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Predicting Long-Term Growth in Students' Mathematics Achievement: The Unique Contributions of Motivation and Cognitive Strategies

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This research examined how motivation (perceived control, intrinsic motivation, and extrinsic motivation), cognitive learning strategies (deep and surface strategies), and intelligence jointly predict long-term growth in students' mathematics achievement over 5 years. Using longitudinal data from six annual waves (Grades 5 through 10; M_{age} = 11.7 years at baseline; N = 3,530), latent growth curve modeling was employed to analyze growth in achievement. Results showed that the initial level of achievement was strongly related to intelligence, with motivation and cognitive strategies explaining additional variance. In contrast, intelligence had no relation with the growth of achievement over years, whereas motivation and learning strategies were predictors of growth. These findings highlight the importance of motivation and learning strategies in facilitating adolescents' development of mathematical competencies.

For decades, researchers in developmental and educational psychology have been concerned with the determinants of academic achievement. Today, there seems to be agreement that both motivational and strategy variables play an important role in explaining academic achievement (for a review, see Robbins et al., 2004). However, although a large portion of previous research has focused on the relation between these variables and academic achievement assessed at a particular time point, fewer studies have investigated whether motivational and strategy variables predict long-term *growth* in academic achievement. This is unfortunate because one of the ultimate goals in education is to facilitate sustainable learning (long-term intraindividual growth, i.e., change relative to current achievement of the individual), rather than to focus on performance attainment at one point in time. Clearly, systematic investigation of the long-term determinants of growth in academic achievement is imperative. In the present research, using longitudinal data from six annual waves over the adolescent years, we examined a variety of motivational variables and cognitive strategies as predictors of both concurrent level and long-term growth in math achievement.

Motivation: Perceived Control and Intrinsic–Extrinsic Motivation

Past studies have identified various motivational factors that affect academic achievement. The present research focused on three of these factors that are regarded as especially important in motivation theory and research: perceived control, intrinsic motivation, and extrinsic motivation (Eccles & Wigfield, 2002; Pekrun, 2006). *Perceived control* is conceptualized as subjective appraisal of the causal link between one's action and outcomes (Perry, Hladkyj, Pekrun, & Pelletier, 2001; Rotter, 1966). That is, perceived control reflects one's expectancy to obtain a desired outcome through an action. Concepts of perceived control and competence (and related constructs of expectancies) play a prominent role in motivation theories (Bandura, 1977; Eccles & Wigfield, 2002; Marsh & Shavelson, 1985; Pekrun, 1993), and many studies have shown that perceived control and competence in academic domains are positively related to achievement (Marsh, 1990; Meece, Wigfield, & Eccles, 1990). By implication, it is straightforward to expect that perceived control

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is positively associated with concurrent level of students' achievement in domains such as mathematics.

Importantly, adolescents' perceived control has also been shown to relate to their learning. Perceived control is linked to active and effortful commitment to learning (Skinner, Wellborn, & Connell, 1990), persistence when performing difficult and challenging tasks (Cervone & Peake, 1986), and intrinsic engagement (Gottfried, 1990). Together these findings suggest that perceived control should help adolescent students acquire new knowledge, and as such, should positively predict growth in their achievement. Indeed, longitudinal research on students' academic self-concepts has produced robust evidence that competence-related self-appraisals can influence subsequent academic achievement (e.g., Marsh, 1990; for reviews, see Marsh & Craven, 2006; Valentine, DuBois, & Cooper, 2004). Although (past) self-concept research relied on lagged analyses that do not consider absolute growth over time, the findings suggest that competence-related appraisals such as perceived control can be a positive predictor of long-term change in students' academic achievement.

Intrinsic motivation is defined as motivation to engage in a task for the sake of interest in the task itself and the inherent pleasure and satisfaction derived from the task, whereas *extrinsic motivation* is defined as motivation to engage in a task for external reasons (Deci & Ryan, 1985). Extrinsic motivation is heterogeneous in that there are a variety of different external rewards that produce motivated behavior. In the present research, we focus on extrinsic motivation driven by the desire to get good grades, as this is one of the most prevalent forms of extrinsic motivation in academic settings (Lemos, 1996; Pekrun, 1993).

Intrinsic motivation is associated with various variables supporting learning, such as active and effortful engagement (Ryan & Connell, 1989), persistence in the face of failure (Elliott & Dweck, 1988), and positive emotional learning experiences (Pekrun, Goetz, Titz, & Perry, 2002). Extrinsic motivation, on the other hand, is typically driven by expected short-term benefits of learning and is linked to instrumental learning independent of interest (Grolnick & Ryan, 1987), overuse of dependent help seeking (Butler, 1998), and self-handicapping (Urdan & Midgley, 2001). As such, extrinsic motivation seems suited to benefit immediate, but rather ephemeral, academic achievement, whereas intrinsic motivation seems ideally suited to benefit enduring, long-term learning. Thus, we propose that intrinsic motivation positively predicts growth in academic achievement (and possibly concurrent achievement as well; see also Marsh, Trautwein, Lüdtke, Köller, & Baumert, 2005), whereas extrinsic motivation has short-term effects that are manifested in a link to current achievement, but does not promote long-term growth. Although these time-dependent relations (i.e., relations that emerge at a particular point in time) of intrinsic and extrinsic motivation are documented in a few experimental studies (Murayama & Elliot, 2011; Vansteenkiste, Simons, Lens, Soenens, & Matos, 2005), little research has demonstrated such a pattern of effects in the context of long-term growth of academic achievement.

Cognitive Strategies: Deep and Surface Learning Strategies

Learning strategies are strategies that are employed by learners to study materials. Herein, we focus on two primary cognitive learning strategies that are widely recognized as having conceptual and predictive utility: *deep learning strategies* (specifically, elaboration of learning material) and *surface learning strategies* (rehearsal or memorization; Ramsden, 1988). Deep strategies involve challenging the veracity of information encountered and attempting to integrate new information with prior knowledge, whereas surface learning strategies characterize the repetitive rehearsal and rote memorization of information (Entwistle & Ramsden, 1983).

The extant data are mixed for the relation between these learning strategies and academic achievement, but tend to show null or positive relations for deep strategies and null or negative relations for surface strategies (Entwistle & Ramsden, 1983; Meece, Blumenfeld, & Hoyle, 1988). However, most of the studies to date have focused on links with the level of academic achievement at one point in time. A few studies have shown that learning-related strategy use has an impact on the growth of academic achievement during early childhood (e.g., McClelland, Acock, & Morrison, 2006), but the long-term relations of learning strategies with achievement during adolescence remain unclear.

