attention item (behavioral engagement: i.e., *I pay attention in class* or *Ich bin aufmerksam in der Klasse/Je suis attentif en classe*, respectively in German and French), which was found to present a slightly higher level of measurement error for German-speaking respondents (standardized uniqueness = .500) than for French-speaking respondents (standardized uniqueness = .259). Overall, these results suggest that the retained measurement models are quite stable and reasonably invariant up to the level of latent means, thus contributing to the construct validity of these measures.

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Table S1

Latent Correlations for the Correlated Factors CFA (Above the Diagonal) and Correlated Factors ESEM (Under the Diagonal) Solutions

Academic Motivation	1	2	3	4	5
1. INT	—	.611 (.018)**	.766 (.016)**	.414 (.022)**	-.254 (.030)**
2. EID	.236 (.039)**	—	.674 (.019)**	.889 (.016)**	-.432 (.024)**
3. EIN	.554 (.017)**	.337 (.043)**	—	.635 (.022)**	-.170 (.030)**
4. ER	.328 (.027)**	.195 (.038)**	.292 (.039)**	—	-.287 (.025)**
5. A	-.305 (.026)**	-.194 (.041)**	-.096 (.026)**	-.298 (.032)**	—

Student Engagement	1	2	3	4	5	6
1. BE	—	-.540 (.022)**	.196 (.024)**	.155 (.022)**	.527 (.019)**	.555 (.019)**
2. BB	-.533 (.021)**	—	-.060 (.025)*	-.036 (.027)	-.431 (.022)**	-.312 (.022)**
3. ES	.184 (.024)**	-.032 (.023)	—	-.039 (.024)	.218 (.023)**	.293 (.023)**
4. EL	.170 (.021)**	-.058 (.025)*	-.049 (.023)*	—	.165 (.024)**	.117 (.027)**
5. CS	.573 (.017)**	-.417 (.020)**	.200 (.023)**	.179 (.022)**	—	.650 (.019)**
6. CA	.545 (.018)**	-.281 (.023)**	.287 (.023)**	.107 (.024)**	.618 (.019)**	—

Note. * $p \leq .05$; ** $p \leq .01$; CFA: Confirmatory Factor Analysis. ESEM: Exploratory Structural Equation Model; INT: Intrinsic motivation; EID: Extrinsic-Identified regulation; EIN: Extrinsic-Introjected regulation; ER: External regulation; A: Amotivation; BE: Behavioral engagement: Effort/attention; BB: Behavioral engagement: Boredom/distraction; ES: Emotional engagement: Social; EL: Emotional engagement: Learning; CS: Cognitive engagement: Strategies; CA: Cognitive engagement: Autoregulation.

Table S2

Standardized Factor Loadings (λ) and Uniquenesses (δ) of the Correlated Factors CFA and ESEM Solutions: Academic Motivation

