



Developing talents: A longitudinal examination of intellectual ability and academic achievement

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ABSTRACT

The Fullerton Longitudinal Study offers a unique opportunity to model the stability of intelligence and achievement and their relations from elementary through secondary school. Using latent variable modeling, we fit a cross-lagged panel model to examine the relations between intelligence and achievement in two academic domains: mathematics and reading. Findings revealed that students' achievement is highly stable across the school years. Childhood intelligence is a strong predictor of initial mathematics and reading achievement. After age 7-years, intelligence is not predictive of either mathematics or reading achievement after accounting for prior achievement. Students who enter school with strong academic skills tend to maintain their academic advantage throughout their elementary and secondary education. We discuss the implications of these results for talent development.

KEYWORDS

Intelligence; academic achievement; longitudinal model; ability; IQ

Intelligence and academic achievement are two of the most important constructs in the fields of education and developmental psychology, and both constructs play a pivotal role in the talent development process (Jensen, 1998). Intelligence and achievement are related, and intelligence predicts later achievement (Deary, Strand, Smith, & Fernandes, 2007; Jensen, 1998). However, the development of intelligence and achievement may also be reciprocal in nature: the development of academic skills may predict subsequent intelligence. This study examines the stability of intelligence and achievement, modeling relations between the two constructs over a 10-year period across elementary and secondary school using the Fullerton Longitudinal Study (FLS) data-set. Using latent variable modeling, we examine the stability of the relations between intelligence and achievement and explore whether this longitudinal relationship varies across two academic domains: mathematics and reading.

Intelligence and educational achievement

Both intelligence and achievement serve as important predictors of later educational and occupational success (Gordon, Lewis, & Quigley, 1988; Gottfredson, 1997; Jensen, 1998). Intelligence relates to career selection and occupational success within virtually any vocation, and the relations between intelligence and job performance appears to increase with job complexity (Gottfredson, 1997). Intelligence also relates to health outcomes in adulthood, and relates to a host of other positive social outcomes (Gottfredson & Deary, 2004).

Intelligence and academic achievement are strongly related, but they are not redundant. Recent research suggests that although intelligence predicts academic achievement, other factors also predict incremental variance in achievement, over and above that which is explained by intelligence. For example, although intelligence is related to both achievement and socioeconomic status, recent research suggests that SES predicts gains in academic performance, even after controlling for intelligence (von Stumm, 2016). In fact, in one recent study, SES predicted a half grade level advantage in achievement for students of the same intelligence by age 16 (von Stumm, 2016). Given that achievement may be more malleable than intelligence, and that achievement predicts adult educational and occupational outcomes, understanding the reciprocal relations of the two constructs across childhood and adolescence can provide valuable insights for educators and psychologists.

Neither intelligence nor achievement can be directly observed: both are latent constructs. Although there is no perfect way to measure intelligence, IQ tests such as the Wechsler Intelligence Scales for Children (WISC) or the Stanford–Binet (SB) often serve as proxies or indicators of intelligence. Similarly, observed achievement scores serve as a surrogate for students' true educational achievement. High-profile, high stakes standardized achievement tests are widely used to make high stakes decisions such as educational placement and college admissions. However, observed scores on both IQ tests and achievement tests are measured with error. Even the most psychometrically sound IQ and achievement tests contain some degree of measurement error. Because correlations between observed variables are attenuated by measurement error, the correlations between observed IQ scores and achievement test scores likely underestimate the actual relations between true intelligence and true achievement.

Studies of the relation between intelligence and educational achievement have commonly examined the correlations between students' performance on achievement tests and IQs (i.e. Deary & Johnson, 2010; Deary et al., 2007; Deary, Whiteman, Starr, Whalley, & Fox, 2004; Duckworth, Quinn, & Tsukayama, 2012; Lassiter & Bardos, 1995; Lynn & Mikk, 2007). These studies differed in terms of the tests used to assess intelligence and/or achievement, achievement areas, and the characteristics of their samples. Generally, the measured correlations between IQs and achievement test scores generally hover at or above .5 (Sternberg, Grigorenko, & Bundy,

2001), which is moderately strong. However, a .5 correlation indicates that one test explains only 25% of the variance in the other (Naglieri & Bornstein, 2003; Neisser et al., 1996). Given that observed scores are measured with error, we would expect the correlation between latent ability and latent achievement to be higher. Using latent variable modeling, Benson, Kranzler, and Floyd (2016) found a strong relation between general cognitive ability and academic achievement. Deary et al. (2007) also estimated a correlation of approximately .80 between latent ability and latent achievement, measured five years later. Kaufman, Reynolds, Liu, Kaufman, and McGrew (2012) estimated correlations of .77 and above between latent cognitive ability and latent cognitive achievement. Kaufman et al. concluded that cognitive ability and academic achievement are distinct, but highly related constructs.

