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Predicting Longitudinal Trajectories of Adolescent Academic Self-Concept: An Application of Growth Mixture Models.

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Abstract

Background

A large body of research indicates that students' academic self-concept is affected by their age, gender and achievement.

Aims

This paper focuses on the development of the academic self-concept during adolescence, with a particular focus on interindividual differences in change trajectories.

Sample

A sample of 1579 Flemish secondary school students was assessed at four moments in time (Grades 7, 8, 10, and 12).

Methods

Data were analysed using latent growth models and growth mixture models.

Results

Students' academic self-concept was found to decline during the period of secondary education. A strong positive relationship between mathematics achievement and academic self-concept was found. Furthermore, girls were shown to have a lower academic self-concept than boys and this gender gap was largest in Grade 10. Growth mixture modelling suggested a two-group model with a normal self-concept development group (about 9 in 10 students) and a problematic self-concept development group (about 1 in 10 students).

Conclusions

The results are discussed in relation to current substantial and methodological issues with respect to predicting self-concept development, modelling interindividual variability, subgroup classification, and the versatility and usefulness of latent growth modelling and growth mixture modelling.

Introduction

Academic Self-concept

The self-concept is the perception that a person holds of himself/herself. It is multidimensional which means that the self-perceptions can vary over different domains like the social, physical or academic domain (Bong & Skaalvik, 2003; Cole et al., 2001; Marsh, 1989; Shavelson, Hubner, & Stanton, 1976; Wigfield, Eccles, Mac Iver, Reuman, & Midgley, 1991; Young & Mroczek, 2003; Zanobini & Usai, 2002). This study focuses on the academic self-concept, the way in which a person judges his/her own competence.

Students' academic self-concept is constructed through evaluations and reinforcements by significant others, and through attributions for one's own behaviour and accomplishments. Research has identified three potentially important predictors for students' academic self-concept: students' age, gender, and the academic success itself (see below).

The Effect of Age, Gender and Achievement

Most studies have documented some degree of individual differences with respect to academic self-concept (Aunola, Leskinen, Onatsu-Arvilommi, & Nurmi, 2002; Young & Mroczek, 2003). Based on this finding, other researchers have begun to examine the variables responsible for these individual differences.

One important factor is age. The studies that looked at the changes in the academic self-concept over a short period (1 year) found that it was stable or increased (Aunola et al., 2002; Young & Mroczek, 2003). The study of Fredericks and Eccles

(2002) covered a broader age range and revealed that self-perceived math competence declined linearly from Grade 1 to Grade 12. According to Marsh (1989), this pattern is not linear but curvilinear. He found a decline during early adolescence, which is followed by a slight increase through late adolescence. Cole et al. (2001) found that the transition from elementary to middle school was marked by a large drop in self-perceived academic competence whereas the transition to high school corresponded with a benefit in self-perceived academic competence. The transition to middle school has been consistently documented to go with a decline in competence beliefs (Anderman & Midgley, 1997; Fredricks & Eccles, 2002; Wigfield & Eccles, 2002; Young & Mroczek, 2003; Zanobini & Usai, 2002). But unlike the results of Cole et al. (2001), Wigfield et al. (1991) reported that the self-concept for math and English continued to decline during Grade 7.

Another factor affecting the academic self-concept is gender. Most studies found that girls are more likely than boys to have a low academic self-concept (Fredricks & Eccles, 2002; Marsh, 1989; Wigfield et al., 1991; Young & Mroczek, 2003). Despite their better achievement in several domains, girls tend to evaluate their accomplishments more negatively than do boys. In the study of Marsh (1989), this gender gap remained relatively stable over time. Fredericks and Eccles (2002) on the other hand found that girls' self-concept for math declined at a slower rate than did boys' which indicates a decreasing gender gap.

