Trajectories of Academic Self-Concept during the Elementary School Years: A Growth Mixture Analysis

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Abstract

In this study, we seek to identify different profiles of children following distinct developmental trajectories of academic self-concept. Moreover, we look at their developmental outcomes regarding school achievement and educational attainment. This study relied on an accelerated longitudinal design that followed three cohorts of elementary school children (445, 479 and 356 students respectively in Grade 2, 3, and 4) during three consecutive school years (49.5 % girls). Results from growth mixture analyses revealed four distinct trajectory profiles: *Low Stable* (28.71%), *Moderate Decreasing* (40.4%), *High Decreasing* (10.71%), and *High Increasing* (20.18%). Compared to children with other profiles, children with a *Low Stable* profile displayed lower levels of academic achievement over the elementary school years, as well as lower educational attainment 9 years later, whereas children with one of the *High* profiles displayed the most desirable levels of achievement and attainment irrespective of their *Increasing* or *Decreasing* trajectories.

Keywords. Academic self-concept; achievement; school performance; educational attainment; trajectories; growth mixture; person-centered.

Academic self-concept (ASC), whether general or specific to school subjects, is defined as a subjective evaluation of students' academic competence that is partly formed through interactions with the school environment (Marsh, 2007; Marsh & Craven, 1997). The development of ASC over the elementary school years has been studied in relation to achievement (Guay et al., 2003), as well as to other desirable educational outcomes (Guay et al., 2004). However, ASC development has mainly been studied in order to uncover change as a function of a general trend (Scherrer & Preckel, 2019). Only a few studies have investigated ASC development to uncover the heterogeneity of this change (i.e., some children might experience a decrease in ASC over the years, whereas others might experience an increase, and a third group might experience stability) and how this heterogeneity relates to outcomes (Archambault et al., 2010; Chapman et al., 2000; Eccles et al., 1993; Musu-Gillette et al., 2015). The present study investigates the developmental heterogeneity of general ASC during the elementary school years. We also consider the implications of this developmental heterogeneity for students' academic achievement and educational attainment.

ASC Development

Not only does ASC appears essential to desirable educational outcomes, it is also an important educational outcome in its own right (Marsh, 2007). This makes it doubly important to uncover the mechanisms underlying its development. Research studying the development of ASC over the elementary school years has typically revealed a constant decline in children's scores (Wigfield et al., 2006). To understand this decline, researchers have outlined the following elements: (1) children's cognitive capacities; (2) the competitive structure of the school setting; and (3) the distinction between effort and ability (Wigfield et al., 2015).

Cognitive capacities

Because of their lower cognitive development, younger children's ASC will tend to be upwardly biased in relation to external indicators. This upward bias slowly fades away as children get older, leading to a general decrease in ASC over time (Harter, 2006). With the beginning of formal schooling, children are progressively exposed to objective standards of achievement and feedback from their peers, parents, and teachers (Boivin et al., 1992; Marsh et al., 2017). This environmental change is coupled with children's cognitive maturation, their growing capacity to perform social comparisons, and the improved accuracy of their academic self-evaluations against socially prescribed standards (Marsh et al., 2017). Because of these increasing cognitive capacities to accurately integrate feedback from past performance, teachers, or parents, children's overly optimistic ASC tends to become more realistic (Guay et al., 2003; Marsh et al., 2018).

The competitive structure of the school setting

In Western countries, summative evaluations become more salient and frequent as children progress from one school year to the next, thereby increasing competition (Wigfield et al., 2015). For instance, Janke et al. (2022) recently showed that when students' perceptions of exposure to a competitive classroom environment are high, their performance approach goals (trying to outperform others), performance avoidance goals (the avoidance of underperforming relative to others), and work avoidance goals (trying to avoid efforts) tended to increase over time, which could in turn decrease their ASC. In fact, these effects are independent from students' own levels of achievement given that, even top performers will always eventually be exposed to someone better than themselves. To this end, a literature review on 30 years of work on ASC (Marsh & Seaton, 2015) suggests avoiding highly competitive environment because it encourages social comparisons underlying the big-fish-little-pond effect, which has been found to reduce ASC.

The distinction between effort and ability

Developmental stages delineate children's capacity to differentiate effort, ability, and performance (Folmer et al., 2008; Fry & Duda, 1997; Nicholls, 1978). Young children (5-6 years old) do not clearly understand the difference between these concepts. As they grow older (7-9 years old), children come to believe that it is their effort that causes their performance. Then, between the ages of 9-12 years old, children come to see effort and ability as different, although which one causes performance remains elusive. It is only during adolescence that effort and ability come to be seen as compensatory approaches to performance. At this stage, efforts are often seen as a sign of weak ability, whereas putting less effort becomes an indicator of strong ability. Because these developmental stages are not absolute but vary from one child to another, we can expect that, by the end of elementary school, some children will come to view effort in a compensatory manner. In other words, because the school curriculum gains in complexity, many elementary children will put more effort in learning new things, which could lead them to believe that they are no longer good at school (lower ASC; Wigfield et al., 2015).

Empirical Evidence on ASC development

Several longitudinal studies have examined how ASC develops during the elementary school years (Boivin et al. 1992; Cole et al., 2001; Ehm et al., 2014; Molloy et al., 2011; Schmidt et al., 2017; Wigfield et al., 1997). In one multi-cohort study covering all six years of elementary school (Michigan, USA), domain-specific ASCs (math and reading) evidenced a sharp decrease during the first three years, after which they remained stable (Wigfield et al., 1997). This stable trend observed in the last three years of elementary school was replicated in another study on general ASC (Molloy et al., 2011). Additional studies even reported an increasing trend during the second half of the elementary school years, suggesting that children may become better at using self-enhancing strategies to rebuild their ASC (Cole et al., 2001). However, some studies observed a significant average decline in mathematical competence beliefs from grade 2 to grade 4 (Weidinger et al., 2018).

These previous studies are interesting but do not focus on the developmental heterogeneity of ASC. Indeed, average trajectories are likely to hide substantial heterogeneity reflecting the presence of subpopulations following qualitatively distinct trajectories. However, Archambault et al. (2010) did so by identifying seven trajectories of ASC in reading from Grade 1 through 12, most of which showed a declining pattern. Zooming in the elementary school years, five out of the seven developmental trajectories started with the same—high—levels of reading ASC in Grade 1. However, they differed with respect to when the decline started and how drastic the decline was. By the time they reached Grade 6, some children still reported high levels of ASC while others reported low levels of ASC. The two other trajectories started in Grade 1 with a lower-than-average level of ASC in reading that did not improve over the years, or worse, kept on decreasing. Likewise, another study focusing on children's perceptions of their own competence in math (a concept close to math ASC) reported similar findings (Musu-Gillette et al., 2015). More precisely, all three developmental trajectories identified in this study conducted between Grades 4 and 14 (college) were characterized by decreases in ASC levels even though they were all characterized by different initial levels of ASC. More precisely, the high trajectory identified in this study corresponding to 39% of the sample started with a high level of math ASC, which decreased slightly over the years. The two other trajectories identified in this study, corresponding to 39% and 22% of the sample, both began with the same moderate levels of ASC. However, one of these trajectories showed a steeper decline than the other. It is important to note that both studies examined ASC in specific domains such as reading and math. While domain-specific ASCs become increasingly differentiated with age (Marsh & Ayotte, 2003), the current study focuses on the developmental of *general* ASC because it mirrors children's *overall* academic functioning and achievement (Muenks et al., 2018).

In sum, the results from previous research focusing on ASC development among elementary school children can be summarized as follows (e.g., Archambault et al., 2010; Chapman et al., 2000; Eccles et al., 1993; Musu-Gillette et al., 2015): (1) Most children's experience a decline in their ASC (a trend evidenced across 12 years of schooling; Fredricks & Eccles, 2002; Jacobs et al., 2002); (2) this change is heterogenous rather than homogenous, and characterized by different initial values, end-states, and developmental trajectories.

ASC and its Relations with Important Educational Outcomes

Given that ASC is a subjective evaluation of one's academic competence anchored in one's repeated exposure to external standards and feedback, it is reasonable to expect ASC and achievement to be positively related. However, ASC does not perfectly mirror the objective reality. Indeed, associations between ASC and objective indicators of achievement are far from perfect, especially in the earlier elementary school years, possibly because of the aforementioned overestimation bias linked to children's more limited cognitive abilities, competition, and the distinction between effort and ability (Guay et al., 2003; Denissen et al., 2007; Davis-Kean et al., 2008; Sewasew & Schroeders, 2019). Thus, in a multicohort multioccasion study of elementary school children, Guay et al. (2003) reported that correlations between general ASC and teacher-reported ratings of achievement increased with age, from moderate (r = .31 to .49) in the 2nd and 3rd of elementary school to strong (r = .47 to .73) in the last three years of elementary school. A similar pattern of increasing correlations as a function of children's age was observed in other studies of domain-specific ASC in mathematics and reading (Denissen et al., 2007; Davis-Kean et al., 2008; Sewasew & Schroeders, 2019).

Not only are ASC and achievement correlated, but ASC is both a driver and an outcome of achievement, as suggested by the reciprocal effects model (Huang, 2011; Marsh, 1990; Valentine et al., 2004). More precisely, increases in ASC levels have been found to predict increases in subsequent levels of achievement. Likewise, increases in levels of achievement have been found to predict increases in subsequent ASC levels. Empirical evidence supports the relevance of this reciprocal effect model to young children (as early as Grade 2; Guay et al., 2003) regardless of their level of achievement (Susperreguy et al., 2018). These findings suggest that experiencing academic difficulties in early elementary school can hinder children from developing a positive ASC, which, in turn, can increase their academic difficulties. This persistent reciprocity can spiral up and drive the "Matthew effect" (i.e., the rich getting richer and the poor getting poorer; Stanovich, 1989) and increase the achievement gap between children. However, there is some empirical evidence that the reciprocal effects model for the relation between self-concept and achievement does not fully apply to young children (see Ehm et al., 2019).

Based on the positive bivariate correlations observed between ASC and achievement and on the reciprocal effect model, we expected children following more adaptive ASC trajectories (i.e., high and stable, decreasing slightly, or even increasing) to present higher levels of achievement over the years. In contrast, children following less positive ASC trajectories (i.e., low and decreasing drastically) should present lower levels of achievement over the years. Furthermore, based on the three developmental principles outlined above, we also expected a diminishing mismatch between ASC and actual achievement over the years.

Whereas many studies have examined the associations between children's ASC and their school achievement levels, little is known about the long-term implications of children's ASC. One exception comes from a Guay et al.'s (2004) longitudinal study of a sample of French-Canadian elementary children in which the authors tested the associations between children's ASC and their level of educational attainment in young adulthood. The results revealed that ASC reported during the elementary school years predicted participants' educational attainment levels in their young adulthood, even after controlling for their prior levels of achievement, SES, and family structure. In line with these findings, we expected children following trajectories characterized by higher ASC levels at the end of elementary school (6^{th} grade) to attain a higher level of education 9 years later, when most, if not all, children from elementary school experience a postsecondary transition while some students might have decided to not pursue their studies in college or at the university.