	CFA		ESEM					
Items	λ	δ	INT (λ)	EID (λ)	EIN (λ)	ER (λ)	A (λ)	δ
1. INT								
Item 1	.690 (.012)**	.525	**.927 (.058)****	-.477 (.075)**	-.123 (.034)**	.184 (.068)**	-.083 (.020)**	.049
Item 2	.561 (.018)**	.686	**.655 (.024)****	-.170 (.060)**	-.014 (.025)	.090 (.048)	.137 (.017)**	.597
Item 3	.666 (.014)**	.557	**.635 (.025)****	.118 (.023)**	.053 (.029)	-.150 (.022)**	-.005 (.018)	.553
Item 4	.740 (.011)**	.452	**.794 (.021)****	.138 (.033)**	-.120 (.024)**	-.058 (.027)*	-.021 (.015)	.416
Item 5	.769 (.011)**	.409	**.773 (.024)****	.279 (.030)**	-.062 (.028)*	-.134 (.041)**	.017 (.014)	.351
Item 6	.743 (.012)**	.448	**.616 (.022)****	.247 (.030)**	.145 (.029)**	-.191 (.039)**	-.051 (.015)**	.397
Item 7	.690 (.012)**	.524	**.611 (.021)****	.047 (.031)	.159 (.024)**	-.085 (.022)**	.061 (.015)**	.528
Item 8	.658 (.013)**	.568	**.344 (.020)****	.039 (.025)	.504 (.023)**	-.062 (.019)**	.021 (.016)	.450
ω	.880		.896					
2. EID								
Item 12	.719 (.012)**	.483	.251 (.019)**	**.221 (.067)****	.036 (.025)	.381 (.036)**	-.148 (.019)**	.503
Item 13	.774 (.013)**	.401	.158 (.017)**	**.340 (.082)****	-.009 (.024)	.493 (.054)**	-.130 (.016)**	.395
Item 14	.738 (.014)**	.456	.117 (.020)**	**.200 (.068)****	.207 (.030)**	.383 (.030)**	-.160 (.018)**	.493
ω	.788			.294				
3. EIN								
Item 9	.726 (.013)**	.473	.229 (.023)**	.083 (.024)**	**.392 (.032)****	.198 (.022)**	-.013 (.017)	.531
Item 10	.751 (.012)**	.436	.201 (.022)**	.024 (.022)	**.593 (.027)****	.034 (.020)	-.027 (.013)*	.437
Item 11	.722 (.013)**	.478	.080 (.019)**	-.063 (.022)**	**.743 (.027)****	.061 (.026)*	-.019 (.012)	.369
ω	.777				.691			
4. ER								
Item 15	.541 (.022)**	.708	.029 (.022)	.247 (.053)**	.048 (.028)	**.392 (.055)****	.007 (.018)	.715
Item 16	.841 (.014)**	.292	.005 (.017)	.331 (.076)**	.084 (.020)**	**.620 (.064)****	-.078 (.012)**	.319
Item 17	.574 (.022)**	.671	-.125 (.019)**	.101 (.045)*	.303 (.024)**	**.468 (.031)****	.033 (.017)	.636
ω	.696					.567		
5. A								
Item 18	.736 (.017)**	.458	-.065 (.016)**	.008 (.019)	-.055 (.020)**	.061 (.020)**	**.714 (.018)****	.472
Item 19	.687 (.018)**	.528	.095 (.016)**	.015 (.017)	-.002 (.019)	.082 (.018)**	**.755 (.018)****	.493
Item 20	.718 (.017)**	.485	.044 (.015)**	-.035 (.015)*	.057 (.019)**	.066 (.014)**	**.748 (.019)****	.474
ω	.757						.774	

Note. * $p \leq .05$; ** $p \leq .01$; CFA: Confirmatory Factor Analysis. ESEM: Exploratory Structural Equation Model; INT: Intrinsic motivation; EID: Extrinsic-Identified regulation; EIN: Extrinsic-Introjected regulation; ER: External regulation; A: Amotivation; Target (main) factor loadings are marked in bold.

Table S3

Standardized Factor Loadings (λ) and Uniquenesses (δ) of the Bifactor-CFA Solution: Academic Motivation

Items	G (λ)	S-INT (λ)	S-EID (λ)	S-EIN (λ)	S-ER (λ)	S-A (λ)	δ
1. INT							
Item 1	.437 (.021)**	.558 (.018)**					.498
Item 2	.329 (.023)**	.480 (.021)**					.661
Item 3	.408 (.028)**	.539 (.025)**					.543
Item 4	.494 (.023)**	.573 (.021)**					.427
Item 5	.521 (.026)**	.575 (.026)**					.397
Item 6	.541 (.031)**	.490 (.032)**					.468
Item 7	.455 (.031)**	.510 (.031)**					.533
Item 8	.543 (.036)**	.349 (.042)**					.584
ω		.801					
2. EID							
Item 12	.690 (.023)**		.168 (.074)*				.495
Item 13	.712 (.034)**		.277 (.095)**				.417
Item 14	.705 (.020)**		.293 (.064)**				.417
ω			.291				
3. EIN							
Item 9	.624 (.025)**			.315 (.045)**			.511
Item 10	.590 (.033)**			.483 (.044)**			.419
Item 11	.558 (.033)**			.522 (.041)**			.417
ω				.564			
4. ER							
Item 15	.461 (.025)**				.264 (.047)**		.718
Item 16	.708 (.027)**				.522 (.064)**		.226
Item 17	.476 (.024)**				.271 (.041)**		.700
ω					.405		
5. A							
Item 18	-.353 (.022)**					.632 (.017)**	.475
Item 19	-.190 (.027)**					.680 (.018)**	.502
Item 20	-.224 (.027)**					.694 (.019)**	.468
ω	.910					.736	