A third important factor in explaining the individual differences in academic self-concept is the student's academic achievement. A large body of research supports a relationship between achievement and academic self-concept (Marsh, Hau, & Kong, 2002; Muijs, 1997; Saunders, Davis, Williams, & Williams, 2004). The relationship between these two constructs is thought to be reciprocal. Academic success reinforces self-perceptions of academic capabilities and an individual's belief that he or she is academically capable enhances motivation and subsequent academic success (Marsh et al., 2002; Muijs, 1997). Several longitudinal studies have tried to unravel the causal ordering of academic self-concept and achievement. Muijs (1997) found that academic achievement is a better predictor of academic self-concept than the other way around. Aunola et al. (2002) found that the reading skills predict the subsequent self-concept for reading. But in the analyses of Marsh et al. (2002), the effects of prior self-concept on subsequent achievement were clearly stronger than those of prior achievement on subsequent self-concept. Either way, the academic self-concept is an important variable in educational research as a means to facilitate other desirable outcomes and as a desired outcome in itself. Thus, early intervention and prevention programs are necessary for students with a low academic self-concept also because these students are more likely to experience emotional and psychosocial difficulties or to drop out of school (Anderman & Maehr, 1994; Eccles, Lord & Midgley, 1991).

Classification of Growth Trajectories

The changes in academic self-concept should be investigated by estimating individual change trajectories (Rogosa, 1995; Singer & Willett, 2003). Growth curve analysis makes it possible to estimate both the average change and the individual change patterns. The average change trajectory illustrates the changes in mean levels of an outcome. The individual growth curves can be very different from the average trajectory, which is a mere summary. That is, students may vary in their growth trajectories. The academic self-concept drops more for some people than for others and some adolescents even experience increases in self-concept (Cole et al., 2001). This heterogeneity in academic self-concept trajectories is a major theme in this study.

In order to illustrate interindividual differences in development, some authors have proposed classifications of growth trajectories. Individuals are then classified into homogeneous groups based on the characteristics of their developmental pattern. Two classification methods are often employed: cluster analysis and growth mixture modelling.

In cluster analysis, individuals are grouped together based on their growth parameters (Aunola et al., 2002; Dumenci & Windle, 2001) or their repeated measures (Hirsh & DuBois, 1991; Zimmerman, Copeland, Shope, & Dielman, 1997). Hirsh and DuBois (1991) identified four self-esteem clusters: consistently high, chronically low, steeply declining, and slightly increasing. Zimmerman et al. (1997) also found four clusters: consistently high, consistently low, steadily decreasing, and moderate and rising.

Growth mixture models (GMM) (Muthén, Khoo, Francis, & Boscardin, 2003) assume that the population is composed of subgroups, each defined by a prototypical developmental trajectory. Wiesner and Silbereisen (2003) for example analyzed delinquent behaviour by means of growth mixture models and found four trajectory groups: high-level offenders, medium-level offenders, low-level offenders and rare offenders. Schaeffer, Petras, Ialongo, Poduska and Kellam (2003) identified four distinct trajectories of aggressive behaviour: a chronic high aggression trajectory, a moderate aggression trajectory, an increasing trajectory and a low aggression trajectory.

The Current Study

The main focus of the present investigation is the development of the academic self-concept during adolescence. Following Marsh (1989), we hypothesize that the academic self-concept declines during early adolescence and increases slightly in late adolescence. In addition to that, we predict that there will be individual differences in the trajectories of the academic self-concept. This variance in change patterns is partially explained by the students' achievement and gender. We hypothesize that a student's mathematics achievement is a good predictor of his/her academic self-concept. We further predict that girls have a lower academic self-concept than boys, based on the studies mentioned in the introduction. These studies, however, are not univocal with regard to the size of the gender difference over time. We therefore do not specifically hypothesize that this gender gap will increase, decrease or remain stable during adolescence. Finally, we maintain that the average change trajectory is a mere summary and that modelling individual trajectories is necessary to enhance insight into inter-individual differences. We hypothesize that the students can be grouped based upon the characteristics of their change trajectories. It will be further investigated what these prototypical profiles look like and if there is a gender effect in the shape of the profiles. We hope that this classification enhances the insight into trends in adolescent academic self-concept.

Data

This study examines covariates of distinctive trajectories of academic self-concept, using data from a longitudinal research project in Flanders, the Dutch-speaking part of Belgium (Van Damme, De Fraine, Van Landeghem, Opdenakker, & Onghena, 2002). The student sample was restricted in two ways. First, the sample was restricted to students that remained in the same school during the study because the transition to another school can affect the student's academic self-concept. A change from a low-ability school to high-ability school, for example, has a negative effect on a student's academic self-concept (Marsh, 1991). Second, only students who provided complete data were retained. The resulting sample contains 1579 students (641 boys and 938 girls).