Developmentally, the correlation between achievement and intelligence may increase with age (McGrew & Knopik, 1993). One explanation for this phenomenon is that the targeted cognitive abilities or the content of the intelligence and achievement tests overlap more with advances in age and educational level (Sternberg et al., 2001). A second explanation is that schooling may affect IQ as well as achievement. For instance, IQs might decline during summer vacation (Ceci, 1991) just as achievement tests do (Rambo-Hernandez & McCoach, 2015). Even so, some evidence suggests that the effects of cognitive ability on academic achievement are stronger in the early years and wane by late childhood or early adolescence (Stipek & Valentino, 2015). Stipek and Valentino provide “one possible explanation for the waning effect of the basic cognitive skills” (p. 785). As children progress through school, individual differences in their academic skills become more entrenched. “Because subject-matter learning builds on previous learning, it is increasingly affected by extant skill levels” (Stipek & Valentino, 2015, p. 785). Generally, intelligence has proven more difficult to modify than achievement. In addition, intelligence appears to be more prone to fade out effects than achievement. Although the long-term effects of cognitive interventions on intelligence appear to fade out across time, long-term intervention effects on academic achievement appear to be more durable (Protzko, 2015).

These findings have led to speculation that achievement mediates the effect of prior cognitive ability on subsequent achievement. A recent study by Soares, Lemos, Primi, and Almeida (2015) examined the relations between intelligence and achievement in middle school using a 2 wave longitudinal study using latent variable modeling. In their study, academic achievement at the end of seventh grade completely mediated the effect of intelligence at the end of seventh grade on academic achievement at the end of ninth grade. Their results suggest that prior achievement is a strong predictor of subsequent achievement, and that prior intelligence only indirectly affects distal achievement through more proximal achievement (Soares et al., 2015).

Although intelligence and achievement are correlated, does intelligence help to predict subsequent academic achievement, after accounting for prior achievement? Or is the effect of intelligence on subsequent achievement mediated by

current achievement? This question holds great importance for educators and psychologists and informs researchers and practitioners about where to focus their intervention efforts to achieve the greatest long-term success.

The current study

Compared to studies examining relations between achievement and intelligence at a given time, far fewer longitudinal studies have investigated the cross-time relation of intelligence and educational achievement from elementary through the secondary school years. The FLS provides a unique opportunity to examine the stability and relations of intelligence and achievement across childhood and adolescence. The data used for the current study contains 13 cognitive test scores collected during the first 17 years of life and 22 achievement test scores collected from the ages of 7- to 17-years of age, allowing us to model the developmental process of intelligence, achievement and the longitudinal relations of intelligence and achievement.

The current research contributes to the growing body of knowledge exploring the linkages between ability and achievement. Using the FLS data, we model predictive pathways of mathematics and reading achievement from ages 7–17. In addition, we explore the relations between intelligence and academic achievement across childhood and adolescence. The goal of this study is to better understand the nature of the relations between reading and math achievement across elementary and secondary school. In addition, modeling the predictive pathway relating cognitive ability to the development and maintenance of academic skills and the potential predictive pathway from academic achievement to later cognitive ability allows for a better understanding of the nature of the relationship between intelligence and achievement. In particular, we examine whether math or reading achievement can predict adolescent intelligence after controlling for childhood intelligence. If achievement helps to predict later intelligence, this suggests that talent can be developed, and the development of academic skills may actually help to increase students' abilities.

