# Predictors, Outcomes, and Inter-Domain Connections of German and Math Academic Motivation Profiles

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## Abstract

The present study investigated the nature and similarity of academic motivation profiles toward German and Math among German elementary school students while accounting for the dual global and specific nature of academic motivation proposed by self-determination theory. The determinants (self-concept, sex) and outcomes (anxiety, academic achievement, effort) were investigated. Latent Markov analyses revealed five profiles (*Highly Extrinsic*, *Controlled*, *Moderately Extrinsic*, *Self-Determined*, and *Non-Motivated*) characterized by differing levels of global and specific motivation. These profiles had similar properties (within-sample similarity) and had a similar membership (within-person similarity) across domains. Self-concept predicted membership into profiles with higher global self-determination, while girls were more likely to belong to the *Highly Extrinsic* profile. Most desirable outcomes were associated with the *Self-Determined* profile, then the *Moderately Extrinsic* profile, followed by the remaining three profiles.

**Keywords:** self-determination theory (SDT); academic motivation; self-concept; latent profile analysis (LPA); elementary school.

Over the years, educational psychological research has clearly documented the key role played by academic motivation in students' school performance and persistence (Howard et al., 2021a; Wigfield et al., 2012). Self-determination theory (SDT; Ryan & Deci, 2017) posits that students' academic motivation, also referred to as behavioral regulations, presents well-differentiated links with a series of outcomes related to their performance, well-being, and persistence (Howard et al., 2021a). Despite their qualitatively distinct nature, these behavioral regulations are also assumed to differ quantitatively from one another, being organized along a theoretical continuum of self-determination, reflecting the extent to which each student's motivational orientation can be considered to be dominated by autonomously-driven motives (e.g., Howard et al., 2018, 2020; Litalien et al., 2017).

SDT acknowledges that most students will typically be driven by a combination of multiple behavioral regulations (Ryan & Deci, 2017; Vallerand, 1997). Person-centered studies (Morin & Litalien, 2019) are naturally suited to uncover which combinations of behavioral regulations most commonly co-occur within distinct subpopulations, or profiles, of students (e.g., Gillet et al., 2017). Although prior research has looked at the nature of university and secondary students' motivation profiles (for a review, see Gillet et al., 2017), no effort has yet been made in the educational area to consider these profiles while relying on a proper disaggregation of the global (i.e., reflecting the overarching continuum structure of motivation) versus specific (i.e., reflecting the unique contribution of each type of behavioral regulation) nature of academic motivation. Given the recognized dual global/specific nature of academic motivation (Howard et al., 2020; Ryan & Deci, 2017), it seems critical for research seeking to achieve a comprehensive understanding of academic motivation to jointly consider both components rather than to adopt a piecemeal approach focused on only one of those components. The present study was designed to specifically address this limitation.

More precisely, the present study sought to identify profiles of elementary school students characterized by different configurations of academic motivation in two distinct school subjects, Math and German. In doing so, this study contributes to our understanding of academic motivation by (1) accounting for the inherent duality (global/specific) of academic motivation; (2) assessing the similarity of the profiles identified across the Math and German domains within our sample (the degree to which the nature of the profiles is similar or different across domains) and within our participants (the extent to which membership into specific profiles overlaps across domains); (3) considering the role of Math and German self-concept and sex as possible predictors of academic motivation profiles; (4) assessing the construct validity of the profiles in relation to key educational outcomes (i.e., perceived effort, anxiety, and academic performance in Math and German); and (5) considering the reality of elementary school students, who are relatively underrepresented in motivational research relative to secondary school and university students.

Finally, the present study relied on an integrative approach to study affective-motivational constructs (see also Gogol et al., 2017; Guay & Bureau, 2018) which entails, on the one hand, investigating relations across affective-motivational constructs within a given school subject (e.g., associations between different forms of motivation, self-concept, and effort, all directed at German) which reflects a within-subject differentiation (Guay & Bureau, 2018; Wolters & Pintrich, 1998). On the other hand, we also investigate relations between affective-motivational constructs directed at different school subjects (e.g., motivation directed at both German and Math; Guay & Bureau, 2018; Guay et al., 2010). With this approach, the constructs of interest are considered to have been assessed as part of a quasi-repeated measures design to examine how similar the nature of the profiles and student profile membership would be across both school subjects (i.e., with school subjects treated as a repeated measure). This approach allowed us to investigate not only whether the same set of profiles would be estimated across subjects, but also how students' profile membership differed, or not, across Math and German (i.e., students could have a differential membership in these two sets of profiles).

**Academic Motivations and Motivation Profiles**

According to SDT (Ryan & Deci, 2017), students can be motivated for a variety of reasons, all of which can be organized along a continuum of self-determination (representing students' global sense of volition and self-directedness) (Howard et al., 2018, 2020). At the most self-determined extreme of this continuum, intrinsic motivation refers to engaging in and performing an activity for the enjoyment and satisfaction that it affords. Identified regulation refers to engaging in an activity because it is perceived as personally important and valued. Intrinsic motivation and identified regulations are typically referred to as autonomous forms of motivation because they symbolize self-driven forms of academic engagement. Next on the continuum comes introjected regulation, which occurs when engagement is driven by internal pressures (e.g., pursuit of self-worth, or avoidance of shame or guilt). Then, external regulation denotes engagement in an activity that is driven by external pressures (e.g., avoidance of punishments or obtainment of rewards). Introjected and external regulations are typically described as controlled forms of motivation because they reflect forms of academic engagement that are mainly driven by internal or external factors. Finally, at the other end of the continuum, amotivation refers to an absence of intention and a lack of drive to engage in academic activities.

Although the predictive validity of these different forms of motivation has been documented using variable-centered analyses (Guay et al., 2008; Ryan & Deci, 2009), these analyses ignore the fact that individual students tend to endorse more than one type of motivation (Vallerand, 1997), so that the effects of each type of motivation may change as a function of the context created by the others. For example, when experienced on its own, external regulation suggests that students feel forced to engage in activities seen as neither interesting nor important as a result of the mandatory nature of elementary education. In contrast, when experienced with high intrinsic motivation and identified regulation, external regulation may reflect a desire to avoid disappointing one's family who is supporting an already high academic involvement.

Adopting a person-centered perspective makes it possible to consider the diverse configurations of behavioral regulations most frequently observed among students, as well as their outcomes. Although several studies adopted such a perspective to identify the most commonly occurring motivational profiles, few of them have considered elementary school students. The results from studies conducted among samples of elementary and secondary students are summarized in Table S1 of the online supplements. These studies have either relied on global indicators of autonomous and controlled motivation (Corpus & Wormington, 2014; Oga-Baldwin & Fryer, 2017) or considered the wider range of behavioral regulations proposed by SDT (Lv et al., 2019; Oga-Baldwin & Fryer, 2018, 2020a, 2020b). Regardless of how motivation was operationalized, these studies have generally converged on the identification of a very similar set of profiles among elementary (Corpus & Wormington, 2014; Oga-Baldwin & Fryer, 2017) and secondary (Hayenga & Corpus, 2010; Vansteenkiste et al., 2009; Wormington et al., 2012) students: (a) autonomous (high autonomous and low controlled: HA-LC); (b) strongly motivated (high autonomous and high controlled: HA-HC); (c) controlled (low autonomous and high controlled: LA-HC); and (d) non-motivated (low autonomous and low controlled: LA-LC). However, other unique configurations have also been identified: a moderately autonomous-HC profile (Lv et al., 2019), a profile characterized by moderate (Oga-Baldwin & Fryer, 2020b; Ratelle et al., 2007) or low (Liu et al., 2009) levels of motivation across all types of behavioral regulations.

Looking at these results more holistically, these studies suggest that some core profiles (i.e., HA-HC, LA-LC, HA-LC, LA-HC) emerge regularly. However, this similarity becomes progressively less apparent when one moves from a simpler (autonomous vs. controlled) to a more complex multidimensional representation of academic motivation (including all specific types of behavioral regulation with, or without, amotivation). For example, when separating autonomous motivation into intrinsic and identified regulations while also considering controlled motivation, Lv et al. (2019) identified a profile characterized by low intrinsic/identified regulation and average controlled motivation. Similarly, both Oga-Baldwin & Fryer (2020b) and Ratelle et al. (2007) identified profiles in which moderate (rather than low) autonomous motivation was coupled with moderate introjected and external regulation. Interestingly, while amotivation typically clusters with the controlled forms of motivation, more discrepancies can be observed with respect to introjected regulation. In some cases, it clusters with controlled forms of motivation (e.g., Liu et al., 2009) whereas in other cases, it clusters with autonomous forms of motivation (Oga-Baldwin & Fryer, 2018). Although the profiles in these specific examples show similarities with the four core profiles mentioned above (HA-HC, LA-LC, HA-LC, LA-HC), their nature is also clearly distinct from them, suggesting that additional profiles might be identified when relying on a wider range of behavioral regulations.

Furthermore, none of these studies have considered the dual global (i.e., reflecting the student position on the global continuum of self-determination) versus specific (i.e., reflecting the unique nature of each type of behavioral regulation) nature of academic motivation among elementary school students. This limitation is particularly important given that ignoring this dual nature is likely to mask finer-grained shape-related (i.e., qualitative) differences between the various motivational profiles. Indeed, when global (i.e., self-determination) and specific (i.e., intrinsic, identified, etc.) constructs co-exist, the failure to properly disaggregate these two layers of analyses led to a lack of precision when identifying latent profiles (Morin et al., 2016b, 2017; Morin & Marsh, 2015), making it impossible to isolate which unique behavioral regulation influences students' motivation profiles beyond their global level of self-determination. Going back to the earlier example of external regulation, which might be salient among this age group given the mandatory nature of schooling, using a traditional operationalization of academic motivation we might come to realize that all profiles display some levels of external regulation, although for many profiles this external regulation may simply reflect a more generalized drive to engage in the activity. The ability of our approach is to isolate profiles that are primarily driven by external regulation beyond their global level of self-determined regulation.

As such, while previous studies remain informative, most of their profiles are likely impacted by "level effects" (Morin & Marsh, 2015) whereby profile definition is dominated by an unexpressed global self-determination factor. This phenomenon has already been observed with respect to work motivation profiles (Howard et al., 2016, 2021) which systematically tended to display shapes matching the SDT continuum (e.g., high intrinsic, moderately high identified, average introjected, moderately low external, low amotivation) when the dual global-specific nature of motivation is not explicitly considered. Despite recent developments, no study has so far adopted this approach to investigate profiles of academic motivation among elementary student samples and done so while considering their generalizability and connections across domains. Therefore, the present study was designed to comprehensively examine the multidimensional nature of German and Math academic motivation profiles while relying on a proper disaggregation of the global and specific components of academic motivation. Despite the novelty of this approach, previous studies allow us to expect that:

**Hypothesis 1.** Students' academic motivation will be best represented by four to six profiles.

**Hypothesis 2.** A subset of these profiles will match the commonly occurring configurations (i.e., LA-LC, LA-HC, moderate, HA-LC, HA-HC) reported in previous research.

**Hypothesis 3.** Additional profiles displaying differentiated configurations of motivation across specific dimensions will also be identified. Given the mandatory nature of elementary school, we expect at least one of the profiles to be characterized by external regulation.

To further enrich our understanding of elementary students' academic motivation profiles and to more systematically assess the generalizability of these profiles, we also examined the extent to which these will have similar (or different) properties across two distinct school subjects (Math and German) at the sample and individual levels (Kam et al., 2016; McLarnon et al., 2021; Morin et al., 2020). Whereas the former type of profile similarity refers to the extent to which the nature of the profiles remains unchanged across subjects, the latter refers to the extent to which individual students correspond to the same motivation profiles in German and Math.

To our knowledge, no study has yet sought to examine either form of profile similarity among samples of students. However, while Oga-Baldwin and Fryer (2020b) did not formally test the within-sample similarity of the profiles across domains, their results showed that Japanese and English motivation profiles tended to be characterized by very similar shapes. Likewise, Corpus and Wormington (2014) and Oga-Baldwin and Fryer (2018) both reported moderate-to-high longitudinal stability in students' membership into various academic motivation profiles. To our knowledge, only two studies conducted among samples of university students have formally investigated profile similarity. In one of those studies, Litalien et al. (2019) investigated the degree to which the nature of academic motivation profiles would be similar across subpopulations of students defined based on their sex (i.e., male or female) or age group (17 to 20; 21 to 23; 24+). The results from these tests supported the complete similarity of their profiles across these subsamples. In the second study, Gillet et al. (2017) more formally investigated, and found support for, the longitudinal within-sample stability of academic motivation profiles and reported that student's membership into these profiles was characterized by a moderate (49.2%) to high (95.9%) within-person stability across profiles. In this study, we expand upon these studies to consider a perhaps even more stringent form of profile similarity by considering the within-sample and within-person similarity of students' academic motivation profiles across Math and German subjects. Based on the aforementioned evidence, we tentatively propose the following hypotheses:

**Hypothesis 4.** We expect to find evidence of within-sample similarity related to the number (configural similarity), shape (structural similarity), within-profile variability (dispersion similarity), and the relative sizes of the profiles (distributional similarity) of the Math and German academic motivation profiles.

**Hypothesis 5.** Profiles will display a moderate-to-high within-person similarity.

**Determinants of Motivation Profiles**

In person-centered analyses, it is important to document the construct validity of the profiles identified in any given study in relation to theoretically meaningful predictors and outcomes to support their interpretation as reflecting meaningful subpopulations (Meyer & Morin, 2016). Academic self-concept has long been recognized as a critically important driver of educational success (Craven & Marsh, 2008; Marsh, 2007), and shown to contribute to positive school attitudes (e.g., Green et al., 2012) and academic performance (e.g., Marsh & Martin, 2011). Self-concept is a multidimensional and hierarchical construct, where the top of the hierarchy is occupied by youth's global self-concepts, with domain-specific self-concepts (e.g., academic, social, or physical) located at the next level of the hierarchy (Shavelson et al., 1976). Thus, whereas the global self-concept reflects students' perceptions of themselves across different domains, the academic self-concept describes students' mental representations of their educational abilities (Craven & Marsh, 2008). This global academic self-concept itself can be divided into subject-specific self-concepts (e.g., math, language) organized along a continuum ranging from Math to verbal subjects (Marsh, 1990, 2007) with science-related domain falling closer to the Math end of the continuum, and humanities-related subjects falling closer to the verbal end of the continuum (Marsh et al., 2014). Because of this organization along a continuum, it appears particularly important for research on the academic self-concept to consider the two extremes of this continuum (Marsh, 1990; Marsh et al., 2015). For this reason, we simultaneously consider Math and German (main language) self-concepts in the present study as potential profile predictors.