At the end of Grade 7, Grade 8, Grade 10, and Grade 12, the students completed a questionnaire that measured different aspects of their non-cognitive adjustment. The questionnaire contains a nine-items scale measuring the general academic self-concept. The items refer to the perception that a student has of his/her academic competence like "I think I am able to deal with the subject matter" and "I think I am good at learning" (for the other items see Van Damme et al., 2002). The scale ranges from 1 (low academic self-concept) to 5 (high academic self-concept) and has a satisfactory internal consistency (see Table 1). The skewness and kurtosis indicate that the distributions at each of the four occasions do not deviate heavily from a normal distribution, except for a large kurtosis in Grade 12.

- Insert Table 1 -

Two explanatory variables were of interest in this study: gender and mathematics achievement. Gender is a time-invariant covariate that was coded 0 for male and 1 for female. The math test was taken at the same four measurement occasions when the academic self-concept was measured. The repeated measures of mathematics achievement are treated as a time-varying covariate (Curran & Hussong, 2002), which is clear from Figure 1 where the Math score affects the concurrent academic self-concept (ASC).

Method

Latent Growth Model

The academic self-concept is modelled by means of a latent growth model (LGM). This technique draws on the many strengths of the structural equation modelling framework (Curran & Hussong, 2002; Dekovic, Buist, & Reitz, 2004; Windle, 2000). One of the basic ideas is that, although we have a set of observed measures of a theoretical construct (e.g., academic self-concept), we are not inherently interested in these observed measures. Instead, we are interested in the latent factor that is thought to have given rise to the observed measures (Curran & Hussong, 2002). In the LGM, latent factors are estimated that represent fairly smooth trajectories that underlie the set of repeated measures over time. The time variable is defined in the measurement model of the latent factors.

Following Marsh (1989), we assumed that student academic self-concept follows a curvilinear trajectory throughout secondary school. The model thus assumes that each student's true change in academic self-concept over time is adequately represented by three latent factors: an intercept (I), a slope (S), and a quadratic factor (Q). The seventh grade was chosen as the reference point so that the estimations for the intercept refer to the estimated academic self-concept at the start of secondary school.

Growth Mixture Models

Researchers using the latent growth model assume that the data come from a single population and that a single trajectory can adequately approximate the individual growth curves. This assumption can be tested by applying a growth mixture model (GMM). This model allows heterogeneity within the population, where different individuals can belong to distinct subpopulations. The population under investigation is considered to consist of a mixture of distinct subgroups defined by a prototypical mean curve (Muthén et al., 2003). The growth mixture model extends the latent growth model to incorporate a categorical latent variable with *K* classes (Li, Duncan, Duncan, & Acock, 2001). This can be seen in Figure 1, where a latent class factor 'C' has been added to the latent growth model. The latent classes represent multiple populations or subgroups (Muthén, 2001).

- Insert Figure 1 -

GMMs are used in psychological and educational research to capture heterogeneity in developmental pathways. These models have been used to date in studies of alcohol use (Li et al., 2001; Dolan, Schmittmann, Lubke, & Neale, 2005), aggressive behaviour (Schaeffer et al., 2003), juvenile delinquency (Wiesner & Silbereisen, 2003), reading development (Muthén et al., 2003), and mathematics development (Muthén, 2004). These are domains in which changes are likely and where different subpopulations are assumed to exist. The GMM has never been applied in research about the changes in academic self-concept, although this development may be heterogeneous so that different groups follow different patterns.

The number of classes can be determined by comparing the BIC (Bayesian Information Criterion) for several models. The BIC is a measure of model fit that penalizes for complexity. The recommendation is to choose the model with the smallest BIC. Group membership is unobserved and must be inferred from the data. The GMM estimates the posterior probabilities for each individual's class membership. An individual may be classified into the class for which he/she has the highest posterior probability. This way, the GMM provides a way to study early indications of problematic development. It is of interest to be able to identify students that are likely to belong to a certain class.

However, an alternative explanation for multiple latent trajectory classes has been emphasized by Bauer and Curran (2003, 2004). Latent classes may indicate a heterogeneous population, but they can also serve to better approximate a nonnormal but homogeneous distribution of repeated measures. Thus, overinterpretation should be avoided when applying growth mixture models (Cudeck & Henly, 2003).

The analyses in this study were carried out by maximum likelihood estimation using M*plus* version 2.13. Start values were varied to avoid local maxima (Li et al., 2001).