Deep learning involves semantic understanding of study materials. Semantic understanding is an essential component in acquiring durable and meaningful knowledge, and the knowledge acquired through this semantic elaboration is more likely to lead to later academic success. Therefore, we anticipated that deep strategies would have positive relations with growth (as well as initial levels) of academic achievement. In contrast, we expected that surface strategies would not predict growth rates in achievement. Surface strategies involve rote memorizing without deep elaboration, and studies have indicated that knowledge acquired through rote memorizing fades quickly (Brown & Craik, 2000). Therefore, we anticipated that surface learning would not support further learning, although these strategies might help immediate academic achievement.

Limitations in Previous Research on Long-Term Growth in Achievement

This study used latent growth curve modeling (McArdle, Anderson, Birren, & Schaie, 1990) to examine predictors of growth in math achievement. One of the advantages of latent growth curve modeling is that it can evaluate the predictors of absolute levels of growth. As noted earlier, previous theorizing and evidence suggest that some motivational variables and learning strategies should predict long-term growth in academic achievement. However, only a few studies have utilized latent growth curve modeling to directly address the predictors of absolute levels of growth in achievement over time. Furthermore, the research available that used latent growth curve modeling has a number of important limitations that substantially reduce possibilities to draw firm inferences.

First, there is a significant lack of work that controlled for intelligence. Intelligence is a ubiquitous, strong predictor of academic achievement (Neisser et al., 1996), implying that it may be the most important confounding variable when examining links between variables of learning, such as motivation and cognitive strategies, and academic achievement (Steinmayr & Spinath, 2009). It is easy to imagine students who have higher levels of intelligence to be more likely to be motivated and to use efficient strategies that result in their higher academic achievement. Therefore, it is important to include intelligence as a predictor to evaluate the predictive utility of motivation and cognitive strategies independently of basic cognitive abilities.

It should also be noted that the utility of intelligence to predict growth of achievement is by itself of theoretical importance. Although researchers agree that intelligence is a strong predictor of students' *level* of academic achievement, they have not reached consensus about its utility in predicting *growth* of achievement over time (Lohman, Ackerman, Kyllonen, & Roberts, 1999). Studies indicated that intelligence scores did not (or only weakly) predict growth curves in performance attainment (e.g., Gutman, Sameroff, & Cole, 2003; Underwood, Boruch, & Malmi, 1978; Woodrow, 1946). These findings suggest that, unlike motivation and cognitive strategies, intelligence may not reflect the capacity to learn new knowledge and skills. Importantly, however, the majority of these studies focused on short-term learning (sometimes learning within one experimental session). Studies investigating the relations of intelligence with the long-term growth of academic achievement are still rare.

Second, much of the previous literature using latent growth curve modeling failed to establish a common metric for assessments of achievement over time. For analyzing growth in academic achievement, if one simply uses achievement test scores or teacher-provided grades, it is not possible to adequately study growth because these scores are likely not comparable across years. To establish a common metric, item response theory (IRT) can be employed, and anchor items can be included across adjacent time points to allow for vertical scaling (McDonald, 1999). Although IRT scaling is generally acknowledged today as an appropriate way to examine academic achievement over time, there still are many studies that have not used this methodology, casting doubt on the validity of their findings on growth (e.g., Gutman et al., 2003; Hart, Hofmann, Edelstein, & Keller, 1997; Johnson, McGue, & Iacono, 2006).

Third, previous studies included relatively small numbers of variables, focusing on either motivational or strategy constructs (e.g., McClelland et al., 2006; Shim, Ryan, & Anderson, 2008). However, given that motivational and strategy variables often show substantial correlations, it is important to include multiple variables from both groups of constructs to examine their unique contributions.

Finally, previous studies failed to consider the possibility that the utility of motivational and strategy variables for predicting academic achievement may change depending on students' developmental stage. Many studies have documented developmental trajectories of motivation and strategies over time (e.g., Fredricks & Eccles, 2002; Frenzel, Goetz, Pekrun, & Watt, 2010; Jacobs, Lanza, Osgood, Eccles, & Wigfield, 2002). It is possible, then, that not only the developmental trajectories but also the *functions* of motivation and learning strategies in shaping students' achievement during early adolescence can change over time. However, few studies have examined developmental change in the functions of these variables.

Overview of the Present Research and Hypotheses

The current study aimed to broaden the extant knowledge about how motivation and cognitive strategies relate to growth in academic achievement, using German longitudinal mathematics achievement data from six annual waves (Grades 5 through 10). We controlled for intelligence to evaluate the contributions of motivation and strategy variables, and utilized IRT to scale academic achievement over time. We included all of the motivation variables (perceived control, intrinsic motivation, and extrinsic motivation) and learning strategy variables (deep and surface strategies) together to investigate their unique contributions. In addition, we compared the predictive power of motivation and strategies at two different time points (Grades 5 and 7) to examine possible functional change in these variables. Grades 5 and 7 were chosen because they represent critical periods in the educational careers of the German students who participated in the study. Specifically, these students attended public schools in the German state of Bavaria that use ability tracking starting in Grade 5. Students are assigned to low-ability schools (*Hauptschule*), medium-ability schools (*Realschule*), and high-ability schools (*Gymnasium*). In Grade 7, students' assignments to low- versus medium-ability schools were reconsidered; thus, part of the student sample were reassigned to a different track. As such, for students in this study, Grades 5 and 7 represented critical career and academic transitions. Furthermore, students in Grades 5 and 7 are in their early adolescence, a period characterized by a great deal of intellectual, social, physical, and emotional change (Lerner, 1993), which may imply that the functions of academic motivation and strategies also undergo change.

Succinctly stated, the study tested the following hypotheses:

Hypothesis 1: Perceived control is a positive predictor of the initial level as well as the growth rate of achievement.

Hypothesis 2: Extrinsic motivation is a positive predictor of the initial level of achievement, whereas intrinsic motivation is a positive predictor of both the initial level and the growth rate of achievement.

Hypothesis 3: Surface learning strategies are a positive predictor of the initial level of achievement, whereas deep learning strategies are a positive predictor of both the initial level and the growth rate of achievement.

Hypothesis 4: Intelligence is a positive predictor of the initial level of achievement, but has no relation with growth rate.

Hypotheses 1–3 were tested while controlling for students' intelligence. Furthermore, although we did not have a specific hypothesis, we expected that the predictive power of motivation and strategies may change from Grade 5 to Grade 7.

