




Cross-Domain Trajectories of Students' Ability Self-Concepts and Intrinsic Values in Math and Language Arts

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Different cross-domain trajectories in the development of students' ability self-concepts (ASCs) and their intrinsic valuing of math and language arts were examined in a cross-sequential study spanning Grades 1 through 12 ($n = 1,069$). Growth mixture modeling analyses identified a *Moderate Math Decline/Stable High Language Arts* class and a *Moderate Math Decline/Strong Language Arts Decline* class for students' ASC trajectories. Students' intrinsic value trajectories included a *Strong Math Decline/Language Arts Decline Leveling Off*, a *Moderate Math Decline/Strong Language Arts Decline*, and a *Stable Math and Language Arts Trajectories* class. These classes differed with regard to student characteristics, including gender, family background, and math and reading aptitudes. They also resulted in different high school math course enrollments, career aspirations, and adult careers.

In expectancy-value theory (EVT), students' expectancies for success and subjective task values (STVs) are posited to be powerful and proximal predictors of their achievement-related behaviors and their academic and career choices (Wigfield, Tonks, & Klauda, 2016). A large body of research has documented an average decline in students' expectancies and STVs across academic domains over their school careers (e.g., Jacobs, Lanza, Osgood, Eccles, & Wigfield, 2002; Nagy et al., 2010; Watt, 2004). Researchers have identified school-based factors that contribute to this decline (e.g., a

lack of fit between adolescents' needs and the school environment; see Wigfield et al., 2015 for a review). However, these changes are also rooted in the cognitive developmental processes involved in the formation of children's expectancies and STVs (Wigfield et al., 2015). For instance, as children get older, they become increasingly aware of their strengths and weaknesses (Harter, 2006), and students' interests in different academic domains become more differentiated and well-formed over time (Hidi & Renninger, 2006; Krapp, 2002; Schiefele, 2009). Importantly, these developmental processes should lead to an increasing *intraindividual differentiation* in expectancies and STVs across different domains over time. That is, individual students are likely to specialize in some domains but disengage from others as they become older and should thus show diverging trajectories across domains. This intraindividual differentiation is likely to result

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in an average decline in students' expectancies and STVs because students maintain high levels of perceived competence and interest only in a few selected domains. For instance, students might specialize in either verbal-intensive or math-intensive domains, which would then inform their academic and career choices (Eccles, 2009; Marsh, 1986; Möller & Marsh, 2013). Unfortunately, few studies have examined inter- and intraindividual differentiation in the development of students' expectancies and STVs across the school years.

Drawing upon EVT (Eccles et al., 1983) and taking advantage of growth mixture modeling (GMM; Muthén, 2004), this study was designed to examine the inter- and intraindividual differentiation of expectancies and STVs across students' school careers. We used data from the Childhood and Beyond (CAB) study, a large-scale longitudinal study that has investigated the development of students' expectancies and STVs in different academic domains from Grades 1 through 12 (see Jacobs et al., 2002). We examined whether qualitatively different latent classes could be identified in the trajectories across math and language arts (e.g., classes in which expectancies and STVs in math decline, whereas expectancies and STVs in language arts remain relatively stable and vice versa). We then investigated possible links between the identified trajectory classes and students' characteristics, as well as between these classes and students' academic and career choices in high school and adulthood.

Theoretical Frameworks: EVT and Dimensional Comparison Theory

Eccles and colleagues' EVT (Eccles et al., 1983; see Eccles & Wigfield, 2002; Wigfield et al., 2016, for reviews) is one of the most influential theories on the development of students' academic motivation in different domains. As noted earlier, these authors posit that the most proximal predictors of students' academic choices are two subjective, task-specific beliefs: their expectancies for how well they will do in a given academic domain and the value they attach to this domain. International research has shown that students' expectancies and STVs are powerful predictors of their academic achievement, educational choices, and career aspirations in different academic domains (for a review, see Wigfield et al., 2016). Eccles et al. (1983) proposed that students' ability self-concepts (ASCs) are a strong determinant of their expectancies for success in the corresponding domain. Students' ASCs and expectancies for success are very highly correlated,

and researchers drawing on EVT have therefore often combined these two constructs (Eccles & Wigfield, 2002). We follow this tradition and use the term "ASC" to describe these beliefs. With regard to STVs, Eccles et al. (1983) distinguished different components that positively influence students' subjective valuing of a given domain, including their intrinsic value (enjoyment in a given domain), attainment value (perceived personal importance of a domain), and utility value (perceived usefulness of a given domain). We focused on students' intrinsic value in this study for two reasons. First, Wigfield (1994) proposed that students' intrinsic value is the first value component to develop and become differentiated. Second, intrinsic value and the related construct of interest (i.e., intrinsic value is closely linked to the affective components of interest) are key predictors of students' long-term engagement (Hidi & Renninger, 2006; Schiefele, 2009; Wigfield et al., 2016).

Both ASCs and intrinsic values have been shown to be highly domain-specific. In particular, there is a strong distinction between math and verbal domains, with students tending to report higher ASCs and intrinsic values in either math or verbal domains (e.g., Gaspard et al., 2018). To explain this phenomenon, Marsh (1986) developed the internal/external frame of reference model, which posits that students' ASCs are affected by contrasting comparisons of their achievements across math and verbal domains; Möller and Marsh (2013) extended these ideas in their dimensional comparison theory (also see Wolff, Helm, & Möller, 2018). For instance, high performance in the verbal domain sets a high standard against which students compare their math performance; consequently, students' verbal performance negatively affects their ASC in math, and vice versa, when performance in the same domain is controlled for (for a meta-analysis, see Möller, Pohlmann, Köller, & Marsh, 2009). Furthermore, several studies have shown that these negative cross-domain comparisons can affect students' intrinsic values as well (e.g., Gaspard et al., 2018; Nagy et al., 2008) and that students' ASCs in math and verbal domains negatively predict each other over time (e.g., Niepel, Brunner, & Preckel, 2014). These negative relations become evident after the early school years (Möller et al., 2009; Weidinger, Steinmayr, & Spinath, 2019), likely resulting in increasing intraindividual differentiation in both ASCs and intrinsic values over time.

Development of Students' ASCs and STVs

As noted earlier, many researchers have shown that, on average, students' ASCs and STVs in

different academic domains decrease across their school careers (e.g., Jacobs et al., 2002; Nagy et al., 2010; Watt, 2004). Some researchers have reported curvilinear trends, with stronger declines in the earlier years and a leveling off during late adolescence (Jacobs et al., 2002; Watt, 2004). With respect to ASC, many young children tend to be overly optimistic in their competence appraisals, but once school begins, they engage more frequently in social comparisons with their peers and receive more evaluative feedback from parents and teachers (Muenks, Wigfield, & Eccles, 2018; Wigfield et al., 2015). Consequently, children develop a more accurate ASC, which can contribute to a decrease in the mean levels of their ASC over time. Children also begin to engage in dimensional comparison processes and become more aware of their potential strengths and weaknesses during their first few years in school (Schmidt et al., 2017; Weidinger et al., 2019). Consequently, they develop increasingly differentiated ASCs over the elementary school years (Eccles, Wigfield, Harold, & Blumenfeld, 1993; Harter, 2006; Marsh & Ayotte, 2003; Schmidt et al., 2017).

With respect to intrinsic values and interests, young children usually have quite general interests that can shift rapidly, but these interests become both more specific and more stable as children get older (Krapp, 2002; Schiefele, 2009). Intraindividual differences in students' interests should thus become more pronounced with age, with some interests remaining high but others declining. Because individual students' interests will remain high in some domains but not in others, this can also contribute to decreases in the mean levels of students' interests over time.