The Present Study

The purpose of this study was two-fold. We first sought to identify developmental trajectories of ASC during the elementary school years. In this regard, we proposed the following hypotheses:

Hypothesis 1: Based on the three developmental mechanisms, we expected a normative decline in ASC levels across the elementary school years.

Hypothesis 2: While we expect this declining trend when examining the sample as a whole, we expect to identify subpopulations (or profiles) of children following qualitatively and quantitatively distinct developmental trajectories of ASC differing in their initial level, rate of change, and end state.

The second aim of the study was to examine how these distinct profiles of ASC trajectories predicted time-specific school achievement levels and educational attainment levels in young adulthood. In this regard, we expected:

Hypothesis 3: Children following more adaptive ASC trajectories (i.e., high and stable, decreasing slightly, or even increasing levels of ASC) will present higher levels of achievement over the years. However, those following less adaptive ASC trajectories of ASC (i.e., low and decreasing more drastically) will present lower levels of achievement over the years.

Hypothesis 4: Achievement levels will not match ASC levels observed in each specific profile of children in the earlier elementary school years, but this degree of mismatch will fade away in subsequent elementary school years.

Hypothesis 5: Children following trajectories characterized by higher levels of ASC at the end of elementary school should attain a higher level of education in their young adulthood.

These hypotheses contribute to the existing literature on two important manners. First, although two past studies have linked prior ASC to subsequent achievement and educational attainment (e.g., Guay et al., 2003, 2004) in young elementary school children, none of these previous publications has tested whether the shape of ASC trajectories (rather than simply the level of ASC) was associated with an increase in achievement or to better educational attainment later on. In other words, if the ASC of some children increases, their achievement should show a similar developmental trend. Moreover, these children should attain a higher educational degree later on, when they reach young adulthood. If these hypotheses are not supported, this would challenge recommendations about the need to increase ASC in all young children. Indeed, if it does not matter for their achievement or educational level whether their ASC increase, decrease, or remain stable over time, this means that ASC levels observed early in development are more important than any changes that occur after this critical period. If such findings are obtained, this could cast some doubts on the efficiency of an interventions that occurs after this critical period. Second, studies on young children (Grade 2) ASC heterogeneous developmental trajectories are relatively rare and have never specifically considered children general ASC. Previous observations of declining domain-specific (math, reading) ASC trajectories among a majority of children does not necessarily means that a similar trend will be observed, or will be equally widespread, when focusing on domain-general ASC. For instance, research conducted on the physical self-concept has clearly demonstrated that domain-specific and domain-general self-concepts tended to change in a very different manner as a function of age (Marsh et al., 2010). We thus need more rigorous findings related to the heterogenous evolution of domain-general ASC among early elementary children, as this information is likely to lead to intervention initiative having long-lasting effects on students' educational development.

Method

Participants and Procedure

Participants were treated in accordance with ethical standards of APA, and the ethic committee of XXXXXX (BLINDED FOR REVIEW) has endorsed this project. This study relied on data collected as part of a previous study on children's social relationships (Hodges et al., 1999) that incorporated self-concept measures (Boivin et al., 1992). This study used data that have been already published in Guay et al. (2003, 2004). Specifically, we relied on data collected during three waves of data collection conducted in 1988 (Time 1- T1), 1989 (T2), and 1990 (T3), as well as on data from a follow-up data collection conducted in 1999. However, it should be noted that the hypotheses tested in this study are totally different than the ones tested in previous publications.

Participants were 1,280 French Canadian children (50.36% girls; M_{age} = 9 years old, ranging from 7 to 13 years), recruited from 10 elementary schools located in Quebec City (Canada), and selected to cover a variety of socioeconomic environments. Participants formed three cohorts of students enrolled in Grade 2 (Cohort 1: n = 445), 3 (Cohort 2: n = 479), and 4 (Cohort 3: n = 356) at the start of the study. Participants were from families that included an average of 2.28 children (SD = 1.07). Active parental consent was required and was obtained for 98% of possible participants.

In May of each school year, two well-trained research assistants visited classrooms and administered questionnaires to children and teachers. In May 1999, participants were contacted by a research assistant and were asked to complete a telephone interview. Among the 1,280 children who participated in the 1988 data collection, 513 (40%) could not be contacted in 1999 because they had moved or changed their telephone number. Among the 767 (60%) that we were able to contact, 465 (60%) agreed to participate in the 9-year follow-up, representing 36% of the original sample.

To ensure that this smaller subsample (n = 465) was equivalent and thus representative of the whole sample (N = 1280), we conducted a multivariate analysis of variance (MANOVA) on all study variables measured in the first wave of data collection. Results revealed a significant effect of attrition on achievement and ASC at T1 [$F(2, 1277) = 21.52$, $p < .001$], suggesting that participants who were lost through attrition reported slightly lower ASC and achievement levels at T1 relative to those who participated in the follow-up. However, the observed differences only corresponded to very small effects sizes (partial eta squared: η_p^2) of .026 for ASC and .027 for achievement (Cohen, 1992).

Measures

Academic Self-Concept

Children completed the ASC subscale from the French version (Boivin et al., 1992) of the Self-Perceptions Profile for Children (Harter, 1985). This 6-item subscale employs a structured alternative format where each item is rated on a 4-point scale, where higher scores reflect higher levels of ASC. The question format was designed specifically to offset social desirability tendencies and to provide participants with a range of response choices easy to understand for children (Harter, 1985). In the present study, each participant was presented with the following six items: 1- Some kids feel that they are very good at their school work BUT Other kids worry about whether they can do the school work assigned to them (reverse scoring), 2- Some kids feel like they are just as smart as other kids their age BUT Other kids aren't so sure and wonder if they are as smart (reverse scoring), 3- Some kids are pretty slow in finishing their school work BUT Other kids can do their school work quickly, 4-Some kids often forget what they learn BUT Other kids can remember things easily, 5- Some kids do very well at their classwork BUT Other kids don't do very well at their classwork (reverse scoring), 6-Some kids have trouble figuring out the answers in school BUT Other kids almost always can figure out the answers. Once they selected a statement, they had to decide whether the description that they have chosen is "Really True for Me" or "Sort of True for Me". Because they have to choose a statement, scores on each item are based on a 4-point scale from 1 to 4, where a score of 1 indicates the lowest perceived competence and a score of 4 reflects this highest level of competence. For each statement, children are asked to decide which kind of kids they are. After recoding statements 1-2-5, the right-side statement reflects higher ASC (after some items are properly recoded). For more details on the procedure behind the scale, we invite the reader to consult the manual (Harter, 2012) that is available online at https://www.apa.org/obesity-guideline/self-preception.pdf. We report the omega (ω) coefficients of composite reliability for this measure in Table S2 of the online supplements (ω = .778 to .832).

Academic Achievement

Once a year, teachers rated the academic performance of the students in three subjects (reading, writing, and math) using one item for each subject. Each item asked teachers to evaluate children's performance relative to that of their classmates using a 5-point scale (1 = quite under the mean, 2 = slightly under the mean, 3 = at the mean, 4 = slightly above the mean, 5 = quite above the mean). We used these three items to form a global indicator of academic achievement. Omega (ω) coefficients of composite reliability are reported in Table S2 of the online supplements (ω = .922 to .926).

Three reasons led us to use teachers' ratings of achievement instead of standardized test scores. First, in the Quebec educational system, no standardized test scores are available until late elementary school. Second, teacher ratings of achievement provide an assessment of children's academic performance in relation to the mean achievement of other children in the same class, thereby controlling for varying levels of strictness in teachers' grading systems. Third, there is empirical evidence supporting the validity of teachers' ratings to indicate students' academic performance. For instance, Guay et al. (2003) found a test-retest correlation of .69 based on responses by different teachers from one year to the next, while Rimfeld et al. (2019) reported high correlations between teacher ratings of achievement and standardized test scores.

Educational Attainment Level

This measure includes one item that asked young adults to report their highest completed level of education. Possible answers ranged from a secondary school degree to a university degree. In the Quebec educational system, after secondary school, students may enroll in a two-year general CEGEP (*Collège d'Enseignement Général et Professionnel*) program (leading to university) or in a three-year vocational CEGEP program (a self-contained program). However, students from all cohorts did not have the same attainment opportunities. For instance, the highest level of education that a child from Cohort 1 could obtain was the second year of CEGEP. In contrast, in Cohort 3, participants could attain the second year of university. To correct these differences, we divided participants' levels of educational attainment by their cohort highest possible level of educational attainment. For example, if a child from Cohort 1 had attained the first year of secondary school, then their attainment value would be .14 or 1/7 (i.e., 1 = first year of high school, 7 = second year of CEGEP). The resulting educational attainment score had a mean of .756 to .773 across cohorts, with a SD of .15 to .16 across cohorts, indicating the presence of sufficient inter-individual heterogeneity. Moreover, a one-way ANOVA revealed no differences on this variable across cohorts: F (2, 462) = 0.47, p = .624.

Preliminary Analyses

Preliminary measurement models were estimated to verify the psychometric properties of the multi-item measures of ASC and achievement over time using confirmatory factor analyses (CFA; Tables S1, S2, S3, and S4). The results support the factor structure of these measures and their invariance across time and cohorts (Millsap, 2011). We used factor scores (estimated in the natural units of the measures, thus ranging from 1 to 4 for ASC and from 1 to 5 for achievement) from these preliminary measurement models as inputs for the main GMA analyses. Because we based these factors scores on longitudinally invariant measurement models (Millsap, 2011), we ensured the comparability in the measures across time. Although factor scores do not explicitly control measurement errors the way latent variables do, they provide partial control for measurement errors by giving more weight to more reliable items (Skrondal & Laake, 2001). Furthermore, factor scores preserve the nature of the underlying measurement structure (e.g., measurement invariance) better than scale scores (Morin et al., 2016). We present descriptive statistics and correlations in Table 1.

Growth Mixture Analyses (GMA)

We conducted analyses using Mplus 8.3's (Muthén & Muthén, 2019) maximum likelihood robust (MLR) estimator and full information maximum likelihood (FIML) procedures to handle missing data (Enders, 2010; Graham, 2009). Thus, we based all analyses on the full sample of 1,280 students. In this study, these students provided a total of 3,004 time-specific ratings (M = 2.35 time-specific ratings per participant), with the majority of participants (n = 643, 50.2%) completing all three waves, 438 (34.2%) completing two waves, and 199 (15.6%) completing a single wave. To avoid converging on a local maxima, we conducted analyses using 10,000 random sets of start values, 1,000 iterations, and 500 solutions for final stage optimization (Hipp & Bauer, 2006).