Note. * $p \leq .05$; ** $p \leq .01$; CFA: Confirmatory Factor Analysis. INT: Intrinsic motivation; EID: Extrinsic-Identified regulation; EIN: Extrinsic-Introjected regulation; ER: External regulation; A: Amotivation; G: Global dimension; S: Specific facet.

Table S4

Standardized Factor Loadings (λ) and Uniquenesses (δ) of the Correlated Factors CFA and ESEM Solutions: Student Engagement

	CFA		ESEM						
Items	λ	δ	BE (λ)	BB (λ)	ES (λ)	EL (λ)	CS (λ)	CA (λ)	δ
1. BE									
Item 1	.816 (.013)**	.335	**.823 (.022)****	.012 (.014)	-.007 (.010)	-.032 (.009)**	-.030 (.015)	.024 (.016)	.350
Item 2	.916 (.007)**	.161	**.988 (.019)****	.008 (.012)	-.005 (.008)	-.020 (.008)*	-.025 (.012)*	-.050 (.014)**	.116
Item 3	.747 (.012)**	.442	**.616 (.026)****	-.033 (.016)*	.037 (.013)**	.057 (.013)**	.078 (.019)**	.072 (.021)**	.443
ω	.868		.866						
2. BB									
Item 4	.652 (.015)**	.575	-.031 (.019)	**.656 (.019)****	.137 (.014)**	-.024 (.014)	-.020 (.020)	.052 (.021)*	.538
Item 5	.769 (.013)**	.408	-.016 (.017)	**.734 (.018)****	-.098 (.012)**	.044 (.013)**	-.050 (.017)**	.013 (.017)	.406
Item 6	.859 (.010)**	.261	.031 (.013)*	**.885 (.016)****	-.018 (.009)*	-.002 (.010)	.047 (.015)**	-.059 (.014)**	.246
ω	.807			.813					
3. ES									
Item 7	.842 (.011)**	.291	.020 (.014)	-.027 (.013)*	**.827 (.012)****	.008 (.010)	-.012 (.015)	.005 (.016)	.309
Item 8	.793 (.013)**	.372	.002 (.014)	.053 (.014)**	**.793 (.015)****	-.065 (.011)**	.000 (.017)	.032 (.018)	.346
Item 9	.695 (.015)**	.517	-.006 (.017)	-.025 (.015)	**.712 (.016)****	.072 (.012)**	.025 (.017)	-.045 (.018)*	.503
ω	.821				.824				
4. EL									
Item 10	.780 (.021)**	.392	.000 (.015)	-.006 (.015)	.020 (.011)	**.784 (.021)****	-.047 (.019)*	.071 (.017)**	.383
Item 11	.648 (.021)**	.579	-.014 (.018)	.035 (.015)*	-.008 (.013)	**.646 (.021)****	.029 (.022)	-.027 (.019)	.583
Item 12	.506 (.020)**	.744	-.001 (.021)	-.008 (.020)	-.008 (.015)	**.514 (.019)****	.015 (.025)	-.063 (.026)*	.736
ω	.686					.689			
5. CS									
Item 13	.580 (.017)**	.663	.074 (.021)**	-.116 (.019)**	.006 (.016)	.032 (.017)	**.457 (.032)****	.006 (.024)	.668
Item 14	.709 (.014)**	.497	.010 (.016)	.076 (.014)**	-.002 (.012)	-.023 (.012)	**.720 (.030)****	.035 (.022)	.488
Item 15	.799 (.013)**	.361	-.046 (.015)**	-.014 (.013)	.008 (.010)	-.010 (.010)	**.843 (.035)****	-.005 (.022)	.327
ω	.741						.733		
6. CA									
Item 16	.606 (.018)**	.633	.101 (.022)**	-.025 (.018)	-.027 (.015)	.121 (.017)**	.090 (.025)**	**.462 (.029)****	.617
Item 17	.757 (.015)**	.428	-.050 (.016)**	-.011 (.012)	.026 (.011)*	-.024 (.011)*	-.062 (.021)**	**.848 (.031)****	.368
Item 18	.807 (.012)**	.348	.016 (.017)	.015 (.014)	-.017 (.011)	-.039 (.011)**	.043 (.021)*	**.775 (.031)****	.361
ω	.770							.764	