Importantly, these possible explanations for the average decline suggest that there should be different patterns in the trajectories of students' ASCs and STVs. Longitudinal research has generally confirmed that students' trajectories follow different patterns, but this research is mostly limited to single-domain analyses (Archambault, Eccles, & Vida, 2010; Musu-Gillette, Wigfield, Harring, & Eccles, 2015; Wang, Chow, Degol, & Eccles, 2016). Specifically, using data from the CAB research program, researchers have found that students' ASCs and STVs follow different trajectories in language arts (Archambault et al., 2010) and math (Musu-Gillette et al., 2015). However, due to their focus on single domains, these studies cannot capture potential intraindividual differentiation in students' ASCs and STVs across domains. Recently, Guo, Wang, Ketonen, Eccles, and Salmela-Aro (2018) investigated joint trajectories of STVs across language arts, math

and science, and social subjects in a sample of Finnish adolescents from Grades 9 to 11. They found three differential STV trajectories across these domains (i.e., a class with high STVs across domains, a class with low levels of STVs across domains, which increased only in math and science over time, and a class with high levels of STVs across domains, which increased in Finnish and decreased in math and science). These trajectories predicted long-term science, technology, engineering, and mathematics (STEM) aspirations. The class characterized by increasing STVs in math and science showed the highest STEM aspirations, and these trajectories also partially explained gender differences in aspirations. This study shows the promises of investigating trajectories across domains, but research investigating the cross-domain trajectories of both ASCs and STVs across longer periods of time is still needed.

Predictors of the Development of ASCs and STVs

Various individual and family background factors have been shown to contribute to heterogeneity in the development of students' ASCs and STVs (see Wigfield et al., 2015). These include students' gender and aptitude, as well as parents' education and income; we therefore considered them in our analyses. Children's gender plays an important role in their motivational development in the domains of math and language arts (Wigfield et al., 2015). Generally, boys tend to have higher ASCs and intrinsic values in math, whereas girls tend to have higher ASCs and intrinsic values in language arts, although the magnitude of these gender differences and their development over time can vary substantially in different national contexts (Frenzel, Goetz, Pekrun, & Watt, 2010; Jacobs et al., 2002; Watt, 2004). Furthermore, students' general cognitive ability as well as domain-specific aptitudes predict changes in ASCs and STVs over time (Jacobs et al., 2002; Marsh, Trautwein, Lüdtke, Köller, & Baumert, 2005; Retelsdorf, Köller, & Möller, 2011, 2014). Students' general cognitive ability should be predictive of their overall level of motivation across domains, whereas domain-specific aptitudes should predict corresponding domain-specific differences in motivation (cf. Brunner, Lüdtke, & Trautwein, 2008; Möller & Marsh, 2013). Finally, researchers have found that higher levels of parental education and income are positively related to the development of their children's ASCs and STVs (Archambault et al., 2010; Retelsdorf et al., 2011; see Wigfield et al., 2015 for review).

Predictions for Students' Academic and Career Choices

Much research has shown that students' ASCs and STVs directly predict their performances and choices in different domains (see Wigfield et al., 2016, for a review). Along with these direct links, Eccles (2009) proposed that *intraindividual hierarchies* or the relative levels in students' ASCs and STVs across domains are key predictors of their educational and occupational choices. Individuals are likely to choose courses or careers in specific domains if they have comparatively high ASCs and STVs for this domain relative to alternative domains. Accordingly, research has shown that patterns in students' ASCs and STVs across subjects predict students' educational and career choices (e.g., Gaspard, Wille, Wormington, & Hulleman, 2019). Notably, negative cross-domain effects of students' ASCs and STVs in math and the verbal domain have been documented on their course choices (Nagy et al., 2008), university majors (Parker et al., 2012), and career aspirations (Lauermann, Chow, & Eccles, 2015) in the noncorresponding domain. This research suggests that students' differentiation across domains can have important implications for their educational and career choices. Indeed, Guo et al. (2018) found that divergent patterns in the cross-domain trajectories of students' STVs predicted students' later STEM career aspirations and participation. To date, no study has looked at cross-domain trajectories in ASCs and STVs across students' entire school careers and how they are related to both academic and career choices.

The Present Study

Drawing on EVT, we examined the cross-domain trajectories of students' ASCs and intrinsic values and their associations with academic and career choices. Several recent studies have used GMM to investigate qualitatively distinct classes in the trajectories of students' ASCs and STVs within single academic domains (Archambault et al., 2010; Musu-Gillette et al., 2015; Wang et al., 2016) or with respect to students' STVs across domains (Guo et al., 2018). GMM analyses are suited to capture not only an average trend in the data (e.g., an average decline in ASCs and STVs) but also interindividual differences between groups of students (e.g., a decline for some students but not others) and intraindividual differences (e.g., an increasing intraindividual differentiation across the math and verbal domains). Furthermore, GMM allows

analyses of the associations of qualitatively distinct patterns of change over time with students' characteristics and academic outcomes. We therefore deemed GMM to be a suitable approach for our study because it allowed us to account for potential heterogeneity in the developmental trajectories between groups of students and for intraindividual differentiation across domains. We investigated three research questions.

First, can qualitatively different latent classes in the trajectories of students' ASCs and intrinsic values across math and language arts be identified? Because of the scarcity of previous research on this topic, we made no specific predictions about the number and shape of such trajectories. However, we expected to find classes in which students' ASCs and intrinsic values would remain high in one domain but would decline in the other domain, which would be consistent with the assumption of increasing intraindividual differentiation.

Second, are individual factors (gender, aptitude) and family background factors (parental education and income) related to students' latent class membership? On the basis of previous research on the links between these variables and the development of students' domain-specific ASCs and STVs, we expected that boys would be overrepresented in classes with more positive trajectories (less of a decline) in math, whereas girls would be overrepresented in classes with more positive trajectories (less of a decline) in language arts. Moreover, we expected high levels of parental education and income as well as high cognitive abilities to predict higher levels of ASCs and intrinsic values across domains. Finally, we expected that domain-specific aptitudes might be associated with more positive trajectories in the same domain (e.g., math) and possibly also with more negative (or declining) trajectories in the other domain (e.g., language arts).

Third, is latent class membership related to students' course enrollment, out-of-school-activities, career aspirations in high school, and the type of career they choose as adults? We expected that students in latent classes with a more positive trajectory in one domain would be comparatively more likely to take courses in this domain, spend more time on related activities in their free time, be more likely to pursue careers in related domains, and to have related careers in adulthood. Because students' choices are to some extent ipsative and driven by intraindividual hierarchies in ASCs and STVs (Eccles, 2009), we also expected that students with more negative trajectories in one domain would be more likely to show higher levels of course

enrollment, relevant out-of-school-activities, career aspirations, and adult careers in the other domain.

Method

Participants and Procedure

The present research used data from the CAB study, which is a cross-sequential study following three cohorts of public school students from elementary through secondary school and beyond (for a detailed description, see garp.education.uci.edu/cab). The CAB study was specifically designed to test the central assumptions of Eccles' et al. (1983) EVT over elementary and secondary school and across school subjects and thus provides a unique data set ideally suited for our research objectives. Data were collected in four primarily middle class school districts in southeastern Michigan. The participants (91% Caucasian) were initially recruited in elementary school during the 1987/1988 school year, when they were in Grade 1 (Cohort 1), Grade 2 (Cohort 2), and Grade 4 (Cohort 3). Ten elementary schools participated in the initial data collection. The same participants were then followed over time as they changed schools. The University of Michigan Institutional Review Board approved all waves of data collection of the CAB study.