Regarding the associations between self-concept and academic motivation, both SDT (Ryan & Deci, 2017) and self-concept theory (Marsh, 2007) propose that students who see themselves as competent academically and confident in their ability to effectively perform academic tasks should be more likely to experience autonomous, as opposed to controlled, forms of motivation. Students who feel competent have a more internal locus of causality and thus tend to experience their involvement in academic work as being more self-determined and less internally or externally pressured. As a result, more adaptive forms of academic motivation are posited to emerge as a result of more positive academic self-concepts (Deci & Ryan, 1985). This proposition has been supported by multiple cross-sectional (Chanal & Guay, 2015; van den Berg & Coetzee, 2014; Wang et al., 2019) and longitudinal (Guay & Vallerand, 1997; Vallerand et al., 1997) variable-centered studies. Although person-centered studies involving academic motivation and self-concept are scarcer, Liu et al. (2009) reported that, among secondary students, the HA-LC and HA-HC profiles were characterized by the highest self-perceived academic competence, followed by the LA-HC and LA-LC profiles. Thus, we expect that:

**Hypothesis 6.** Higher self-concept will predict a greater likelihood of membership into more desirable profiles.

The consideration of students' sex as another possible predictor of profile membership is predicated on previous results demonstrating that motivational and learning processes tend to vary between boys and girls (Meece et al., 2006; Voyer & Voyer, 2014), although empirical evidence remains mixed and conflicting in this regard. some studies showed that girls were more likely to correspond to profiles dominated by moderate or high levels of autonomous motivation (HA-HC, HA-LC, moderate A-LC) whereas boys were more likely to belong to profiles characterized by moderate levels of motivation across all forms, or to profiles dominated by controlled forms of motivation (LA-HC) (Gillet et al., 2017; Ratelle et al., 2007). In contrast, other studies reported no sex differences in the size of the profiles (Corpus & Wormington, 2014; Liu et al., 2009), or in the definition and size of the profiles (Litalien et al., 2019).

**Research Question 1.** In light of these inconclusive results, we leave as an open research question the presence and direction associations between sex and profile membership.

**Outcomes of Motivation Profiles**

Our final objective is to document the implications of academic motivation profiles for students' functioning. Demonstrating that the extracted latent profiles have well-differentiated and meaningful relations with several relevant educational outcomes is also critical to establishing their construct validity and practical relevance (Meyer & Morin, 2016). Maintaining and improving students' mental health and well-being is recognized as one of the most important public health issues around the world (Cuijpers et al., 2019; Holm-Hadulla & Koutsoukou-Argyraki, 2015). In this regard, anxiety is considered a key indicator of ill-being (Keyes, 2005), and has been linked with a variety of undesirable developmental outcomes (Ost & Treffers, 2001). In the present study, we consider students' experience of anxiety (i.e., defined as an unpleasant emotional reaction characterized by feelings of nervousness, uneasiness, and stressful anticipations) specific to their Math and German lessons (Zeidner, 2007). SDT suggests that higher anxiety should be associated with more controlled forms of motivation (i.e., introjected and external regulations) by making students more aware of, or sensitive to, a variety of internal and external contingencies (e.g., Ryan & Deci, 2017; Ryan & Connell, 1989). In addition, when students are driven by internal or external pressures, they might struggle to allocate enough time to the learning process itself (i.e., the mastery of academic tasks, rather than simply the demonstration of performance on these tasks), thus increasing their likelihood of falling behind in class, which in turn reinforces their risk of experiencing anxiety (Beilock & Maloney, 2015). The few person-centered studies that considered anxiety as an outcome similarly showed that students corresponding to the HA-HC and LA-HC profiles tended to report the highest anxiety, followed by those corresponding to the HA-LC and LA-LC profiles (González et al., 2012; Vansteenkiste et al., 2009).

Academic achievement (typically operationalized as grade point average) is a critical indicator of students' academic functioning and a crucial determinant of educational attainment and earnings in adulthood (French et al., 2015). Person-centered research has demonstrated that students corresponding to the HA-LC and HA-HC profiles tended to present higher academic achievement than those corresponding to the LA-HC or LA-LC profiles (Gillet et al., 2017; Oga-Baldwin & Fryer, 2020a; Vansteenkiste et al., 2009), whereas some of those studies have also suggested that students corresponding to HA-LC profile may present higher academic achievement than those corresponding to the HA-HC profile (Corpus & Wormington, 2014). Finally, effort represents a positive manifestation of students' behavioral engagement in their studies, reflecting the extent to which students invest their capacities, time, and energy in their academic activities (Gillet et al., 2017; McAuley et al., 1989). Person-centered research has shown that students corresponding to the HA-LC profile tended to display higher effort than those corresponding to the other profiles (Gillet et al., 2017; Vansteenkiste et al., 2009; Wang et al., 2017). Considering all of these results, we propose that:

**Hypothesis 7.** The most desirable profiles will display lower anxiety, and higher effort and academic achievement than the less desirable profiles.

## Method

### Participants and Procedure

A total of 529 German fourth graders (250 girls), aged between 9 and 12 years ($M$ = 9.95, $SD$ = 0.65), participated in this study. These students attended 39 classes from 15 elementary schools located in the Lower Saxony region of Germany. In Germany, elementary school ends in fourth grade. Authorization for the study was obtained from the Ministry of Education and the school principals. Parents actively provided their written consent prior to the research. Students were informed of the purpose of the study and assured that their participation was voluntary, that they could withdraw at any time, and that their responses were confidential. Data collection was performed by trained research assistants. All items were read aloud to the children during regular classroom lessons to facilitate understanding. Students took about 20 minutes to complete the questionnaires. All procedures were approved by the university research ethics committee of the second author's institution and were performed according to the ethical principles and human subjects' guidelines of the American Psychological Association (2017).

### Measures

***Academic motivation.*** Students' motivation in German and Math was measured separately with a simplified German version (Freund & Lohbeck, 2021) of the Academic Motivation Scale (Vallerand et al., 1992). Items started with the stem 'I learn German/Math...', followed by three items related to each type of motivation (e.g., external regulation: "because otherwise, I get into troubles with my parents"; introjected regulation: "because otherwise, I have a bad conscience"; identified regulation: "because I would like to learn new things in German/Math"; integrated regulation: "because German/Math can help me in my life"; intrinsic motivation: "because I enjoy German/Math"). In contrast, items for amotivation began with the stem: "I do not learn German/Math", followed by three further items (e.g., "because German/Math makes no fun"). Responses were provided on a 4-point scale (1-*strongly disagree* to 4-*strongly agree*).

***Academic self-concept.*** Self-concept in German and Math was assessed with the short German version of the Self-Description Questionnaire I (SDQ I-GS; Arens et al., 2013). Both domains were assessed using three positively worded items (e.g., "I learn things quickly in German/Math") rated on a 5-point scale (1-*completely false* to 5-*completely true*). The SDQ I-G was derived from the original (English) SDQ-1 (Marsh, 1990), which included 76 items and eight subscales.

***Anxiety***. Children's anxiety when attending German/Math classes was measured with the relevant subscale (focusing on anxiety experienced in the classroom context; 5 items; e.g., "I am scared in German/Math") from Achievement Emotions Questionnaire-Elementary School version (AEQ-ES), initially developed in German (Lichtenfeld et al., 2012). These items were rated on a 5-point scale (1-*not at all* to 5-*very much*).

***Academic achievement.*** Achievement in German and Math was measured by asking students to report their final grades from their last school report. As German grades range from 1 (*excellent*) to 6 (*insufficient*), grades were recoded so that higher values indicate better achievement. While many factors could impact recall accuracy (e.g., memory biases), students self-reported their grades shortly after receiving their school reports (within 1-2 weeks). Their self-reported grades can thus be considered to represent reasonably valid indicators of academic achievement. This assumption is supported by previous studies relying on samples of German fourth graders (Dickhäuser & Plenter, 2005; Schneider & Sparfeldt, 2016), as well as by research reporting high correlations between self-reported and actual school grades (Kuncel et al., 2005; Noftle & Robins, 2007)

***Perceived effort.*** Students' perceived effort in German and Math was measured using three positively worded items (e.g., "I make much effort in German/Math lessons"), derived from the Self-Description Questionnaire I (Marsh, 1990) by Lohbeck (2019). These three items were rated on a 5-point scale (1-*false* to 5-*true*).

## Analyses

### Preliminary Analyses

Preliminary measurement models were estimated to obtain factor scores for the main analyses. To ascertain that the measures were comparable over German and Math domains, factor scores were saved from fully invariant measurement models in standardized units with $M = 0$ and $SD = 1$. More information on these preliminary analyses is provided in Appendix 1 of the online supplements.

### Latent Profile Analyses (LPA) and Latent Markov analyses

LPAs were conducted in Mplus 8.4 (Muthén & Muthén, 2018), using the robust maximum-likelihood estimator (MLR) and design-based correction procedures to account for students' nesting within classrooms (Asparouhov, 2005). Solutions including one to eight profiles were estimated with freely estimated means[1] separately for both German and Math academic motivation. Once the optimal solution was selected for each domain, a LPA solution (where the Math and German domains were considered to be repeated measures for each student) was estimated to conduct tests of within-sample similarity across domains in the following sequence (Morin, & Litalien, 2017; Morin, Meyer, et al., 2016): (1) *configural* (same number of profiles across domains); (2) *structural* (same profile indicator means); (3) *dispersion* (same profile indicator variances); and (4) *distributional* (same relative size).

The most similar longitudinal LPA solution was converted into a single model using a latent Markov connection (Collins & Lanza, 2010; Nylund-Gibson et al., 2014) to assess the within-person similarity of profile membership across the German and Math domains. This approach allowed us to examine whether students with certain German motivation profiles had the same Math motivation profiles. Although these types of analyses are typically used to assess longitudinal stability in profile membership over time (i.e., latent transition analyses), the latent Markov link function underpinning them can be used to connect any forms of person-centered solutions (Nylund-Gibson et al., 2014).

### Predictors and Outcomes

Associations between the predictors and the likelihood of profile membership were assessed by the direct inclusion of the predictors in the latent Markov model using a multinomial logistic regression function. Three alternative models were contrasted. In the first model, these associations were freely estimated for both German and Math domains and the predictions of membership in the Math motivation profiles were free to vary across the German motivation profiles. In a second model, the associations

[1] Models in which the variances of the profile indicators were also freely estimated converge on improper solutions (e.g., negative variance estimates) or failed to converge, suggesting that these models might have been overparameterized (Bauer & Curran, 2003; Chen et al., 2001).

between predictors and profile membership were freely estimated across domains, but not allowed to vary as a function of students' membership into the German motivation profiles. Finally, to test for *predictive similarity*, the third model constrained these predictions to be equal across domains.

The outcomes were directly integrated into the final latent Markov. In a first model, these profile-specific outcome levels were allowed to differ across profiles and domains. In a second model, we tested the *explanatory similarity* of these associations by constraining the means of the outcomes to be equal across domains (Morin, & Litalien, 2019). Mplus' MODEL CONSTRAINT function was used to examine the statistical significance of the mean differences between each pair of profiles, using the multivariate delta method (Raykov & Marcoulides, 2004).

## Results

### Profile Selection and Interpretation

Results pertaining to the selection of the optimal subject-specific LPAs are reported in Appendix 2 of the online supplements. These results converged on the selection of a five-profile solution for both subjects. The results from the further tests of profile similarity conducted across domains are presented in the middle section of Table 1 which supported the complete similarity of this 5-profile solution across domains. The final model of distributional similarity was thus retained for interpretation and further analyses. This solution, identical across domains, is illustrated in Figure 1, and parameter estimates are reported in Table S11 of the online supplements.

Profile 1 (*Highly Extrinsic*; 6.73%) characterized students presenting slightly lower than average global self-determination, accompanied by close to average specific amotivation, intrinsic motivation, identified regulation and integrated regulation, slightly above average specific introjected regulation, and very high specific external regulation. Profile 2 (*Controlled*; 15.30%) characterized students with low global self-determination, close to average specific intrinsic motivation, identified regulation, integrated regulation and amotivation, and moderately high specific introjected and external regulation. Profile 3 (*Moderately Extrinsic*; 15.76%) characterized students presenting slightly lower than average global self-determination coupled with close to average specific intrinsic motivation, identified regulation, integrated regulation and amotivation, slightly above average specific introjected regulation and high external regulation. Despite their conceptual similarity, these three profiles appeared early in the class enumeration process (i.e., they were already present in the 4-profile solution), which supports their relevance. Whereas both the *Highly Extrinsic* and *Moderately Extrinsic* profiles are dominated by high to very high specific extrinsic regulation, the *Controlled* profile is rather dominated by moderately high specific both introjected and external regulations coupled by lower global self-determination than the other two profiles.

Contrasting with these three profiles, Profile 4 (*Self-Determined*; 45.62%) characterized students with higher-than-average global self-determination and specific intrinsic motivation, close to average specific identified regulation, integrated regulation, introjected regulation and amotivation, and lower than average specific external regulation. Finally, Profile 5 (*Non-Motivated;* 16.60%) characterized students presenting low global self-determination, accompanied by moderately low specific intrinsic motivation and external regulation, and by close to average specific identified regulation, integrated regulation, and amotivation.

### Latent Connections between Profiles Across Domains

A latent Markov connection was added to the retained LPA model of distributional similarity to examine whether students tend to have similar or different motivation profiles in German and Math. The joint probabilities of profile membership across domains are reported in Table 2 and graphically depicted in Figure 2. These results show that the *Highly Extrinsic* profile was the most often generalized across domains, with 71.7% of the students corresponding to this profile in one domain also corresponding to the same profile in the other domain. For members of this profile in German who did not display the same profile in Math, the most common Math profile was the *Moderately Extrinsic* (19.2%) and *Controlled* (6%) profiles. The *Moderately Extrinsic* profile presented a moderately high generalizability across domains (60.2%). For students corresponding to this profile in German who did not display the same profile in Math, the most common Math profiles were the *Highly Extrinsic* (17.5%), *Self-Determined* (13.8%), and *Controlled* (8%) profiles. The *Self-Determined* profile also displayed a moderately high generalizability across domains (54.6%). For students corresponding to this profile in German but not in Math, the most common Math profiles were the *Non-Motivated* (17.6%), *Controlled* (15.2%), and *Moderately Extrinsic* (11.6%) profiles. The *Controlled* profile displayed slightly lower generalizability across domains (46.6%). Students corresponding to this profile in German but not in Math were likely to be members of the *Self-Determined* (29.7%), *Moderately Extrinsic* (15.5%), *Non-Motivated* (4.7%), and *Highly Extrinsic* (3.5%) profiles in Math. Finally, the *Non-Motivated* profile was the least generalizable across domains (31.1%), as members of this profile in German were equally likely to correspond to the *Self-Determined* (31.1%) profile in Math. Members of this *Non-Motivated* profile in German were also likely to be members of the *Controlled* (12.6%) and *Moderately Extrinsic* (10.3%) profiles in Math.