We estimated and compared Linear[1] GMAs with one to eight latent trajectories of ASC. GMAs are built from latent curve models (Bollen & Curran, 2006) and aim to identify subpopulations of participants following distinct longitudinal trajectories (Grimm et al., 2016; Morin et al., 2011a). Linear GMAs summarize repeated measures by estimating random intercepts and slope factors that reflect, respectively, the initial level of these trajectories in Grade 2 and the change occurring of these trajectories for each increase of one grade level from Grade 2 to 6. Our reliance on data from the three cohorts of students made it possible to estimate longitudinal trajectories spanning 5 years of elementary school (Grades 2 to 6). To estimate these trajectories as a function of individually-varying time codes defined as a function of cohort-specific elementary grades, we relied on Mplus' MODEL CONSTRAINT function (Grimm et al., 2016). More precisely, the time codes used to reflect the passage of time for students from Cohort 1 (Grade 2 at T1) were 0 at T1 (to locate the intercept of the trajectories in Grade 2), 1 at T2, and 2 at T3. For Cohort 2, matching time codes were respectively 1-2-3 while they were 2-3-4 for Cohort 3. Because grades were very strongly correlated with age (r = .82, p < .01), and because 83% (Cohorts 2 and 3) to 86% (Cohort 1) of the children 1 had the appropriate age for their grade level, we were confident that relying on grades instead of age to calculate slopes did not introduce serious bias. Moreover, using grades instead of age is more appropriate in education settings, because the practical implications of the findings have a clearer connection to the educational level of the students.

Ideally, all GMA parameters (intercepts and slope means, intercept and slope variances and covariances, and time-specific residuals) should be freely estimated (Diallo et al., 2016; Morin et al., 2011a). However, this is not always possible due to the tendency of these more complex models to converge on improper solutions or not to converge at all (Diallo et al., 2016). This typically reflects overparameterization and the need to rely on simpler models (Bauer & Curran, 2003; Chen et al., 2001). This was the case in the present study. In such situations, the recommendation is to implement equality constraints across profiles on model parameters to achieve a more parsimonious representation of growth trajectories (Diallo et al., 2016). In this study, we constrained to equality the time-specific residuals across time and profiles (Li & Hser, 2011; Tofighi & Enders, 2008), whereas freely estimating other parameters (i.e., intercept and slopes, and their variances and covariance). This specification of the residuals is consistent with the typical operationalization of growth models estimated in the multilevel framework based on individually-varying time codes.

[1] With a maximum of three time points for each participant, it was not possible to model nonlinearity, despite the fact that the cohort sequential nature of this data set made it possible to model trajectories spanning five grades.

Table 1

Descriptive Statistics and Correlations (with Standard Errors in Parentheses) for All Variables Used in the Present Study

	1	2	3	4	5	6	7
1 ASC Time 1	---						
2 ASC Time 2	.725 (.017)**	---					
3 ASC Time 3	.742 (.016)**	.867 (.008)**	---				
4 Achievement (intercept)	.638 (.018)**	.629 (.017)**	.672 (.015)**	---			
5 Achievement (slope)	.063 (.028)*	.151 (.026)**	.233 (.026)**	.183 (.025)**	---		
6 Attainment	.405 (.040)**	.385 (.038)**	.407 (.040)**	.466 (.036)**	.124 (.039)**	---	
7 Time score at Time 1 (Cohort 0-1-2)	-.056 (.029)	.021 (.028)	.029 (.293)	.021 (.460)	.086 (.048)	-.038 (.043)	---
Mean	2.868	2.844	2.858	3.347	-.027	.765	.930
SD	.474	.516	.497	.910	.022	.155	.788

Note. * $p < .05$; ** $p \leq .01$; ASC = Academic self-concept.

Table 2

Results from the Growth Mixture Analyses

	LL	#fp	Scaling	AIC	CAIC	BIC	ABIC	Entropy
1 profile	-1414.377	6	1.3632	2840.754	2877.682	2871.682	2852.623	na
2 profiles	-1309.982	12	1.1788	2643.964	2717.819	2705.819	2667.701	.391
3 profiles	-1262.508	18	1.3271	2561.015	2671.798	2653.798	2596.622	.480
4 profiles	-1241.238	24	1.0653	2530.476	2678.187	2654.187	2577.951	.503
5 profiles	-1234.771	30	1.1615	2529.543	2714.181	2684.181	2588.886	.481
6 profiles	-1228.093	36	1.2228	2528.185	2749.751	2713.751	2599.398	.452
7 profiles	-1209.640	42	1.0230	2503.281	2761.774	2719.774	2586.362	.491
8 profiles	-1203.684	48	.9729	2503.368	2798.789	2750.789	2598.318	.474

Note. LL = Model Log Likelihood; #fp = Number of free parameters; AIC = Akaïke Information Criteria; CAIC = Constant AIC;

BIC = Bayesian Information Criteria; ABIC = Sample-Size adjusted BIC; na = Not applicable.

In determining the number of latent trajectory profiles in the data, it is critical to consider the substantive meaning, theoretical conformity, and statistical adequacy of the solution (Bauer & Curran, 2003; Marsh et al., 2009; Muthén, 2003), as well as statistical indices: The Akaïke Information Criterion (AIC), the Consistent AIC (CAIC), the Bayesian Information Criterion (BIC), and the sample-size Adjusted BIC (ABIC)[2]. A lower value on these indicators suggests a better-fitting model. Simulation studies indicate that the CAIC, BIC, and ABIC are particularly effective (Diallo et al., 2016, 2017; Nylund et al., 2007; Peugh & Fan, 2013; Tein et al., 2013; Tofighi & Enders, 2008), while advising against relying on the AIC. However, we reported all statistical indices, including the AIC to ensure full disclosure. A recent simulation study (Diallo et al., 2016) suggests that the BIC and CAIC should be privileged under conditions of high entropy (e.g., ≥ .800). In contrast, the ABIC appears to perform better in conditions of low entropy (e.g., ≤ .500). Because these indicators remain heavily influenced by the sample size (Marsh et al., 2009), they may keep on decreasing without reaching a minimum. In these cases, they should be graphically presented through "elbow plots" illustrating the gains associated with each estimated additional profile (Morin et al., 2011a, 2016). In these plots, the point after which the slope flattens suggests the optimal number of profiles.

Outcomes of Profile Membership

Once we selected the optimal number of profiles, we investigated the relations between these profiles and our outcomes (i.e., time-specific achievement levels and educational attainment). To be able to assess the associations between (a) ASC trajectories modeled as a function of grade level and (b) the factor scores reflecting participants' achievement levels at the same grade level, we relied on a strategy initially proposed by Morin et al. (2011a). We saved factor scores reflecting achievement from preliminary latent curve models (Bollen & Curran, 2006). We estimated these as a function of grade level to reflect the intercept (level in Grade 2) and slope (rate of change per increase in grade level) of participants' achievement trajectories.

A strong assumption of person-centered analyses is that the profiles should remain unaffected by the inclusion of the covariates (Diallo et al., 2017; Marsh et al., 2009; Morin et al., 2011b). Observing such change indicates that the nature of profiles depends on the choice of covariates and calls into question the assumption that the ordering is from the profiles to the outcomes (Marsh et al, 2009). To ensure that this did not happen, we included outcomes as additional indicators into a solution defined using the start values from the final unconditional GMA (Diallo et al., 2017; Morin et al., 2016). Outcome levels were then contrasted across profiles using the multivariate delta method (Raykov & Marcoulides, 2004) implemented in Mplus using the MODEL CONSTRAINT function[3].

Results

Developmental Profiles

We report the unconditional GMAs (Table 2) and their graphic representations (Figure S1 of the online supplements). While the AIC kept on decreasing with the addition of profiles, the CAIC and BIC tentatively supported the 3-profile solutions (values on these indicators were very close for the 3- and 4-profile solutions, whereas the ABIC more clearly supported the 4-profile solution. Based on Diallo et al.'s (2016) recommendations, the ABIC (supporting the 4-profile solution) should be favored given the relatively low levels of entropy associated with these models. Examination of the 4-profile solutions, together with the adjacent 3- and 5- profile solutions, indicated that all solutions were statistically proper, and that additional profiles resulted in a meaningful addition to the solution up to the 4-profile solution. However, adding further profiles to the solution only resulted in relatively small profiles (corresponding to 6% or less of the sample) characterized by trajectories that were not meaningfully distinct from those already included in the solution. Thus, we retained the 4-profile solution for interpretation and further analyses. We present the graphic solution (Figure 1) and profile-specific parameter estimates (Table 3). This solution resulted in a moderate level of classification accuracy of participants into their most likely profile (see Table S5 of the online supplements), ranging from 59.6% to 91.2% across profiles, consistent with its moderate entropy value (.503).

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

[3] Readers interested in learning about the estimation of growth mixture analyses with and without outcomes should consult Morin and Litalien (2019). We also provide the Mplus input file for our final model at the end of online supplements.

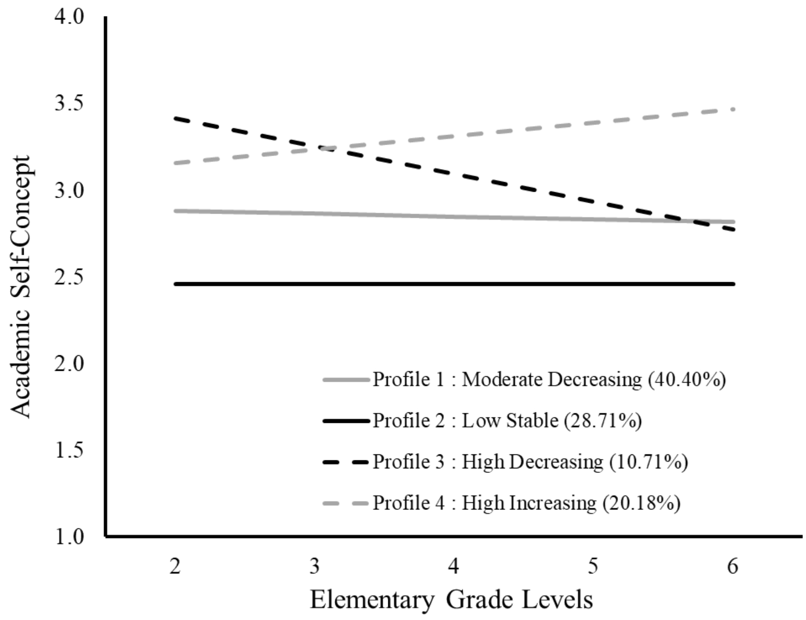

Figure 1
Developmental Trajectories of Academic Self-Concept during the Elementary Grade Levels

Profiles 3 (*High Decreasing*; corresponding to 10.71% of the sample) and 4 (*High Increasing*; corresponding to 20.18% of the sample) were both characterized by high initial levels of ASC. However, Profile 3 was characterized by a decreasing tendency (corresponding to a decrease of .16 ASC unit per grade level, keeping in mind that ASC has an SD of roughly .50). In contrast, Profile 4 was characterized by an increasing tendency (corresponding to an increase of.08 ASC unit per grade level). The largest profile (corresponding to 40.40% of the sample) was Profile 1 (*Moderate Decreasing*). This profile corresponded to children who reported average levels of ASC in Grade 2, followed by a slightly decreasing tendency (corresponding to a decrease of .02 ASC unit per grade level). Finally, Profile 2 (*Low Stable*) corresponded to roughly one fourth of the students (28.71%) characterized by *low* levels of ASC that remained stable over the course of the study.