Results

Unconditional Latent Growth Model

The results of the latent growth model (Table 2) confirm that the academic self-concept declines during adolescence. In Grade 7, the average academic self-concept is estimated at 3.742, which is followed by a decline of 0.099 points per grade. However, this decline decelerates over time as indicated by the positive quadratic parameter (0.099).

- insert Table 2 -

The variances of the growth parameters indicate that the development process of the academic self-concept shows considerable heterogeneity. There was a significant variance estimate for both the intercept (0.144) and the linear parameter (0.012). Thus, some students were reporting high levels of academic self-concept in Grade 7, whereas others were reporting low levels. And some children were reporting small decreases in their academic self-concept over time whereas others experienced a steep decrease. There was no significant variance in the quadratic parameter. The negative covariance between the intercept and the linear parameter indicates that students with a high initial academic self-concept tend to experience a steeper decline. Equal residual variances across occasions were assumed.

Because we found significant individual differences, we may now introduce student characteristics to try to capture this variability.

Conditional Latent Growth Model

The results of the conditional latent growth model in Table 3 indicate that gender significantly predicts the growth trajectory of the academic self-concept.

- Insert Table 3 -

Girls have a lower intercept than boys and their academic self-concept shows a stronger linear decline. The decline of the girls decelerates over time, as can be seen in Figure 2. It is also clear from the figure that the gender gap is largest in Grade 10.

- Insert Figure 2 -

There is a positive effect of the mathematics scores on the time-specific measures of academic self-concept above and beyond the effects of the underlying developmental trajectory of academic self-concept (Curran & Hussong, 2002).

Growth Mixture Model: Determining the Number of Latent Classes

Growth mixture models were applied to look for different subgroups in the sample. In all models, gender was used as a predictor of both the growth factors and the latent class (Muthén, 2004). The latent class variable is typically viewed as time-invariant, and is thus not predicted by the mathematics score.

- Insert Table 4 -

The model-fitting strategy recommended by Muthén (2001) was followed. First, several latent class growth mixture analysis models (LCGA) are fitted to the data. In the LCGA, the growth factor covariance matrix is fixed at zero, whereas the GMM allows for within-class variation in individual trajectories (Delucchi, Matzger, & Weisner, 2004; Nagin, 1999). We found that even with six latent classes, the BIC value is smaller than all LCGA models with a smaller number of latent classes (see Table 3). The LGCA-models thus do not provide us with good information on the number of latent classes. The specification that any individual deviations from the class mean trajectories are random error probably is a too strong restriction (Bauer & Curran, 2004). Muthén (2001) advises to plot the estimated curves for the number of classes above the solution in which no important drop in BIC occurs. We therefore plotted the three-class solution and we found that the third group consists of 45 students, following a strange pattern, characterized by a large positive quadratic parameter.

In a second step, growth mixture models were applied with the covariance matrix of the growth factors variant over classes (see Table 4). The model with two latent classes yielded the lowest BIC value and is thus preferable over the models with more latent classes. Further inspection of this model showed that setting the growth factor variances invariant over the two classes yielded a model with an even better BIC value. The BIC thus points at a model with two classes: an average self-concept trajectory group and a low self-concept trajectory group.

Finally, we employed two tests for checking the model fit: the Lo-Mendell-Rubin Likelihood Ratio Test (LMR LRT) and the Skewness Kurtosis Test (Muthén, 2003; 2004). The LMR LRT points to at least two classes with a strong rejection ($p < 0.001$) of the 1-class model. The SK tests reject the one-class model ($p < 0.001$ for both multivariate skewness and kurtosis) but they do not reject the two-class model (p = 0.15 and p = 0.12). The LMR LRT for 2 versus 3 or more classes obtained a high p-value in support of 2 classes. Taken together, the statistical evidence points to a model with two classes.

The Two Class Model

The model with two latent classes is given in Table 5. The shape of the growth curve (quadratic) is the same for the two subpopulations. The variances and the covariances of the growth parameters are the same for the two classes, since that model provided a better fit (see Table 4). The residual variance however, is larger in the low self-concept group than in the normal self-concept group.

- Insert Table 5 -

Even given class membership, the student gender still has a within-class influence on the growth factors. In the normal self-concept trajectory class, the student gender clearly affects the shape of the growth curve. In the low self-concept trajectory class, there is only a statistical significant difference between boys and girls with regard to the linear parameter. The effect of the mathematics scores also differs across the two subpopulations. In the normal academic self-concept class, student with higher mathematics scores tend to have a higher academic self-concept. In the low class, this effect is only present in Grade 7. Class-variation in the influence of covariates on growth factors or outcomes also provides a better understanding of the data. It seems like the students in the low self-concept group experience a problematic development.