Method

Participants and Design

The sample consisted of German students who participated in the Project for the Analysis of Learning and Achievement in Mathematics (PALMA; see Frenzel et al., 2010; Frenzel, Pekrun, Dicke, & Goetz, in press; Pekrun et al., 2007). This project included a longitudinal study involving annual assessments during the secondary school years (Grades 5–10) to investigate the development of mathematics achievement. At each grade level, the PALMA math achievement test was administered toward the end of the school year. Students' intelligence and the self-reported motivational and strategy variables used in the current study were assessed toward the end of the school year in Grades 5 and 7.

Samples were drawn from secondary schools in the state of Bavaria, and were drawn so that they were sufficiently representative of the student population of Bavaria (Pekrun et al., 2007). The samples included students from all three school types within the Bavarian public school system as described earlier, including lower-track schools (*Hauptschule*), intermediate-track schools (*Realschule*), and higher-track schools (*Gymnasium*). These three school types differ in academic demands and students' entry-level academic ability. German students typically enter one of these schools in Grade 5 (i.e., the 1st year of the assessment), based largely on their prior academic achievement.

At the first assessment (Grade 5), the sample comprised 2,070 students from 42 schools (49.6% female, M_{age} = 11.7 years; 37.2% lower-track school students, 27.1% intermediate-track school students, and 35.7% higher-track school students). In each subsequent year, the study tracked the students who had participated in the previous assessment(s) and also included those students who had not yet participated in the study, but had become students of PALMA classrooms at the time of the assessment (see Pekrun et al., 2007). Overall, the study sample consisted of 3,530 students (49.7% female) who participated in at least one assessment (see Supporting Information Appendix S1 available online for further details).

Measures

Socioeconomic Status (SES)

Family SES was assessed by parent report using the EGP classification (Erikson, Goldthorpe, & Portocarero, 1979) which consists of six ordered categories of parental occupational status. In the current analysis, the scores are coded so that higher values represent higher family SES.

Mathematics Achievement

Mathematics achievement was assessed by the PALMA Mathematics Achievement Test (vom Hofe, Kleine, Pekrun, & Blum, 2005; vom Hofe, Pekrun, Kleine, & Götz, 2002). Using both multiple-choice and open-ended items, this test measures students' modeling competencies and algorithmic competencies in arithmetics, algebra, and geometry. It also comprises subscales pertaining to more specific contents (e.g., fractions, ratios, or functions).

The test was constructed using multimatrix sampling with a balanced incomplete block design (for details, see vom Hofe et al., 2002). Specifically, for each measurement point, two different test versions were prepared that consisted of approximately 60–90 items each, and students completed one of these two test booklets. Anchor items were included to allow for the linkage of the two different test forms as well as the six different measurement points. The obtained achievement scores were scaled using one-parameter logistic item-response theory (Rasch scaling; Wu, Adams, Wilson, & Haldane, 2007), with $M = 100$ and $SD = 15$ at Grade 5 (i.e., the first measurement point). Additional analyses confirmed the unidimensionality and longitudinal invariance of the test scales (see Supporting Information Appendix S1 available online).

Motivation and Learning Strategies

Motivation and learning strategies were assessed by self-report scales developed for PALMA. All scales pertained to the domain of mathematics, and reliability and validity of all the scales were ascertained in two large-sample pilot studies (*N*s = 784 and 1,613; Pekrun et al., 2007). Coefficient Omega was used to estimate the reliability of the scale scores (see Table 1). Omega provides more fine-tuned estimates of scale reliability as compared with the commonly used Cronbach's Alpha (McDonald, 1999).

Table 1
Descriptive Statistics and Internal Consistencies of the Predictors

	M	*SD*	Observed range	Coefficient of reliability
Grade 5				
Perceived control	3.87	0.72	1.17–5.00	.75
Intrinsic motivation	3.21	1.18	1.00–5.00	.87
Extrinsic motivation	3.37	0.99	1.00–5.00	.80
Deep learning strategies	2.38	0.78	1.00–4.00	.67
Surface learning strategies	2.49	0.75	1.00–4.00	.64
Intelligence	104.75	13.41	61–132	—
Grade 7				
Perceived control	3.43	0.83	1.00–5.00	.81
Intrinsic motivation	2.57	1.07	1.00–5.00	.84
Extrinsic motivation	2.87	0.97	1.00–5.00	.78
Deep learning strategies	2.03	0.70	1.00–4.00	.64
Surface learning strategies	2.26	0.73	1.00–4.00	.65
Intelligence	99.61	14.56	55–145	—

Perceived control. Pekrun et al.'s (2007) Perceived Academic Control scale was used to assess students' perceived control in mathematics (six items; e.g., "When doing math, the harder I try, the better I perform"). Participants responded on a 1 (*strongly disagree*) to 5 (*strongly agree*) scale.

Intrinsic motivation. Three items from Pekrun's (1993) Intrinsic Academic Motivation scale were used to assess students' intrinsic motivation in mathematics (e.g., "I invest a lot of effort in math, because I am interested in the subject"). Participants responded on a 1 (*strongly disagree*) to 5 (*strongly agree*) scale.

Extrinsic motivation. Four items from Pekrun's (1993) Extrinsic Academic Motivation scale were used to assess students' extrinsic motivation in mathematics (sample item: "In math I work hard, because I want to get good grades"). Participants responded on a 1 (*strongly disagree*) to 5 (*strongly agree*) scale.

Deep learning strategies. The PALMA elaboration strategies scale (Pekrun et al., 2007) was used to assess students' deep learning strategies (three items; e.g., "When I study for exams, I try to make connections with other areas of math"). Participants responded on a 1 (*strongly disagree*) to 4 (*strongly agree*) scale.

Surface learning strategies. The PALMA rehearsal strategies scale (Pekrun et al., 2007) was used to assess students' surface learning strategies (three items; sample item: "For some math problems I memorize the steps to the correct solution"). Participants responded on a 1 (*strongly disagree*) to 4 (*strongly agree*) scale.

Intelligence. Intelligence was measured using the 25-item nonverbal reasoning subtest of the German adaptation of Thorndike's Cognitive Abilities Test (Kognitiver Fähigkeitstest [KFT 4–12 + R]; Heller & Perleth, 2000).