For the present analyses, we used data from all students who had reported on their ASCs and intrinsic values at least once across six waves of data collection, resulting in a total of 1,069 students (49% male) from the original three cohorts ($N = 318$ for Cohort 1, $N = 330$ for Cohort 2, and $N = 421$ for Cohort 3). Data collection was conducted in the spring of each school year. The first three waves occurred 1 year apart. No data were collected for the next 3 years due to a gap in funding, after which annual data collections were continued for 3 years. The combined data set provides information on Grades 1 through 12 (see Table 1). Attrition in the sample was due mostly to one school district dropping out of the study after Wave 3 ($N = 122$) and children moving away from the sampled school districts. Every effort was made to locate the participants each year, and the longitudinal sample included children who continued to live in the same general area, even if they had changed schools. In 2013–2014, approximately 15 years after graduation from high school, when the participants were in their 30s (age range = 32–37 years), data about major career and family milestones were collected via a short survey ($n = 375$).

Table 1

Sample Description by Cohort Grade Level, and Age at Each Time Point of Data Collection

Time and variable	Cohort 1	Cohort 2	Cohort 3
Time 1: 1987–1988			
Grade level	Grade 1	Grade 2	Grade 4
<i>N</i>	289	314	261
Mean age in years (<i>SD</i>)	6.76 (0.38)	7.73 (0.39)	9.70 (0.36)
Time 2: 1988–1989			
Grade level	Grade 2	Grade 3	Grade 5
<i>N</i>	273	286	395
Mean age in years (<i>SD</i>)	7.76 (0.39)	8.72 (0.38)	10.70 (0.38)
Time 3: 1989–1990			
Grade level	Grade 3	Grade 4	Grade 6
<i>N</i>	241	250	366
Mean age in years (<i>SD</i>)	8.76 (0.38)	9.71 (0.37)	11.70 (0.36)
Time 4: 1993–1994			
Grade level	Grade 7	Grade 8	Grade 10
<i>N</i>	187	194	278
Mean age in years (<i>SD</i>)	12.75 (0.38)	13.73 (0.38)	15.69 (0.35)
Time 5: 1994–1995			
Grade level	Grade 8	Grade 9	Grade 11
<i>N</i>	131	129	187
Mean age in years (<i>SD</i>)	13.73 (0.37)	14.69 (0.37)	16.66 (0.34)
Time 6: 1995–1996			
Grade level	Grade 9	Grade 10	Grade 12
<i>N</i>	154	155	199
Mean age in years (<i>SD</i>)	14.73 (0.37)	15.71 (0.36)	17.67 (0.34)

Note. The average age was computed as of January 1 of each year shown (e.g., January 1, 1988).

Measures

ASCs and Intrinsic Values

ASCs and intrinsic values in math were measured with nearly identical wording over the years. Items measuring students' beliefs in the domain of language arts also had parallel wording across time, but referred to *reading* in elementary school and to *English* at later time points in order to capture what students were learning at each stage (Durik, Vida, & Eccles, 2006). To ensure that students understood the items, all questions were read aloud to the children during the first two waves and to the youngest cohort in the third wave.

All items were answered using 7-point response scales. Students' ASCs were assessed with five items indicating their self-judgments of ability and expected future success in each domain; for example, "How good at math [reading/English] are you?" ranging from 1 (*not at all good*) to 7 (*very good*), and "How well do you expect to do in math [reading/English] this year?" ranging from 1 (*not at*

all well) to 7 (*very well*). As in previous expectancy-value research, we did not distinguish between ASC and expected future success because these measures were found to be highly correlated and did not form distinct factors (Eccles et al., 1993). Of note, the scale included one item that explicitly evoked dimensional comparisons (i.e., “Compared with other subjects, how good are you at math [reading/English]?”). To ensure that this item did not artificially lead to more differentiated responses across domains, we ran preliminary analyses from which we excluded this item. As these analyses did not yield substantially different latent classes, we retained the full scale for the analyses. Students’ intrinsic values in math and reading were assessed with two items in each domain; for example, “How much do you like math [reading/English]?” ranging from 1 (*a little*) to 7 (*a lot*). This set of items was included at all time points, with the exception of items related to language arts, which were not asked in Wave 5. The internal consistencies of all scales were acceptable across the different time points for all cohorts (math ASC $\alpha = .70-.95$, math intrinsic value $\alpha = .70-.91$, language arts ASC $\alpha = .76-.95$, language arts intrinsic value $\alpha = .60-.87$), although lower values were observed for younger children (see Appendix S2 for descriptive statistics by cohort and wave). These scales have been validated across grade levels in prior research (Eccles et al., 1993; Jacobs et al., 2002; Simpkins, Fredricks, & Eccles, 2015).

Student Characteristics Assessed in Elementary School

We examined a set of demographic variables, students’ cognitive ability, and teacher-rated aptitudes—all assessed in elementary school—as potential predictors of students’ trajectories (see Appendix S3 for descriptive statistics). At the beginning of the study, parents provided demographic information, including their child’s gender, their own level of education, and the family income. Gender was coded as 0 = “female” and 1 = “male.” Parents’ educational level was assessed on a scale ranging from 1 (*some high school*) to 8 (*Ph.D. or advanced professional degree*), and the parent with the highest level of education was used to indicate the child’s family educational background (Durik et al., 2006). Family income was reported on a 9-point scale (1 = *under \$ 10,000 a year* to 9 = *over \$ 80,000 a year*). All children were given the Slosson Intelligence Test–Revised (Slosson, Nicholson, & Hibpshman, 1991) to assess their general cognitive ability at the beginning of the study. The participating

students’ elementary school teachers evaluated their math and reading aptitude in the first four waves of data collection starting when the participating children were in kindergarten, first grade, and third grade. Because our analyses began with the Wave 2 data, the maximum number of teacher ratings we had was three (for the children in Cohorts 2 and 3). There were two items in each domain, for example, “Compared to other children, how much innate ability or talent does this child have in math [reading]?” ranging from 1 (*very little*) to 7 (*a lot*). The internal consistency of this two-item scale at each wave and within each domain ranged from $\alpha = .84$ to $\alpha = .89$. Each student thus received up to four teacher ratings in each domain across the four waves. The interrater agreement (intraclass correlation) between teachers across waves ranged from .67 to .77 for math aptitudes and from .73 to .83 for reading aptitudes and was .84 for mathematics and .88 for reading for participants with four ratings across all four waves. The average of all available teacher ratings per student was thus used as an indicator of their math and reading aptitude in elementary school ($\alpha = .91$ in math; $\alpha = .92$ in language arts).

Outcomes Assessed in High School

The outcome measures included students’ self-reported math course enrollment in Grades 11–12, their career aspirations in Grade 12, and reading for pleasure in Grade 12 (see Appendix S3 for descriptive statistics). In Grade 12, students reported the types of math courses they had taken throughout high school (Simpkins, Davis-Kean, & Eccles, 2006). The types of math courses included Algebra, Algebra II, Geometry, Precalculus, Trigonometry, Calculus, and Advanced Placement Calculus/Advanced Placement Analysis. Two sum scores were calculated for the total number of math courses taken in high school and the number of advanced math courses taken by each student. Most schools required at least 2 years of math courses, but students were able to choose the number and type of math courses in which they enrolled in high school. An analogous measure was not available for language arts classes. However, in Grade 12, students reported the amount of time per week they spent reading for pleasure (Durik et al., 2006). We included this scale as a measure of students’ out-of-school activities related to the language arts domain. The response options were 1 (*none*), 2 (< 1 hr), 3 (2–3 hr), 4 (4–6 hr), 5 (7–10 hr), 6 (16–20 hr), and 7 (21 hr or more). Career aspirations

were assessed in Grade 12 for all three cohorts. Students were asked to rate their likelihood of pursuing a career in different fields on a scale ranging from 1 (*very unlikely*) to 7 (*very likely*). We included students' aspirations to have careers in science or math-related fields and in human services in our analyses. We chose these two categories because they were most strongly related to the domains of math and language arts, respectively (see Lauermann et al., 2015; Parker et al., 2012).