All students in this group have a low and declining academic self-concept, which cannot be enhanced by better mathematics scores. Most students in the normal self-concept group also experience a declining self-concept, but their self-concept remains higher than that of the students in the low self-concept group.

The prototypical trajectories for the two classes in Figure 3 should be interpreted as the estimated curves for boys and girls from the two subpopulations, given average math scores at the four measurement occasions. The average growth curve of the boys in both groups has a highly similar shape: a roughly linear decline of 0.210 points (normal group) or 0.250 points (low group) between Grade 7 and Grade 12. The main difference between the boys in both groups is the level of their academic self-concept.

- Insert Figure 3 -

The girls from the low self-concept class have an average trajectory that declines faster compared to the average trajectory of the girls in the normal self-concept class. In the low self-concept class the deceleration is remarkable. The average academic self-concept reaches its lowest level in Grade 11 and subsequently increases. In the normal self-concept class, the average trajectory reaches a minimum halfway through Grade 12, but the increase is hardly noticeable. It seems that especially the girls in the low self-concept group experience a problematic development because of the strong decline between Grade 7 and Grade 11.

For boys, the probability of belonging to the low self-concept class is 0.176. For girls, however, the probability is 0.150. Or, in terms of odds ratios: comparing the low self-concept class to the normal self-concept class, the odds ratio for female versus male is 0.824.

Individual Growth Curves

A useful side-product of the analysis is the estimates of posterior probabilities for each individual's class membership (Muthén et al., 2003). Based on their most likely class membership, 1421 (90%) of the students belong to the normal self-concept group and 158 students (10%) belong to the low self-concept group. Of the boys, 11.5% were classified in the low self-concept group, whereas 9% of the girls was classified into this group.

Given this most likely class membership, an intercept, a slope and a quadratic parameter for each individual can be estimated as factor scores. Figure 4 shows these factor scores. A negative relation between the linear and the quadratic scores is apparent. The growth curve of students experiencing a strong linear decrease is often characterized by a positive quadratic parameter and thus a deceleration.

- Insert Figure 4 -

But the eye-catching finding from these figures is that the group of girls clearly consists out of two distinct subpopulations. For the boys, however, the difference between the normal self-concept group and the low self-concept group is less clear-cut.

Discussion

This study focused on changes in academic self-concept in secondary school years. A sample of 1579 students was followed from Grade 7 to Grade 12, and their academic self-concept was measured four times. Latent growth models indicated that average academic self-concept declines in the initial years, followed by a deceleration. The student's math achievement proved to be a strong predictor of his/her academic self-concept. Girls were found to have a lower self-concept than boys in all grades, but the gender gap widens from seventh to tenth grade and subsequently narrows. Growth mixture models identified two qualitatively distinct developmental patterns of academic self-concept. The majority of the students experience a normal, declining self-concept but a small group of students tend to have a low and declining academic self-concept throughout secondary school.

Distinctive Developmental Patterns

Growth curve models are based on the view that individual change trajectories underlie the observed repeated measures (Raudenbush, 1995; Rogosa, 1995; Singer & Willett, 2003). In this study, the academic self-concept scores were modelled as a quadratic function of time. Considerable individual differences in developmental pathways were found. Students vary in terms of the height of their academic self-concept and the rate of decline. The variance in the quadratic parameter, however, was close to zero. The conventional growth curve model assumes that all individuals belong to one population. Although this model captures individual differences in trajectories, it is not always realistic to assume that a single-population model can account for all types of individual differences. Therefore, the growth mixture model was used to determine whether subgroups exist within the population that follow distinct developmental trajectories. Growth mixture models allow for cross-group differences in the shape of trajectories, whereas latent curve models assume that the shape is the same for the entire sample. In this study, GMMs proved to be a flexible approach for identifying distinct trajectories of academic self-concept during adolescence. The individual growth trajectories were grouped into two distinctive developmental patterns. A quadratic growth model held for both subgroups.

An important part of GMM is the prediction of these class membership probabilities from covariates. In our study, boys had a higher probability of belonging to the low self-concept group, but the girls in the low self-concept group showed a more declining pattern. Some girls are experiencing a strong declining academic self-concept in the early years of secondary school. Thus, teachers should explicitly give more attention to the academic self-concept of these girls.