**Predictors of Profile Membership**

The results from the predictive models are reported in the bottom section of Table 1 and support the superiority of the model of predictive similarity, suggesting that the relations between the predictors and profiles are equivalent across domains, and that these predictors do not directly contribute to the prediction of specific profile connections across domains. The results from the multinomial logistic regressions estimated within this model are reported in Table 3. These results show that girls were more likely than boys to correspond to the *Highly Extrinsic* profile relative to the *Controlled*, *Moderately Extrinsic,* and *Self-Determined* profiles. Students with a higher self-concept in each domain were more likely to correspond to the *Self-Determined* profile relative to all other profiles, and to the *Moderately Extrinsic* profile relative to the *Controlled* profile. Furthermore, students with higher self-concept in each domain were less likely to correspond to the *Non-Motivated* profile relative to the *Highly Extrinsic*, the *Controlled*, and the *Moderately Extrinsic* profiles.

**Outcomes of Profile Membership**

The results from the models including the outcomes are reported in the lowest section of Table 1 and support the superiority of the model of explanatory similarity. This suggests that the relations between the profiles and the outcomes are equivalent across domains. The results from this last model are reported in Table 4 and reveal that the most adaptive outcomes (i.e., high effort and grades, low anxiety) were associated with the *Self-Determined* profile, followed by the *Moderately Extrinsic* profile. The remaining three profiles (*Highly Extrinsic*, *Controlled*, *Non-Motivated*) did not differ from one another with respect to the outcomes but were all associated with undesirable outcome levels (i.e., low effort and grades, high anxiety).

## Discussion

The present study sought to identify naturally occurring motivational combinations for Math and German classes among a sample of elementary school students. In doing so, we relied on a recent operationalization of academic motivation (Howard et al., 2018, 2020; Litalien et al., 2017) allowing us to achieve a proper disaggregation of students' global self-determined academic motivation from the uniqueness of the specific forms of behavioral regulations in both domains.

**Characteristics of Academic Motivation Profiles**

Supporting Hypothesis 1, we found that five profiles best represented the academic motivation configurations of elementary school students. Supporting Hypothesis 2, three of these five profiles were highly similar to some of the most commonly occurring profiles identified previously while relying on a typical operationalization of academic motivation. Thus, we identified a *Self-Determined* profile which corresponds to the typical HA-LC configuration identified in previous studies (e.g., Corpus & Wormington, 2014). We also identified a *Controlled* profile which presents important similarities with the LA-HC profiles often identified in previous research (e.g., Lv et al., 2019). Finally, we identified a *Non-Motivated* profile which presents similarities with the LA-LC profiles reported in previous studies (e.g., Oda-Baldwin & Fryer, 2020a).

Supporting Hypothesis 3, we also identified two profiles displaying a more precise configuration than what previous studies had been able to identify using a traditional operationalization of academic motivation. The first of these profiles presented a *Moderately Extrinsic* configuration that was clearly dominated by high specific external regulation, while the second of these profiles presented a *Highly Extrinsic* configuration dominated by very high specific external regulation. The identification of these profiles is less surprising when considering the educational system. Typically, elementary school education is compulsory around the world and parents are obligated to send their children to formal educational institutions for a certain period of time. In Germany, students start compulsory education around the age of six and have to complete nine years of formal education (Eurydice, 2021). Even though some students might not be self-driven to go to school, they have to do so for external reasons. At the end of the fourth grade, teachers provide students a formal recommendation for a secondary school track depending on their achievement levels. This educational transition to secondary education might be seen as a strong external drive for students.

Interestingly, the present study is the first to specifically focus on the motivational profiles of elementary school children, and the identification of these two profiles suggests that profiles dominated by external regulation might be more frequent in younger students, as similar profiles have never been identified among older students (e.g., Gillet et al., 2017; Litalien et al., 2019). This tentative conclusion aligns with prior SDT research documenting the decrease of extrinsic motivation over childhood and adolescent years (e.g., Corpus et al., 2009; Lee & Ju, 2021; Otis et al., 2005; Ratelle et al., 2004). This normative decline in extrinsic motivation and the differentiation of students' motivations could, at least in part, be explained by the changes in their basic psychological need satisfaction. As children undergo cognitive, emotional and social developments, schools are less and less successful at satisfying their need for autonomy (a sense of control and volition in studies), competence (feeling confident about their own abilities), or relatedness (having positive social relationships with others). Later in their academic career, as their educational and occupational aspirations crystallize (Eccles et al., 1993), students have more opportunities to decide what they want to study and specialize in (satisfying their need for autonomy). As a result, they start focusing on a particular field and eventually master it to a high degree (satisfying their need for competence). Finally, at an older age, they are also more likely to become members of peer groups formed around mutual interests and specializations (satisfying their need for relatedness). As such, when their basic psychological needs are satisfied, older students are more likely to develop autonomous forms of motivation toward their studies. This, in turn, might lead to other motives becoming more salient than external ones that they experience early on when attending school is mandatory. For example, apart from pursuing studies for enjoyment (i.e., intrinsic motivation), students might start to perceive their studies as important (i.e., identified regulation) or their external pressures (i.e., external regulation) might progressively become self-imposed (i.e., introjected regulation) over time. These propositions about the importance of basic needs have already been supported among adolescents where need satisfaction was shown to help them remain intrinsically motivated (Gnambs & Hanfstingl, 2016).

When students' psychological needs are not satisfied, they might start questioning the subjective value of schooling and their studies. Expectancy-value theory (EVT; Eccles & Wigfield, 2020; Wigfield & Cambria, 2010), one of the major motivational theories that has conceptual similarities with SDT (Anderman, 2020), argues that children are initially optimistic about their abilities and might form unrealistic expectations about them. However, as they mature, they become better at understanding and interpreting the feedback they receive due to the development of their cognitive abilities. They also tend to engage more in social comparisons with their peers. If this feedback is negative, they might feel less competent in a given domain which might, in turn, diminish their beliefs about the value of school and their studies, leading to feeling less motivated for their studies. The subjective devaluation of tasks and activities might also serve a self-protective purpose when facing difficulties (Fredricks & Eccles, 2002). As a general pattern, EVT research (e.g., Archambault et al., 2010; Musu-Gillette et al., 2015; Scherrer & Preckel, 2019; Watt, 2008) arrives at conclusions similar to SDT by showing that subjective task values (the intrinsic, utility or attainment values students place on pursuing a particular task or activity) tend to decline for the majority of students as they progress in their academic careers. Still, additional future research is needed to verify these interpretations as well as the importance of extrinsic regulation among elementary schoolers.

Overall, our results add to the accumulating evidence (Howard et al., 2020; Litalien et al., 2017), and support the recently introduced bifactor-ESEM operationalization of SDT-based motivations. By explicitly accounting for the global/specific nature of academic motivation, this analytical approach more precisely identifies which behavioral regulations tend to uniquely influence students' motivation profiles beyond their global self-determination. While global self-determination levels defined three profiles (Profiles 2, 4, 5), four of them (Profiles 1, 2, 3, 5) were also strongly characterized by one, or more, specific behavioral regulations. More specifically, elementary school students' global self-determination as well as their introjected and external regulations appear to be particularly important defining characteristics of their academic motivation configurations. These conclusions could not have been reached with a traditional operationalization of motivation. Indeed, based on prior research (Howard et al., 2016, 2021), motivation profiles tend to be influenced by students' global self-determination and, as a result, they might not clearly display qualitative differences, thus masking the unique effects of the individual behavioral regulations. By separating level and shape effects (Morin & Marsh, 2015), we addressed the limitations of previous person-centered studies in which the multidimensional nature of academic motivation was not explicitly taken into account.

**Within-Sample and Within-Person Similarity Across Domains**

Supporting Hypothesis 4, the five profiles identified in the present study were found to be fully equivalent (in number, shape, variability, and size) across German and Math. These results align with those from previous studies of university students and working adults supporting the generalizability of these profiles as a function of age, sex and professional groups (Litalien et al., 2019), as well as their within-sample stability over time (Gillet et al., 2017).

Although we expected these profiles to display a moderate-to-high within-person similarity across domains, our results only partially supported these expectations (Hypothesis 5). Students corresponding to the *Highly Extrinsic* and *Moderately Extrinsic* profiles tended to display similar motivational configurations across subjects. While some students corresponding to these profiles did display different profiles across domains (e.g., the *Moderately Extrinsic* German profile in connection to the *Self-Determined* Math profile), most of these connections occurred between these two extrinsically driven profiles. These results suggest that students mainly oriented by an external motivational regulation tend to display a similar configuration across school subjects. Likewise, the *Controlled* and *Self-Determined* profiles displayed moderate within-person similarity across domains, suggesting that close to 50% of the students corresponding to these profiles present the same motivational configuration across school subjects. However, some students with a *Controlled* German profile displayed a conceptually similar *Moderately Extrinsic* Math profile, and many of them displayed a quite different *Self-Determined* Math profile. Likewise, students presenting a *Self-Determined* German profile seemed equally likely to display a *Controlled, Moderately Extrinsic,* or *Non-Motivated* Math profile. These observations are consistent with the known opposition between Math-related versus verbal-related self-concepts, which are systematically found to be negatively correlated despite the fact that levels of achievement in both domains are typically correlated (Marsh, 2007; Marsh et al., 2014). These results suggest that, for some students at least, the motivational orientation displayed toward Math can be drastically opposed to that displayed toward German. Finally, the *Non-Motivated* profile proved to be the least stable, while also reinforcing this aforementioned cross-domain opposition. Students with a *Non-Motivated* German profile seemed to be even less likely to display a similar *Non-Motivated* Math profile as they were to display a diametrically opposed *Self-Determined* Math profile.

The rates of within-person similarity across domains identified in the present study across subjects are similar, albeit slightly lower, to the longitudinal stability rates previously reported by Gillet et al. (2017) among university students over a period of two months. This observation thus suggests that motivational profiles seem to be more malleable across domains in younger populations than they are for the same domain over time. Moreover, these rates are also consistent with the previous indication that more extreme levels (i.e., the *Non-Motivated* profile in the present study) are less stable than average levels (Gillet et al., 2018). From a practical standpoint, these results reinforce the idea that motivation profiles can be both a function of the context provided by a specific subject or classroom as well as a function of the students themselves, thus highlighting the idea that these profiles can change across domains, in addition to over time. However, given that the two extrinsically driven profiles seemed to display the highest within-person similarity across domains, students in these profiles should be targeted through more universal intervention strategies focusing on the value of schooling and learning in general rather than on the value of each specific subject. In contrast, *Non-Motivated* and *Controlled* students seemed equally likely to benefit from broadband intervention strategies as they are to benefit from subject-specific intervention strategies highlighting the value and interest of their least liked subject.

**Predicting Academic Motivation Profile Membership**

Supporting Hypothesis 6, our results revealed that students with stronger academic self-concept in one domain had a higher likelihood of corresponding to the *Self-Determined* profile in that domain relative to all other profiles, as well as a lower likelihood of corresponding to the *Non-Motivated* profile in that domain relative to all other profiles. Students with stronger academic self-concept in one domain were also more likely to belong to the *Moderately Extrinsic* profile in that domain relative to the *Controlled* profile. These results thus support the role of self-concept as an important driver of academic motivation (Craven & Marsh, 2008; Marsh, 2007), and suggests the associations between academic self-concepts and profile membership to be mainly related to students' global self-determination. Thus, students who feel competent in Math and German are more likely to display a self-directed, volitional approach toward learning German and Math. These findings are consistent with other SDT investigations, demonstrating that global self-determination tends to present the strongest associations with a variety of external variables (Howard et al., 2018; Litalien et al., 2017).

In response to our Research Question 1, students' sex appeared to be associated with students' likelihood of membership into the various motivational profiles. Girls were more likely to belong to the *Highly Extrinsic* profile relative to the *Controlled*, *Moderately Extrinsic*, and *Self-Determined* profiles (but not to the *Non-Motivated* profiles). When considering this unexpected result, it is important to reinforce the discrepant nature of previous results in this regard. Although some have reported that girls tend to report higher autonomous motivation than boys (e.g., Vansteenkiste et al., 2009; Vallerand et al., 1997), others have reported a lack of statistically significant sex differences (e.g., Oga-Baldwin & Fryer, 2020a), and yet others have reported that girls tended to display higher extrinsic motivation than boys (e.g., Boggiano et al., 1991; Davis et al., 2006). Our results thus support this last set of studies and might be explained by girls' tendency to ascribe more importance to social relationships than to performance (Gabriel & Gardner, 1999; Javo et al., 2006), by girls' greater sensitivity to punishment than boys (Cross et al., 2011), and their tendency to be more compliant and cooperative than boys (e.g., Chen et al., 2003). All of these previous observations may have contributed to increase girls' likelihood to display a motivation profile clearly driven by external forms of regulation. However, the relatively small size of this *Highly Extrinsic* profile may explain the discrepant results obtained in previous studies by indicating that this gender difference may remain confined to a very small subset of the population. Nevertheless, future research is needed to verify whether these results are sample-specific or could be replicated on other samples.