Strategy of Data Analysis

Growth curve models can be fit in both structural equation modeling (SEM) and multilevel modeling frameworks. We decided to use the SEM framework because it allows us to assess the overall fit between the empirical data and the growth curve models we specified. Specifically, we evaluated the comparative fit index (CFI), the Tucker–Lewis index (TLI), the root mean square error of approximation (RMSEA), and the standardized root mean square residual (SRMR). It should be noted that nearly all current SEM packages compute CFI and TLI based on an inappropriate baseline model when evaluating the fit of latent growth curve models (Wu, West & Taylor, 2009). In our analysis of latent growth curve models, we corrected the CFI and TLI by specifying the appropriate baseline model (see Wu et al., 2009). Following conventions, we regarded values higher than .90 for CFI and TLI, lower than .08 for the RMSEA, and lower than .10 for the SRMR as indicating an acceptable fit.

Prior to the analyses, all the predictors except for demographic variables were standardized with zero mean and unit variance, and SES was mean centered to facilitate the interpretation of the results. Based on Muthén and Muthén (2004), we adjusted the standard errors and chi-square statistics to correct for potential statistical biases resulting from non-normality of the data. Due to the longitudinal design of the study, there is a certain proportion of missing data. Accordingly, to make full use of the data from students who only partially participated in the investigation, we applied the full information maximum likelihood method to deal with missing data (Enders, 2006). Additional analyses that addressed issues of measurement error and the nested structure of the data (i.e., individuals nested within schools) are reported in Supporting Information Appendix S1 available online.

Results

Longitudinal Analysis of Measurement Invariance for Motivation and Strategies

The descriptive statistics of the predictor variables for Grades 5 and 7 are provided in Table 1. Because we wanted to compare the predictive utility of motivational and strategy variables across two different time points (i.e., Grades 5 and 7), we used confirmatory factor analysis to assess measurement equivalence across these time points. Specifically, we evaluated the full scalar and error variance invariance model (see Steenkamp & Baumgartner, 1998), in which the item intercept, factor loadings, factor variances and covariances, and error variances were set to be equal across the time points. Support for this model would provide strong evidence for longitudinal invariance of the measures. All of the motivation and learning strategy variables were analyzed together. The residuals associated with indicators of the same items in Grades 5 and 7 were allowed to correlate. The results supported the longitudinal invariance of the scales, with good fit to the data, $\chi^2(663) = 2{,}548.98$, $p < .01$, CFI = .92, TLI = .92, RMSEA = .031, SRMR = .060. These findings suggest that it is legitimate to compare the predictive utility of the motivational and strategy variables across time points.

The disattenuated correlations of the latent factors for the same constructs over time were .37 to .47 (ps < .01). The size of these coefficients indicates that the motivational and strategy variables were to some extent stable across the 2 years but also showed change, suggesting that it is possible that their functional roles for predicting academic achievement also changed over time. Comparison of factor means indicated a decline in all of the motivation and strategy variables from Grades 5 to 7 (ps < .01), which is largely consistent with previous findings (e.g., Jacobs et al., 2002; Otis, Grouzet & Pelletier, 2005).

Latent Growth Curve Modeling

In the latent growth curve analysis, we first constructed a growth curve model without motivational and strategy variables to specify the basic functional form of growth in mathematical achievement. In this model, math achievement scores across six different time points (Grades 5–10) are modeled by a set of common factors representing the functional form of growth. Our initial exploration of the data indicated that a linear growth model (a model including an intercept and a linear slope) did not fit the data well, suggesting that the growth curve includes nonlinear change. Accordingly, we decided to use an exponential growth curve model (Grimm, Ram, & Hamagami, 2011; for details about model selection, see Supporting Information Appendix S1 available online).

Exponential growth curve modeling has several advantages over the commonly used quadratic growth curve model. Notably, exponential growth models provide interpretable parameters describing growth, such as the total amount of change over time. This point is of particular importance for our study, as we are interested in the factors that influence the overall amount of growth over years. The model is represented by the following equation.

$$y_t = \eta_0 + \eta_1[1 - \exp(-\alpha \cdot x_t)] + \varepsilon_t; \quad t = 5, 6, 7, 8, 9, 10 \tag{1}$$

where y_t is the math achievement score at grade t, and η_0 and η_1 are the latent variables representing the intercept and total amount of (asymptotic) growth. α is a free parameter representing the rate of growth. ε_t is the error term for grade t, and we constrained the variances of this term to be equal across the time points [i.e., $\mathrm{var}(\varepsilon_5) = \mathrm{var}(\varepsilon_6) = \mathrm{var}(\varepsilon_7) = \mathrm{var}(\varepsilon_8) = \mathrm{var}(\varepsilon_9) = \mathrm{var}(\varepsilon_{10})$; Hertzog, von Oertzen, Ghisletta, & Lindenberger, 2008]. x_t represents the fixed time coding at grade t anchored at the initial time point [i.e., $x_5 = 0$, $x_6 = 1$, $x_7 = 2$, $x_8 = 3$, $x_9 = 4$, $x_{10} = 5$]. By this particular coding of time point, we can interpret η_0 as the predicted math achievement score at the initial time point, and η_1 as the asymptotic total amount of growth from the initial time point.

To control for participants' demographic background, variables representing gender, school type, and SES were included in the model. Gender was treated as a dummy-coded variable (GENDER; 0 = female, 1 = male), and school type was represented by two orthogonal contrast variables. The first school-type variable represents the difference between higher-track schools and the pooled intermediate- and lower-track schools (SCTYPE_1; higher-track school = 2, intermediate-track school = −1, lower-track school = −1). The second variable represents the difference between intermediate-track schools and lower-track schools (SCTYPE_2; higher-track school = 0, intermediate-track school = 1, lower-track school = −1). The following equations show the mathematical representation of this part of the model.

$$\eta_0 = \mu_{\eta 0} + \gamma_{01}\mathrm{GENDER} + \gamma_{02}\mathrm{SCTYPE}_1 + \gamma_{03}\mathrm{SCTYPE}_2 + \gamma_{04}\mathrm{SES} + \zeta_0 \tag{2}$$

$$\eta_1 = \mu_{\eta 1} + \gamma_{11}\mathrm{GENDER} + \gamma_{12}\mathrm{SCTYPE}_1 + \gamma_{13}\mathrm{SCTYPE}_2 + \gamma_{14}\mathrm{SES} + \zeta_1 \tag{3}$$

where γ represents the path coefficients of the corresponding variable. ζ is the error (or disturbance) term for each growth component.