The results from the preliminary measurement models, reported in Table S4 of the online supplements, support the latent mean invariance of the ASC measure over time (and cohorts), consistent with a lack of normative decrease in ASC levels over time. Specifically, the model fit indices associated with the model of latent mean invariance (Model 7 in Table S4), in which the latent means of ASC are constrained to equality over time, does not differ meaningfully from that of the previous model of latent variance-covariance invariance (Model 6 in Table S4) in which these means were allowed to differ over time. However, the profile-specific trajectories identified in our main analyses show a slight normative decrease in ASC trajectories characterizing roughly half of the sample (*High Decreasing:* 10.71%; *Moderate Decreasing*: 40.40%), whereas only one in five students exhibited an increasing trajectory (*High Increasing*: 20.18%).

Profile-specific Relations to Outcomes

Results comparing outcomes' levels across profiles reported in Table 4, profile-specific outcome trajectories of achievement in Figure 2, and profile-specific attainment levels reported in Figure 3. We showed that the four profiles were clearly differentiated from one another in relation to achievement and educational attainment. In Grade 2, achievement levels were the highest in the *High Increasing* profile, followed by the *High Decreasing* profile, then by the *Moderate Decreasing* profile, and finally by the *Low Stable* profile. We found that achievement levels decreased slightly over time across all profiles. However, this decrease was most pronounced in the *High Decreasing* profile, followed by the *Low Stable* profile, and was the least present in the *High Increasing* and *Moderate Decreasing* profiles. In relation to educational attainment, the *High Increasing* and *High Decreasing* profiles both displayed the highest level of educational attainment 9 years after the last measurement point (1990), followed by the *Moderate Decreasing* profile, and finally by the *Low Stable* profile. Overall, these findings indicate that having a low to moderate ASC constitutes a high-risk factor for lower achievement and educational attainment.

Table 3

Parameters Estimates from the Final Unconditional Growth Mixture Analysis

Parameter	Moderate Decreasing Estimate *(t)*	Low Stable Estimate (*t*)	High Decreasing Estimate (*t*)	High Increasing Estimate (*t*)
Intercept Mean	2.879 (92.239)**	2.458 (27.199)**	3.411 (95.819)**	3.156 (50.555)**
Slope Mean	-.016 (-2.405)*	.000 (.022)	-.160 (-4.215)**	.077 (5.030)**
Intercept variability $(SD=\sqrt{s})$	.251 (4.987)**	.428 (4.778)**	.000	.152 (1.640)
Slope variability $(SD=\sqrt{s})$	.000	.197 (4.721)**	.000	.000
Intercept-Slope Correlation	.000	-.043 (-4.020)**	.000	.000
$SD(e_{yi})$	.214 (18.638)**	.214 (18.638)**	.214 (18.638)**	.214 (18.638)**

Note. * $p \leq .05$; ** $p \leq .01$; t = Estimate / standard error of the estimate (t values are computed from the original variance estimate); $SD(e_{yi})$= Standard deviation of the time-specific residuals.

Table 4

Association between Profile Membership and the Outcomes

	Moderate Decreasing (1)		Low Stable (2)		High Decreasing (3)		High Increasing (4)		Significant Differences
	M	CI	*M*	CI	*M*	CI	*M*	CI	
Achievement (Intercept)	3.430	[3.359, 3.501]	2.445	[2.339, 2.551]	3.914	[3.751; 4.077]	4.527	[4.456; 4.598]	2 < 1 < 3 < 4
Achievement (Slope)	-.027	[-.029, -.025]	-.033	[-.035, -.031]	-.035	[-.041; -.029]	-.018	[-.020; -.016]	3 = 2 < 1 < 4
Attainment	.760	[.735, .735]	.611	[.568, .654]	.869	[.865; .873]	.850	[.830; 0.870]	3 = 4 > 1 > 2

Note. *M* = Mean; CI = 95% confidence interval.

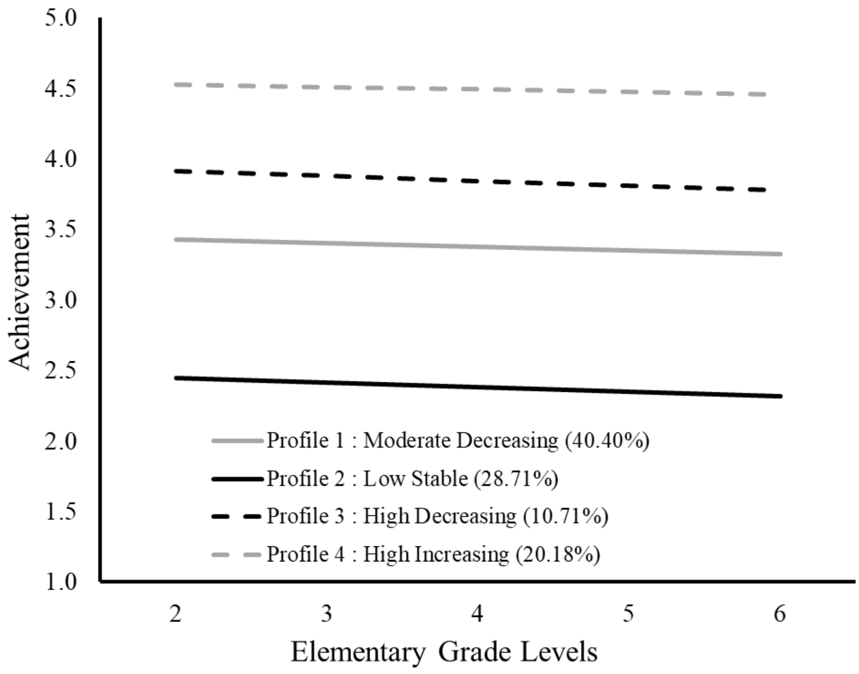

Figure 2
Profile-Specific Trajectories of Achievement

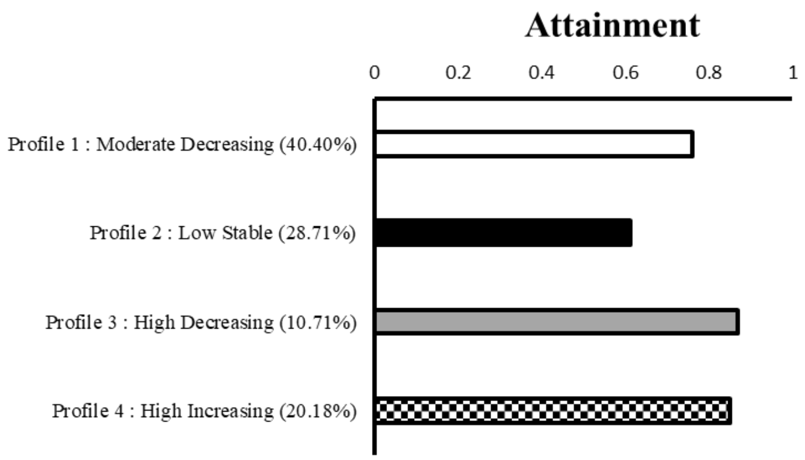

Figure 3
Profile-specific Comparison of Educational Attainment 9 years Later

Discussion

The present study sought to (1) identify profiles of children following distinct trajectories of academic self-concept (ASC) over the elementary school years and (2) examine the consequences of these profiles in terms of academic achievement and educational attainment. Evidence was mixed regarding the normative decline in ASC levels expected in Hypothesis 1. Our results suggest that the previously reported normative decline in ASC levels might be limited to roughly half of the students, although it remained minimal for most of them (40.40%) and pronounced for only 10.71% of them. However, we also observed increasing and stable trajectories. Indeed, and supporting Hypothesis 2, we observed four different profiles characterized by different initial levels, rates of change, and end-states. These profiles corresponded to different proportions of children (*Low Stable*: 28.71%; *High Increasing*: 20.18%; *High Decreasing*: 10.71%; *Moderate Decreasing*: 40.40%). In relation to the outcomes, the results mainly supported Hypotheses 3 and 5, showing that children characterized by more adaptive profiles (characterized by higher – increasing or decreasing – levels of ASC over time) presented higher levels of achievement over the years and reported higher levels of educational attainment 9 years after the last measurement point taken during elementary school. Finally, and supporting Hypothesis 4, children seemed to be less well-calibrated in their perceptions of their academic performance in Grade 2 as shown in the initial mismatch between the ASC and achievement levels associated with *High Increasing* and *High Decreasing* profiles at the start of the study.

Developmental Mechanisms

GMA offers the possibility to uncover different longitudinal patterns of change in ASC levels and the initial value at which these patterns start (Guay et al., 2021). We first observed that not all children started Grade 2 with the same level of ASC, and that their developmental trajectories of ASC evidenced substantial inter-individual heterogeneity over the elementary school years. Specifically, children corresponding to the *High Increasing* trajectory profile began Grade 2 with high ASC scores that increased over the four subsequent years. In contrast, two other profiles reported high (*High Decreasing*) and average (*Moderate Decreasing*) levels of ASC in Grade 2 evidenced declining ASC trajectories. Finally, the last profile (*Low Stable*) displayed low levels of ASC in Grade 2 that neither increased nor decreased over time. These findings thus indicate that 51% of the children experienced a small (40.40%) to marked (10.71%) decline, 20% an increase, and 29% stability in their ASC trajectories over their elementary school years. These findings are thus challenging past research of a normative decline in ASC levels over the elementary school years (Fredricks & Eccles, 2002; Jacobs et al., 2002; Marsh, 1989), at least when domain-general ASC is considered. In fact, the current result enrich our understanding of domain-general ASC development by showing that the previously reported decline seems limited to a subset of children, and to a small subset if we consider those from whom this decline is pronounced. These results clearly align with previous research uncovering developmental heterogeneity in children's ASC trajectories (Musu-Gilette et al., 2015), by showing that increasing and stable trajectories remain possible for a non-negligible proportion of children.

Two of the identified profiles started Grade 2 with clearly distinct levels of ASC, to attain a similar end-state by the end of the study. More precisely, the *High Decreasing* trajectory started with the highest level of ASC, but exhibited a drop in ASC levels of time, leading them to an end state corresponding to that of the *Moderate Decreasing* profile started the study with drastically lower ASC levels. Thus, these results suggest that starting Grade 2 with relatively high levels of ASC scores does not necessarily guarantee that children's ASC levels will remain high over the long run, as 10% of the children included in this study experienced such a significant decrease over time. Thus, future research needs to identify who these children are and what mechanism played a role in their decreasing trajectories. Did they have a cognitive bias leading them to overestimate their capabilities in Grade 2? Did they become more precise in their self-perceptions of ability and effort as they grew older? Or did they experience a competitive climate leading them to believe that they were not as good as they thought in school? Fortunately, our results related to the implications of the outcomes of these profiles allow us to offer some tentative explanations for this result.