Method

Participants

The present study employed data from the FLS (Gottfried, Gottfried, Bathurst, & Guerin, 1994; Gottfried, Gottfried, & Guerin, 2006, 2009), launched in 1979, is an ongoing longitudinal investigation in which 130 children were followed from infancy (age 1-year) into adulthood. Infants were selected from notifications of all births from hospitals surrounding the university. Families were invited to participate prior to the infants' 1-year birthday. Infants free of neurological and visual problems, of normal birth weight, and whose parents spoke English were eligible to enter the study. Prior to school entry the sample was assessed semi-annually and

then annually throughout the formal school years. These data served as the basis for the present study. A study sample approximating this size has been deemed sufficient for modeling longitudinal data (Bentler, 2007; Liu, Rovine, & Molenaar, 2012).

From infancy through age 17-years, participants completed a comprehensive battery of standardized measures at each assessment occasion. Throughout the entire span of investigation, the retention rate of participants was substantial, with at least 80% of the original sample returning at any assessment. Missing data were minimal and there was no evidence of attrition bias in the course of investigation (Guerin, Gottfried, Oliver, & Thomas, 2003). When the investigation was launched, participants resided in proximity to the research site. Geographic mobility has long been known to be common and expected in extensive longitudinal projects (Harway, Mednick, & Mednick, 1984) and as anticipated, the study population gradually resided throughout the United States. Furthermore, participants attended public as well as private schools.

Socioeconomic status of families was determined using the Hollingshead Four-Factor Index of Social Status (see Gottfried, Gottfried, Bathurst, Guerin, & Parramore, 2003; Hollingshead, 1975). This index is based on mothers' and fathers' level of education and occupational ranking. SES of the families varied, ranging from semi-skilled workers with no high school degree through professionals. The mean Hollingshead Social Status Index was 45.6 ($SD = 11.9$) at the initiation of the study and 48.6 ($SD = 11.4$) at the 17-year assessment. The gender ratio of the participants was approximately equal (52% males). Ethnicities included 117 White, 7 Latino, 1 Asian, 1 East Indian, 1 Hawaiian, 1 Iranian, and 2 interracial children. This reflected the demographics of the area at the outset of the investigation.

Instruments

To explore the longitudinal relations of unobserved latent variables of intelligence and achievement, IQ and achievement scores served as the indicators of their respective constructs.

Intelligence tests

In the FLS, age-appropriate intelligence tests were administered at various intervals from age 1- to 17-years. Starting at 12 months, participants were assessed using Bayley Scales of Infant Development (BSID; Bayley, 1969) three times at 6-month intervals (12, 18, and 24 months). BSID Mental Development Index (MDI) scores are standardized scores with a mean of 100 and a standard deviation (SD) of 16. This is comparable to what is done with IQ tests. For *BSID* MDI scores, the internal consistency (Kuder-Richardson correction) is .79 during the first month and ranges from .84 to .94 between 2 and 15 months, the test-retest reliability is about .76, and the inter-rater reliability is .84 (Bayley, 1969). The reported split-half reliabilities of the *BSID* MDI scores have a median value of .88

Table 1. Descriptive statistics of intellectual assessment results.

Measure	Age	N	Return rate (%)	Sample statistics			
				Min	Max	Mean	SD
BSID ^a Mental Development Index	12m	130	100.0	89	140	113.3	10.3
	18m	128	98.5	76	150	113.4	16.6
	24m	121	93.1	70	150	114.8	20.3
MSCA ^b GCI	30m	104	80.0	74	150	112.2	13.9
	36m	112	86.2	77	133	108.3	13.0
	42m	115	88.5	76	129	112.4	10.7
WISC-R ^c	6y	105	80.8	87	147	114.5	12.6
	7y	106	81.5	85	147	116.4	13.3
	8y	107	82.3	84	145	116.0	14.2
	12y	104	80.0	87	143	114.1	12.0
WISC-III ^d	15y	108	83.1	70	140	108.0	13.4
WAIS-R ^e	17y	109	83.8	81	139	110.4	12.4

^aBSID: Bayley Scales of Infant Development;

^bMSCA: McCarthy Scales of Children's Abilities;

^cWISC-R: Wechsler intelligence scale for children-revised;

^dWISC-III: Wechsler intelligence scale for children third edition;

^eWAIS-R: Wechsler adult intelligence scale-revised.