The model showed an acceptable fit to the data, $\chi^2(36) = 757.48$, $p < .01$, CFI = .96, TLI = .94, RMSEA = .075, SRMR = .090. The results (see Table 2) revealed that the mean total amount of growth was significantly positive ($\mu_{\eta 1} = 144.17$, $p < .01$) with a positive growth rate ($\alpha = .06$, $p < .01$). In addition, most of the path coefficients for gender, school type, and SES variables were significant, suggesting variability in growth trajectories across demographic background variables. Figure 1 displays the estimated growth curves for male and female students from different types of schools.

An interesting observation in Figure 1 is that the difference between school tracks became larger with increasing grade level, as indicated by the significantly positive relation of school type with total amount of change ($\gamma_{12} = 12.74$, $p < .01$; $\gamma_{13} = 9.27$, $p < .01$). This finding suggests that the tracking system used in Germany may be a source of a "Matthew effect" in math achievement—a phenomenon where the gap between high-achieving and low-achieving students increases with time (Bast & Reitsma, 1997; Baumert, Nagy, & Lehmann, 2012). To quantitatively evaluate the link between tracking and the Matthew effect, we

Table 2
Parameter Estimates for the Growth Curve Model Including Gender and School Type

	Estimate	*SE*
Intercept		
Mean ($\mu_{\eta 0}$)	99.28**	0.31
Gender (γ_{01})	3.24**	0.45
School type 1 (high vs. mid or low track; γ_{02})	4.51**	0.17
School type 2 (mid vs. low track; γ_{03})	6.24**	0.27
Family socioeconomic status (γ_{03})	0.66**	0.13
Total amount of growth		
Mean ($\mu_{\eta 1}$)	144.17**	18.1
Gender (γ_{11})	−1.08	2.37
School type 1 (high vs. mid or low track; γ_{12})	9.27**	1.29
School type 2 (mid vs. low track; γ_{13})	12.74**	2.02
Family socioeconomic status (γ_{13})	0.85	0.67

**$p < .01$.

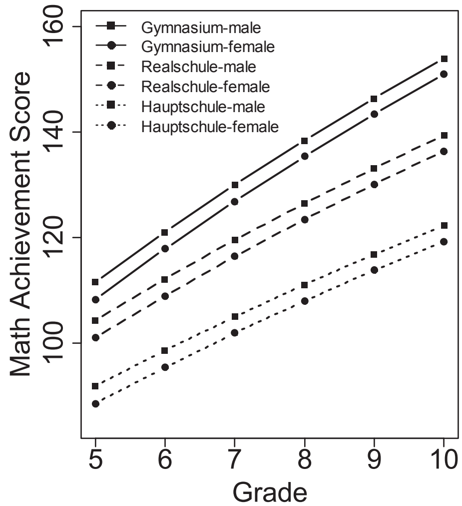

Figure 1. Estimated growth curve of math achievement from Grades 5 to 10 as a function of gender and school type.
Note. Gymnasium = higher-track school; Realschule = intermediate-track school; Hauptschule = lower-track school.

computed the correlation between the intercept (η_0) and the total amount of change (η_1) before and after including the school-type variables. When the school-type variables were not included, this correlation was positive ($r = .29$, $p < .01$), indicating the presence of a Matthew effect. Controlling for these variables dramatically decreased the correlation ($r = .01$, $p = .79$), suggesting that the Matthew effect observed in the data is linked to tracking as used in the German secondary school system.

Predictive Relations of Motivation and Strategies Assessed at Grade 5

To examine the relations of Grade 5 motivational and strategy variables with the growth curve of achievement, we included these variables as predictors of the growth components. We also included intelligence as a predictor to control for students' basic cognitive abilities and to investigate the predictive utility of intelligence for the growth components. Specifically, Equations 2 and 3 were expanded to take the following form:

$$\begin{aligned}\eta_0 =&\mu_{\eta 0} + \gamma_{01}\mathrm{GENDER} + \gamma_{02}\mathrm{SCTYPE}_1\\&+ \gamma_{03}\mathrm{SCTYPE}_2 + \gamma_{04}\mathrm{SES} + \gamma_{05}\mathrm{CONT}\\&+ \gamma_{06}\mathrm{INT} + \gamma_{07}\mathrm{EXT} + \gamma_{08}\mathrm{DEEP} + \gamma_{09}\mathrm{SURFACE}\\&+ \gamma_{10}\mathrm{IQ} + \zeta_0\end{aligned} \tag{4}$$

$$\begin{aligned}\eta_1 =&\mu_{\eta 1} + \gamma_{11}\mathrm{GENDER} + \gamma_{12}\mathrm{SCTYPE}_1\\&+ \gamma_{13}\mathrm{SCTYPE}_2 + \gamma_{14}\mathrm{SES} + \gamma_{15}\mathrm{CONT}\\&+ \gamma_{16}\mathrm{INT} + \gamma_{17}\mathrm{EXT} + \gamma_{18}\mathrm{DEEP}\\&+ \gamma_{19}\mathrm{SURFACE} + \gamma_{20}\mathrm{IQ} + \zeta_1\end{aligned} \tag{5}$$

where CONT, INT, EXT, DEEP, SURFACE, and IQ represent the variables of perceived control, intrinsic motivation, extrinsic motivation, deep learning strategies, surface learning strategies, and intelligence assessed at Grade 5.

The model showed an acceptable fit to the data, $\chi^2(60) = 843.00$, $p < .01$, CFI = .97, TLI = .93, RMSEA = .061, SRMR = .059. The parameter estimates of the model are presented in Table 3. Not surprisingly, intelligence had a strong positive relation with the intercept ($\gamma_{10} = 4.72$, $p < .01$). In addition, however, most of the motivational and

Table 3
Parameter Estimates for the Growth Curve Model Including Motivational and Strategy Variables Assessed at Grade 5

	Estimate	*SE*
Intercept		
Mean ($\mu_{\eta 0}$)	99.68**	0.30
Gender (γ_{01})	2.42**	0.42
School type 1 (high vs. mid or low track; γ_{02})	3.36**	0.17
School type 2 (mid vs. low track; γ_{03})	4.67**	0.27
Family socioeconomic status (γ_{04})	0.45**	0.12
Perceived control (γ_{05})	2.21**	0.27
Intrinsic motivation (γ_{06})	1.53**	0.29
Extrinsic motivation (γ_{07})	0.74**	0.28
Deep learning strategies (γ_{08})	−0.41	0.31
Surface learning strategies (γ_{09})	−1.60**	0.27
Intelligence (γ_{10})	4.72**	0.27
Total amount of change		
Mean ($\mu_{\eta 1}$)	142.34**	17.6
Gender (γ_{11})	−1.22	2.49
School type 1 (high vs. mid or low track; γ_{12})	8.15**	1.26
School type 2 (mid vs. low track; γ_{13})	11.69**	2.00
Family socioeconomic status (γ_{14})	0.66	0.66
Perceived control (γ_{15})	3.78*	1.72
Intrinsic motivation (γ_{16})	1.04	1.84
Extrinsic motivation (γ_{17})	1.56	1.72
Deep learning strategies (γ_{18})	−2.52	1.88
Surface learning strategies (γ_{19})	−5.99**	1.71
Intelligence (γ_{20})	0.24	1.61