Note. * $p \leq .05$; ** $p \leq .01$; CFA: Confirmatory Factor Analysis. ESEM: Exploratory Structural Equation Model; BE: Behavioral engagement: Effort/attention; BB: Behavioral engagement: Boredom/distraction; ES: Emotional engagement: Social; EL: Emotional engagement: Learning; CS: Cognitive engagement: Strategies; CA: Cognitive engagement: Autoregulation; G: Global dimension; S: Specific facet; Target (main) factor loadings are marked in bold.

Table S5

Standardized Factor Loadings (λ) and Uniquenesses (δ) of the Bifactor-CFA and Bifactor-ESEM Solutions: Student Engagement

	Bifactor-CFA			Bifactor-ESEM							
Items	G (λ)	S (λ)	δ	G (λ)	BE (λ)	BB (λ)	ES (λ)	EL (λ)	CS (λ)	CA (λ)	δ
1. BE											
Item 1	.607 (.021)**	.525 (.028)**	.356	**.609 (.020)****	**.515 (.029)****	-.067 (.015)**	-.004 (.012)	-.015 (.011)	-.011 (.015)	.030 (.013)*	.358
Item 2	.678 (.018)**	.662 (.023)**	.102	**.688 (.019)****	**.645 (.028)****	-.093 (.010)**	-.008 (.010)	.004 (.009)	-.006 (.011)	-.014 (.010)	.101
Item 3	.684 (.017)**	.330 (.028)**	.423	**.726 (.024)****	**.278 (.034)****	.000 (.018)	.004 (.013)	.037 (.013)**	-.062 (.024)**	-.042 (.021)*	.388
ω		.723			.709						
2. BB											
Item 4	-.297 (.027)**	.581 (.019)**	.575	**-.299 (.028)****	-.094 (.020)**	**.585 (.021)****	.168 (.017)**	-.025 (.015)	-.045 (.020)*	.047 (.019)*	.526
Item 5	-.464 (.024)**	.598 (.021)**	.427	**-.473 (.023)****	-.037 (.016)*	**.600 (.020)****	-.047 (.013)**	.070 (.014)**	-.014 (.016)	.055 (.018)**	.405
Item 6	-.456 (.023)**	.750 (.019)**	.229	**-.480 (.024)****	-.025 (.016)	**.717 (.020)****	.036 (.012)**	.030 (.013)*	.042 (.016)**	.022 (.018)	.250
ω		.751				.754					
3. ES											
Item 7	.286 (.023)**	.794 (.014)**	.289	**.221 (.024)****	.026 (.012)*	.009 (.014)	**.801 (.013)****	-.023 (.012)	.014 (.014)	.054 (.014)**	.304
Item 8	.230 (.026)**	.762 (.014)**	.367	**.205 (.025)****	-.031 (.015)*	.103 (.016)**	**.768 (.014)****	-.103 (.013)**	-.021 (.016)	.041 (.016)*	.343
Item 9	.243 (.022)**	.661 (.016)**	.505	**.189 (.023)****	-.005 (.017)	.015 (.016)	**.676 (.015)****	.043 (.013)**	.020 (.016)	.003 (.017)	.504
ω		.809					.814				
4. EL											
Item 10	.197 (.020)**	.738 (.020)**	.417	**.201 (.024)****	-.023 (.018)	.046 (.018)*	-.031 (.014)*	**.734 (.020)****	-.049 (.019)*	.002 (.020)	.415
Item 11	.092 (.022)**	.660 (.020)**	.556	**.035 (.024)**	.061 (.017)**	.001 (.017)	-.026 (.015)	**.684 (.023)****	.099 (.018)**	.033 (.018)	.516
Item 12	.077 (.021)**	.508 (.019)**	.736	**.104 (.025)****	-.039 (.020)*	.030 (.021)	-.054 (.016)**	**.496 (.019)****	-.033 (.023)	-.090 (.022)**	.728
ω		.680						.688			
5. CS											
Item 13	.542 (.017)**	.216 (.027)**	.660	**.532 (.025)****	-.018 (.026)	-.069 (.021)**	-.018 (.016)	.028 (.017)	**.237 (.030)****	-.027 (.027)	.654
Item 14	.543 (.018)**	.473 (.032)**	.481	**.506 (.019)****	.013 (.014)	.035 (.014)**	.017 (.014)	.008 (.014)	**.526 (.029)****	.099 (.016)**	.456
Item 15	.623 (.017)**	.528 (.037)**	.332	**.617 (.020)****	-.058 (.018)**	-.013 (.015)	.008 (.012)	.009 (.012)	**.513 (.033)****	.038 (.021)	.352
ω		.601							.527		
6. CA											
Item 16	.585 (.020)**	.228 (.028)**	.606	**.579 (.022)****	-.022 (.020)	.061 (.017)**	-.024 (.016)	.095 (.017)**	-.001 (.020)	**.252 (.030)****	.587
Item 17	.528 (.021)**	.614 (.038)**	.344	**.503 (.021)****	-.010 (.014)	.044 (.013)**	.093 (.014)**	-.033 (.014)*	.036 (.015)*	**.622 (.042)****	.347
Item 18	.598 (.019)**	.517 (.035)**	.375	**.570 (.023)****	.012 (.020)	.063 (.016)**	.046 (.013)**	-.045 (.012)**	.081 (.018)**	**.535 (.044)****	.374
ω	.855	.582		.848						.603	