Adult Careers

The participants' open-ended descriptions of their current or most recent occupation, official job title, and important job activities and duties were used to code adult careers according to occupational titles in the Occupational Information Network database (O*Net 18.0, U.S. Department of Labor Employment & Training Administration, 1998; see onetcenter.org). O*Net is a database of all occupations recognized by the U.S. Department of Labor. In addition, the participants were asked to list their educational and occupational history in a table, and this information was used to check the plausibility of assigned occupational titles for the participants' current or most recent occupation. Furthermore, the occupational data of 27 individuals were obtained by conducting a search of personal and professional websites. Occupations were then categorized according to whether they were in the fields of science, technology, engineering, mathematics, or medicine (STEMM) versus other fields. This broad categorization of math-related careers has been used with the Longitudinal Study of American Youth, where it was shown that mathematics is a primary gateway to a STEMM career (Miller & Kimmel, 2012). Although more specific codes were available in the data set, we refrained from using them because of their low proportions, which led to convergence problems in subsequent analyses.

Data Analysis Strategy

All analyses were run in Mplus Version 7.31 (Muthén & Muthén, 1998–2015). The full information maximum likelihood approach implemented in Mplus was used in all analyses to deal with missing data (Graham, 2009). This approach takes all available information into account when estimating the model parameters. We followed a multistep process to examine trajectories in ASCs and intrinsic values and their associations with student

characteristics and outcomes (see Petras & Masyn, 2010 for recommendations on model building in growth mixture analyses). Each step is described in more detail in the following section. We used the same procedure described next for ASCs and intrinsic values. The steps encompassed (a) examination of the functional form of change across the sample, (b) class enumeration using growth curve mixture modeling, and (c) examination of differences between classes in student characteristics and outcomes.

First, we examined the shape of growth over time using latent growth curve analyses. Due to the study's cross-sequential design and the resulting pattern of missing data (see Table 1), multiple group analysis was used to model growth as a function of students' grade levels at each time point across the three cohorts. The models for the three cohorts differed only in the time codes, and joint growth parameters across cohorts were estimated (see Duncan, Duncan, & Hops, 1996; Muthén & Khoo, 1998). We tested both linear and quadratic growth models for all constructs. These models included a latent intercept factor as well as a linear slope factor or a linear and a quadratic growth slope factor, respectively. The time codes for these growth factors were based on students' grade levels but centered on Grade 6. Grade 6 represents the midpoint of the time span under study and was used as the reference grade. Covariances between the measures of the two subjects at the same time point as well as between the same measures at two adjacent time points were allowed in order to account for method effects due to parallel measures and time-specific effects (Marsh & Hau, 1996). Model fit was evaluated with the comparative fit index (CFI), the root mean square error of approximation (RMSEA), and the standardized root mean square residual (SRMR).

Building on the model chosen in the first step and using the same growth model specifications as described earlier, we then used GMM (Muthén, 2004) to examine whether there were different classes underlying the cross-domain trajectories in students' ASCs and intrinsic values (*Research Question 1*). GMM is used to examine whether there are unobserved subgroups of individuals (i.e., latent classes) that differ in the distribution of the latent growth factors (e.g., intercept, linear, and quadratic terms) and classifies individuals into these latent classes in a probabilistic manner. Whereas we used parallel process models to jointly investigate the development in students' ASCs and intrinsic values across the two domains (see Muthén & Muthén,

1998–2015), we performed the analyses separately for ASCs and intrinsic values due to the complexity of the models. The latent classes were thus based on the latent intercept and slope factors in the two domains and their covariances. More specifically, we used a multiple group growth mixture model in which the cohorts defined the groups, to deal with the specificities of the cross-sequential design. With the exception of the time coding, which captured the cross-sequential study design, no differences in the parameters of the latent class model between the three cohorts were allowed. This implies that class-specific parameters are estimated based on the cross-sequential design and thus can be interpreted consistently across cohorts. However, the model allowed for differences in the proportions of latent classes between cohorts.

We compared models with increasing numbers of classes. Comparisons across models were based on the Akaike information criterion (AIC), Bayesian information criterion (BIC) fit statistics, and the sample-adjusted BIC (SABIC), with smaller values indicating superior fit to the data. Of these information criteria, the BIC has been shown to perform best in this type of analysis (Nylund, Asparouhov, & Muthén, 2007), and so we mostly relied on this criterion. Likelihood ratio tests, which can generally also be used to compare the fit of models with different numbers of profiles, are currently unavailable in Mplus when multiple groups are specified. Additional criteria included the proportion of students assigned to a given class and the interpretability of the solutions. We also inspected the entropy value (ranging from 0 to 1) as an indicator of classification accuracy, with values $> .70$ indicating a good classification accuracy (Reinecke, 2006). For reasons of parsimony, we first tested models in which variances and covariances were assumed to be equal across classes and then compared them to models in which variances and covariances were allowed to differ between classes.

We then investigated differences in our set of student characteristics and outcomes across the previously identified classes (*Research Questions 2 and 3*). To do so, we used a three-step approach, as recommended in the literature (Asparouhov & Muthén, 2014a; Vermunt, 2010). Compared with other approaches, three-step approaches have the advantage that they take classification error into consideration, and the measurement model for the latent class variable is not affected when covariates are included (Asparouhov & Muthén, 2014a; Vermunt, 2010). In order to be able to use this approach in combination with the multiple group

analysis (across the three cohorts), we implemented a manual three-step approach estimating class-specific means in student characteristics and outcomes, following guidelines provided by Asparouhov and Muthén (2014a). Equal variances of student characteristics and outcomes across classes were assumed as recommended by Asparouhov and Muthén (2014b) because models with unequal variances did not converge properly.

Results

Students' ASCs for Math and Language Arts

Step 1 of the analysis procedure involved exploring the functional form of growth in students' ASCs for math and language arts across the full sample. Because the mean and variance of the quadratic growth factor for math were not significantly different from zero, we chose a model that included both a linear and a quadratic growth factor for language arts, but only a linear growth factor for math. This model exhibited good fit to the data (CFI = .957, RMSEA = .037, SRMR = .088), and corresponds to the functional form underlying the development of ASCs in math and language arts reported by Jacobs et al. (2002). In this model, the linear slope factors for math and language arts were significantly negative and the quadratic slope factor for language arts was significantly positive (see Appendix S5 for estimates). The variances in all growth factors were significantly different from zero.

Our Step 2 analyses addressed *Research Question 1* concerning which latent classes in students' trajectories can be identified. Initially, a model estimating the variances and covariances of all latent factors within classes was specified. However, there was no significant variance in the linear and quadratic language arts slopes within classes, and there were convergence problems with some models, possibly due to insufficient variance in change over time within the identified latent classes. The within-class variances for the linear and the quadratic language arts slopes were therefore constrained to zero. Models with up to eight latent classes could then be tested without convergence problems (see Appendix S6 for fit indices). A model with two latent classes showed a considerably better fit relative to a one-class (i.e., undifferentiated) model. The BIC, the AIC, and the SABIC continued to decrease slightly for solutions with three and four classes. However, the three- and four-class solutions produced relatively small additional classes ($< 10\%$ of the sample), which were not easily interpretable

(see Appendices S7 and S8). We therefore chose the solution with two classes, both of which were identifiable across models and thus represent the most robust solution across analyses. With an entropy of .754, classification accuracy into the latent classes was satisfactory. We further tested for heterogeneity in the estimated variances and covariances across classes (i.e., the intercepts for math and language arts and the linear slope for math), finding that this did not change the model fit or the identified classes. Homogeneous variances and covariances were therefore assumed.