**Outcomes of Academic Motivation Profiles**

The final objective of this study was to document the implications of academic motivation profiles in terms of students' anxiety, academic achievement, and effort. Our results generally matched our a priori expectations, and thus provided support for Hypothesis 7, by showing that students belonging to the most desirable profile (i.e., *Self-Determined*) also reported the lowest anxiety and the highest academic achievement and effort. These results are in accordance with those from previous studies and SDT in the educational context, demonstrating the greater desirability of autonomous forms of motivation (e.g., Gillet et al., 2017; Vansteenkiste et al., 2009), as well as the theoretical importance attributed to students' global self-determination (Ryan & Deci, 2017). This profile was followed, in terms of outcome desirability, by the *Moderately Extrinsic* profile. The relative position of this profile is not surprising when we consider the fact that it was characterized by close to average global self-determination which, even though only close to average instead of high, might be able to protect students against the deleterious effects of high external regulation. Such a buffering effect has previously been reported in the educational context among university students (Gillet et al., 2017). Not all profiles differed from one another on all outcomes, however. The remaining three profiles (*Highly Extrinsic*, *Controlled*, and *Non-motivated*) were impossible to distinguish from one another, suggesting that these profiles had an equally negative association with students' functioning. Again, these results are in line with SDT (Ryan & Deci, 2017) and the documented negative implications of controlled forms of motivation (e.g., Vansteenkiste et al., 2009) or of a lack of motivation (e.g., Legault et al., 2006).

**Practical Implications**

From a practical perspective, our results suggest that teachers and practitioners should pay attention to students displaying *Controlled*, *Highly Extrinsic*, or *Non-Motivated* configurations as these students might be at risk of undesirable educational implications. To observe these profiles in the real world, practitioners may wish to discuss with their students to identify their most salient academic motivation. These discussions could be complemented with students' self-reported responses to, for example, the Academic Motivation Scale. Until automated user-friendly solutions are developed, as suggested by Perreira et al. (2018), practitioners could rely on the Mplus statistical package in the calculation of sample-specific means. This has the added value of weighting items based on their contributions to the global and specific factors simultaneously. It has to be noted, however, that classification error might need to be considered, much like in the present study where classification accuracy remained imperfect. Even though the results showed that, in our sample, students held similar Math and German motivational configurations, practitioners may also wish to be aware that students' motivations might demonstrate context specificity which may translate into students showing distinct motivational configurations in distinct lessons, depending on the topic of interest.

In terms of improving students' motivational configurations, practitioners might help students belonging to these profiles transition into more adaptive motivation profiles by helping them find reasons to engage in school activities for autonomous reasons. For example, practitioners could use goal framing (Vansteenkiste et al., 2006) to help students develop an interest in German and Math by highlighting the pleasurable aspects of these school subjects or by promoting their relevance and meaningfulness. Given the impact of self-concept on profile membership, practitioners should create an environment that fosters students' basic psychological need for competence via positive feedback and optimal challenges. As students are more likely to be motivated to engage in activities they understand and master, practitioners should emphasize students' learning and provide information about mastering the task (Niemiec & Ryan, 2009), in turn allowing students to improve their competence. In addition, general need supportive strategies could also be used which do not only reflect on competence but autonomy and relatedness as well (Reeve & Halusic, 2009). Finally, multiple interventions designed to improve youth self-concepts are available to help schools nurture more positive self-concepts, and in turn more desirable motivation profiles (O'Mara et al., 2006).

**Limitations and Future Directions**

In terms of limitations, the cross-sectional design used in this study makes it impossible to investigate the directionality of the observed associations between profiles, predictors, and outcomes as we cannot rule out reciprocal influences, reverse causality, or spurious associations. To assess the stability of profile membership and predictors of changes in profile membership over time as well as their directionality, future studies should rely on longitudinal study designs. Another purpose of replication would be to inform which motivation profiles should be considered core (i.e., emerging systematically across contexts) versus peripheral (i.e., only emerging in specific contexts or samples). Our study relied on self-reported measures which might be influenced by a variety of biases, suggesting that future studies would do well in verifying the extent to which our results replicate and generalize using multi-informant (e.g., from teachers) or more objective (e.g., actual dropout) data. As the sample used in the present study was recruited within a specific geographical region of Germany, the generalizability of our results remains uncertain both within and beyond this region. We thus encourage future replications to be conducted in other countries, languages, and school levels. Ideally, these replications would be made in relation to school subjects other than German and Math.

Recent suggestions argue that there might be a difference between the nature of context-specific and context-general constructs (Pekrun & Marsh, 2022). More specifically, it has been proposed (Chanal & Guay, 2015; Chanal & Paumier, 2020) that autonomous motivations (intrinsic and identified regulation) might be more differentiated than controlled motivations (introjected and external regulation) because they are more strongly related to a particular situation (i.e., school subjects) than to the context in which the situation occurs (i.e., school). In our case, this would mean the presence of differing associations between autonomous motivations and correlates. Moreover, this perspective also suggests that a global academic drive might underpin students' motivation across domains, suggesting the possible presence of a domain-general self-determination factor accompanied by domain-specific autonomous motivation factors. Even though our study generated novel insights into the domain-specificity of academic motivation by demonstrating the similarity of the factor structure of our academic motivation measure as well the similarity of our profiles across school subjects, future investigations should take this perspective into account and consider motivation as it simultaneously occurs across school subjects.

Finally, future studies should also document the construct validity of academic motivation profiles in relation to a wider range of relevant predictors and outcomes. Given the conceptual overlap between self-concept and the basic psychological need for competence, a logical next step would be to consider autonomy and relatedness needs, possibly by considering their multidimensional nature as well. Investigating the effect of other profile determinants (e.g., teachers' interpersonal behaviors) might also prove fruitful. Our study only focused on one negative indicator of well-being (i.e., anxiety), thus we suggest future studies to incorporate a wider range of well-being (e.g., positive affect) and ill-being (e.g., academic burnout) outcomes in order to better capture the mental health implications of academic motivations.

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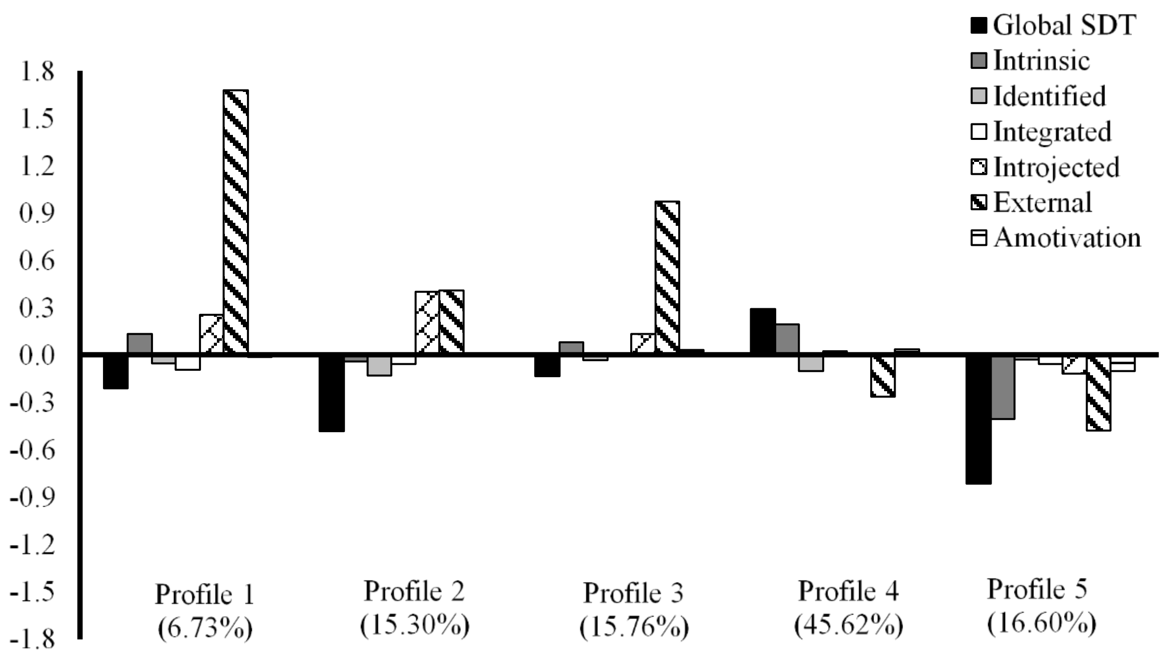


**Figure 1**

*Final 5-Profile Solution (Distributional Similarity: Identical Across Subjects)*

*Note.* Profile indicators were standardized factor scores (M = 0, SD = 1) derived from preliminary measurement models. This solution comes from the model of distributional similarity (supported in our analyses) in which the profiles were identical across the two school subjects. Distributional profile similarity indicates that the number of profiles, the mean of the profile indicators, the variance of the profile indicators and the sizes of the profiles are identical for the Math and German language subjects (Morin et al., 2016); SDT: Self-determined motivation; Profile 1: Highly Extrinsic; Profile 2: Controlled; Profile 3: Moderately Extrinsic; Profile 4: Self-Determined; Profile 5: Non-Motivated.

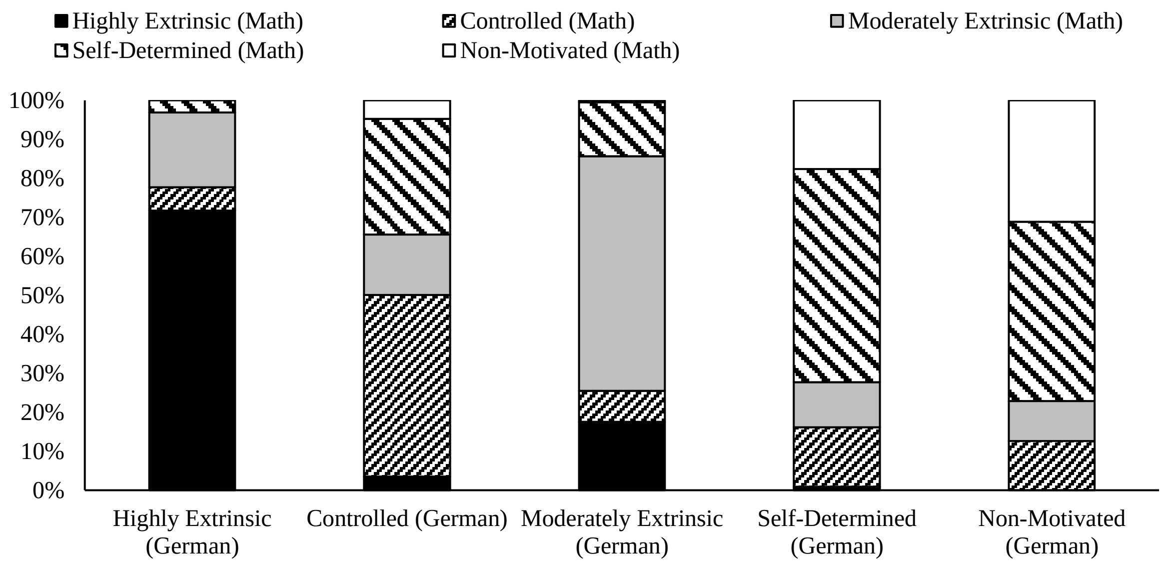


**Figure 2**

*Final Joint Classification Probabilities of Profile Membership Across Domains*

*Note*. Proportions along the X-axis sum up to 100%.

**Table 1**

*Model Fit Results from the Latent Profile and Latent Transition Analyses*

| Model | LL | #fp | Scaling | AIC | CAIC | BIC | SSABIC | Entropy | aLMR | BLRT |
|---|---|---|---|---|---|---|---|---|---|---|
| *Latent Profile Analysis (German motivation)* | | | | | | | | | | |
| 1 profile | −3586.915 | 14 | 1.092 | 7201.830 | 7275.624 | 7261.624 | 7217.184 | | | |
| 2 profiles | −3454.336 | 22 | 1.170 | 6952.672 | 7068.634 | 7046.634 | 6976.800 | .921 | < .001 | < .001 |
| 3 profiles | −3366.510 | 30 | 1.177 | 6793.020 | 6951.150 | 6921.150 | 6825.921 | .952 | < .001 | < .001 |
| 4 profiles | −3319.062 | 38 | 1.238 | 6714.125 | 6914.422 | 6876.422 | 6755.800 | .911 | .022 | < .001 |
| 5 profiles | −3266.699 | 46 | 1.324 | 6625.398 | 6867.864 | 6821.864 | 6675.847 | .908 | .099 | < .001 |
| 6 profiles | −3224.205 | 54 | 1.295 | 6556.411 | 6841.044 | 6787.044 | 6615.633 | .843 | .022 | < .001 |
| 7 profiles | −3196.391 | 62 | 1.440 | 6516.782 | 6843.583 | 6781.583 | 6584.778 | .852 | .618 | < .001 |
| 8 profiles | −3155.064 | 70 | 1.268 | 6450.128 | 6819.097 | 6749.097 | 6526.898 | .921 | .124 | < .001 |
| *Latent Profile Analysis (Math motivation)* | | | | | | | | | | |
| 1 profile | −3578.700 | 14 | 1.044 | 7185.400 | 7259.194 | 7245.194 | 7200.754 | | | |
| 2 profiles | −3491.399 | 22 | 1.093 | 7026.799 | 7142.760 | 7120.760 | 7050.926 | .856 | < .001 | < .001 |
| 3 profiles | −3424.858 | 30 | 1.091 | 6909.717 | 7067.846 | 7037.846 | 6942.618 | .926 | < .001 | < .001 |
| 4 profiles | −3378.957 | 38 | 1.143 | 6833.914 | 7034.212 | 6996.212 | 6875.589 | .855 | .002 | < .001 |
| 5 profiles | −3333.678 | 46 | 1.270 | 6759.357 | 7001.822 | 6955.822 | 6809.805 | .862 | .235 | < .001 |
| 6 profiles | −3288.545 | 54 | 1.213 | 6685.091 | 6969.724 | 6915.724 | 6744.313 | .896 | .027 | < .001 |
| 7 profiles | −3254.684 | 62 | 1.153 | 6633.368 | 6960.169 | 6898.169 | 6701.364 | .907 | .017 | < .001 |
| 8 profiles | −3229.284 | 70 | 1.284 | 6598.568 | 6967.568 | 6897.568 | 6675.338 | .887 | .557 | < .001 |
| *Profile Similarity* | | | | | | | | | | |
| Configural similarity | −6600.378 | 92 | 1.465 | 13384.755 | 13869.686 | 13777.686 | 13485.652 | .885 | Na | Na |
| Structural similarity | −6644.119 | 57 | 1.638 | 13402.238 | 13702.684 | 13645.684 | 13464.750 | .863 | Na | Na |
| Dispersion similarity | −6654.780 | 50 | 1.715 | 13409.561 | 13673.110 | 13623.110 | 13464.396 | .862 | Na | Na |
| Distributional similarity | −6662.418 | 46 | 1.749 | 13416.835 | 13659.301 | 13613.301 | 13467.284 | .862 | Na | Na |
| *Latent Markov Analysis with Predictors* | | | | | | | | | | |
| Effects free across domains and profiles | −1228.854 | 80 | 0.760 | 2617.707 | 3039.386 | 2959.386 | 2705.444 | .848 | Na | Na |
| Effects free across time domains | −1246.078 | 40 | 1.008 | 2572.155 | 2782.995 | 2742.995 | 2616.023 | .844 | Na | Na |
| Predictive similarity | −1249.437 | 32 | 1.003 | 2562.874 | 2731.546 | 2699.546 | 2597.969 | .843 | Na | Na |
| *Latent Markov Analysis with Outcomes* | | | | | | | | | | |
| Effects free across domains and profiles | −5216.071 | 60 | 1.256 | 10552.142 | 10868.402 | 10808.402 | 10617.945 | .860 | Na | Na |
| Explanatory similarity | −5229.316 | 45 | 1.414 | 10548.632 | 10785.827 | 10740.827 | 10597.984 | .864 | Na | Na |

*Note.* LL: loglikelihood; fp: number of free parameters; AIC: Akaike Information Criterion; CAIC: Consistent AIC; BIC: Bayesian Information Criterion; SSABIC: Sample-Size Adjusted BIC; aLMR: p-value associated with the adjusted Lo-Mendel-Rubin likelihood ratio test; BLRT: Bootstrap Likelihood Ratio Test; Na: not applicable.