Achievement and Educational Attainment

Several distinctions were observed between profiles in relation to children's levels of educational achievement and attainment, thus supporting their discriminant validity. More precisely, the achievement trajectories observed in these four profiles indicated that children with higher levels of ASC tended to perform better than other children. This rank-order stability of achievement as a function of ASC seems to be crystallized as early as Grade 2. While achievement showed a decreasing trend (i.e., a negative slope) in all profiles, the rank-ordering of achievement levels remained stable over time: The stronger the ASC, the higher the achievement. One important point is that our measure of achievement was a rank-order one. Indeed, teachers were asked to rate each child's academic performance relative to that of all other classmates. At best, these findings suggest a strong ASC tends to be associated with stronger rank-ordered achievement levels (i.e., better performance than that of one's classmates). Interestingly, this early advantage of having a strong ASC in relation to achievement appears to be translated over the long term into higher levels of educational attainment. Possibly, a positive ASC helps children to stay motivated in academics (e.g., greater self-efficacy, values, interest), in turn helping them to go further in their education.

The *Low Stable* profile is a cause for concern. As expected, educational outcome levels were generally at their lowest for children corresponding to this profile. These children started Grade 2 with relatively low academic achievement levels, which experienced a slight decrease over the years (despite the stability of their ASC trajectories). These children also displayed the lowest educational attainment 9 years later. These students seem to struggle academically (as evidenced in their lower ASC and achievement trajectories). It seems plausible to assume that a greater proportion of them might have repeated a grade, which would have directly impacted their level of educational attainment 9 years later. Indeed, when considering these results, it is important to keep in mind that, for many participants, our last measurement point was taken before the end of their educational trajectories, suggesting that a longer follow up might have revealed alternative results in relation to students who repeated a grade and yet stayed in the education system. It is unfortunate that we did not have data to investigate whether children corresponding to this *Low Stable* profile were from lower socioeconomic backgrounds, had a lower initial level of cognitive ability, or came from specific family backgrounds (e.g., harsh parenting, immigrants, single parents household, etc.). Clearly, this is an area worth considering in future research. In any case, school professionals should pay extra attention to children with low ASC at the beginning of elementary grades. This observation also reinforces the need to better prepare preschool children in relation to numeracy and literacy skills (Garon-Carrier et al., 2018) to alleviate the risk of developing a poor ASC early in elementary school.

Albeit indirectly, given that we did not pursue tests of directionality in this study, our findings also support the reciprocal effects model (Marsh & Yeung, 1997) and the "Matthew effect" (the rich getting richer and the poor getting poorer; Stanovich, 1986). More precisely, children starting with average or low ASC scores (i.e., *Moderate Decreasing* and *Low Stable* profiles) seem to be at higher risk of seeing these scores remain stable or to decrease further over time. Furthermore, their initially lower-than-average levels of academic performance also seem to feed into this downward trajectory of ASC, which may explain the longer-term associations between these ASC trajectories and educational attainment 9 years later. In contrast, children starting with higher ASC scores (i.e., *High Increasing* and *High Decreasing* profiles)—irrespective of whether these scores reflect an upward bias or not—were more likely to retain a high level of ASC over time, irrespective of whether these high levels followed an upward or downward trajectory. Once again, the initially above-average levels of academic performance of these youths seemed to feed into their more desirable ASC trajectories, leading to higher levels of educational attainment 9 years later. Thus, differences observed as early as Grade 2 in ASC levels remain roughly present at least until Grade 5, given that the *High Decreasing* profile presented ASC levels corresponding to those observed in the *Moderate Decreasing* profile in Grade 6, and have implications that are still observable 9 years later.

The downward trajectory observed in the *High Decreasing* profile also caught our attention. Indeed, children corresponding to this profile started with the highest level of ASC, but not the highest levels of achievement. In addition, they finished the study with a moderate level of ASC, although they were able to maintain relatively stable levels of achievement over time despite their decreasing ASC trajectories, and were able to attain a high level of education 9 years later (comparable to that of the *High Increasing* profile). One possible explanation for this unique pattern is that the initially high levels of ASC observed specifically in this profile might have been the result of the aforementioned upward bias previously associated with young children ASC (Harter, 2003). Their relatively lower levels of achievement also support this interpretation. Then, as these children progress in school and interact with higher achieving students, this initial upward bias comes to progressively fade away until their ASC levels come to match their achievement levels. This finding suggests the importance of helping align children's ASC with objective standards of excellence at the onset of formal schooling. However, they also highlight the possibility that the upward bias typically associated with younger children's lower levels of cognitive development (Guay et al., 2003) might be more pronounced for a small subset of roughly 10% of elementary school children.

Overall, our results show that starting Grade 2 with a low ASC puts students at risk of experiencing negative outcomes (i.e., lower teacher-rated academic performance and lower educational attainment 9 years later). These results are troublesome because they suggest that problematic educational trajectories seem to be fixed from the start, leaving little room for improvement, at least in the absence of intervention. Thus, these results clearly demonstrate the need for preventive interventions specifically targeted at increasing the ASC of this subset of at-risk children corresponding to close to a third of the population. Clearly, more research is needed to identify conditions under which the effects of ASC interventions will yield the most benefits and how to adapt these interventions to distinct student profiles. More importantly, more research is also needed to identify the mechanisms underpinning the formation of these distinct ASC profiles and the extent to which they will be generalized to other samples and cultures.

Strengths and Limitations

This study is characterized by methodological strengths, including an accelerated cohort sequential longitudinal design covering most elementary school years (5 out of 6 years) in the Quebec educational system, a large sample size, and a set of sophisticated analyses to test our research hypotheses. However, this study also has some weaknesses. First, one of the outcomes (educational attainment) was self-reported by students and taken before the end of the possible educational trajectories of these students. This means that self-report biases could, to some extent, have played a role in the observed relations. It also means that levels of educational attainment could have been downwardly biased for students who had to repeat grades, as well as for those who ended up with the highest educational degrees. It would be interesting for future research to consider implementing a wider range of observational, cognitive, biological (i.e., stress levels), or informant-reported (teachers, parents) measures in order to better understand the developmental mechanisms at play in these developmental trajectories, and to rely on an even longer-term design to obtain a more accurate picture of educational attainment. Second, we relied on teacher evaluations of students' achievement. More standardized measures would have helped to understand better the associations between the observed trajectories and students' achievement. Moreover, we cannot define an absolute level for low achievement because the measure is a rank-order one. Third, the number and variety of outcomes considered in this study were limited, although somehow compensated by the estimation of longitudinal trajectories for achievement. Further research could assess learning strategies, well-being, self-regulation, and persistence as ASC trajectories outcomes. Fourth, the three developmental mechanisms outlined have not been tested directly, but used indirectly to explain ASC change over the years. It would be important in future studies to, rather than relying on inference, directly test these mechanisms and their associations with the ASC trajectories. Fifth, ASC has always been conceptualized as a pyramid (e.g., Arens & Morin, 2017; Marsh, 2007). Global self-conceptions (across all life domains) occupy the top of the pyramid, whereas domain specific self-concepts (such as ASC or the physical self-concept) occupy the next level, with the next lower level occupied by self-concepts related to specific subdomains (such as math or writing). Although our study was specifically designed to focus on ACS, as a one-dimensional domain-specific construct, it would be interesting for future research to investigate whether and how our results would generalize to the subdomain level, as well as to the affect versus competence components of these subdomains (e.g., Arens & Morin, 2016). Finally, with only three measurement points, it was not possible to estimate nonlinear trajectories. It would be interesting for future studies, relying on more measurement occasions, to test for possible nonlinearity in ASC development.

Conclusion

The present study provides valuable insights on the development of ASC during the elementary school years. Our findings go beyond finding that the normative downward trend observed in other studies was limited to a subset of children, suggesting that ASC follows *heterogeneous* developmental trajectories, with half of the children experiencing the downward trend. At the same time, some also experience an upward trend or stable trajectories. The best scenario for students' educational outcomes still is to nurture initially high levels of ASC, even if those prove to be upwardly biased, and to support the development of increasingly positive ASC, anchored in strong levels of achievement, over the elementary school years. What was particularly worrisome is the observation that children who start their formal schooling with negative ASCs seem to already be at risk for negative long-term consequences in the absence of intervention. As a result, particular attention should be devoted to these students to ensure that their school environment is able to provide them the right conditions to develop stronger self-perceptions of themselves as competent and able learners.

References

Archambault, I., Eccles, J.S., & Vida, M.N. (2010). Ability self-concepts and subjective value in literacy: Joint trajectories from grades 1 through 12. *Journal of Educational Psychology*, *102*, 804-816. https://doi.org/10.1037/a0021075

Arens, A.K., & Morin, A.J.S. (2016). Examination of the structure and grade-related differentiation of multidimensional self-concept instruments for children using ESEM. *Journal of Experimental Education*, *84*, 330-355. https://doi.org/10.1080/00220973.2014.999187

Arens, A.K., & Morin, A.J.S. (2017). Improved representation of the Self-Perception Profile for Children through bifactor exploratory structural equation modeling. *American Educational Research Journal*, *54*, 59-87. https://doi.org/10.3102/0002831216666490

Bauer, D.J., & Curran, P.J. (2003). Distributional assumptions of growth mixture models: implications for overextraction of latent trajectory classes. *Psychological Methods*, *8*, 338-363. https://doi.org/10.1037/1082-989X.8.3.338

Boivin, M., Vitaro, F., & Gagnon, C. (1992). A reassessment of the Self-Perception Profile for Children: Factor structure, reliability, and convergent validity of a French version among second through sixth grade children. *International Journal of Behavioral Development*, *15*, 275-290. https://doi.org/10.1177/016502549201500207

Bollen, K.A., & Curran, P.J. (2006). *Latent Curve Models: A Structural Equation Perspective*. Wiley.

Chapman, J.W., Tunmer, W.E., & Prochnow, J.E. (2000). Early reading-related skills and performance, reading self-concept, and the development of academic self-concept. *Journal of Educational Psychology*, *92*, 703-708. https://doi.org/10.1037/0022-0663.92.4.703

Chen, F., Bollen, K.A., Paxton, P., Curran, P. J., & Kirby, J.B. (2001). Improper solutions in structural equation models: Causes, consequences, and strategies. *Sociological Methods & Research*, *29*, 468-508. https://doi.org/10.1177/0049124101029004003

Chen, S.-K., Yeh, Y.-C., Hwang, F.-M., & Lin, S.S.J. (2013). The relationship between academic self-concept and achievement: A multicohort–multioccasion study. *Learning & Individual Differences*, *23*, 172-178. https://doi.org/10.1016/j.lindif.2012.07.021

Ciccheti, D., & Rogosch, F.A. (1996). Equifinality and multifinality in developmental psychopathology. *Development and Psychopathology*, *8*, 597-600. https://doi.org/10.1017/S0954579400007318

Cole, D.A., Maxwell, S.E., & Martin, J. (2001). The development of multiple domains of child and adolescent self-concept. *Child Development*, *72*, 1723-1746. https://doi.org/10.1111/1467-8624.00375

Davis-Kean, P.E., Huesmann, L.R., Jager, J., Collins, W.A., Bates, J.E., & Lansford, J.E. (2008). Changes in the relation of self-efficacy beliefs and behaviors across development. *Child Development*, *79*(5), 1257-1269.