(Gregory, 2004). The sample means and SDs of BSID MDI scores are, respectively, 113.3 and 10.3 for age one, 113.4 and 16.6 for age one and a half, and 114.8 and 20.3 for age two. The three measures of BSID served as the indicators of the latent variable *infant intelligence*.

From 30- to 42-months of age, participants were assessed using McCarthy Scales of Children's Abilities (MSCA) (McCarthy, 1972) at 6-month intervals. MSCA General Cognitive Index (GCI) scores have a mean of 100 with a SD of 16. The reported split-half reliabilities have an average value of .93 (Gregory, 2004), and the test-retest reliability over a month interval was .8 (McCarthy, 1972). The sample means and SDs of MSCA GCI scores are, respectively, 112.2 and 13.9 at 30 months old, 108.3 and 13.0 at 36 months old, and 112.4 and 10.7 at 42 months old. The three measures of MSCA served as the indicators of the latent variable *preschool intelligence*.

The Wechsler Intelligence Scales for Children-Revised (WISC-R) (Wechsler, 1974) were administered four times, annually at ages 6-, 7-, and 8-years and then at age 12-years. The Wechsler Intelligence Scale for Children third edition (WISC-III) (Wechsler, 1991) was administered at age 15-years, and Wechsler Adult Intelligence Scale-Revised (WAIS-R) (Wechsler, 1981) was administered at age 17-years. Wechsler full scale IQ scores have a mean of 100 with a SD of 15. The test-retest reliability of Wechsler intelligence tests is generally over .90 and so is the internal consistency (Wechsler, 1974, 1981, 1991). The sample mean full scale IQ scores ranged between 110 and 117 across the six time points, and the sample SDs range between 12.0 and 14.2. The WISC full-scale IQ scores at ages 6-, 7-, and 8-years were used as the indicators of the latent variable *childhood intelligence*. The WISC and WAIS full-scale IQ scores at ages 12-, 15-, and 17-years served as the indicators of the latent variable *adolescent intelligence*. Table 1 contains descriptive

Table 2. Correlation matrix of the observed IQ scores.

Stages measures	Infant					Preschool			Early childhood				Adolescence				
	BSID MDI					MSCA GCI			WISC-R				WAIS-R				
	12m	18m	24m	30m	36m	42m	6y	7y	8y	12y	15y	17y					
Infant	1																
	.41**	1															
	.43**	.62**	1														
Preschool	.33**	.63**	.64**	1													
	.37**	.65**	.67**	.79**	1												
	.37**	.54**	.68**	.74**	.76**	1											
Early childhood	.26**	.45**	.60**	.57**	.60**	.67**	1										
	.22*	.41**	.55**	.56**	.60**	.63**	.79**	1									
	.20*	.42**	.54**	.55**	.60**	.62**	.79**	.83**	1								
Adolescence	.17	.39**	.51**	.42**	.47**	.47**	.72**	.78**	.80**	1							
	.15	.35**	.48**	.40**	.45**	.45**	.64**	.70**	.77**	.80**	1						
	.16	.39**	.43**	.44**	.49**	.44**	.67**	.70**	.77**	.82**	.85**	1					

Notes: "m" stands for months; "y" stands for years.

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

Table 3. Descriptive statistics of WJ age percentiles from ages 7- through 17-years.

Measure	Age	N	Return rate (%)	Age percentiles rank			
				Min	Max	Mean	SD
Reading	7y	106	81.5	2	97	63.1	26.6
	8y	107	82.3	5	99	63.0	27.6
	9y	107	82.3	4	99	62.9	26.1
	10y	105	80.8	4	99	62.9	25.5
	11y	104	80.0	7	99	71.0	24.9
	12y	104	80.0	8	99	74.7	23.8
	13y	109	83.8	7	99	75.7	23.4
	14y	108	83.1	13	99	77.4	23.3
	15y	107	82.3	4	99	77.4	23.9
	16y	109	83.8	7	99	76.2	24.2
	17y	109	83.8	6	99	77.2	23.0

Note: "y" stands for years.

statistics for the intelligence measures. Table 2 contains the correlations among the intelligence measures across all 12 time points.