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

strategy factors yielded significant incremental relations with the initial achievement score, over and above intelligence. Specifically, perceived control, intrinsic motivation, and extrinsic motivation were significant predictors of the intercept factor (γ_{05} = 2.21, γ_{06} = 1.53, and γ_{07} = 0.74, *p*s < .01), whereas surface learning strategies were a negative predictor (γ_{09} = −1.60, p < .01). Deep learning strategies did not show any significant relation (p = .18).

Intriguingly, in contrast to the relations with the intercept factor, intelligence did not predict the total amount of growth of math achievement over time (γ_{20} = 0.24, p = .88). However, two of the motivational and strategy variables turned out to be significant predictors of growth of math achievement over time. Specifically, perceived control was a significantly positive predictor of the slope factor (γ_{15} = 3.78, p < .05), whereas surface learning strategies were a significantly negative predictor (γ_{19} = −5.99, p < .01). This result underscores the unique importance of motivational and strategy variables in affecting not only current achievement but also the long-term growth of achievement.

To facilitate the interpretation of the findings on growth, we estimated the growth curves of students with scores of 1.5 *SD* above the mean for perceived control and 1.5 *SD* below the mean for surface learning strategies ("high-growth students"), and students with scores of 1.5 *SD* below the mean for perceived control and 1.5 *SD* above the mean for surface learning strategies ("low-growth students"). To avoid redundancy, Figure 2 presents the estimated growth curves only for male higher-track (Gymnasium) students. The shape of the growth curves for females and for intermediate- or lower-track students was basically the same. Figure 2 visually confirms that the slope is steeper for high-growth than for low-growth students.

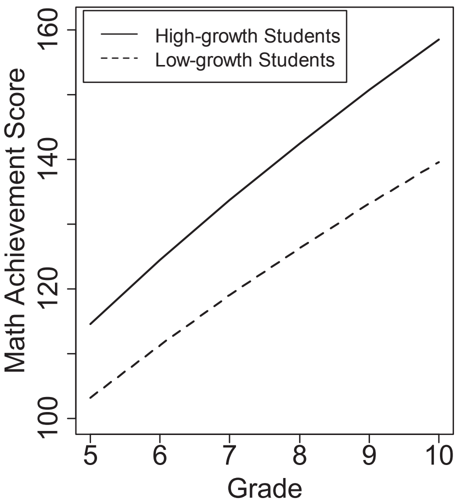

Figure 2. Estimated math achievement growth curve from 5th to 10th grades for high-growth and low-growth students.
Note. To avoid redundancy, only male Gymnasium students are plotted. High-growth students = 1.5 *SD* above the mean for perceived control and 1.5 *SD* below the mean for surface learning strategies. Low-growth students = 1.5 *SD* below the mean for perceived control and 1.5 *SD* above the mean for surface learning strategies.

Predictive Relations of Motivation and Strategies Assessed at Grade 7

The previous analysis partially supported our hypotheses in that (a) intelligence had strong positive relations with initial level of math achievement but showed null relations with growth rate and (b) perceived control had positive relations not only with initial level but also with the growth rate. To further explore our hypotheses, we next focused on students' growth in math achievement from Grades 7–10. Specifically, we investigated whether the growth curve estimated in the Grades 7–10 data can be predicted by motivation and learning strategies assessed at the Grade 7. The model was the same as in the previous analysis, Equations 1, 4, and 5, with the following exceptions. First, Equations 4 and 5 included the motivational and strategy variables and intelligence assessed at Grade 7 instead of Grade 5, as our focus was to examine the predictive utility of the variables assessed at Grade 7. Participants' school type was also coded based on the information at Grade 7. Second, we used the math achievement scores assessed across Grades 7–10, that is, t = 7, 8, 9, 10 in Equation 1 and $x_7 = 0$, $x_8 = 1$, $x_9 = 2$, $x_{10} = 3$. Third, we fixed the growth rate parameter to the value obtained in the previous analysis (i.e., α = .06) to make the Grade 5 and Grade 7 analyses comparable. This constraint improved model fit in terms of the Akaike information criterion and the Bayesian information criterion, and did not significantly increase the chi-square fit statistics, $\Delta\chi^2(1)$ = 1.09, p = .30.

The model showed an acceptable fit to the data, $\chi^2(28)$ = 477.79, p < .01, CFI = .97, TLI = .91, RMSEA = .073, SRMR = .060. The parameter estimates of the model are presented in Table 4. For the prediction of the intercept, the pattern of results was almost the same as in the Grade 5 analysis; in addition to the strong positive explanatory power of intelligence (γ_{10} = 6.10, p < .01), perceived control and extrinsic motivation were significantly positive predictors of the initial level of math achievement (γ_{05} = 3.35, p < .01; γ_{07} = 1.18, p < .01), whereas surface learning strategies were a significantly negative predictor

(γ_{09} = −1.49, $p < .01$). These results again corroborate the importance of motivational and strategy factors in accounting for current math achievement over and above intelligence. On the other hand, intrinsic motivation and deep learning strategies were not significant predictors of the intercept factor.

Intriguingly, for the prediction of total amount of growth, the Grade 7 analysis showed a pattern of results that differed substantially from the Grade 5 findings. Specifically, whereas perceived control, extrinsic motivation, and surface learning strategies did not predict growth of math achievement, intrinsic motivation and deep learning strategies were significantly positive predictors of the total amount of growth (γ_{16} = 4.51, $p < .05$; γ_{18} = 4.64, $p < .05$). Again, intelligence had null relations with the amount of growth (γ_{20} = 0.37, p = .87).