The two latent classes we found are illustrated in Figure 1 (for the corresponding parameters, see

Table 2). The first class, which included 71.9% of the students in our sample, exhibited a moderate linear decline in math ASC across grade levels, as well as a linear decline in language arts ASC leveled out by a significantly positive quadratic trend. Accordingly, whereas students' math ASC declined steadily in this class, their ASC for language arts remained at a comparatively high level. We therefore labeled this class *Moderate Math Decline/Stable High Language Arts*. At the end of high school, students in this class exhibited a high language arts ASC, but a comparatively lower math ASC. The second class, which included 28.1% of the students in our sample, exhibited a similarly

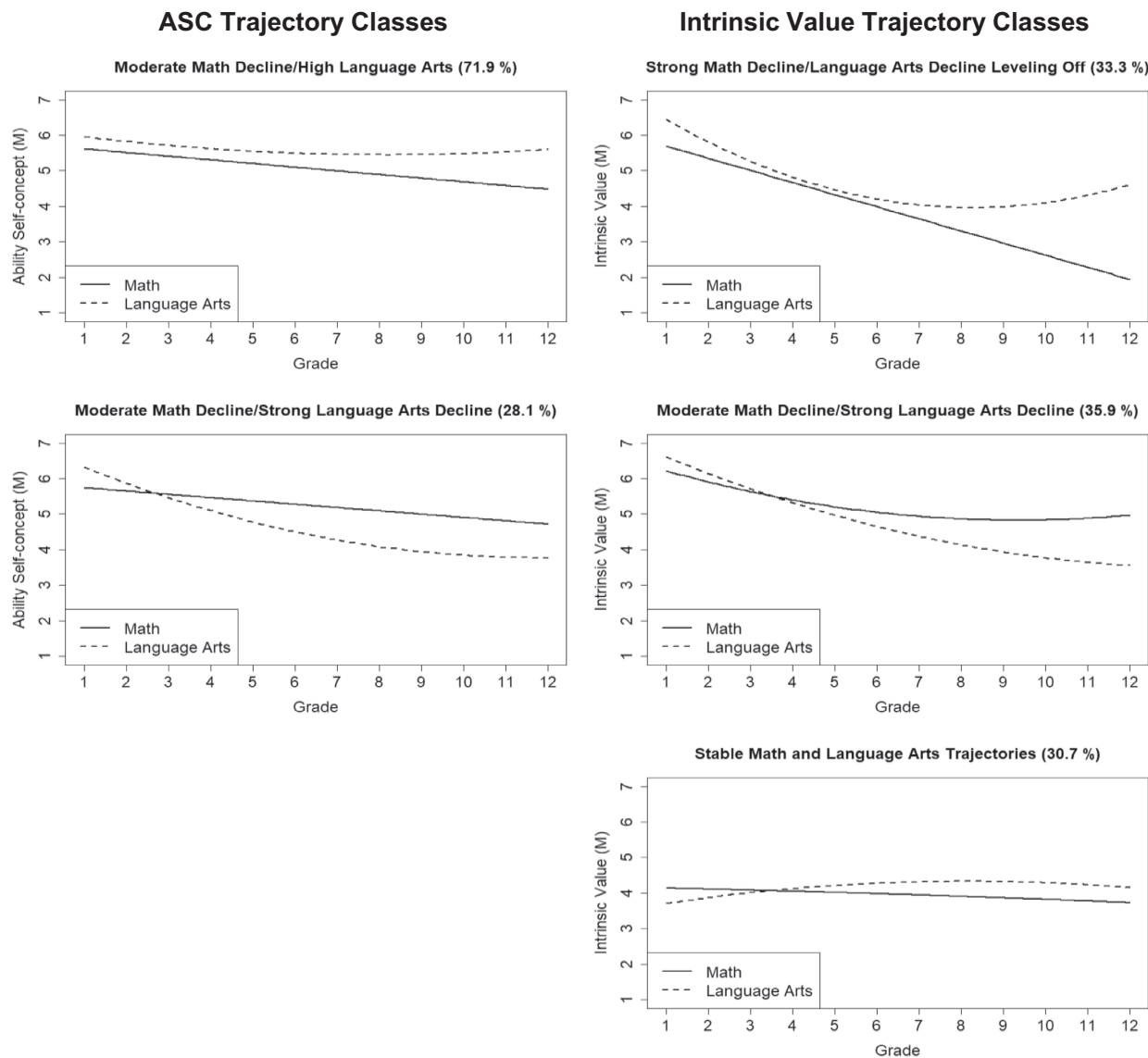


Figure 1. Trajectories of math and language arts ability self-concepts (ASCs; on the left) and intrinsic values (on the right) by class.

Table 2

Results of Growth Mixture Models for Ability Self-Concepts (ASCs) and Intrinsic Values: Means and Variances in Growth Parameters for the Latent Classes

	ASC				Intrinsic value					
	Moderate Math Decline/Stable High Language Arts		Moderate Math Decline/Strong Language Arts Decline		Strong Math Decline/Language Arts Decline Leveling Off		Moderate Math Decline/Strong Language Arts Decline		Stable Math And Language Arts Trajectories	
	M	Variance	M	Variance	M	Variance	M	Variance	M	Variance
Intercept math	5.10***	0.50***	5.28***	0.50***	3.99***	0.46*	5.05***	0.03	3.99***	1.46***
Linear slope math	-0.10***	0.02***	-0.09***	0.02***	-0.34***	0.00	-0.13***	0.00	-0.04	0.00
Quadratic slope math	—	—	—	—	0.00	0.00	0.02**	0.00	0.00	0.00
Intercept language arts	5.50***	0.29***	4.51***	0.29***	4.21***	0.71***	4.66***	0.00	4.28***	1.50***
Linear slope language arts	-0.04**	0.00	-0.25***	0.00	-0.21***	0.00	-0.30***	0.00	0.05	0.00
Quadratic slope language arts	0.01***	0.00	0.02***	0.00	0.05***	0.00	0.02**	0.00	-0.01	0.00
$\Delta (M_{\text{Grade 11}} - M_{\text{Grade 12}})$										
Math	1.13		1.02		3.75		1.25		0.41	
Language arts	0.36		2.55		1.84		3.06		-0.44	

Note. For ASC, no quadratic slope factor was estimated for math. Variances were constrained to be the same across classes. Variances for the linear and quadratic language arts slopes were fixed to zero because there was little variance in these parameters overall and estimating variance in these parameters resulted in convergence problems. For intrinsic value, variances for the linear and quadratic language arts slopes were fixed to zero because there was only little variance in these parameters overall and estimating variance in these parameters resulted in convergence problems. In the *Moderate Math Decline/Strong Language Arts Decline* class, the variance for the language arts intercept was additionally fixed to zero because a non-significant, negative variance would otherwise be estimated.

* $p < .05$. ** $p < .01$. *** $p < .001$.

pronounced decline in math ASC. However, it also showed a much more pronounced (nonlinear) decline in ASC for language arts. The significant quadratic trend resulted from a slowdown in the decline in language arts ASC over time. We therefore labeled this class *Moderate Math Decline/Strong Language Arts Decline*. At the end of high school, students in this class reported a moderate math ASC, but a comparatively lower language arts ASC. In both classes, students' ASCs in the two domains increasingly diverged over the school years, indicating intraindividual differentiation over time. Whereas there was within-class variance in the linear slope factors in math, the two classes were very similar in their average math trajectories. That is, the two trajectory classes differed primarily in their trajectories in language arts, and the within-class variance in the slope factors approached zero in this domain.