Denissen, J.J., Zarrett, N.R., & Eccles, J.S. (2007). I like to do it, I'm able, and I know I am: Longitudinal couplings between domain-specific achievement, self-concept, and interest. *Child development*, *78*(2), 430-447.

Diallo, T.M.O., Morin, A.J.S., & Lu, H. (2016). Impact of misspecifications of the latent variance–covariance and residual matrices on the class enumeration accuracy of growth mixture models. *Structural Equation Modeling*, *23*, 507-531. https://doi.org/10.1080/10705511.2016.1169188

Diallo, T.M.O., Morin, A.J.S., & Lu, H. (2017). The impact of total and partial inclusion or exclusion of active and inactive time invariant covariates in growth mixture models. *Psychological Methods*, *22*, 166-190. https://doi.org/10.1037/met0000084

Eccles, J., Wigfield, A., Harold, R.D., & Blumenfeld, P. (1993). Age and gender differences in children's self-and task perceptions during elementary school. *Child Development*, *64*, 830-847.

Ehm, J.H., Lindberg, S., & Hasselhorn, M. (2014). Reading, writing, and math self-concept in elementary school children: Influence of dimensional comparison processes. *European Journal of Psychology of Education*, *29*(2), 277-294.

Enders, C.K. (2010). *Applied missing data analysis*. Guilford.

Folmer, A.S., Cole, D.A., Sigal, A.B., Benbow, L.D., Satterwhite, L.F., Swygert, K.E., & Ciesla, J.A. (2008). Age-related changes in children's understanding of effort and ability: implications for attribution theory and motivation. *Journal of experimental child psychology, 99*, 114–134. https://doi.org/10.1016/j.jecp.2007.09.003

Fredricks, J.A., & Eccles, J.S. (2002). Children's competence and value beliefs from childhood through adolescence: Growth trajectories in two male-sex-typed domains. *Developmental Psychology, 38,* 519-533. https://doi.org/10.1037/0012-1649.38.4.519

Fry, M.D., & Duda, J.L. (1997). A developmental examination of children's understanding of effort and ability in the physical and academic domains. *Research Quarterly for Exercise and Sport*, *68*, 331-344.

Graham, J.W. (2009). Missing data analysis: making it work in the real world. *Annual Review of Psychology, 60*, 549-576. https://doi.org/10.1146/annurev.psych.58.110405.085530

Garon-Carrier, G., Boivin, M., Lemelin, J.P., Kovas, Y., Parent, S., Séguin, J.R., ... & Dionne, G. (2018). Early developmental trajectories of number knowledge and math achievement from 4 to 10 years: Low-persistent profile and early-life predictors. *Journal of school psychology*, *68*, 84-98.

Grimm, K.J., Ram, N., & Estabrook, R. (2016). *Growth modeling: Structural equation and multilevel modeling approaches*. Guilford.

Guay, F., Larose, S., & Boivin, M. (2004). Academic self-concept and educational attainment level: A ten-year longitudinal study. *Self and Identity, 3,* 53-68. https://doi.org/10.1080/13576500342000040

Guay, F., Marsh, H.W., & Boivin, M. (2003). Academic self-concept and academic achievement: Developmental perspectives on their causal ordering. *Journal of Educational Psychology, 95*, 124-136. https://doi.org/10.1037/0022-0663.95.1.124

Guay, F., Morin, A.J.S., Litalien, D., Howard, J.L., & Gilbert, W. (2021). Trajectories of self-determined motivation during the secondary school: A growth mixture analysis. *Journal of Educational Psychology, 113,* 390-410. https://doi.org/10.1037/edu0000482

Harter, S. (1985). *Manual for the self-perception profile for children*. University of Denver.

Harter, S. (2003). The development of self-representations during childhood and adolescence. In M.R. Leary & J.P. Tangney (Eds.), Handbook of self and identity (p. 610–642). Guilford.

Harter, S. (2006). Developmental and Individual Difference Perspectives on Self-Esteem. In D. K. Mroczek & T. D. Little (Eds.), Handbook of personality development (p. 311–334). Erlbaum.

Hipp, J.R., & Bauer, D.J. (2006). Local solutions in the estimation of growth mixture models. *Psychological Methods, 11*, 36-53. https://doi.org/10.1037/1082-989X.11.1.36

Hodges, E.V., Boivin, M., Vitaro, F., & Bukowski, W.M. (1999). The power of friendship: protection against an escalating cycle of peer victimization. *Developmental Psychology*, *35*, 94.

Huang, C. (2011). Self-concept and academic achievement: a meta-analysis of longitudinal relations. *Journal of School Psychology, 49*, 505-528. https://doi.org/10.1016/j.jsp.2011.07.001

Jacobs, J.E., Lanza, S., Osgood, D.W., Eccles, J.S., & Wigfield, A. (2002). Changes in children's self-competence and values: Gender and domain differences across grades one through twelve. *Child Developpement, 73*, 509-527. https://doi.org/10.1111/1467-8624.00421

Janke, S., Daumiller, M., Praetorius, A.K., Dickhäuser, O., Dresel, M. (2021). What reduces the adverse development of motivation at the beginning of secondary education. In Lazarides, R., Raufelder, D. (eds), Motivation in unterrichtlichen fachbezogenen Lehr-Lernkontexten (pp. 179–210). Springer. https://doi.org/10.1007/978-3-658-31064-6_7

Li, L., & Hser, Y.-I. (2011). On inclusion of covariates for class enumeration of growth mixture models. *Multivariate Behavioral Research*, *46*, 266-302. https://doi.org/10.1080/00273171.2011.556549

Marsh, H.W. (1989). Age and sex effects in multiple dimensions of self-concept: Preadolescence to early adulthood. *Journal of Educational Psychology, 81*, 417-430. https://doi.org/10.1037/0022-0663.81.3.417

Marsh, H.W. (1990). Causal ordering of academic self-concept and academic achievement: A multiwave, longitudinal panel analysis. *Journal of Educational Psychology, 82*, 646-656. https://doi.org/10.1037/0022-0663.82.4.646

Marsh, H.W. (2007). *Self-concept theory, measurement and research into practice: The role of self-concept in educational psychology*. British Psychological Society.

Marsh, H.W., & Ayotte, V. (2003). Do multiple dimensions of self-concept become more differentiated with age? The differential distinctiveness hypothesis. *Journal of Educational Psychology, 95*, 687-

706. https://doi.org/10.1037/0022-0663.95.4.687
Marsh, H.W., & Craven, R. (1997). Academic self-concept: Beyond the dustbowl. In G.D. Phye (Ed.), *Handbook of Classroom Assessment* (pp. 131−198). Academic Press.
Marsh, H.W., Craven, R., & Debus, R. (1998). Structure, stability, and development of young children's self-concepts: A multicohort-multioccasion study. *Child Development, 69*, 1030-1053. https://doi.org/10.2307/1132361
Marsh, H.W., Martin, A.J. & Jackson, S. (2010). Introducing a short version of the Physical Self Description Questionnaire: New strategies, short-form evaluative criteria, and applications of factor analyses. *Journal of Sport & Exercise Psychology*, *32*, 438-482. https://doi.org/10.1123/jsep.32.4.438
Marsh, H.W., Pekrun, R., Murayama, K., Arens, A.K., Parker, P.D., Guo, J., & Dicke, T. (2018). An integrated model of academic self-concept development: Academic self-concept, grades, test scores, and tracking over 6 years. *Developmental Psychology*, *54*, 263–280. https://doi.org/10.1037/dev0000393
Marsh, H.W., Lüdtke, O., Trautwein, U., & Morin, A.J.S. (2009). Classical latent profile analysis of academic self-concept dimensions: Synergy of person-and variable-centered approaches to theoretical models of self-concept. *Structural Equation Modeling, 16*, 191-225. https://doi.org/10.1080/10705510902751010
Marsh, H.W., Martin, A.J., Yeung, A.S., & Craven, R.G. (2017). Competence self-perceptions. In A. J. Elliot, C. S. Dweck, & D. S. Yeager (Eds.), Handbook of competence and motivation: Theory and application (p. 85–115). Guilford.
Marsh, H.W., & Seaton, M. (2015). The big-fish–little-pond effect, competence self-perceptions, and relativity: Substantive advances and methodological innovation. In Advances in motivation science (Vol. 2, pp. 127-184). Elsevier
Millsap, R.E. (2011). *Statistical approaches to measurement invariance*. Routledge.
Molloy, L.E., Ram, N., & Gest, S.D. (2011). The storm and stress (or calm) of early adolescent self-concepts: within- and between-subjects variability. *Developpmental Psychology*, *47*, 1589-1607. https://doi.org/10.1037/a0025413
Morin, A.J.S., & Litalien, D. (2019). Mixture modelling for lifespan developmental research. In *Oxford Research Encyclopedia of Psychology*. Oxford University Press. https://doi.org/10.1093/acrefore/9780190236557.013.364
Morin, A.J.S., Maïano, C., Nagengast, B., Marsh, H.W., Morizot, J., & Janosz, M. (2011a). General growth mixture analysis of adolescents' developmental trajectories of anxiety: The impact of untested invariance assumptions on substantive interpretations. *Structural Equation Modeling*, *18*, 613-648. https://doi.org/10.1080/10705511.2011.607714
Morin, A.J.S., Meyer, J. P., Creusier, J., & Biétry, F. (2016). Multiple-group analysis of similarity in latent profile solutions. *Organizational Research Methods, 19*, 231-254. https://doi.org/10.1177/1094428115621148
Morin, A.J.S., Morizot, J., Boudrias, J.-S., & Madore, I. (2011b). A multifoci person-centered perspective on workplace affective commitment: A latent profile/factor mixture analysis. *Organizational Research Methods, 14*, 58-90. https://doi.org/10.1177/1094428109356476
Muenks, K., Wigfield, A., & Eccles, J.S. (2018). I can do this! The development and calibration of children's expectations for success and competence beliefs. *Developmental Review*, *48*, 24-39. https://doi.org/10.1016/j.dr.2018.04.001
Musu-Gillette, L.E., Wigfield, A., Harring, J.R., & Eccles, J.S. (2015). Trajectories of change in students' self-concepts of ability and values in math and college major choice. *Educational Research and Evaluation*, *21*, 343-370. https://doi.org/10.1080/13803611.2015.1057161
Muthen, B. (2003). Statistical and substantive checking in growth mixture modeling. *Psychological Methods*, *8*, 369-377. https://doi.org/10.1037/1082-989X.8.3.369
Muthén, L.K., & Muthén, B. (2019). *Mplus Users' Guide*. Muthén & Muthén.
Nicholls, J.G. (1978). The development of the concepts of effort and ability, perception of academic attainment, and the understanding that difficult tasks require more ability. *Child development*, 800-814.
Nylund, K.L., Asparouhov, T., & Muthén, B. (2007). Deciding on the number of classes in latent class analysis and growth mixture modeling: A Monte Carlo simulation study. *Structural Equation Modeling*, *14*, 535-569. https://doi.org/10.1080/10705510701575396