The return rates were over 90% among the first two years and at least 80% during the later years, so the sample size at any given time point was over 100. All SEM analyses used full-information maximum likelihood techniques (FIML) to deal with missing data. Table 1 contains descriptive statistics for the sample. In this sample, there were no children with extremely low cognitive abilities (two standard deviations lower than the mean, 68 for the BSID MDI scores and MSCA GCI scores, 70 for Wechsler full IQs) in the sample. In fact, the sample means are consistently higher than the standardization population means across time and over two-thirds of the participants (>70%) in this study score above the population mean (100).

Achievement tests

Annually from 7- to 17-years of age, participants completed the Woodcock Johnson Psycho-Educational Batteries (henceforth referred to as WJ) (Revised edition from ages 11 years onward,) (Woodcock & Johnson, 1977, 1989). This study focused on achievement in mathematics and reading, the two common subjects across the 11 years. The return ratios of WJ reading and math tests were over 80% across the 11 years; therefore, the sample size exceeded 100 at each time point. Several types of scores were reported for the WJ tests: raw scores, age/grade equivalents, and age/grade percentile ranks. Raw scores were not recommended for analytic use (Woodcock & Johnson, 1989). Given that IQ scores are age-based norm-referenced scores and our study was conducted to explore the longitudinal relationship between achievement and intelligence, we favored WJ test scores that were age-based over grade-based and percentile ranks over grade equivalents. Because age percentile ranks are ordinal scores, we transformed them into z scores and then into scale scores¹ with the mean of 100 and the SD of 15 and used the transformed scale scores in the analytic models. Table 3 contains the descriptive statistics for the achievement tests.

The cross-lagged panel analysis model with latent variables of achievement

To model math and reading achievement across time, we fit a Cross-Lagged Panel Analysis (CLPA) with latent variables. The CLPA model with latent variables separates the error variance from the disturbance variance, which allows for the more accurate estimation of the stability of achievement over time. In CLPA, the autoregressive path estimates the effects of prior achievement in the same subject (math or reading) on achievement, after controlling for achievement in the other subject area. The cross-lag path estimates the effects of prior achievement in the one subject area on subsequent achievement in the other subject area, after controlling for prior achievement in the same subject area. For example, a cross-lag path from reading at age 7 to math at age 8 estimates the relation between reading achievement at age 7 and math achievement at age 8, after controlling for math achievement at age 7. The existence of a substantial cross-lagged path suggests that reading achievement may influence subsequent math achievement.

Using Maximum Likelihood estimation (ML) in Mplus 7, we fit a series of SEMs to explore the nature of the relations between intelligence and achievement from early childhood through adolescence. Prior to fitting the structural equation model, we fit a measurement model with the four latent intelligence variables. The measurement model for the 4 latent variables exhibited adequate fit. The chi-square was not statistically-significant. ($\chi^2_{48} = 53.4, p = .273$). Further, the RMSEA (.03) and both the CFI (.995) and TLI (.993) were indicative of good fit. Further details about the measurement model for the latent intelligence factors can be found in Yu, McCoach, Gottfried, and Gottfried (2017).

After establishing the adequacy of the measurement model, we fit a structural model which included all cross-lagged paths. We trimmed non-statistically significant cross-lagged paths and compared the fit of the trimmed model to the fully specified model. The first model we present is a structural model including only math and reading achievement variables. The second model includes the 4 latent intelligence variables as well as the latent achievement variables across the 10-year age span. Given the sample size, reducing the number of freely estimated parameters was beneficial.

Results

Correlations between observed variables

Correlations among achievement test scores across time

Figure 1 graphically depicts the correlations of the achievement measures across time. The correlations between the achievement scores within the same subject are strong at adjacent time points, and dampen as the lag between time points increases. For example, the correlation between reading achievement at ages 7 and 8 is stronger than the correlation between reading achievement at ages 7 and 10. This decrease in correlations across time lags that are further apart is more