Finally, we tested for between-class differences in student characteristics and outcomes (Step 3, *Research Questions 2 and 3*). The mean levels of the student characteristics and outcomes in the two classes are shown in Table 3. Male students were overrepresented in the *Moderate Math Decline/Strong Language Arts Decline* class, whereas female

students were overrepresented in the *Moderate Math Decline/Stable High Language Arts* class. Students in these two classes also differed in terms of their family background, with students in the *Moderate Math Decline/Stable High Language Arts* class tending to come from families with comparatively higher levels of parental education and family income. Students in this class also had higher cognitive abilities. There were no significant differences in teacher-rated math aptitude, but students in the *Moderate Math Decline/Stable High Language Arts* class had comparatively higher teacher-reported reading aptitude.

In terms of the outcomes, students in the *Moderate Math Decline/Strong Language Arts Decline* class took more math classes in total as well as more advanced math classes than students in the *Moderate Math Decline/Stable High Language Arts* class. Students in the *Moderate Math Decline/Strong Language Arts Decline* class also reported more math-/science-related career aspirations and fewer human-services-related career aspirations compared to students in the *Moderate Math Decline/Stable High Language Arts* class. Furthermore, students in the *Moderate Math Decline/Strong Language Arts Decline* class were significantly more likely to have a

Table 3
Mean Levels of Student Characteristics and Outcomes in the Two Ability Self-Concept (ASC) and the Three Intrinsic Value Trajectory Classes

Variable	ASC			Intrinsic value				
	M ₁ (Moderate Math Decline/ Stable High Language Arts)	M ₂ (Moderate Math Decline/ Strong Language Arts Decline)	M ₁ (Strong Math Decline/ Language Arts Leveling Off)	M ₂ (Moderate Math Decline/ Strong Language Arts Decline)	M ₃ (Stable Math and Language Arts Trajectories)	D _{M1-M2}	D _{M1-M3}	D _{M2-M3}
Student characteristics								
Gender (% male)	0.42	0.61	0.45	0.41	0.62	0.04	-0.17*	-0.21**
Parental education	5.20	4.03	4.59	4.76	4.95	-0.17	-0.36	-0.19
Family income	5.94	5.15	5.85	5.67	5.36	0.19	0.49	0.30
Cognitive ability	116.94	111.81	114.08	114.37	116.73	-0.30	-2.65	-2.35
Teacher-rated math aptitude	5.14	4.98	4.92	5.27	5.11	-0.35*	-0.20	0.15
Teacher-rated reading aptitude	5.38	4.73	5.08	5.27	5.09	-0.19	-0.01	0.19
Outcomes								
Total number of math classes	3.67	4.90	3.62	4.97	4.80	-1.34***	-1.18**	0.17
Number of advanced math classes	0.59	1.26	0.57	1.26	1.24	-0.70**	-0.67**	0.03
Reading for pleasure	2.76	2.69	2.75	2.84	2.58	-0.10	0.16	0.26
Math-/science-related career aspirations	1.66	5.92	1.58	5.51	6.14	-3.93***	-4.56***	-0.63
Human-services-related career aspirations	3.82	3.06	3.78	3.66	2.60	0.12	1.18*	1.06
STEMM career	0.16	0.47	0.17	0.44	0.37	-0.27	-0.21	0.06

Note. *D* = difference between the means for the different classes. Differences between classes were tested with a model constraint. STEMM = science, technology, engineering, mathematics, or medicine.

p* < .05. *p* < .01. ****p* < .001.

STEMM career than students in the other class. No differences between the two classes were found for reading for pleasure.

Students' Intrinsic Values for Math and Language Arts

As was the case for students' ASCs, we first explored the functional form of growth in students' intrinsic values for math and language arts (Step 1). A quadratic growth model fit the data reasonably well (CFI = .916, RMSEA = .058, SRMR = .086). The quadratic growth model identified significant negative linear slope factors and significant quadratic slope factors in both math and language arts (see Appendix S5 for estimates). All of the growth factors except for the quadratic growth factor in math also exhibited significant variance, but the variances of the slope factors were relatively small.

Next, in Step 2, we addressed *Research Question 1* by exploring the number of underlying latent classes using a quadratic growth model. As we did for students' ASCs, we tried to specify a model that estimated the variances and covariances of all latent factors within classes. However, given the near-zero variance in the linear and quadratic slope factors overall, this model had convergence problems. Therefore, we constrained the variances of all linear and quadratic slopes within classes to zero. We were then able to test models with up to eight classes (see Appendix S9 for fit indices). Although the AIC and the SABIC continued to decrease for higher numbers of classes, the three-class solution exhibited the lowest BIC value. We then also tested heterogeneity in variances and covariances between classes. Again, we found that a three-class solution had the lowest BIC. Because this model also exhibited a slightly better fit than the model with equal variances and covariances and because one of the classes was different in this solution and easier to interpret, we chose the model with unequal variances and covariances as our final model. Its entropy value (.758) was also good, indicating that it provided appropriate classification accuracy across the identified latent classes.

These three latent classes are illustrated in Figure 1 (see Table 2 for the corresponding parameters). The first class, which included 33.3% of the students in our sample, showed a pronounced linear decline in intrinsic value for math over time, combined with a U-shaped trajectory in intrinsic value for language arts. That is, intrinsic value for language arts in this class first declined and then leveled off. We therefore labeled this class *Strong Math Decline/Language Arts Decline Leveling Off*. At

the end of high school, students in this class exhibited relatively high levels of intrinsic value for language arts combined with very low levels of intrinsic value for math. There was significant variance in the intercepts for math and language arts in this class. The second class, which included 35.9% of the students in our sample, exhibited curvilinear declines in intrinsic values for both math and language arts over time. However, the decline in language arts was more pronounced than the decline in math. We therefore labeled this class *Moderate Math Decline/Strong Language Arts Decline*. At the end of high school, students in this class had relatively higher intrinsic values in math compared to language arts. There was no significant variance in the intercepts for math and language arts in this class. The third class, which included 30.7% of the students in our sample, showed no significant linear or quadratic growth in intrinsic value for math or language arts over time. We therefore labeled this class *Stable Math and Language Arts Trajectories*. Overall, students' intrinsic value for language arts was somewhat higher than for math. However, this class also exhibited the highest variances in the intercepts for math and language arts. Although the level of intrinsic value for both language arts and math was moderate over time, it varied substantially within this class, and this variation likely also captured students with higher levels of intrinsic values for math compared to language arts (and vice versa).

We then tested for differences between the three classes in student characteristics and outcomes (Step 3, *Research Questions 2 and 3*). The mean levels of the student characteristics and outcomes for the three classes can be found in Table 3. There was a significantly higher percentage of males in the *Stable Math and Language Arts Trajectories* class compared to the other two classes. No differences between the three classes were found for parental education, family income, and students' cognitive abilities. Students in the *Strong Math Decline/Language Arts Decline Leveling Off* class had lower teacher-rated math aptitude compared to students in the *Moderate Math Decline/Strong Language Arts Decline* class. No differences between the three classes were found in teacher-rated reading aptitude.

In terms of the outcomes, students in the *Strong Math Decline/Language Arts Decline Leveling Off* class took a lower number of math classes in total and a lower number of advanced math classes compared to students in the other two classes. They also reported lower math-/science-related career aspirations compared to students in the remaining two

classes and higher human-services-related career aspirations than students in the *Stable Math and Language Arts Trajectories* class. Students in the *Moderate Math Decline/Strong Language Arts Decline* and the *Stable Math and Language Arts Trajectories* classes did not differ significantly in the number of math classes taken or in their career aspirations. Consistent with our findings for career aspirations, the *Strong Math Decline/Language Arts Decline Leveling Off* class showed the lowest proportion of STEM careers in early adulthood; however, the differences across classes in careers were not statistically significant. No differences between the three classes were found for reading for pleasure.