Peugh, J., & Fan, X. (2013). Modeling unobserved heterogeneity using latent profile analysis: A Monte Carlo simulation. *Structural Equation Modeling, 20*, 616-639. https://doi.org/10.1080/10705511.2013.824780

Raykov, T., & Marcoulides, G.A. (2004). Using the delta method for approximate interval estimation of parameter functions in SEM. *Structural Equation Modeling, 11*, 621-637. https://doi.org/10.1207/s15328007sem1104_7

Rimfeld, K., Malanchini, M., Hannigan, L.J., Dale, P.S., Allen, R., Hart, S.A., & Plomin, R. (2019). Teacher assessments during compulsory education are as reliable, stable and heritable as standardized test scores. *Journal of Child Psychology and Psychiatry, 60*, 1278-1288. https://doi.org/10.1111/jcpp.13070

Scherrer, V., & Preckel, F. (2019). Development of motivational variables and self-esteem during the school career: A meta-analysis of longitudinal studies. *Review of Educational Research, 89*(2), 211-258.

Schmidt, I., Brunner, M., Keller, L., Scherrer, V., Wollschläger, R., Baudson, T. G., & Preckel, F. (2017). Profile formation of academic self-concept in elementary school students in grades 1 to 4. *PloS One, 12*(5), e0177854.

Sewasew, D., & Schroeders, U. (2019). The developmental interplay of academic self-concept and achievement within and across domains among primary school students. *Contemporary Educational Psychology*, *58*, 204-212. https://doi.org/10.1016/j.cedpsych.2019.03.009

Skrondal, A., & Laake, P. (2001). Regression among factor scores. *Psychometrika, 66*, 563-575. https://doi.org/10.1007/BF02296196

Stanovich, K.E. (1989). Matthew effects in reading: Some consequences of individual differences in the acquisition of literacy. *Reading Research Quarterly*, *21*, 360-401. https://doi.org/10.1598/RRQ.21.4.1

Susperreguy, M.I., Davis-Kean, P.E., Duckworth, K., & Chen, M. (2018). Self-concept predicts academic achievement across levels of the achievement distribution: Domain specificity for math and reading. *Child Development*, *89*, 2196-2214. https://doi.org/10.1111/cdev.12924

Tein, J.-Y., Coxe, S., & Cham, H. (2013). Statistical power to detect the correct number of classes in latent profile analysis. *Structural Equation Modeling, 20*, 640-657. https://doi.org/10.1080/10705511.2013.824781

Tofighi, D., & Enders, C.K. (2007). Identifying the correct number of classes in growth mixture models. In G.R. Hancock & K.M. Samuelsen (Eds.), *Advances in latent variable mixture models* (pp. 317-341). Information Age

Valentine, J.C., DuBois, D.L., & Cooper, H. (2004). The relation between self-beliefs and academic achievement: A meta-analytic review. *Educational Psychologist*, *39*, 111-133. https://doi.org/10.1207/s15326985ep3902_3

Weidinger, A.F., Steinmayr, R., & Spinath, B. (2019). Ability self-concept formation in elementary school: No dimensional comparison effects across time. *Developmental Psychology, 55*(5), 1005.

Wigfield, A., Eccles, J.S., Fredricks, J.A., Simpkins, S., Roeser, R.W., & Schiefele, U. (2015). Development of achievement motivation and engagement. In M. E. Lamb & R. M. Lerner (Eds.), *Handbook of child psychology and developmental science: Socioemotional processes* (pp. 657–700). Wiley. https://doi.org/10.1002/9781118963418.childpsy316

Wigfield, A., Eccles, J.S., Schiefele, U., Roeser, R.W., & Davis-Kean, P. (2006). *Development of achievement motivation.* John Wiley & Sons, Inc..

Wigfield, A., Eccles, J.S., Yoon, K.S., Harold, R.D., Arbreton, A.J.A., Freedman-Doan, C., & Blumenfeld, P.C. (1997). Changes in children's competence beliefs and subjective task values across the elementary school years: A 3-year study. *Journal of Educational Psychology*, *89*, 451-469. https://doi.org/10.1037/0022-0663.89.3.451

Zhao, W., Song, Y., Zhao, Q., & Zhang, R. (2019). The effect of teacher support on primary school students' reading engagement: the mediating role of reading interest and chinese academic self-concept. *Educational Psychology*, *39*, 236-253. https://doi.org/10.1080/01443410.2018.1497146

Online Supplements for:

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Table S1

Fit Statistics of the Time Specific CFA Measurement Models

Model	χ^2	df	#fp	RMSEA	90% CI	CFI	TLI
Time 1	37.616	26	28	.023	.000; .039	.995	.993
Time 2	75.988	26	28	.039	.029; .049	.986	.980
Time 3	40.254	26	28	.024	.006; .038	.995	.992

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

Table S2

Standardized Factor Loadings (λ) and Uniqueness (δ) from the CFA Measurement Model

	F1 λ	F2 λ	δ
TIME 1			
Academic self-concept			
Item 1	**.598**		.643
Item 2	**.441**		.806
Item 3	**.641**		.589
Item 4	**.574**		.671
Item 5	**.703**		.505
Item 6	**.730**		.467
Achievement			
Item 1		**.937**	.121
Item 2		**.923**	.148
Item 3		**.828**	.314
ω	.778	.926	
TIME 2			
Academic self-concept			
Item 1	**.659**		.566
Item 2	**.497**		.753
Item 3	**.582**		.662
Item 4	**.637**		.594
Item 5	**.733**		.463
Item 6	**.760**		.423
Achievement			
Item 1		**.931**	.133
Item 2		**.922**	.150
Item 3		**.832**	.308
ω	.808	.924	
TIME 3			
Academic self-concept			
Item 1	**.673**		.547
Item 2	**.531**		.718
Item 3	**.612**		.626
Item 4	**.687**		.528
Item 5	**.758**		.426
Item 6	**.787**		.381
Achievement			
Item 1		**.949**	.099
Item 2		**.899**	.191
Item 3		**.823**	.323
ω	.832	.922	

Notes. CFA: Confirmatory factor analysis; F: factor; ω: omega coefficient of composite reliability. Target loadings are marked in bold. All parameters are statistically significant ($p \leq .000$).

Table S3

Correlations from the Time-Specific CFA Measurement Model

	Time 1	Time 2	Time 3
Academic Self-Concept with Achievement	.471*	.528*	.609*

Notes. * $p \leq .01$

Table S4

Measurement Invariance across Time and Cohort

Model	X^2	df	CFI	TLI	RMSEA	Δ X^2	Δ df	Δ CFI	Δ TLI	Δ RMSEA
Model 1: Configural Invariance	1023.265*	846	.985	.982	.022					
Model 2: Weak invariance	1085.072*	902	.983	.980	.023	61.831	56	-.002	-.002	.001
Model 3: Strong Invariance	1264.737*	958	.974	.972	.027	192.258*	56	-.009	-.008	.004
Model 4: Strict Invariance	1737.640*	1030	.942	.940	.040	365.301*	72	-.032	-.032	.013
Model 4A: Strict Invariance (Time only)	1586.162*	1012	.953	.951	.036	256.751*	54	-.021	-.021	.009
Model 4B: Strict Invariance (Cohort only)	1299.254*	994	.974	.973	.027	38.632	36	.000	.001	.000
Model 4C: Strict Invariance (Partial)	1446.253*	1019	.965	.964	.031	152.529*	61	-.009	-.008	.004
Model 5: Corr. Uniqueness Invariance	1567.633*	1073	.959	.960	.033	116.260*	54	-.006	-.004	+.002
Model 6: Latent Var.-Covar. Invariance	1628.555*	1097	.956	.958	.034	67.113*	24	-.003	-.002	.001
Model 7: Latent Means Invariance	1670.955	1113	.954	.957	.034	44.681*	16	-.002	-.001	.000

Note. * $p < .001$; X^2 : Scaled 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; Δ : change in fit relative to the previous model (models 4, 4A, 4B, and 4C are compared to model 3); scaled chi-square difference tests where calculated using the Satorra-Bentler correction (Satorra, 2000).

Table S5

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

	Profile 1	Profile 2	Profile 3	Profile 4
Profile 1	**.852**	.075	.033	.040
Profile 2	.182	**.816**	.001	.001
Profile 3	.270	.001	**.596**	.133
Profile 4	.061	.000	.027	**.912**

Note. Profile 1: Moderate Decreasing; Profile 2: Low Stable; Profile 3: High Decreasing; Profile 4: High Increasing.