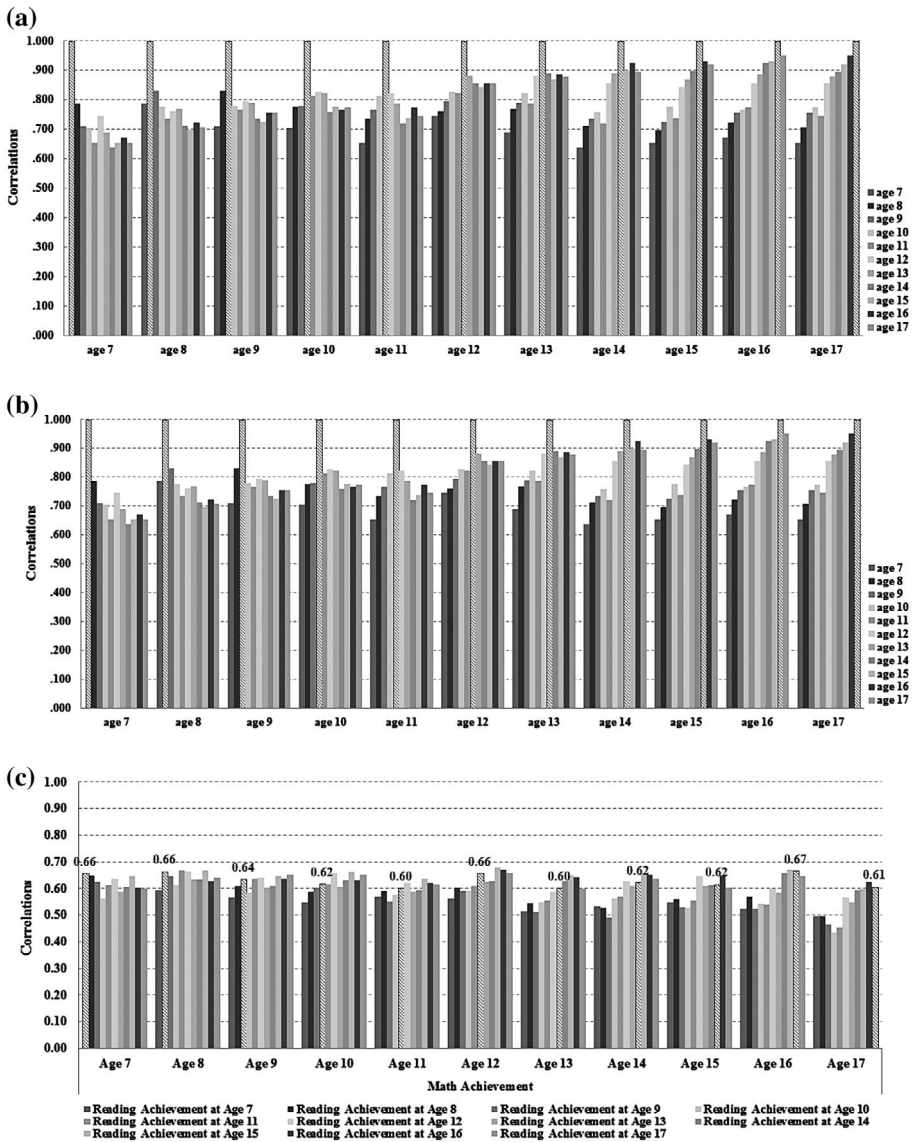


Figure 1. Plots of correlations between WJ APRs across the 11 time points. (a) Correlations among reading achievement scores across the 11 time points. (b) Correlations among math achievement scores across the 11 time points. (c) Cross-subject correlations across time.

pronounced in math than in reading, which suggests that reading achievement is more stable than math achievement. In addition, the correlations between the math achievement scores after age 11 are higher than the correlations between the math achievement scores before age 11. The correlations among reading achievement scores across time are somewhat stronger than the corresponding correlations among math achievement scores across time. Finally, correlations between reading and math achievement scores at the same age are moderately to strongly correlated with each other ($.5 \leq r \leq .7$), indicating that students' performance on