Problematic Development

No distal outcomes were investigated in this study, but some authors indicated that a low and declining self-concept could predict further problems. Students with a low academic self-concept are more likely to experience emotional and psychosocial difficulties or to drop out of school (Anderman & Maehr, 1994; Eccles et al., 1991). Zimmerman et al. (1997) found that the change pattern in self-esteem predicts problem behaviour like alcohol use, low school grades, and tolerance for deviance. The GMM is well suited for early detection of likely membership in a problematic class. The identification of these students is necessary to direct the intervention and prevention efforts. The model can be used to assign students belonging to different trajectory classes to different treatments. Resources should be targeted at subgroups of high-risk students.

We want to highlight, however, that the existence of the two latent classes might also result from the nonnormality of the distribution of the repeated measures (see Bauer & Curran, 2003, 2004). In fact, we can never know whether the two latent classes correspond to true subpopulations or whether they serve simply to approximate a complex distribution. In fact, the application of mixture modelling requires a good theoretical underpinning (Dolan et al., 2005), which is lacking in the domain of changes in academic self-concept. Here, a GMM was applied because our interest was mainly in the distribution of individual trajectories.

Limitations and Directions for Future Research

This is an explorative study, intended to enhance the insight into the changes in academic self-concept during adolescence. It also promotes the GMM as a methodology to identify problematic developmental trajectories. Some of the limitations of this study can guide further research.

First, a very selective sample of students was analyzed in this study. It was comprised of only those students that stayed in the same secondary school and that filled out the questionnaire four times. But even within this selective sample, a subgroup of students with a problematic academic self-concept was detected.

Second, the effect of the class and the school on the academic self-concept were not addressed. Inclusion of these levels in further studies could indicate whether some schools or classes are more beneficial than others for their students' academic self-concept (Van Landeghem, Van Damme, Opdenakker, De Fraine, & Onghena, 2002).

Third, it was unfortunate that only the general academic self-concept was examined. Future studies should pay attention to the domain specific self-concept since girls tend to have a higher self-concept in language whereas boys have a higher self-concept in mathematics (Wigfield et al., 1991).

Fourth, only two explanatory variables were investigated: student gender and mathematics achievement. Future studies can include more explanatory variables like ethnicity or intelligence. The inclusion of distal outcomes can enhance the insight into the importance of the academic self-concept.

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Table 1. *Descriptive Statistics for the Repeated Measures of Academic Self-Concept*

	Grade 7	Grade 8	Grade 10	Grade 12
M	3.71	3.71	3.49	3.48
SD	0.48	0.51	0.50	0.51
Skew	-0.05	-0.18	-0.15	-0.54
Kurtosis	0.12	0.50	0.45	1.45
Cronbach alpha	0.78	0.80	0.79	0.81

Table 2. *Unconditional Latent Growth Model*

	Estimate		Estimate
Intercept Mean	3.742 (0.012)	Intercept Variance	0.144 (0.009)
Linear Mean	-0.099 (0.009)	Linear Variance	0.012 (0.006)
Quadratic Mean	0.009 (0.002)	Quadratic Variance	0.000 (0.000)
		Covariance I – L	-0.007 (0.005)
Log Likelihood	-3762.57	Covariance I – Q	-0.001 (0.001)
BIC	7598.79	Covariance L - Q	-0.001 (0.001)
df	10	Residual Variance	0.108 (0.004)

Table 3. C*onditional Latent Growth Model*

	Mean	Gender Effect		
Intercept Mean	3.778 (0.019)	-0.061 (0.025)*		
Linear Mean	-0.040 (0.014)	-0.099 (0.018)*		
Quadratic Mean	-0.001 (0.003)	0.017 (0.003)*		
		Time-varying Covariate		
	Math Effect			
Grade 7	0.060 (0.014)*			
Grade 8	0.061 (0.014)*			
Grade 10	0.019 (0.007)*			
Grade 12	0.066 (0.010)*			
		Variances and Model Fit		
Intercept Variance	0.136 (0.009)		Covariance I – L	-0.008 (0.005)
Linear Variance	0.010 (0.006)		Covariance I – Q	-0.001 (0.001)
Quadratic Variance	0.000 (0.000)		Covariance L - Q	-0.001 (0.001)
			Residual Variance	0.109 (0.005)
Log Likelihood	-3693.49		BIC	7512.17
df	17			