**Table 2**
*Likelihood of membership into the German Motivation Profiles as a Function of Membership into Each of the Math Motivation Profiles*

| German Motivation | Math Motivation Profiles | | | | |
|---|---|---|---|---|---|
| Profiles | Profile 1 | Profile 2 | Profile 3 | Profile 4 | Profile 5 |
| Profile 1 | .717 | .060 | .192 | .031 | .000 |
| Profile 2 | .035 | .466 | .155 | .297 | .047 |
| Profile 3 | .175 | .080 | .602 | .138 | .005 |
| Profile 4 | .009 | .152 | .116 | .546 | .176 |
| Profile 5 | .000 | .126 | .103 | .460 | .311 |

*Note.* Profile 1: Highly Extrinsic; Profile 2: Controlled; Profile 3: Moderately Extrinsic; Profile 4: Self-Determined; Profile 5: Non-Motivated.

**Table 3**

*Results from the Multinomial Logistic Regressions Evaluating the Relations between Predictors and Profile Membership*

| Predictors | Profile 1 vs. Profile 2 | | Profile 1 vs. Profile 3 | | Profile 1 vs. Profile 4 | | Profile 1 vs. Profile 5 | | Profile 2 vs. Profile 3 | |
|---|---|---|---|---|---|---|---|---|---|---|
| | Coeff. (SE) | OR | Coeff. (SE) | OR | Coeff. (SE) | OR | Coeff. (SE) | OR | Coeff. (SE) | OR |
| Self-concept | .225 (.254) | 1.252 | −.394 (.207) | .674 | −1.146 (.204)** | .318 | .733 (.233)** | 2.081 | −.619 (.186)** | .538 |
| Sex | .704 (.314)* | 2.022 | 1.081 (.292)** | 2.948 | .671 (.298)* | 1.956 | .460 (.358) | 1.584 | .376 (.286) | 1.456 |
| | Profile 2 vs. Profile 4 | | Profile 2 vs. Profile 5 | | Profile 3 vs. Profile 4 | | Profile 3 vs. Profile 5 | | Profile 4 vs. Profile 5 | |
| | Coeff. (SE) | OR | Coeff. (SE) | OR | Coeff. (SE) | OR | Coeff. (SE) | OR | Coeff. (SE) | OR |
| Self-concept | −1.371 (.164)** | .254 | .508 (.205)* | 1.662 | −.752 (.157)** | .471 | 1.127 (.211)** | 3.086 | 1.879 (.194)** | 6.547 |
| Sex | −.033 (.221) | .968 | −.245 (.338) | .783 | −.410 (.225) | .664 | −.621 (.323) | .537 | −.211 (.268) | .810 |

*Note.* * $p < .05$; ** $p < .01$; Predictors are factor scores estimated in standardized units (M = 0, SD = 1); Profile 1: Highly Extrinsic; Profile 2: Controlled; Profile 3: Moderately Extrinsic; Profile 4: Self-Determined; Profile 5: Non-Motivated; OR: odds ratio. The coefficients and OR reflects the effects of the predictors on the likelihood of membership into the first listed profile relative to the second listed profile; Sex was coded as 0 = male, 1 = female. SE: standard error of the coefficient.

**Table 4**

*Outcome Means and Pairwise Comparisons between the Five Profiles*

| Outcome | Profile 1 Mean [95% CI] | Profile 2 Mean [95% CI] | Profile 3 Mean [95% CI] | Profile 4 Mean [95% CI] | Profile 5 Mean [95% CI] | Differences between profiles |
|---|---|---|---|---|---|---|
| Anxiety | .659 [.346, .972] | .648 [.397, .900] | -.134 [−.384, .116] | −.436 [−.544, −.327] | .536 [.388, .683] | 4 < 3 < 1 = 2 = 5 |
| Effort | −.515 [−.936, −.095] | −.645 [−.961, −.329] | .304 [.080, .528] | .580 [.465, .696] | −.724 [−.825, −.622] | 1 = 2 = 5 < 3 < 4 |
| Grades | −.400 [−.753, −.047] | −.634 [−.972, −.296] | .295 [.078, .513] | .552 [.455, .649] | −.583 [−.770, −.397] | 1 = 2 = 5 < 3 < 4 |

*Note*. SE: Standard error; Outcomes are factor scores estimated in standardized units (M = 0, SD = 1); Profile 1: Highly Extrinsic; Profile 2: Controlled; Profile 3: Moderately Extrinsic; Profile 4: Self-Determined; Profile 5: Non-Motivated.

***Online Supplements for:***

**Predictors, Outcomes, and Inter-Domain Connections of German and Math Academic Motivation Profiles**

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

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

# Appendix 1
# Preliminary Measurement Models

## Analyses

### *Models Specification*

A series of preliminary measurement models were estimated to verify the psychometric properties of our measures, as well as to obtain factor scores for the main analyses. When compared to manifest scale scores (i.e., the summary or the average of the items forming a scale), factor scores provide a way to preserve the nature of the underlying measurement model (e.g., bifactor, invariance; Morin et al., 2016c, 2016d, 2017) and to partially control for unreliability (Skrondal & Laake, 2001).

Within self-determination theory (SDT; Ryan & Deci, 2017), recent empirical (Howard et al., 2018; Litalien et al., 2017) and theoretical (Howard et al., 2020) evidence have advocated the relevance of bifactor exploratory structural equation modeling (bifactor-ESEM; Morin et al., 2016a, 2016b) to represent the underlying structure of motivation measures aligned with SDT. Bifactor-ESEM makes it possible to estimate a global (G-) factor representing students' global level of academic self-determination toward German and Math, together with non-redundant specific (S-) motivational factors reflecting the unique quality of each motivation subscale left unexplained by the G-factor (Howard et al., 2018, 2020; Litalien et al., 2017). The G-factor is defined by all motivation items through a pattern of factor loadings matching their theoretical position on the SDT motivation continuum: strong positive loadings from the intrinsic motivation items, moderate positive loadings from the integrated and identified regulation items, smaller positive loadings from the introjected regulation items, null or negative loadings from the external regulation items, and stronger negative loadings from the amotivation items. In contrast, the S-factors are simply defined by the items a priori allocated to each subscale, and reflect the variance shared among these items and left unexplained by the G-factor. Finally, the ESEM component allows the free estimation of all cross-loadings between the S-factors (while "targeting" them to be as close to zero as possible). The free estimation of cross-loadings has been previously shown to result in more accurate factor definitions even when cross-loadings as small as .100 are present in the data, and to result in unbiased parameters even in the absence of cross-loadings (Asparouhov et al., 2015; Morin et al., 2020).

To verify the appropriateness of this bifactor-ESEM representation, we followed recommendations from Morin and colleagues (Morin et al., 2016c, 2017, 2020) and contrasted four alternative motivation measurement models: (a) a correlated factor confirmatory factor analytic (CFA) solution (including neither cross-loadings nor a G-factor); (b) a correlated factor ESEM solution (including cross-loadings but not a G-factor); (c) bifactor-CFA solution (including a G-factor but no cross-loadings); and (d) our a priori bifactor-ESEM solution (including a G-factor and cross-loadings). In the correlated factors CFA solution, items were specified as being only associated with their a priori factors, all cross-loadings were constrained to zero, and factors were allowed to correlate freely with one another. In the correlated factors ESEM solution, factors were defined in the same manner as in the CFA, but all cross-loadings were freely estimated and targeted to be as close to zero as possible via the application of a confirmatory oblique target rotation (Browne, 2001). In the bifactor-CFA solution, all items were associated with the self-determined motivation G-factor as well as with their a priori S-factors, cross-loadings were constrained to zero between the S-factors, and factors were specified as orthogonal as per typical bifactor specifications (Morin et al., 2020; Reise, 2012). In the bifactor-ESEM solution, factors were defined as in bifactor-CFA, but cross-loadings were freely estimated between all S-factors and targeted to be close to zero via the application of a confirmatory orthogonal target rotation.

When contrasting the correlated factors CFA and ESEM models, support for the ESEM solution comes from the observation of equally well-defined and reliable factors coupled with reduced estimates of factor correlations (Morin et al., 2016c, 2017, 2020). When comparing correlated factors and bifactor models, support for the bifactor solution comes from the observation of a well-defined and reliable self-determined motivation G-factor (that has to match the continuum structure of motivation in the present study: Howard et al., 2018; Litalien et al., 2017) together with at least a subset of well-defined and reliable S-factors (Morin et al., 2016c, 2017, 2020). The four measurement models were first estimated separately for German and Math domains.

For the correlates, the measurement model underpinning the multi-item measures was estimated using a CFA approach including three correlated factors representing self-concept, effort, and anxiety. As with academic motivation, this CFA measurement model was first estimated separately for the

German and Math domains.

***Tests of Measurement Invariance***

After selecting the optimal solution for academic motivation and the correlates, tests of measurement invariance were conducted to ascertain that we relied on comparable sets of factor scores across domains (German and Math). These tests were performed in the following sequence (Millsap, 2011): (1) configural invariance (same model), (2) weak invariance (equality of loadings), (3) strong invariance (equality of loadings and thresholds), (4) strict invariance (equality of loadings, thresholds, and uniquenesses); (5) invariance of the latent variance-covariance matrix (equality of loadings, thresholds, uniquenesses, and latent variances and covariances); and (6) latent means invariance (equality of loadings, thresholds, uniquenesses, latent variances and covariances, and latent means).

***Model Estimation***

These preliminary analyses were conducted using Mplus 8.4 (Muthén & Muthén, 2019) and the weighted least squares mean- and variance-adjusted estimator (WLSMV) which has been found to outperform maximum-likelihood estimation methods when relying on ordered-categorical items (i.e., Likert ratings) and particularly when the response categories of these items follow asymmetric thresholds (for a review, see Finney & DiStefano, 2013). Additionally, recent empirical studies (Fernet et al., 2020; Gillet et al., 2017; Guay et al., 2015; Litalien et al., 2015; Tóth-Király et al., 2020, 2021) on the structure of SDT-based motivation measures also supported the value of WLSMV estimation.

Measurement models were evaluated using typical goodness-of-fit indices (Hu & Bentler, 1999; Marsh et al., 2005): the chi-square test ($\chi^2$), the comparative fit index (CFI), the Tucker-Lewis Index (TLI), and the root mean square error of approximation (RMSEA). CFI and TLI values are considered to be adequate or excellent when they are above .90 and .95, respectively. RMSEA values are considered to be adequate or excellent below .08 and .06, respectively. As the chi-square test is known to be oversensitive to minor model misspecifications and sample size (Marsh et al., 2005), it is simply reported for the sake of transparency, but not used in model evaluation. Nested models' comparisons in tests of measurement invariance were based on examination of changes ($\Delta$) in fit indices where a decrease of .010 or higher for CFI and TLI and an increase of at least .015 or higher for RMSEA indicating lack of invariance across samples (Chen, 2007; Cheung & Rensvold, 2002). We also calculated model-based omega ($\omega$) coefficients of composite reliability (McDonald, 1970) to assess the reliability of the factors (Morin et al., 2020).

**Results**

The results associated with the German motivation models are reported in Tables S2 (goodness-of-fit), S3 (CFA and ESEM solutions), S4 (CFA and ESEM factor correlations), and S5 (Bifactor-ESEM solution). These results first show that the correlated factors ESEM solution resulted in a slightly higher level of fit to the data when compared to the six-factor CFA solution ($\Delta$CFI = +.003, $\Delta$TLI = +.002, $\Delta$RMSEA = -.003). Standardized parameter estimates from these two solutions are reported in Table S3. These results show that all factors remain well-defined ($\lambda$ = .520-.960, $M$ = .796) and reliable ($\omega$ =.885 and .948) in the ESEM solution, which also resulted in the estimation of a substantial number (i.e., 24) of cross loadings greater than .100. Importantly, factor correlations (Table S4) were also reduced in the six-factor ESEM ($|r|$ = .037-.805, $M$ = .351) relative to the six-factor CFA ($|r|$ = .024-.902, $M$ = .411) solution.

The correlated factors ESEM solution was thus retained, and contrasted with its bifactor counterpart. The results from this alternative solution are reported in Table S5. This new solution resulted in similar level of fit to the data ($\Delta$CFI = +.001, $\Delta$TLI = +.001, $\Delta$RMSEA = -.003), but revealed a reliable ($\omega$ = .973) G-factor well-defined by factor loadings matching the SDT continuum from intrinsic ($\lambda$ between .789 and .896, $M$ = .850), integrated ($\lambda$ between .596 and .671, $M$ = .633), identified ($\lambda$ between .796 and .839, $M$ = .822), introjected ($\lambda$ between -.096 and .156, $M$ = .095), external ($\lambda$ between -.192 and -.230, $M$ = .214), and amotivation ($\lambda$ between -.800 and -.844, $M$ = -.823) items. Likewise, the S-factors related to external regulation ($\lambda$ = .821-.874, $M$ = .853; $\omega$ = .943), integrated regulation ($\lambda$ = .595-.627, $M$ = .606; $\omega$ = .839), and introjected regulation ($\lambda$ = .590-.887, $M$ = .783; $\omega$ = .893) were also generally well-defined. Finally, although the remaining S-factors appeared to be more weakly defined then the previous ones, the S-factors associated with amotivation ($\lambda$ = .319-.447, $M$ = .388; $\omega$ = .754), intrinsic motivation ($\lambda$ = .268-.483, $M$ = .377; $\omega$ = .806), and identified regulation ($\lambda$ = .231-.456, $M$ = .321; $\omega$ = .648) still appeared to retain a meaningful level of specificity (associated with ω values greater than .500; see Perreira et al., 2018; Morin et al., 2020) once the variance explained by the G-factor was taken into account. These results support the value of the bifactor-ESEM solution.