Note. * $p \leq .05$; ** $p \leq .01$; CFA: Confirmatory Factor Analysis. ESEM: Exploratory Structural Equation Model; BE: Behavioral engagement: Effort/attention; BB: Behavioral engagement: Boredom/distraction; ES: Emotional engagement: Social; EL: Emotional engagement: Learning; CS: Cognitive engagement: Strategies; CA: Cognitive engagement: Autoregulation; G: Global dimension; S: Specific facet; Target (main) factor loadings are marked in bold.

Table S6

Tests of Measurement Invariance: Academic Motivation

	χ^2	*df*	*CFI*	*TLI*	*RMSEA [90% CI]*	$\Delta\chi 2$	Δ*df*	Δ*CFI*	Δ*TLI*	Δ*RMSEA*
Gender										
Configural	713.933*	170	.976	.946	.040 [.037; .043]					
Weak	845.155*	254	.974	.961	.034 [.031; .037]	148.172*	84	-.002	+.015	-.006
Strong	916.336*	268	.971	.959	.035 [.032; .037]	82.684*	14	-.003	-.002	+.001
Strict	1052.436*	288	.966	.955	.036 [.034; .039]	111.539*	20	-.005	-.004	+.001
Latent variance-covariance	1138.166*	309	.963	.955	.036 [.034; .039]	84.322*	21	-.003	.000	.000
Latent means	1269.786*	315	.958	.949	.039 [.037; .041]	122.475*	6	-.005	-.006	+.003
Language										
Configural	639.326*	170	.980	.954	.037 [.034; .040]					
Weak	866.638*	254	.973	.960	.034 [.032; .037]	234.272*	84	-.007	+.006	-.003
Strong	1056.087*	268	.966	.951	.038 [.036; .041]	233.589*	14	-.007	-.009	+.004
Strict	1228.038*	288	.959	.946	.040 [.038; .042]	185.263*	20	-.007	-.005	+.002
Latent variance-covariance	1385.385*	309	.953	.942	.041 [.039; .044]	192.271*	21	-.006	-.004	+.001
Latent means	1506.997*	315	.948	.937	.043 [.041; .045]	43.763*	6	-.005	-.005	+.002
Age groups										
Configural	826.584*	255	.975	.943	.041 [.038; .044]					
Weak	1082.339*	423	.971	.961	.034 [.032; .037]	282.072*	168	-.004	+.018	-.007
Strong	1219.817*	451	.966	.957	.036 [.033; .038]	156.166*	28	-.005	-.004	+.002
Strict	1279.468*	491	.965	.959	.035 [.032; .037]	80.712*	40	-.001	+.002	-.001
Latent variance-covariance	1355.615*	533	.964	.961	.034 [.032; .036]	80.994*	42	-.001	+.002	-.001
Latent means	1435.439*	545	.961	.959	.035 [.033; .037]	63.118*	12	-.003	-.002	+.001