* p <.05

Table 4. *Model Fit Statistics for Models with K Latent Classes*

	LCGA			GMM with variant covariance matrix			GMM with invariant covariance matrix		
K	LL	*df*	BIC	LL	*df*	BIC	LL	*df*	BIC
1	-4417.16	11	8915.34	-3693.49	17	7512.17	-3693.49	17	7512.17
2	-3955.95	24	8088.65	-3549.73	36	7364.59	-3560.01	30	7340.95
3	-3696.14	37	7664.77	-3529.27	55	7463.58	-3537.39	43	7391.46
4	-3634.65	50	7637.53						
5	-3589.22	63	7642.42						
6	-3540.70	76	7641.11						

Table 5. *Growth Mixture Model with Two Latent Classes*

	Normal Self-concept Class				Low Self-concept Class			
	Mean		Gender Effect		Mean		Gender Effect	
Intercept	3.827	(0.024)*	-0.100	(0.031)*	3.544	(0.090)*	0.107	(0.107)
Linear	-0.037	(0.017)*	-0.075	(0.020)*	-0.055	(0.068)	-0.238	(0.101)*
Quadratic	-0.001	(0.003)	0.013	(0.004)*	0.001	(0.014)	0.036	(0.020)
Latent Class					-1.541	(0.424)	-0.194	(0.251)

Time-varying Covariate

	Normal Self-concept Class		Low Self-concept Class	
	Math Effect		Math Effect	
Grade 7	0.045	(0.015)*	0.114	(0.048)*
Grade 8	0.071	(0.016)*	-0.023	(0.072)
Grade 10	0.012	(0.008)	0.027	(0.028)
Grade 12	0.074	(0.011)*	-0.024	(0.072)

Variances and Model Fit

Intercept Variance	0.128	(0.008)	Covariance I – L	-0.008	(0.005)
Linear Variance	0.005	(0.005)	Covariance I – Q	-0.001	(0.001)
Quadratic Variance	0.000	(0.000)	Covariance L - Q	0.000	(0.001)
Residual Variance Normal Class	0.080	(0.007)			
Residual Variance Low Class	0.293	(0.052)			
Log Likelihood	-3560.01		BIC	7340.95	
df	30				