Discussion

This study is the first to examine developmental processes of inter- and intraindividual differentiation in students' ASCs and intrinsic values in the domains of math and language arts from Grades 1 to 12. The major results are the following. First, we found meaningful trajectory classes in both ASCs and intrinsic values. There were two distinct latent classes for ASC trajectories: a *Moderate Math Decline/Strong Language Arts Decline* class and a *Moderate Math Decline/Stable High Language Arts* class. As expected, ASCs in the two domains for students in these two classes increasingly diverged over time, suggesting increasing intraindividual differentiation across domains. We found three latent trajectory classes for students' intrinsic values: a *Strong Math Decline/Language Arts Decline Leveling Off* class, a *Moderate Math Decline/Strong Language Arts Decline* class, and a *Stable Math and Language Arts Trajectories* class. The intrinsic values of students in the first two classes exhibited increasing differentiation by domain. In contrast, the intrinsic values of students in the third class were relatively stable in both domains. Our findings of distinct classes underscore the importance of accounting for heterogeneity in students' ASC and STV trajectories in developmental analyses.

Second, we found that students' gender, aptitudes, and parental education and income levels were associated with class membership in ways consistent with previous research on how these factors typically influence students' ASCs and STVs. Third, we extended the EVT-based research on how individuals' ASCs and STVs are related to their educational and career choices by showing that students' ASC and intrinsic value trajectories were associated with the number of math courses they

took in high school, their career aspirations at the end of high school, and the careers they had as adults. Students in the trajectory classes with less decline in ASC and intrinsic valuing of one domain (e.g., math) compared to the other domain (e.g., language arts) took more advanced courses, had higher career aspirations and more often chose careers in that domain. We discuss these findings in greater detail in the following sections.

Developmental Trajectories of ASCs and Intrinsic Values Across Math and Language Arts

Motivational theorists from different theoretical traditions have suggested that students' ASCs, STVs, and interests across academic domains become increasingly differentiated over the school years (Eccles, 2009; Marsh & Ayotte, 2003; Schiefele, 2009). If the ASCs and STVs of individual students decline in some domains but remain relatively high in others, this increasing intraindividual differentiation can lead to an average decline in ASCs and STVs across groups of students and domains. Our findings were generally consistent with this pattern of intraindividual differentiation across domains, with the exception of one class with relatively stable levels of intrinsic value in math and language arts. Comparing the findings for ASCs and intrinsic values, two of the trajectory classes we found were relatively consistent across these two constructs, with students showing a pattern of increasing intraindividual differentiation and reporting higher motivational beliefs in math compared to language arts at the end of high school and vice versa.

However, we also found a class with relatively stable trajectories with respect to intrinsic values. Although Hidi and Renninger (2006) stated that young children's interests are quite variable in their developmental model, and Wigfield et al. (1997) reported low stability correlations for young children's valuing of math and reading using the CAB data set, our results suggest that there is a subgroup of students whose valuing of math and reading stabilizes quite early. However, it is important to note that we examined mean-level stability rather than stability correlations. This means that there still could be some unsystematic fluctuations in this class over time. It is also important to note that this class cannot necessarily be described as showing an undifferentiated pattern. Significant variance in the estimated levels of students' intrinsic valuing of math and language arts suggests that students' intrinsic values stabilized at different levels. Accordingly, the trajectories of students' intrinsic values in

this class are characterized by their stability over time; however, this class includes students with more differentiated patterns (i.e., high and stable levels of intrinsic value for math but low and stable intrinsic value for language arts, and vice versa) as well as undifferentiated ones. These results are similar to results from Guo et al. (2018), who found three classes in cross-domain trajectories of students' STVs, with one class showing stable trajectories across domains. Guo et al. examined these trajectories from Grades 9 to 12; our results extend their findings all the way back to first grade. Potential reasons why such a class with stable trajectories emerged only for intrinsic values and not for ASCs could be the close association between students' ASCs and their school achievements (Marsh et al., 2005) and also the fact that interests are shaped by more than achievement (Hidi & Renninger, 2006).

Our results extend previous research that showed that there are different patterns of change in individuals' ASCs and STVs across academic domains. Eccles (2009) proposed that it is the "hierarchies" of individuals' ASCs and STVs that are more crucial determinants of choices than are ASCs and STVs in a given domain. The process of intraindividual differentiation in students' ASCs and intrinsic values we found likely contributes to the development of these hierarchies and can be seen as an important development as students get to know their strengths and weaknesses and their interests become more specialized in particular domains. This may facilitate students' educational and career decisions as they try to identify opportunities that are a good fit for their strengths and interests (Krapp, 2002; Möller & Marsh, 2013).

Associations Between ASC and Intrinsic Value Trajectories and Student Characteristics

The trajectory classes we found varied by students' gender, abilities, and family background. Interestingly, these differences were somewhat more pronounced for ASC trajectories than for intrinsic value trajectories. Here, we found two ASC trajectory classes with a pronounced difference in the trajectories in language arts, and a decline in ASC for language arts seemed to be more likely for students with associated risk factors (i.e., being male, having a lower family background, having lower cognitive and reading abilities; see also Archambault et al., 2010; Jacobs et al., 2002). Regarding gender, the differences are in line with gender stereotypes about language arts, and girls have also been found to perform better in language

arts than boys (e.g., Retelsdorf et al., 2011). The pattern of gender differences in intrinsic value trajectories was somewhat less clear. Male students were overrepresented in the *Stable Math and Language Arts Trajectories* class compared with the other two classes. This is in line with Archambault et al. (2010), who found a higher proportion of male students in a class that followed a low and stable motivational trajectory for language arts. The *Strong Math Decline/Language Arts Decline Leveling Off* and the *Moderate Math Decline/Strong Language Arts Decline* classes did not differ in terms of the numbers of boys and girls in each, which could have been expected given stereotypical differences in boys' and girls' interests in these domains (Frenzel et al., 2010; Watt, 2004). Previous research using the CAB data also failed to find gender differences in the development of students' STVs in math (Jacobs et al., 2002; Musu-Gillette et al., 2015). As both Frenzel et al. (2010) and Watt (2004) relied on non-U.S. samples, cultural differences might account for the differences observed between studies.

We found that family background was associated with class membership; specifically, membership in the *Moderate Math Decline/Strong Language Arts Decline* ASC trajectory class compared to the *Moderate Math Decline/Stable High Language Arts* class was associated with lower levels of parental education and family income. Given that these two trajectory classes differed primarily in language arts trajectories, this finding is in line with previous research that identified low parental education and low family income as risk factors for the development of ASC in the language arts domain (Archambault et al., 2010; Retelsdorf et al., 2011). Parents with lower education and incomes may be less well-equipped to support children in the relevant competencies such that their children experience more pronounced declines in their perceived competence in language arts (Eccles, 2007). On the other hand, parents with comparatively higher levels of education and income most likely provide more learning opportunities in this domain as well as in math (Simpkins et al., 2015). Family background was not associated with students' intrinsic value trajectories, in contrast to our findings for students' ASCs and previous research showing that family background is associated with students' general academic functioning (Eccles, 2007). However, the three intrinsic value trajectories did not differ much in terms of the overall level of intrinsic value across domains over time. Other family factors or characteristics, such as parents' provision of specific experiences and opportunities related to these domains,

may better explain the development of students' intrinsic values in specific domains (Eccles, 2007; Simpkins et al., 2015).