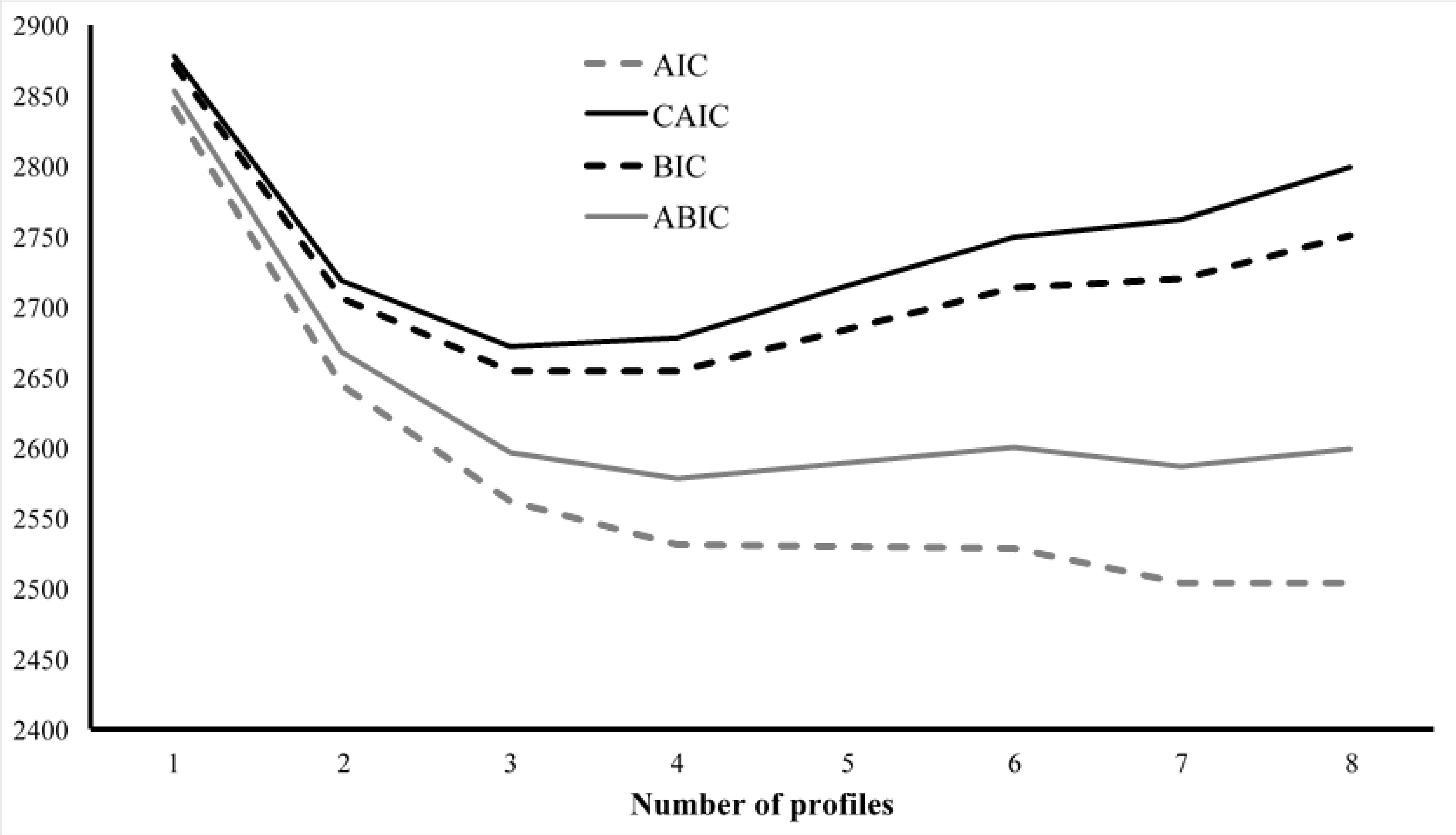

Figure S1
Elbow Plot of the Value of the Information Criteria for Solutions Including Different Number of Latent Profiles

Mplus Input Code for the Main Models

Readers interested in learning about the estimation of growth mixture analyses with and without outcomes should consult Morin and Litalien (2019) and Morin et al. (2020). We also provide the Mplus input file for our final model at the end of online supplements.

Morin, A.J.S., & Litalien, D. (2019). Mixture modelling for lifespan developmental research. In *Oxford Research Encyclopedia of Psychology*. Oxford University Press. https://doi.org/10.1093/acrefore/9780190236557.013.364

Morin, A.J.S., McLarnon, M.J.W., & Litalien, D. (2020). Mixture modeling for organizational behavior research. In Y. Griep, & S.D. Hansen (Eds.), *Handbook on the Temporal Dynamics of Organizational Behavior* (pp. 351-379). Edward Elgar.

```
TITLE:
Mplus Input File for the Final Unconditional 4-Profile Growth Mixture Solution;
! Text in greyscale following ! are annotations
DATA:
FILE IS Save_follow.DAT;
VARIABLE:
NAMES ARE T1ASC T2ASC T3ASC COHORT Attain INT_ACH SLO_ACH;
MISSING ARE ALL (-999);
USEVAR are T1ASC T2ASC T3ASC;
! The CONSTRAINT variable (COHORT) is the variable that identifies time in this data set.
! It has a value of 1 in cohort 1 (starting in grade 2), 2 in cohort 2 (starting in Grade 3) and 3 in
! cohort 3 (starting in Grade 3). This variable is only used on the MODEL CONSTRAINT section
CONSTRAINT=COHORT;
CLASSES= C(4);
ANALYSIS:
TYPE = MIXTURE;
ESTIMATOR = MLR;
Process = 3;
STARTS = 10000 500;
STITERATIONS = 1000;
MODEL:
 %OVERALL%
! Defining the intercept factor
 I BY t1asc@1 t2asc@1 t3asc@1;
! The slope factor. Loadings (i.e., time codes) are identified by labels as they vary across cohorts
S BY t1asc*(L1)
 t2asc(L2)
 t3asc(L3);
! Time-specific intercepts fixed to 0 to allow the mean structure to be expressed at the trajectory level.
[t1asc@0 t2asc@0 t3asc@0];
! Requesting the free estimation of the growth parameters (means, variance, and residuals)
I S ; [I S ]; I WITH S ;
t1asc t2asc t3asc;
```

```
! The class specific sections % c#1% %c#2% specify which parameters are freely estimated across
! profiles. Here the intercept and slope means ([I S];), variances (I S;) and time specific residuals
! (t1asc t2asc t3asc;), although these are constrained to equality across time by using a label
! (r1) (r2) that differs across profiles.
! The intercepts and slope factors are labelled (e.g., IP1, SP1) for the Plot function.
%c#1%
[I] (IP1);
[S] (SP1);
I; S; I WITH S; t1asc t2asc t3asc (r1);
%c#2%
[I] (IP2);
[S] (SP2);
I; S; I WITH S; t1asc t2asc t3asc (r1);
%c#3%
[I] (IP3);
[S] (SP3);
I; S; I WITH S; t1asc t2asc t3asc (r1);
%c#4%
[I] (IP4);
[S] (SP4);
I; S; I WITH S; t1asc t2asc t3asc (r1);
! This section is used to define the time.
! The time code corresponding to L1 is based on students' cohort. By subtracting 1 from the cohort
! code at Time 1, the intercept of the trajectories are located in Grade 2, and then increase by one
! grade level in each cohort, and by one grade level at each time point for all cohorts, resulting in
! trajectories ranging from Grade 2 (Time 1 in Cohort 1) to Grade 6 (Time 3 in Cohort 3).
MODEL CONSTRAINT:
L1 = cohorte - 1;
L2 = cohorte;
L3 = cohorte + 1;
! The Plot function is used to graph profile-specific trajectories (Prof1 = profile 1, etc.).
! The loop function asks for trajectories to be graphed for Time values ranging from 0 (the position of
! the intercept in Grade 2) to 4 (the last time point, corresponding to Grade 6 (Time 3 in Cohort 3).
! Time increments of 0.5 units are used in the graphs to maximise the precision.
! Then, the trajectories in each profile (Prof1 = profile 1, etc.) are defined as a function of the
! intercept and slopes of the trajectories based on the labels used in each profile (IP1 and SP1
! in profile 1) and the passage of time defined in the LOOP function.
PLOT (Prof1 Prof2 Prof3 Prof4);
LOOP(Time,0,4,0.5);
Prof1 = IP1+Time*SP1;
Prof2 = IP2+Time*SP2;
Prof3 = IP3+Time*SP3;
Prof4 = IP4+Time*SP4;
OUTPUT:
STDYX SAMPSTAT CINTERVAL RESIDUAL svalues TECH1 TECH7 TECH11 TECH14;
```

```
TITLE:
Mplus Input File for the Final Unconditional 4-Profile Growth Mixture Solution;
! Modifications from the previous input are bolded.
DATA:
FILE IS Save_follow.DAT;
VARIABLE:
NAMES ARE T1ASC T2ASC T3ASC COHORT Attain INT_ACH SLO_ACH;
MISSING ARE ALL (-999);
USEVAR are T1ASC T2ASC T3ASC Attain INT_ACH SLO_ACH;
CONSTRAINT=COHORT;
CLASSES= C(4);
ANALYSIS:
TYPE = MIXTURE;
ESTIMATOR = MLR;
Process = 3;
STARTS = 10000 500;
STITERATIONS = 1000;
! To make sure that the final unconditional solution is replicated, one should use user-defined start
! values (using the results form the previous models) and fix them (@), while turning off the START
! function (STARTS = 0;).
MODEL:
 %OVERALL%
 I BY t1asc@1 t2asc@1 t3asc@1;
S BY t1asc*(L1)
 t2asc(L2)
 t3asc(L3);
! Time-specific intercepts fixed to 0 to allow the mean structure to be expressed at the trajectory level.
[t1asc@0 t2asc@0 t3asc@0];
I S ; [I S ]; I WITH S ;
t1asc t2asc t3asc;
%c#1%
[I] (IP1);
[S] (SP1);
I; S; I WITH S; t1asc t2asc t3asc (r1);
! Request the free estimation of the outcome means and variances. Using labels for the means.
[INT_ACH] (o1p1);
[SLO_ACH] (o2p1);
[Attain] (o3p1);
  INT_ACH SLO_ACH Attain;
%c#2%
[I] (IP2);
[S] (SP2);
I; S; I WITH S; t1asc t2asc t3asc (r1);
[INT_ACH] (o1p2);
[SLO_ACH] (o2p2);
[Attain] (o3p2);
  INT_ACH SLO_ACH Attain;
%c#3%
[I] (IP3);
[S] (SP3);
I; S; I WITH S; t1asc t2asc t3asc (r1);
[INT_ACH] (o1p3);
[SLO_ACH] (o2p3);
[Attain] (o3p3);
  INT_ACH SLO_ACH Attain;
```

```
%c#4%
[I] (IP4);
[S] (SP4);
I; S; I WITH S; t1asc t2asc t3asc (r1);
[INT_ACH] (o1p4);
[SLO_ACH] (o2p4);
[Attain] (o3p4);
  INT_ACH SLO_ACH Attain;
MODEL CONSTRAINT:
L1 = cohorte - 1;
L2 = cohorte;
L3 = cohorte + 1;
! The following rely on the labels used for the outcomes, and request tests of statistical significance of
! comparisons across profiles.
  New (intp1p2 intp1p3 intp1p4 intp2p3 intp2p4 intp3p4);
  intp1p2 = o1p1 - o1p2;
  intp1p3 = o1p1 - o1p3;
  intp1p4 = o1p1 - o1p4;
  intp2p3  = o1p2 - o1p3;
  intp2p4 = o1p2 - o1p4;
  intp3p4= o1p3 - o1p4;
  New (slop1p2 slop1p3 slop1p4 slop2p3 slop2p4 slop3p4);
  slop1p2 = o2p1 - o2p2;
  slop1p3 = o2p1 - o2p3;
  slop1p4 = o2p1 - o2p4;
  slop2p3  = o2p2 - o2p3;
  slop2p4 = o2p2 - o2p4;
  slop3p4= o2p3 - o2p4;
  New (newp1p2 newp1p3 newp1p4 newp2p3 newp2p4 newp3p4);
  newp1p2 = o3p1 - o3p2;
  newp1p3 = o3p1 - o3p3;
  newp1p4 = o3p1 - o3p4;
  newp2p3  = o3p2 - o3p3;
  newp2p4 = o3p2 - o3p4;
  newp3p4= o3p3 - o3p4;
OUTPUT:
STDYX SAMPSTAT CINTERVAL RESIDUAL svalues TECH1 TECH7 TECH11 TECH14;
```