Figure Captions

Figure 1. *Growth Mixture Diagram*

Figure 2. *Average Change Trajectories for Boys and Girls*

Figure 3. *Average Change Trajectories for the Two Classes*

Figure 4. *Individual Growth Parameters for Boys and Girls*

Figure 1. *Growth Mixture Diagram*

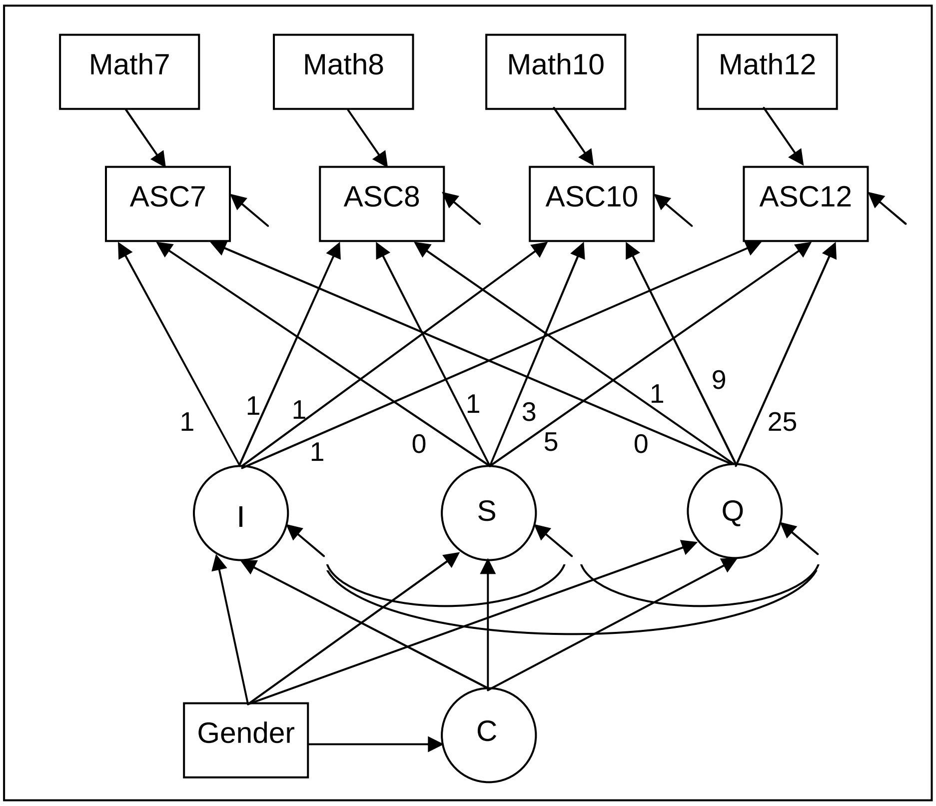

Figure 2. *Average Change Trajectories for Boys and Girls*

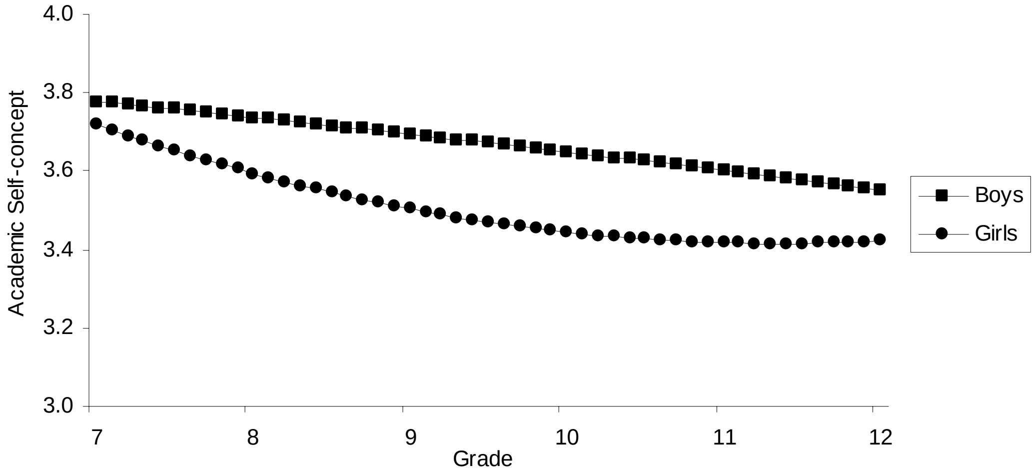

Figure 3. *Average Change Trajectories for the Two Classes*

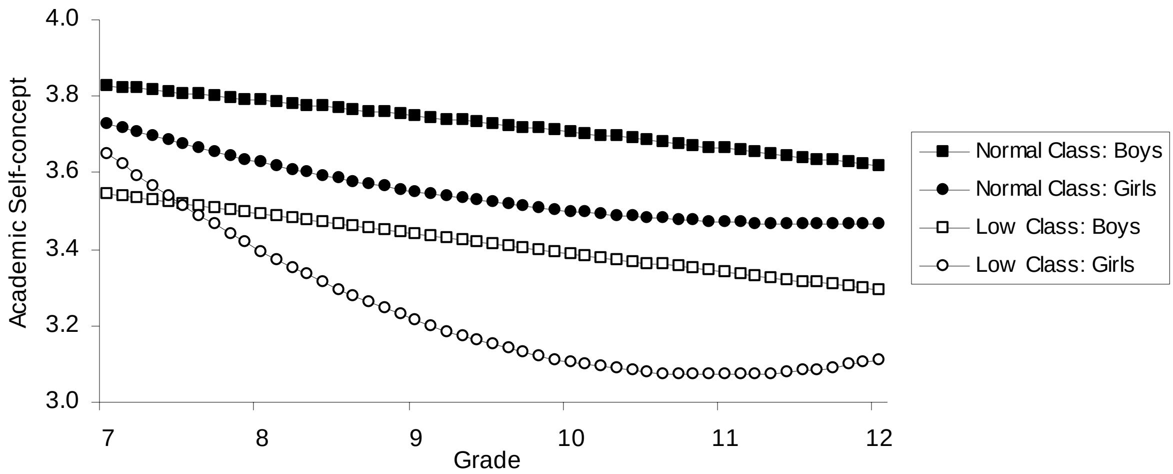

Figure 4. *Individual Growth Parameters for Boys and Girls*