Note. *$p < .01$; χ^2: chi square; df: degrees of freedom; CFI: Comparative Fit Index; TLI: Tucker-Lewis Index; RMSEA: Root Mean Square Error of Approximation; CI: Confidence Interval; Δ: Change relative to the previous model.

Table S7

Tests of Measurement Invariance: Student Engagement

	χ^2	*df*	*CFI*	*TLI*	*RMSEA [90% CI]*	$\Delta\chi 2$	Δdf	ΔCFI	ΔTLI	$\Delta RMSEA$
Gender										
Configural	952.985*	224	.963	.949	.040 [.038; .043]					
Weak	958.777*	247	.964	.955	.038 [.035; .040]	21.574	23	+.001	+.006	-.002
Strong	1057.872*	258	.959	.952	.039 [.037; .042]	103.047*	11	-.005	-.003	+.001
Strict	1131.889*	276	.956	.952	.039 [.037; .042]	73.962*	18	-.003	.000	.000
Latent variance-covariance	1207.650*	283	.953	.949	.040 [.038; .043]	80.807*	7	-.003	-.003	+.001
Latent means	1340.491*	290	.946	.943	.042 [.040; .045]	113.415*	7	-.007	-.006	+.002
Language										
Configural	929.752*	224	.965	.952	.039 [.037; .042]					
Weak	989.951*	247	.963	.954	.039 [.036; .041]	66.175*	23	-.002	+.002	.000
Strong	1096.261*	258	.958	.951	.040 [.038; .043]	111.755*	11	-.005	-.003	+.001
Strict	1415.056*	276	.943	.937	.045 [.043; .048]	267.128*	18	-.015	-.014	+.005
Partial strict	1180.062*	275	.955	.950	.040 [.038; .043]	81.346*	17	-.003	-.001	.000
Latent variance-covariance	1228.356*	282	.953	.949	.041 [.038; .043]	48.994*	7	-.002	-.001	+.001
Latent means	1271.303*	289	.951	.948	.041 [.039; .043]	39.050*	7	-.002	-.001	.000
Age groups										
Configural	1041.798*	336	.964	.951	.040 [.037; .042]					
Weak	1047.868*	382	.966	.960	.036 [.033; .039]	26.541	46	+.002	+.009	-.004
Strong	1104.585*	404	.965	.960	.036 [.033; .038]	56.547*	22	-.001	.000	.000
Strict	1320.954*	440	.956	.954	.039 [.036; .041]	190.337*	36	-.009	-.006	+.003
Latent variance-covariance	1326.695*	454	.956	.956	.038 [.035; .040]	6.698	14	.000	+.002	-.001
Latent means	1350.861*	468	.956	.956	.037 [.035; .040]	27.319	14	.000	.000	-.001

Note. $*p < .01$; χ^2: chi square; df: degrees of freedom; CFI: Comparative Fit Index; TLI: Tucker-Lewis Index; RMSEA: Root Mean Square Error of Approximation; CI: Confidence Interval; Δ: Change relative to the previous model.