As in the Grade 5 analysis, these findings indicate that motivational and strategy variables uniquely contribute to growth of math achievement. Furthermore, these findings also indicate that there is developmental change in the predictive power of these variables. As assessed at Grade 7, intrinsic motivation and deep learning strategies did not have any significant relations with the intercept factor but related to subsequent growth, suggesting that they may not have immediate utility but may provide long-term benefits in facilitating math achievement at this age. As an illustration for the nature of this finding, Figure 3 displays the estimated growth curves of male higher-track (Gymnasium) students with scores 1.5 *SD* above the mean for intrinsic motivation and deep learning strategies ("high-growth students") and students with scores 1.5 *SD* below the mean for these variables ("low-growth students"). The shape of the growth curves for females and for intermediate- or lower-track students was basically the same. Figure 3 visually confirms that high-growth and low-growth students did not differ in terms of the initial status at Grade 7, but developed differently across the subsequent grade levels.

Table 4
Parameter Estimates for the Growth Curve Model Including Motivational and Strategy Variables Assessed at Grade 7

	Estimates	*SE*
Intercept		
Mean ($\mu_{\eta 0}$)	114.57**	0.28
Gender (γ_{01})	1.85**	0.43
School type 1 (high vs. mid or low track; γ_{02})	4.47**	0.17
School type 2 (mid vs. low track; γ_{03})	6.88**	0.28
Family socioeconomic status (γ_{04})	0.33**	0.12
Perceived control (γ_{05})	3.35**	0.27
Intrinsic motivation (γ_{06})	0.37	0.29
Extrinsic motivation (γ_{07})	1.18**	0.28
Deep learning strategies (γ_{08})	−0.49	0.28
Surface learning strategies (γ_{09})	−1.49**	0.25
Intelligence (γ_{10})	6.10**	0.27
Total amount of change		
Mean ($\mu_{\eta 1}$)	134.39**	2.41
Gender (γ_{11})	6.41	3.40
School type 1 (high vs. mid or low track; γ_{12})	3.80**	1.42
School type 2 (mid vs. low track; γ_{13})	6.23*	2.76
Family socioeconomic status (γ_{14})	1.69	0.96
Perceived control (γ_{15})	−2.76	2.18
Intrinsic motivation (γ_{16})	4.51*	2.25
Extrinsic motivation (γ_{17})	−0.55	2.10
Deep learning strategies (γ_{18})	4.64*	2.23
Surface learning strategies (γ_{19})	−0.81	2.02
Intelligence (γ_{20})	0.37	2.28

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

Discussion

This research examined the predictive power of motivation, cognitive strategies, and intelligence for explaining the long-term growth of adolescents'

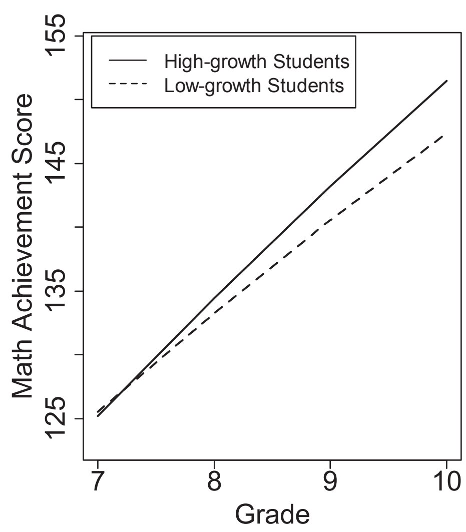

Figure 3. Estimated math achievement growth curve from 7th to 10th grades for high-growth and low-growth students.
Note. To avoid redundancy, only male Gymnasium students are plotted. High-growth students = 1.5 *SD* above the mean for intrinsic motivation and deep learning strategies. Low-growth students = 1.5 *SD* below the mean for intrinsic motivation and deep learning strategies.

achievement in mathematics from Grades 5 to 10. The results showed that motivation and strategies predicted current math achievement over and above intelligence. Furthermore, our findings revealed that motivation and strategies also explained the growth of achievement. Growth was positively predicted by perceived control, intrinsic motivation, and deep learning strategies, and it was negatively predicted by surface learning strategies. In contrast, intelligence turned out not to be a predictor of growth (after controlling for demographic variables), despite being a strong predictor of current math achievement. Overall, these findings largely support our hypotheses.

Relations of Motivation and Strategies With Initial Level and Growth of Achievement

Among the motivational factors, both perceived control and intrinsic motivation predicted long-term growth in math achievement. Specifically, perceived control (assessed at Grade 5) and intrinsic motivation (assessed at Grade 7) positively predicted the total amount of growth in math achievement. This lends support to the notion that these constructs do not merely reflect subjective perceptions of current ability (perceived control) or transient, ephemeral positive emotion (intrinsic motivation), but motivational tendencies that shape future learning and resulting achievement (Deci & Ryan, 1985; Marsh & Craven, 2006). In contrast, extrinsic motivation predicted only initial levels but not growth in achievement, illustrating an interesting contrast with the relations observed for intrinsic motivation. The short-lived nature of extrinsic motivation and long-term benefit of intrinsic motivation are in accordance with previous experimental findings (Murayama & Elliot, 2011; Vansteenkiste et al., 2005), and our results provide the first evidence that this pattern is evident even over long periods of time.

With regard to learning strategies, both deep strategies and surface strategies were related to long-term growth in math achievement, but their relations had opposite signs (deep learning strategies were positively linked, whereas surface learning strategies were negatively linked to growth). Furthermore, surface learning strategies were also negatively linked to initial level of achievement. Although we had not expected that surface learning strategies would lead to lower initial levels and smaller growth rates of math achievement, it is plausible that relying on surface, rehearsal-based strategies can interfere with the use of more efficient strategies and thus be deleterious for achievement outcomes. It should be noted, however, that the present findings do not indicate that surface learning strategies are maladaptive in any situations, as the effectiveness of learning strategies may largely depend on learning materials and phases of learning (Alexander & Murphy, 1998). Surface learning strategies may be useful for some tasks (e.g., skill tasks) or at initial stages of learning.

A seemingly counterintuitive finding is that intrinsic motivation (assessed at Grade 7) and deep learning strategies (assessed at Grades 5 and 7) were unrelated to concurrent achievement. Although unexpected, this is actually consistent with the extant literature suggesting that the relation between these constructs and performance is unclear (Meece et al., 1988; Murphy & Alexander, 2002; Utman, 1997). Students with high intrinsic motivation are less concerned about how well they perform on upcoming achievement tests. Accordingly, although intrinsic motivation should provide long-term benefits, such a noninstrumental approach to learning may not add much to current performance. As for deep, elaborative learning strategies, previous studies indicated that elaborative learning may not be an efficient means of dealing with an upcoming achievement test because semantic elaboration is a relatively slow learning process and therefore costly if time is limited (Garner, 1990). Given the somewhat counterintuitive nature of this phenomenon, further research is needed to replicate the present findings and to examine possible conditions under which these constructs are positively related to (concurrent) achievement scores.