The results associated with the Math motivation models are reported in Tables S2 (goodness-of-fit), S4 (CFA and ESEM factor correlations), S6 (CFA and ESEM solutions), and S7 (Bifactor-ESEM solution). These results generally matched those obtained for the German motivation model, and thus also support the superiority of the bifactor-ESEM solution. However, to more precisely assess the extent to which results from this solution were replicated across the two domains, tests of measurement invariance across domains were conducted on this solution. The results from these tests, reported in the middle section of Table S2, support the complete measurement invariance of this solution (ΔCFI/TLI ≤ .010, ΔRMSEA ≤.015). The final parameter estimates from the model of latent mean invariance are reported in Table S8 and generally match those described above for the bifactor-ESEM solution. More specifically, the self-determined motivation G-factor was well-defined and reliable (λ between -.857 and .896, *M* = .568, ω = .967) and associated with factor loadings that matched the hypothesized SDT continuum: intrinsic (λ between .846 and .896, *M* = .876), integrated (λ between .519 and .628, *M* = .560), identified (λ between .775 and .823, *M* = .797), introjected (λ between -.141 and .039, *M* = .104), external (λ between -.214 and -.265, *M* = .234), and amotivation (λ between -.803 and -.857, *M* = -.835) items. Likewise, the S-factors related to external regulation (λ = .827-.882, *M* = .848; ω = .928), introjected regulation (λ = .551-.854, *M* = .751; ω = .855), and integrated regulation (λ = .613-.691, *M* = .659; ω = .857) were also generally well-defined. Finally, although the remaining S-factors appeared to be more weakly defined then the previous ones, the S-factors associated with intrinsic motivation (λ = .273-.413, *M* = .335; ω = .754), amotivation (λ = .265-.383, *M* = .342; ω = .672), and identified regulation (λ = .258-.363, *M* = .314; ω = .576) also retained a meaningful level of specificity (associated with ω values greater than .500; see Perreira et al., 2018; Morin et al., 2020) once the variance explained by the G-factor was taken into account. Factor scores were saved from this model and used as input for the main analyses.

Turning our attention to the correlates, as shown in Table S2, the measurement model estimated in both samples resulted in a satisfactory level of fit to the data, while tests of measurement invariance supported the complete equivalence of this solution across the German and Math domains. Standardized parameter estimates from the latent mean invariant CFA model are reported in Tables S9 and show that self-concept (λ = .877-.901, *M* = .885; ω = .916), effort (λ = .713-.934, *M* = .842; ω = .883), and anxiety (λ = .843-.942, *M* = .888; ω = .949) were all well-defined by their target loadings and associated with satisfactory estimates of composite reliability. Factor scores were saved from this model for the main analyses. Correlations among all factor scores are reported in Table S10.

## Appendix 2
## Estimating and Selecting the Optimal Number of Profiles

### Model Estimation, Selection and Comparison

When estimating the domain-specific latent profiles, we used 5000 random start values, 1000 iterations, and 200 final optimizations (Hipp & Bauer, 2006). In the selection of the optimal number of profiles, we considered the meaning, the theoretical conformity, and the statistical adequacy of the solutions, as well as various statistical indicators (e.g., Marsh et al., 2009; Morin, 2016; Morin & Litalien, 2019): the Akaike Information Criterion (AIC), the Bayesian Information Criterion (BIC), the Consistent AIC (CAIC), the Sample-Size-Adjusted BIC (SSABIC), the adjusted Lo-Mendell-Rubin (aLMR) likelihood ratio test, and the Bootstrap Likelihood Ratio Test (BLRT). However, extensive statistical research has demonstrated the utility of the CAIC, BIC, SSABIC, and BLRT as indicators of the optimal number of profiles, while showing that the AIC and aLMR were not reliable indicators of this optimal number of profiles (e.g., Diallo et al., 2016, 2017; Peugh & Fan, 2013). For this reason, we do not consider the aLMR and AIC and only report them to ensure transparency. Lower values on BIC, CAIC, and SSABIC suggest a better fitting solution, whereas a non-significant p-value for the BLRT suggests the superiority of a model including one less profile. However, as the BIC, CAIC, and SSABIC often keep improving when adding profiles, the graphical examination of "elbow plots" tends to facilitate this process where a plateau on these plots suggest that the optimal number of profiles have been reached (Morin & Litalien, 2019). Entropy (i.e., classification accuracy) is also reported with values ranging from 0 (low) to 1 (high). With respect to profile similarity, it was achieved when two indicators out of the Akaike Information Criterion (AIC), the Bayesian Information Criterion (BIC), the Consistent AIC (CAIC), the Sample-Size-Adjusted BIC (SSABIC) have a lower value relative to the previous model.

### Results

The results from the solutions including different number of profiles are reported in the upper section of Table 1 and graphically displayed in Figure S1 of the online supplements. Entropy values remained high for all solutions in both domains (between .843 to .952 for German, between .855 and .926 for Math), suggesting high levels of classification accuracy across domains and solutions. The CAIC, BIC, and SSABIC kept on decreasing with the inclusion of additional profiles for the German and Math domains. Similarly, the BLRT failed to support any specific solution across domains. For both domains, the elbow plots revealed a first inflexion point in the decrease of the information criteria around 3 profiles, and a second one around 6-profiles. As a result, solutions including 3 to 6 profiles were inspected. This inspection revealed that all solutions were statistically proper, similar across domains (providing early evidence of configural similarity), and that increasing the number of profiles resulted in theoretically meaningful, interpretable, and distinct profiles up to the 5-profile solution for both domains. In contrast, adding a sixth (or seventh) profile to the solution did not bring additional information but rather simply resulted in the division of one existing profile into smaller ones characterized by similar shapes. For these reasons, the 5-profile solution was retained for both domains, supporting its configural similarity.

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**Table S1**

*Previous Person-Centered Studies on Academic Motivational Profiles*

| Study | Design | Sample characteristics | Domain under study | Profile indicators | Indicator characteristics | Profiles identified |
|---|---|---|---|---|---|---|
| Corpus & Wormington (2014) | Longitudinal (2 time points) | N = 490 (elementary) | General | Intrinsic<br>Extrinsic | Manifest indicators (standardized) | High quantity: high intrinsic and extrinsic (HA-HC)<br>Primarily intrinsic: high intrinsic, low extrinsic (HA-LC)<br>Primarily extrinsic: low intrinsic, high extrinsic (LA-HC) |
| Hayenga & Corpus (2010) | Longitudinal (2 time points) | N = 343 (elementary) | General | Intrinsic<br>Extrinsic | Manifest indicators (standardized) | High quantity: high intrinsic and extrinsic (HA-HC)<br>Good quality: high intrinsic, low extrinsic (HA-LC)<br>Poor quality: low intrinsic, high extrinsic (LA-HC)<br>Low quality: low intrinsic, low extrinsic (LA-LC) |
| Liu et al. (2009) | Cross-sectional | N = 767 (secondary) | General | Intrinsic<br>Identified<br>Introjected<br>External<br>Amotivation | Manifest indicators (standardized) | High self-determined/high controlled (HA-HC)<br>High self-determined/low controlled (HA-LC)<br>Low self-determined/high controlled (LA-HC)<br>Low self-determined/low controlled (LA-LC) |
| Lv et al. (2019) | Cross-sectional | N = 2137 (elementary) | Math | Intrinsic<br>Identified<br>Controlled | Manifest indicators (standardized) | High quality: close to average intrinsic and identified, low controlled<br>High quantity: close to average intrinsic and identified, high controlled<br>Low quantity: low intrinsic and identified, close to average controlled (LA-LC)<br>Poor quality: low intrinsic and identified, high controlled (LA-HC)<br>Low autonomous: low intrinsic and identified, average controlled |
| Oga-Baldwin & Fryer (2017) | Cross-sectional | N = 100 (elementary) | General | Intrinsic<br>External<br>Engagement | Manifest indicators (standardized) | High quantity: high intrinsic and external, average engagement (HA-HC)<br>Good quality: high intrinsic and engagement, low external (HA-LC)<br>Poor quality: low intrinsic and engagement, high external (LA-HC) |
| Oga-Baldwin & Fryer (2018) | Longitudinal (2 time points) | N = 513 (elementary) | English language | Intrinsic<br>Identified<br>Introjected<br>External | Manifest indicators | High quantity: high intrinsic and identified, low introjected, average external (HA-HC)<br>Good quality: high intrinsic and identified, low introjected and external (HA-LC)<br>Poor quality: low intrinsic, identified, introjected, high external (LA-HC) |

| | | | | | | |
|---|---|---|---|---|---|---|
| Oga-Baldwin & Fryer (2020a) | Cross-sectional | N = 830 (secondary) | English language<br>Japanese language | Intrinsic<br>Identified<br>Introjected<br>External | Manifest indicators | Low: low on all four indicators (LA-LC)<br>Good: high on intrinsic and identified, average introjected, low external (HA-LC)<br>Poor: low intrinsic, identified, introjected, high external (LA-HC)<br>High: high on all four indicators (HA-HC)<br>Moderate: average on all four indicators |
| Oga-Baldwin & Fryer (2020b) | Cross-sectional | N = 398 (elementary) | English language | Intrinsic<br>Identified<br>Introjected<br>External | Manifest indicators | High quality: high intrinsic, identified and external, moderate introjected (HA-HC)<br>Good quality: high intrinsic and identified, low introjected and external (HA-LC)<br>Poor quality: low intrinsic and introjected, moderate identified and external (LA-HC) |
| Ratelle et al. (2007) | Cross-sectional | Study 1: N = 4498 (secondary)<br>Study 2: N = 942 (secondary) | General | Intrinsic<br>Identified<br>Introjected<br>External<br>Amotivation | Manifest indicators | High autonomous/high controlled (HA-HC)<br>Moderate autonomous-controlled with low amotivation<br>Controlled (LA-HC) |
| Vansteenkiste et al. (2009) | Cross-sectional | N = 887 (secondary) | General | Autonomous<br>Controlled | Manifest indicators (standardized) | High quantity: high autonomous and controlled (HA-HC)<br>Good quality: high autonomous, low controlled (HA-LC)<br>Poor quality: low autonomous, high controlled (LA-HC)<br>Low quantity: low autonomous and controlled (LA-LC) |
| Wormington et al. (2012) | Cross-sectional | N = 1066 (secondary) | General | Intrinsic<br>Introjected<br>External | Manifest indicators | High quantity: high on all three indicators (HA-HC)<br>Good quality: high intrinsic, moderate introjected and external (HA-LC)<br>Poor quality: moderate intrinsic and introjected, high external<br>Low quantity with poor quality: low intrinsic and introjected, high external (LA-HC) |

*Note*. N = sample size.

**Table S2**

*Goodness-of-Fit Statistics for the Estimated Measurement Models*

| | $\chi^2$ | df | CFI | TLI | RMSEA (90% CI) | $\Delta\chi^2$ | $\Delta$df | $\Delta$CFI | $\Delta$TLI | $\Delta$RMSEA |
|---|---|---|---|---|---|---|---|---|---|---|
| *German Motivation* | | | | | | | | | | |
| Correlated factors CFA | 183.880* | 120 | .995 | .993 | .032 (.022, .041) | | | | | |
| Correlated factors ESEM | 86.470* | 60 | .998 | .995 | .029 (.013, .042) | | | | | |
| Bifactor CFA | 915.210* | 117 | .935 | .915 | .114 (.107, .120) | | | | | |
| Bifactor ESEM | 64.574 | 48 | .999 | .996 | .026 (.000, .040) | | | | | |
| *Math Motivation* | | | | | | | | | | |
| Correlated factors CFA | 149.298* | 120 | .997 | .996 | .021 (.006, .032) | | | | | |
| Correlated factors ESEM | 74.673 | 60 | .999 | .996 | .022 (.000, .036) | | | | | |
| Bifactor CFA | 525.808* | 117 | .962 | .950 | .081 (.074, .088) | | | | | |
| Bifactor ESEM | 59.242 | 48 | .999 | .997 | .021 (.000, .037) | | | | | |
| *Correlates* | | | | | | | | | | |
| German | 104.017* | 41 | .991 | .989 | .054 (.041, .067) | | | | | |
| Math | 136.439* | 41 | .990 | .987 | .066 (.054, .079) | | | | | |
| *Tests of Measurement Invariance (Motivation)* | | | | | | | | | | |
| Configural invariance | 391.075 | 353 | .998 | .996 | .014 (.000, .022) | | | | | |
| Weak invariance | 450.317 | 430 | .999 | .998 | .009 (.000, .018) | 75.850 | 77 | +.001 | +.002 | −.005 |
| Strong invariance | 478.805 | 459 | .999 | .998 | .009 (.000, .018) | 34.673 | 29 | +.000 | .000 | .000 |
| Strict invariance | 518.323 | 477 | .997 | .997 | .013 (.000, .020) | 44.853* | 18 | −.002 | −.001 | +.004 |
| Latent variance-covariance invariance | 591.638* | 505 | .995 | .993 | .018 (.011, .024) | 53.875* | 28 | −.002 | −.004 | +.005 |
| Latent mean invariance | 632.133* | 512 | .993 | .991 | .021 (.015, .026) | 23.519* | 7 | −.002 | −.002 | +.003 |
| *Tests of Measurement Invariance (Correlates)* | | | | | | | | | | |
| Configural invariance | 300.403* | 183 | .991 | .988 | .035 (.028, .042) | | | | | |
| Weak invariance | 313.936* | 191 | .990 | .988 | .035 (.028, .042) | 25.187* | 8 | −.001 | .000 | .000 |
| Strong invariance | 359.059* | 221 | .989 | .989 | .034 (.028, .041) | 70.158* | 30 | −.001 | +.001 | −.001 |
| Strict invariance | 366.630* | 232 | .989 | .989 | .033 (.027, .039) | 14.938 | 11 | .000 | .000 | −.001 |
| Latent variance-covariance invariance | 438.936* | 238 | .984 | .984 | .040 (.034, .046) | 38.615* | 6 | −.005 | −.005 | +.007 |
| Latent mean invariance | 436.657* | 241 | .984 | .985 | .039 (.033, .045) | 9.363 | 3 | .000 | +.001 | −.001 |