Finally, the differences in student aptitudes we found between the trajectory classes can help explain how these trajectories are shaped. In line with research showing that students' aptitudes are important predictors of their ASCs (Retelsdorf et al., 2014), the two ASC trajectory classes differed in their level of cognitive and reading abilities. However, it is important to keep in mind that students' ASCs and achievements are reciprocally related, such that changes in one impact changes in the other and vice versa (Marsh et al., 2005; Retelsdorf et al., 2014). Students' aptitudes were also associated with membership in the different intrinsic value trajectory classes; for instance, students with lower math aptitudes were more likely to be in trajectories exhibiting strong declines in intrinsic value for math. However, teacher-rated student aptitude in reading and students' general cognitive abilities did not vary according to class membership. As the three intrinsic value trajectory classes differed in their trajectories in the two domains, but not so much in their level of intrinsic value overall, we would not have expected them to differ in the general measure of intelligence used in the CAB study. Previous research has found that the development of students' intrinsic values is somewhat less closely related to their achievements than that of their ASCs but that it is also shaped by social and dimensional comparisons (Gaspard et al., 2018; Marsh et al., 2005). In line with dimensional comparison processes, the class with the most differentiated aptitude profile (i.e., the *Strong Math Decline/Language Arts Decline Leveling Off* class, which had lower math aptitude compared to reading aptitude) also exhibited the most differentiated development in intrinsic values over time. Their more positive trajectory in the language arts domain may be driven by intraindividual comparisons with their relatively low math achievement rather than by their achievement in language arts alone.

Academic and Career Choices as Outcomes of ASC and Intrinsic Value Trajectories

We found that intraindividual patterns in students' ASC and intrinsic value trajectories across domains predicted students' academic and career choices, with consistent results across ASCs and intrinsic values. As mentioned earlier, Eccles proposed that ASCs and STVs are not just direct predictors but also that intraindividual hierarchies in

ASCs and STVs drive academic choices (Eccles, 2009). Our results strongly support this proposition, and importantly, this is the first study to do so by looking at how trajectories of students' ASCs and STVs from Grade 1 to Grade 12 influence different choices. Our results thus extend cross-sectional research on intraindividual hierarchies in ASCs and STVs (e.g., Gaspard et al., 2019) as well as Guo et al.'s (2018) shorter term longitudinal study. Taken together, our findings and those of these other studies show that to understand individuals' educational and career choices, it is critical to examine patterns in their ASC and STV trajectories across domains. Equally important, both the final levels of ASCs and STVs and their trajectories over time can contribute to these outcomes. For example, students in the two ASC trajectory classes took different numbers of math classes in high school and differed in their math/science- and human-services-related career aspirations at the end of high school as well as in their STEM career attainment in adulthood. Given that the two classes were very similar in their math ASC trajectories, the decline in students' ASC for language arts and the resulting lower final levels of ASC for language arts in comparison with math might have discouraged them from pursuing courses and careers related to this domain and therefore pushed them toward alternative courses and careers related to math.

Similarly, we found that the different intrinsic value trajectory classes affected the number of math classes students took and their career aspirations. Students in the *Strong Math Decline/Language Arts Decline Leveling Off* class, which exhibited the most differentiated pattern in intrinsic value trajectories across the two domains, were much more likely than those in the other two classes to aspire to language arts-related careers and avoid math-related careers and courses. In comparison, the *Moderate Math Decline/Strong Language Arts Decline* class had strong aspirations toward math-related careers and courses; this likely is due to the strong decline in this class's intrinsic values for language arts. Interestingly, the *Stable Math and Language Arts Trajectories* class also showed high math-related course choices and career aspirations, but lower human-services-related career aspirations. This may be accounted for by their stable trajectories in math (as compared to the declining trajectories in the other two classes) or by the higher number of males in this class and gender differences in career aspirations (cf. Lauermann et al., 2015; Watt et al., 2012). When we included gender

as a covariate to test this hypothesis, all differences in math-related course choices and career aspirations remained significant, but the difference in human-services-related career aspirations was no longer significant. Although we found similar patterns for STEMM careers in adulthood, these differences were not statistically significant. Still, in line with the findings by Guo et al. (2018), it is reasonable to assume that a decline in math STVs over the school years can explain a lower likelihood of choosing a related career.

We investigated students' reading for pleasure as an outcome representing their out-of-school-activities. Durik et al. (2006) found (using CAB data) that students' ASC and intrinsic value for language arts in Grade 10 predicted reading for pleasure at the same time point. However, we found no differences between the trajectory classes for this variable. It may be that such associations are more pronounced for concurrent levels of motivation and are harder to find for trajectories over a longer time span. It is also worth noting that students reported that they spent relatively little time reading for pleasure in Grade 12 (between 1 and 2 hr per week on average), so our results could also be affected by the students' age.

Limitations and Future Research

Although the CAB data set has many strengths, for example, its long-term design and the richness of the data included in it, it also has important limitations. First, the sample is primarily a white, lower middle to middle class sample. Second, the data on students' ASCs and STVs were collected from 1988 to 1996. Theorists (e.g., Harter, 2006; Krapp, 2002; Wigfield, 1994) examining the development of ASCs, interests, and STVs have proposed that intraindividual differentiation of these constructs occurs across childhood and through adolescence, and our results broadly support these views. However, the exact form of such developmental trajectories probably varies in accordance with the children's cultural and temporal contexts and factors such as the prevailing gender stereotypes at a given time in a given culture. It is important to note that declines in students' ASCs and STVs as well as gender differences in ASCs and STVs have been found in more recently collected data from several Western countries (Frenzel et al., 2010; Watt, 2004). Even so, an important step for future research will be to examine whether similar trajectory patterns and associations with student characteristics and outcomes can be

found in other groups in the United States and other countries. More longitudinal studies with more diverse samples are thus needed to examine the generalizability of our findings across time periods, cultural contexts, and diverse groups of students.

Furthermore, although the trajectory classes were meaningfully associated with student characteristics, the kinds of data available in CAB do not allow for the identification of the psychological and other processes driving the differentiation of students' ASCs and STVs. Such processes likely include dimensional comparisons (Marsh & Ayotte, 2003; Möller & Marsh, 2013; Schiefele, 2009). To further examine how students' achievements in different domains are associated with the development of ASCs and STVs, one approach would be to include measures of achievement along with students' ASCs and STVs at each time point. However, a challenge in longitudinal research is to have achievement measures with comparable meanings and metrics across time. Research on other individual and school characteristics associated with such trajectories is also needed.

Conclusions

Our findings build in important ways on the extant literature on the development of students' ASCs and STVs across the school years by showing that there are qualitatively different cross-domain trajectories in students' ASCs and intrinsic values. Thus, as posited by EVT theorists (e.g., Eccles, 2009; Wigfield, 1994), there is increasing differentiation in students' ASCs and STVs both within and across these domains across their school careers, thereby illustrating how intraindividual hierarchies in ASCs and STVs develop over time. Furthermore, the trajectories differ with regard to students' gender, family background, and aptitudes. Importantly, students' ASC and intrinsic value trajectories are also associated with proximal and distal outcomes, including their course choices, career aspirations, and adult careers. These associations highlight the importance of investigating students' motivational development jointly across multiple domains and thus support assumptions about the importance of intraindividual hierarchies across domains made in EVT (Eccles, 2009). Future research should explore the generalizability of our results to other student populations and the psychological processes that drive the development of students' ASCs and intrinsic values across domains.

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Supporting Information

Additional supporting information may be found in the online version of this article at the publisher's website:

Appendix S1. Self-Report Measures From the Childhood and Beyond Study Used in the Present Study

Appendix S2. Descriptive Statistics for Ability Self-Concept and Value Scales by Domain, Time Point, and Cohort

Appendix S3. Descriptive Statistics for Student Characteristics and Outcomes

Appendix S4. Correlations Between All Study Variables

Appendix S5. Parameter Estimates of the Latent Growth Curve Models

Appendix S6. Selection Criteria for Different Class Solutions for Trajectories of Ability Self-Concept

Appendix S7. Results of Growth Mixture Models for Ability Self-Concept: Means and Variances in Growth Parameters for the Four-Class Solution

Appendix S8. Trajectories of Math and Language Arts Ability Self-Concepts by Class for Four-Class Solution

Appendix S9. Selection Criteria for Different Class Solutions for Trajectories of Intrinsic Values