Developmental Differences in the Functions of Motivation and Strategies

It is noteworthy that the motivational and strategy variables predicted growth at different developmental stages. For motivational factors, the relation between perceived control and growth in math achievement was observed when perceived control was assessed at Grade 5, whereas differential relations for intrinsic versus extrinsic motivation emerged only when motivation was assessed at Grade 7.

One possible explanation is that our findings reflect developmental differences in students' understanding of different dimensions of motivation. Perceived control (i.e., cognitive representations of action–outcome contingencies) seems to be a straightforward notion that may require little cognitive capacity to understand. Thus, it is likely that students develop individual appraisals of personal control over achievement and that these appraisals influence their academic achievement from early on (e.g., in the first grades of elementary school). In contrast, understanding the intrinsic versus extrinsic reasons underlying one's behavior is quite complicated and may require higher order thinking. As a result, comprehension of the intrinsic–extrinsic distinction to the extent that intrinsic motivation can clearly relate to long-term achievement growth may occur only later (e.g., in early adolescence). In fact, previous findings indicate that children's perceptions of control (expectancy beliefs) differentiate into subject-specific, distinct constructs at a very early stage in elementary school. In contrast, subcomponents of task value (such as intrinsic value vs. utility value) are less differentiated among younger children, but become more distinct during early adolescence (Wigfield & Eccles, 1992).

We also observed that perceived control at Grade 5 predicted growth in math achievement, whereas perceived control at Grade 7 failed to do so. One possible explanation is that, as mathematics content becomes more difficult, students' judgments of personal control over achievement are anchored more to concrete experiences with current math problems rather than to judgments of personal math ability and possible future trajectories of developing math competence (see Vallacher & Wegner, 1987), resulting in less predictive power for long-term growth. In accord with this interpretation, contrary to the predictive relations with growth, the link between perceived control and concurrent achievement was stronger at Grade 7 than at Grade 5.

With regard to strategy variables, growth in math achievement was positively predicted by deep learning strategies at Grade 7, but not yet at Grade 5. Previous developmental studies on strategy use have shown that students exhibit an increasing readiness across adolescence to deploy strategies that are elaborative and generative (Christopoulos, Rohwer, & Thomas, 1987; Pressley, Borkowski, & Johnson, 1987). In addition, these studies also revealed a "utilization deficiency," a phenomenon whereby children, up until a particular developmental stage, are able to use a learning strategy, but are unable to reap its performance benefits (Bjorklund, Coyle, & Gaultney, 1992; Miller & Seier, 1994). Our findings shed light on these findings, suggesting that an effective use of deep learning strategies may occur only later in students' academic career.

The Role of Intelligence and the Matthew Effect

One of the features of the current investigation is that we controlled for intelligence when examining the predictive relations of motivation and cognitive strategies. This is by itself of considerable importance, as discussed at the outset. In addition, the inclusion of intelligence as a predictor produced interesting findings: Long-term growth in math achievement was predicted by motivational and strategy factors, but not by students' intelligence (after controlling for demographic variables). This stands in marked contrast to the commonly observed finding that intelligence explains a much larger proportion of the variance in current achievement scores, as compared to motivational and strategy variables (e.g., Spinath, Spinath, Harlaar, & Plomin, 2006). We should be aware that this study focused on the development of achievement in one academic domain only. Nonetheless, our findings clearly underscore the importance of paying attention to adolescents' motivation and learning strategies when wanting to understand the development of their academic achievement. Thus, an intriguing message from this study is that the critical determinant of growth in achievement is not how smart you are, but how motivated you are and how you study.

Another interesting finding is the Matthew effect, a phenomenon that over time more able individuals become even better and less able individuals become even worse, thus widening the gap between haves and have-nots. The Matthew effect has been investigated in a number of different domains, such as reading ability (Stanovich, 1986) and job payment (Tang, 1996). The current study observed the Matthew effect in the domain of math achievement during adolescence, and the findings suggest that the effect may have been linked to the German school tracking system. It should be kept in mind, however, that the current analysis provides little information about the background characteristics of students attending schools from different tracks (e.g., in terms of learning environments at home) or the educational quality of these schools that may have produced this Matthew effect. These varied explanations would have different educational implications (see also Baumert et al., 2012). Further research is needed to investigate such mechanisms that widen the gap between students differing in initial achievement.

Limitations and Directions for Future Research

Our findings should be interpreted in the context of several limitations that suggest directions for future research. First, although the IRT scaling has the great advantage of establishing a common metric across different grade levels—an issue that was not addressed in many previous studies—it rests on the critical assumption that all math achievement test items measure a single unidimensional construct. By testing the dimensionality and longitudinal invariance of the PALMA Math Achievement Test, we were able to show that there was no major violation of unidimensionality assumptions in this study (see Supporting Information Appendix S1 available online). However, unidimensionality assumptions cannot be completely met in longitudinal studies of academic achievement, given the need to include items measuring various contents that match the diversity of the curriculum both within and across grade levels. Future research would do well to investigate the impact of such local heterogeneity of items on growth trajectories.

Second, although the present research produced evidence about the predictive power of motivational and strategy variables on growth (after controlling for demographic variables and intelligence), these relations are still correlational in nature. Thus, one should exercise caution when interpreting these links in terms of causality. Although this was not the primary concern of our research, alternative approaches such as a cross-lagged analysis (e.g., Marsh & Craven, 2006) or dual change score analysis (see McArdle & Hamagami, 2001) may be better suited to examine causal ordering and possible reciprocal effects. Previous research has shown that students' academic self-concepts and their achievement can be linked by reciprocal causation (Marsh, 1990). It seems likely that students' intrinsic and extrinsic motivation and surface versus deep strategy use also are reciprocally linked with their academic achievement. Future research should examine the nature of these reciprocal associations.

Conclusion

Numerous studies have been conducted to better understand students' motivation and learning strategies as promoting the academic development of competence and knowledge. Researchers defined motivation as the process whereby goal-directed activity is instigated and sustained (Pintrich & Schunk, 2002). Learning strategies are described as planned sets of coordinated study tactics that are directed by a learning goal and aim to acquire a new skill or gain understanding (Alexander & Murphy, 1998). According to these views, motivation and learning strategies should, by their nature, facilitate long-term learning processes. The present research documents that these variables are indeed important for students' academic growth over the school years.

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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. Additional Analyses.