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

**Table S3**

*Standardized Parameter Estimates from the Correlated Factors CFA and ESEM Solutions for the Academic Motivation Scale for German*

| | CFA | | ESEM | | | | | | |
|---|---|---|---|---|---|---|---|---|---|
| | Factor (λ) | δ | Intrinsic (λ) | Integrated (λ) | Identified (λ) | Introjected (λ) | External (λ) | Amotivation (λ) | δ |
| Intrinsic motivation | | | | | | | | | |
| Item 1 | .910** | .173 | **.790**** | .095** | −.016 | −.009 | .041 | −.116* | .153 |
| Item 7 | .950** | .097 | **.839**** | −.014 | .100* | .043 | −.075* | −.066 | .070 |
| Item 13 | .939** | .118 | **.674**** | −.029 | .205** | −.058 | .012 | −.154** | .136 |
| ω | .953 | | .937 | | | | | | |
| Integrated regulation | | | | | | | | | |
| Item 2 | .852** | .273 | .076 | **.818**** | .047 | .016 | .016 | .069 | .272 |
| Item 8 | .886** | .215 | .026 | **.886**** | .028 | −.003 | −.007 | .043 | .196 |
| Item 14 | .901** | .187 | −.143** | **.824**** | .094 | −.008 | −.011 | −.133* | .189 |
| ω | .912 | | | .907 | | | | | |
| Identified motivation | | | | | | | | | |
| Item 3 | .906** | .179 | .312** | .130* | **.548**** | .080 | −.048 | .006 | .216 |
| Item 9 | .874** | .235 | .048 | .104* | **.667**** | −.025 | .001 | −.146** | .229 |
| Item 15 | .887** | .213 | .001 | .144* | **.744**** | .015 | −.051 | −.090 | .143 |
| ω | .919 | | | | .867 | | | | |
| Introjected motivation | | | | | | | | | |
| Item 4 | .929** | .138 | −.046 | .075 | −.226** | **.944**** | .011 | −.159* | .118 |
| Item 10 | .670** | .551 | −.058 | −.077 | .273* | **.520**** | .193** | −.020 | .537 |
| Item 16 | .907** | .177 | .058 | −.032 | .101 | **.960**** | −.075* | .164* | .109 |
| ω | .879 | | | | | .885 | | | |
| External motivation | | | | | | | | | |
| Item 5 | .911** | .170 | −.153* | −.057 | .125* | −.048 | **.944**** | −.016 | .137 |
| Item 11 | .942** | .112 | .073 | .076 | −.047 | .003 | **.931**** | .099 | .104 |
| Item 17 | .905** | .181 | .094 | −.018 | −.132 | .115** | **.838**** | −.059 | .166 |
| ω | .943 | | | | | | .948 | | |
| Amotivation | | | | | | | | | |
| Item 6 | .939** | .119 | −.099* | −.120** | .018 | .021 | −.019 | **.805**** | .114 |
| Item 12 | .916** | .160 | −.262** | −.027 | −.019 | .069 | −.032 | **.654**** | .181 |
| Item 18 | .887** | .214 | .085 | .071 | −.115* | −.059 | .092* | **.934**** | .147 |
| ω | .938 | | | | | | | .928 | |

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

**Table S4**

*Latent Factor Correlations from the Correlated Factors CFA (below the diagonal) and ESEM (above the diagonal) Solutions for the Academic Motivation Scale*

| | Intrinsic | Integrated | Identified | Introjected | External | Amotivation |
|---|---|---|---|---|---|---|
| *German motivation* | | | | | | |
| Intrinsic motivation | — | .486** | .615** | .037 | -.126* | -.805** |
| Integrated regulation | .572** | — | .720** | .072 | -.125* | -.536** |
| Identified regulation | .813** | .815** | — | .064 | -.150** | -.631** |
| Introjected regulation | .024 | .094 | .072 | — | .582** | .082 |
| External regulation | -.181** | -.143* | -.201** | .614** | — | .229** |
| Amotivation | -.902** | -.593** | -.787** | .078 | .271** | — |
| *Math motivation* | | | | | | |
| Intrinsic motivation | — | .416** | .730** | -.207** | -.208** | -.792** |
| Integrated regulation | .493** | — | .681** | -.078 | -.163** | -.411** |
| Identified regulation | .838** | .738** | — | .016 | -.132* | -.649** |
| Introjected regulation | -.219** | -.065 | -.020 | — | .539** | .225** |
| External regulation | -.229** | -.173** | -.203** | .573** | — | .241** |
| Amotivation | -.906** | -.516** | -.809** | .230** | .296** | — |

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

**Table S5**

*Standardized Parameter Estimates from the Bifactor-ESEM Measurement Model for the Academic Motivation Scale for German*

| | SDT (λ) | Intrinsic (λ) | Integrated (λ) | Identified (λ) | Introjected (λ) | External (λ) | Amotivation (λ) | δ |
|---|---|---|---|---|---|---|---|---|
| Intrinsic motivation | | | | | | | | |
| Item 1 | **.789**** | **.483**** | −.026 | .044 | .017 | .071* | −.146** | .114 |
| Item 7 | **.864**** | **.381**** | −.106** | −.014 | .057 | −.020 | −.065* | .088 |
| Item 13 | **.896**** | **.268**** | −.115** | −.064 | −.011 | .020 | −.014 | .107 |
| ω | | .806 | | | | | | |
| Integrated regulation | | | | | | | | |
| Item 2 | **.596**** | .025 | **.595**** | .145** | .070 | .033 | .023 | .262 |
| Item 8 | **.632**** | −.027 | **.627**** | .054 | .048 | .001 | .049 | .200 |
| Item 14 | **.671**** | −.137** | **.596**** | .017 | .034 | −.016 | .015 | .173 |
| ω | | | .839 | | | | | |
| Identified motivation | | | | | | | | |
| Item 3 | **.796**** | .136** | .119** | **.456**** | .104* | .009 | −.004 | .114 |
| Item 9 | **.830**** | −.114** | .119** | **.231**** | .020 | .006 | .051 | .228 |
| Item 15 | **.839**** | −.135** | .175** | **.276**** | .049 | −.028 | .076* | .162 |
| ω | | | | .648 | | | | |
| Introjected motivation | | | | | | | | |
| Item 4 | **−.096** | .094* | .083* | .056 | **.887**** | .303** | −.155** | .069 |
| Item 10 | **.156*** | −.149 | −.034 | −.081 | **.590**** | .351** | .166* | .447 |
| Item 16 | **−.034** | .035 | .044 | .072 | **.873**** | .264** | .101* | .149 |
| ω | | | | | .893 | | | |
| External motivation | | | | | | | | |
| Item 5 | **−.230**** | −.112* | −.018 | −.028 | .226** | **.865**** | .080 | .127 |
| Item 11 | **−.220**** | .053 | .056 | .023 | .273** | **.874**** | .031 | .106 |
| Item 17 | **−.192**** | .101* | −.027 | .001 | .332** | **.821**** | −.068 | .163 |
| ω | | | | | | .943 | | |
| Amotivation | | | | | | | | |
| Item 6 | **−.844**** | −.105** | −.013 | .045 | .044 | .003 | **.397**** | .116 |
| Item 12 | **−.824**** | −.162** | .060 | .063 | .071 | −.002 | **.319**** | .181 |
| Item 18 | **−.800**** | −.013 | .088* | −.016 | .020 | .088* | **.447**** | .144 |
| ω | .973 | | | | | | .754 | |

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

**Table S6**

*Standardized Parameter Estimates from the Correlated Factors CFA and ESEM Solutions for the Academic Motivation Scale for Math*

| | CFA | | ESEM | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|
| | Factor (λ) | δ | Intrinsic (λ) | Integrated (λ) | Identified (λ) | Introjected (λ) | External (λ) | Amotivation (λ) | δ |
| Intrinsic motivation | | | | | | | | | |
| Item 1 | .939** | .118 | **.770**** | −.018 | .117 | −.098** | .058* | −.103* | .109 |
| Item 7 | .943** | .111 | **.887**** | .065 | −.045 | .032 | −.029 | −.088* | .090 |
| Item 13 | .948** | .102 | **.699**** | .008 | .187** | −.043 | .008 | −.104* | .115 |
| ω | .960 | | .946 | | | | | | |
| Integrated regulation | | | | | | | | | |
| Item 2 | .849** | .280 | .030 | **.834**** | −.060 | .052 | −.005 | −.071 | .303 |
| Item 8 | .827** | .315 | .086 | **.972**** | −.027 | −.001 | −.048 | .214** | .149 |
| Item 14 | .878** | .228 | −.180* | **.691**** | .187 | −.074 | .098 | −.213** | .288 |
| ω | .888 | | | .894 | | | | | |
| Identified motivation | | | | | | | | | |
| Item 3 | .854** | .271 | .152* | .120 | **.562**** | −.020 | −.042 | −.079 | .307 |
| Item 9 | .838** | .298 | .150 | .074 | **.750**** | .071 | −.074* | .080 | .235 |
| Item 15 | .913** | .167 | −.011 | .063 | **.737**** | .016 | −.017 | −.197** | .164 |
| ω | .902 | | | | .856 | | | | |
| Introjected motivation | | | | | | | | | |
| Item 4 | .886** | .216 | −.068 | −.053 | −.004 | **.932**** | −.005 | −.138** | .153 |
| Item 10 | .600** | .640 | −.002 | −.063 | .277 | **.465**** | .124* | .172* | .624 |
| Item 16 | .898** | .194 | .025 | .080 | −.082 | **.892**** | −.013 | .031 | .221 |
| ω | .844 | | | | | .840 | | | |
| External motivation | | | | | | | | | |
| Item 5 | .862** | .258 | −.001 | .020 | −.114 | .016 | **.850**** | −.065 | .264 |
| Item 11 | .907** | .176 | .082 | −.019 | −.015 | .008 | **.930**** | .019 | .138 |
| Item 17 | .883** | .220 | −.022 | .021 | .049 | .031 | **.842**** | .073 | .235 |
| ω | .915 | | | | | | .915 | | |
| Amotivation | | | | | | | | | |
| Item 6 | .872** | .240 | −.090 | −.027 | −.164** | .066 | .014 | **.637**** | .254 |
| Item 12 | .932** | .132 | −.314** | −.006 | .007 | −.055 | .083* | **.649**** | .143 |
| Item 18 | .829** | .312 | .010 | −.068 | −.051 | .022 | .008 | **.795**** | .261 |
| ω | .910 | | | | | | | .868 | |

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

**Table S7**

*Standardized Parameter Estimates from the Bifactor-ESEM Measurement Model for the Academic Motivation Scale for Math*

| | SDT (λ) | Intrinsic (λ) | Integrated (λ) | Identified (λ) | Introjected (λ) | External (λ) | Amotivation (λ) | δ |
|---|---|---|---|---|---|---|---|---|
| Intrinsic motivation | | | | | | | | |
| Item 1 | **.878**** | **.310**** | −.104** | .011 | −.075* | .063* | −.037 | .112 |
| Item 7 | **.859**** | **.410**** | −.065* | .006 | −.011 | .017 | −.087** | .082 |
| Item 13 | **.905**** | **.258**** | −.072* | .019 | −.018 | .035 | .001 | .108 |
| ω | | .760 | | | | | | |
| Integrated regulation | | | | | | | | |
| Item 2 | **.522**** | −.023 | **.630**** | .052 | .056 | .000 | −.022 | .324 |
| Item 8 | **.433**** | .063 | **.820**** | .143** | .011 | −.055 | .046 | .110 |
| Item 14 | **.629**** | −.202** | **.566**** | −.010 | .013 | .075 | .052 | .235 |
| ω | | | .859 | | | | | |
| Identified motivation | | | | | | | | |
| Item 3 | **.770**** | .047 | .159** | **.265**** | .058 | −.002 | −.011 | .305 |
| Item 9 | **.751**** | .050 | .174** | **.371**** | .168** | .008 | .073 | .232 |
| Item 15 | **.849**** | −.072 | .135** | **.278**** | .130** | .038 | .007 | .160 |
| ω | | | | .545 | | | | |
| Introjected motivation | | | | | | | | |
| Item 4 | **−.140**** | −.099* | −.044 | −.063 | **.880**** | .253** | .045 | .124 |
| Item 10 | **−.068** | −.037 | .017 | .113 | **.513**** | .263** | .157* | .624 |
| Item 16 | **−.256**** | .088 | .097* | .133* | **.838**** | .218** | −.108* | .139 |
| ω | | | | | .849 | | | |
| External motivation | | | | | | | | |
| Item 5 | **−.238**** | −.038 | −.023 | −.137 | .206** | **.796**** | .050 | .244 |
| Item 11 | **−.204**** | .014 | −.033 | −.057 | .234** | **.857**** | .066 | .160 |
| Item 17 | **−.309**** | .065 | .053 | .205** | .210** | **.832**** | −.090 | .111 |
| ω | | | | | | .923 | | |
| Amotivation | | | | | | | | |
| Item 6 | **−.796**** | −.050 | .026 | −.046 | .057 | .015 | **.334**** | .245 |
| Item 12 | **−.845**** | −.140** | .100** | .037 | −.002 | .046 | **.333**** | .142 |
| Item 18 | **−.786**** | .048 | .035 | .086 | .033 | .004 | **.337**** | .256 |
| ω | .966 | | | | | | .611 | |

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

**Table S8**

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

| | SDT (λ) | Intrinsic (λ) | Integrated (λ) | Identified (λ) | Introjected (λ) | External (λ) | Amotivation (λ) | δ |
|---|---|---|---|---|---|---|---|---|
| Intrinsic motivation | | | | | | | | |
| Item 1 | **.846**** | **.413**** | −.038* | −.015 | −.018 | .063** | −.058** | .105 |
| Item 7 | **.886**** | **.319**** | −.083** | −.003 | −.001 | .022 | −.019 | .105 |
| Item 13 | **.896**** | **.273**** | −.046 | .013 | .010 | .006 | −.005 | .120 |
| ω | | .754 | | | | | | |
| Integrated regulation | | | | | | | | |
| Item 2 | **.519**** | .078 | **.672**** | .166** | .059* | .007 | −.038 | .241 |
| Item 8 | **.534**** | −.031 | **.691**** | .060 | .048 | −.019 | .094** | .221 |
| Item 14 | **.628**** | −.194** | **.613**** | .046 | .027 | .010 | .012 | .189 |
| ω | | | .857 | | | | | |
| Identified motivation | | | | | | | | |
| Item 3 | **.775**** | .090** | .153** | **.363**** | .063* | .026 | −.002 | .231 |
| Item 9 | **.792**** | −.060* | .173** | **.258**** | .093** | −.002 | .097** | .255 |
| Item 15 | **.823**** | −.062* | .199** | **.320**** | .100** | .016 | .043 | .166 |
| ω | | | | .576 | | | | |
| Introjected motivation | | | | | | | | |
| Item 4 | **−.141**** | .047 | .008 | .046 | **.849**** | .314** | −.027 | .155 |
| Item 10 | **.039** | −.116* | .025 | −.027 | **.551**** | .322** | .184** | .543 |
| Item 16 | **−.132*** | −.038 | .065** | .032 | **.854**** | .282** | .017 | .166 |
| ω | | | | | .855 | | | |
| External motivation | | | | | | | | |
| Item 5 | **−.265**** | .035 | .028 | −.057 | .164** | **.836**** | .020 | .198 |
| Item 11 | **−.224**** | .031 | −.003 | .060* | .209** | **.882**** | .009 | .124 |
| Item 17 | **−.214*** | −.009 | −.023 | −.026 | .291** | **.827**** | .006 | .183 |
| ω | | | | | | .928 | | |
| Amotivation | | | | | | | | |
| Item 6 | **−.844**** | −.053* | .009 | .012 | .030 | .017 | **.377**** | .141 |
| Item 12 | **−.857**** | −.116** | .083** | .088** | .019 | .023 | **.265**** | .167 |
| Item 18 | **−.803**** | .014 | .039 | .002 | .010 | .050 | **.383**** | .205 |
| ω | .967 | | | | | | .672 | |

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

**Table S9**

*Final Standardized Parameter Estimates from the Correlates Measurement Model (Latent Mean Invariance)*

| | Self-concept (λ) | Effort (λ) | Anxiety (λ) | δ |
|---|---|---|---|---|
| Self-concept | | | | |
| Item 1 | .901** | | | .187 |
| Item 2 | .877** | | | .230 |
| Item 3 | .877** | | | .230 |
| ω | .916 | | | |
| Effort | | | | |
| Item 1 | | .934** | | .128 |
| Item 2 | | .713** | | .491 |
| Item 3 | | .879** | | .228 |
| ω | | .883 | | |
| Anxiety | | | | |
| Item 1 | | | .860** | .261 |
| Item 2 | | | .942** | .113 |
| Item 3 | | | .927** | .141 |
| Item 4 | | | .843** | .289 |
| Item 5 | | | .867** | .247 |
| ω | | | .949 | |

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

**Table S10**

*Correlations Between the Variables Used in This Study*

| | 1 | 2 | 3 | 4 | 5 | 6 | 7 | 8 | 9 | 10 | 11 | 12 |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| 1. Global SDT (G) | — | | | | | | | | | | | |
| 2. Intrinsic (G) | 0 | — | | | | | | | | | | |
| 3. Integrated (G) | 0 | 0 | — | | | | | | | | | |
| 4. Identified (G) | 0 | 0 | 0 | — | | | | | | | | |
| 5. Introjected (G) | 0 | 0 | 0 | 0 | — | | | | | | | |
| 6. External (G) | 0 | 0 | 0 | 0 | 0 | — | | | | | | |
| 7. Amotivation (G) | 0 | 0 | 0 | 0 | 0 | 0 | — | | | | | |
| 8. Global SDT (M) | .330** | -.172** | .143** | .282** | -.053 | -.073 | .001 | — | | | | |
| 9. Intrinsic (M) | -.203** | .071 | -.045 | .019 | -.089** | -.024 | .160** | 0 | — | | | |
| 10. Integrated (M) | .047 | -.060 | .340** | .038 | -.016 | .002 | -.011 | 0 | 0 | — | | |
| 11. Identified (M) | .102* | -.042 | .068 | .276** | .110* | .011 | .192** | 0 | 0 | 0 | — | |
| 12. Introjected (M) | .021 | .056 | .033 | .005 | .647** | .220** | .052 | 0 | 0 | 0 | 0 | — |
| 13. External (M) | -.086* | .059 | .030 | .057 | .179** | .656** | .051 | 0 | 0 | 0 | 0 | 0 |
| 14. Amotivation (M) | .006 | .116** | .099* | .080 | .095* | .050 | .376** | 0 | 0 | 0 | 0 | 0 |
| 15. Sex | .093* | .149** | -.063 | -.070 | -.031 | .009 | .005 | -.162** | -.130** | .008 | -.010 | .003 |
| 16. Self-concept (G) | .589** | .255** | -.070 | -.073 | -.005 | -.091* | -.084 | .167** | -.054 | -.040 | .009 | -.027 |
| 17. Self-concept (M) | .104* | -.145** | .089* | .125** | -.187** | -.136** | .019 | .680** | .369** | -.182** | -.016 | -.210** |
| 18. Effort (G) | .622** | .215** | .007 | -.021 | -.006 | -.046 | -.092* | .249** | -.076 | .023 | .090* | -.009 |
| 19. Effort (M) | .207** | -.119** | .085 | .139** | -.147** | -.115** | .001 | .704** | .277** | -.118** | .077 | -.150** |
| 20. Anxiety (G) | -.439** | -.120** | -.014 | .059 | .153** | .204** | .178** | -.135** | .037 | -.021 | .053 | .207** |
| 21. Anxiety (M) | .019 | .222** | -.115** | -.113** | .272** | .213** | .062 | -.551** | -.325** | .120** | .065 | .326** |
| 22. Grades (G) | .352** | .131** | -.036 | -.072 | -.155** | -.117** | -.068 | .159** | -.006 | -.048 | -.017 | -.146** |
| 23. Grades (M) | .070 | -.069 | .058 | .078 | -.193** | -.096* | .031 | .417** | .283** | -.146** | -.072 | -.218** |

(continued on next page)

*Note.* *$p$ < .05, **$p$ < .01; Variables (with the exception of sex, which is coded 0 for boys and 1 for girls) are factor scores estimated in standardized units (M = 0, SD = 1); G: German; M: Math; SDT: self-determined motivation.

**Table S10 (continued)**

| | 13 | 14 | 15 | 16 | 17 | 18 | 19 | 20 | 21 | 22 | 23 |
|---|---|---|---|---|---|---|---|---|---|---|---|
| 1. Global SDT (G) | | | | | | | | | | | |
| 2. Intrinsic (G) | | | | | | | | | | | |
| 3. Integrated (G) | | | | | | | | | | | |
| 4. Identified (G) | | | | | | | | | | | |
| 5. Introjected (G) | | | | | | | | | | | |
| 6. External (G) | | | | | | | | | | | |
| 7. Amotivation (G) | | | | | | | | | | | |
| 8. Global SDT (M) | | | | | | | | | | | |
| 9. Intrinsic (M) | | | | | | | | | | | |
| 10. Integrated (M) | | | | | | | | | | | |
| 11. Identified (M) | | | | | | | | | | | |
| 12. Introjected (M) | | | | | | | | | | | |
| 13. External (M) | — | | | | | | | | | | |
| 14. Amotivation (M) | 0 | — | | | | | | | | | |
| 15. Sex | -.042 | .077 | — | | | | | | | | |
| 16. Self-concept (G) | -.147** | .022 | .102* | — | | | | | | | |
| 17. Self-concept (M) | -.102* | -.114** | -.178** | .346** | — | | | | | | |
| 18. Effort (G) | -.145** | .016 | .162** | .796** | .280** | — | | | | | |
| 19. Effort (M) | -.106** | -.126** | -.080 | .312** | .830** | .527** | — | | | | |
| 20. Anxiety (G) | .192** | .123** | .018 | -.653** | -.255** | -.551** | -.235** | — | | | |
| 21. Anxiety (M) | .131** | .216** | .255** | -.050 | -.746** | -.049 | -.637** | .491** | — | | |
| 22. Grades (G) | -.144** | .010 | .031 | .593** | .352** | .469** | .307** | -.385** | -.143** | — | |
| 23. Grades (M) | -.088* | -.060 | -.149** | .260** | .677** | .201** | .563** | -.194** | -.514** | .539** | — |

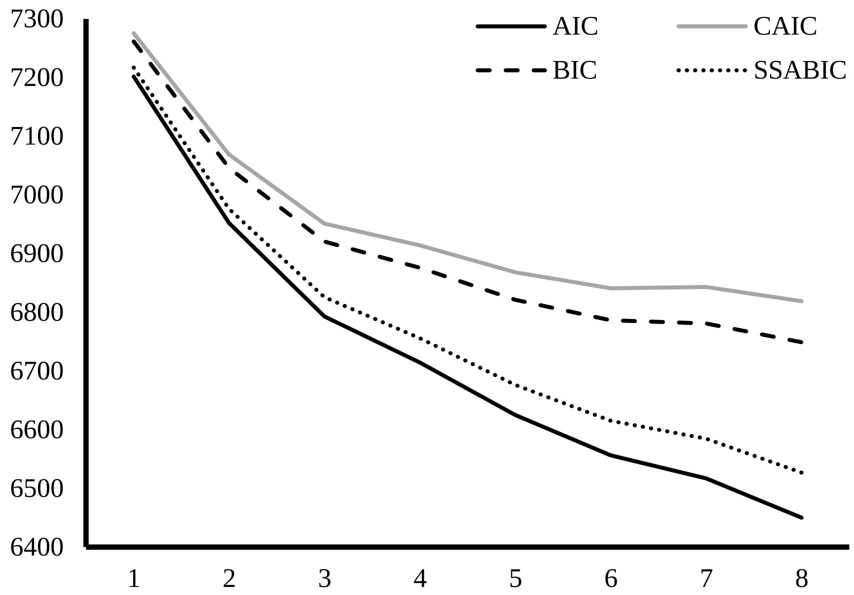
Note. *$p < .05$, **$p < .01$; Variables (with the exception of sex, which is coded 0 for boys and 1 for girls) are factor scores estimated in standardized units (M = 0, SD = 1); G: German; M: Math; SDT: self-determined motivation.

**Table S11**

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

| | Profile 1 | Profile 2 | Profile 3 | Profile 4 | Profile 5 | Profiles 1 to 5 |
|---|---|---|---|---|---|---|
| | Mean [95% CI] | Mean [95% CI] | Mean [95% CI] | Mean [95% CI] | Mean [95% CI] | Variances [95% CI] |
| Global SDT | -.213 [-.535, .109] | -.481 [-.653, -.308] | -.134 [-.313, .045] | .292 [.168, .416] | -.813 [-.974, -.651] | .471 [.407, .536] |
| Intrinsic | .135 [.016, .255] | -.040 [-.154, .074] | .082 [-.039, .202] | .194 [.118, .270] | -.404 [-.599, -.208] | .301 [.255, .348] |
| Identified | -.054 [-.217, .109] | -.132 [-.278, .013] | -.031 [-.159, .098] | -.101 [-.176, -.026] | -.030 [-.241, .181] | .427 [.377, .477] |
| Integrated | -.093 [-.231, .045] | -.058 [-.147, .030] | -.003 [-.097, .091] | .025 [-.036, .086] | -.056 [-.208, .096] | .269 [.234, .303] |
| Introjected | .253 [.002, .504] | .399 [.230, .568] | .135 [.012, .257] | .009 [-.081, .099] | -.119 [-.278, .040] | .453 [.399, .508] |
| External | 1.676 [1.577, 1.776] | .407 [.335, .480] | .972 [.890, 1.055] | -.262 [-.279, -.246] | -.479 [-.513, -.444] | .025 [.022, .028] |
| Amotivation | -.013 [-.182, .156] | .003 [-.109, .115] | .033 [-.080, .146] | .037 [-.048, .121] | -.103 [-.325, .120] | .343 [.300, .386] |

*Note.* SDT: Self-determined motivation; CI: Confidence interval; Factors were estimated from factor scores with a mean of 0 and a standard deviation of 1; Profile 1: Highly Extrinsic; Profile 2: Controlled; Profile 3: Moderately Extrinsic; Profile 4: Self-Determined; Profile 5: Non-Motivated.



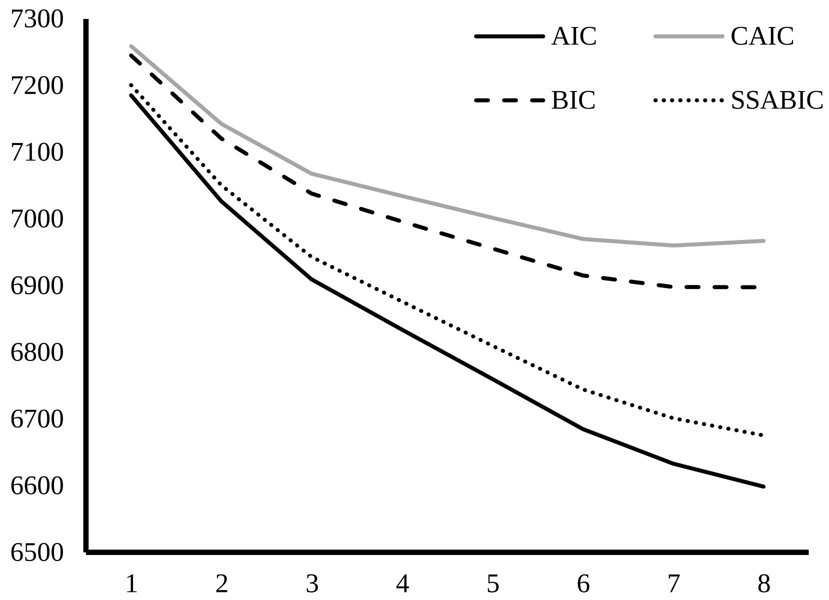




**Figure S1**

*Elbow Plots for the Information Criteria Used in Class Enumeration for German (Left) and Math (Right) Domains*

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