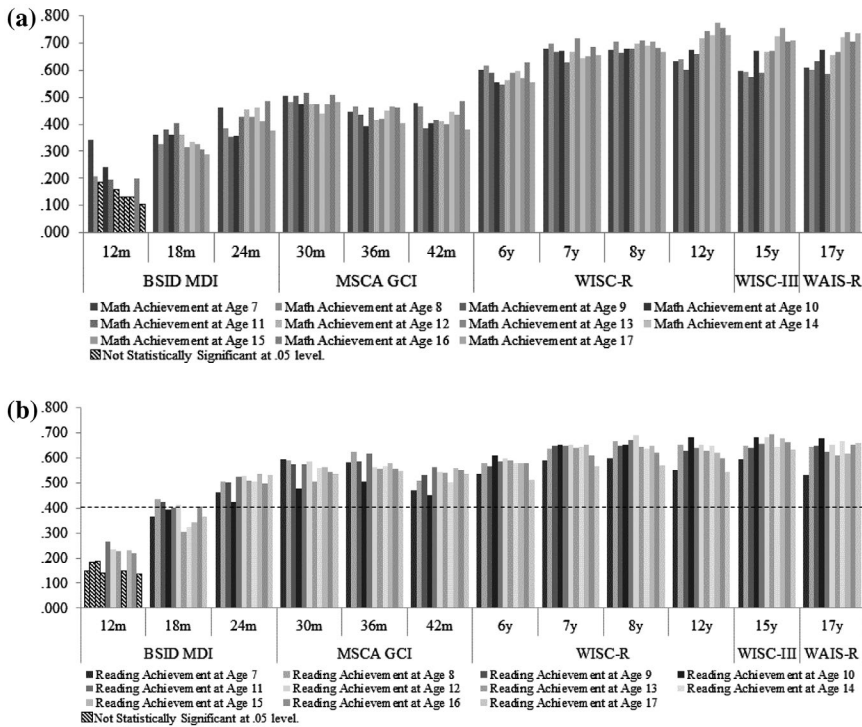


Figure 2. Correlations among observed IQ scores and math and reading achievement scores. (a) Correlations between IQ scores and math achievement scores. (b) Correlations between IQ scores and reading achievement scores.

achievement tests is consistent across these two subject areas. In other words, students with higher reading achievement also tend to have higher math achievement and vice versa. Figure 1 depicts the correlations for achievement measures. Figure 2 depicts the correlations between IQ measures and achievement measures (Table 4).

Results from the CLPA models

Starting with a fully specified CLPA model, we tested all the auto-regressive paths between two latent achievement variables of the same subject and all the cross-lagged regression paths between two latent achievement variables of different subjects at two adjacent time points. Then, all non-statistically significant cross-lagged regression paths were deleted from the CLPA model. Only one cross-lagged regression path remained in the final model (shown in Figure 3): the path from reading achievement at age 13 to math achievement at age 14, and this path was relatively small ($\beta = .134$). In addition, we were able to impose several more constraints without worsening the fit of the model: (1) the stabilities of reading achievement were constrained to be equal across time, and the stabilities of math achievement were constrained to be equal across time (except for the path between



Table 4. Correlation Matrices of the Observed Achievement Test Scores.

	7y	8y	9y	10y	11y	12y	13y	14y	15y	16y	17y
<i>(a) Correlations among WJ Age Percentiles of Reading Achievements</i>											
	WJ Age Percentiles of Reading Ach.										
7y	.881**										
8y	.836**	.926**									
9y	.813**	.889**	.894**								
10y	.802**	.893**	.891**	.871**							
11y	.766**	.859**	.863**	.862**	.898**						
12y	.712**	.809**	.826**	.827**	.869**	.875**					
13y	.697**	.793**	.817**	.798**	.824**	.859**	.870**				
14y	.693**	.800**	.821**	.803**	.846**	.861**	.846**	.852**			
15y	.700**	.758**	.807**	.781**	.794**	.834**	.837**	.840**	.859**		
16y	.662**	.751**	.785**	.755**	.780**	.834**	.790**	.844**	.844**	.859**	
17y											.893**
<i>(b) Correlations among WJ Age Percentiles of Math Achievements</i>											
	WJ Age Percentiles of Math Ach.										
7y	.785**										
8y	.676**	.795**									
9y	.644**	.717**	.723**								
10y	.565**	.665**	.693**	.724**							
11y	.707**	.717**	.744**	.758**	.741**						
12y	.636**	.726**	.769**	.769**	.717**	.836**					
13y	.558**	.648**	.648**	.701**	.636**	.815**	.879**				
14y	.572**	.623**	.638**	.725**	.679**	.798**	.850**	.874**			
15y	.593**	.670**	.678**	.717**	.705**	.809**	.859**	.904**	.909**		
16y	.564**	.635**	.669**	.707**	.663**	.789**	.846**	.869**	.899**	.943**	
17y											.943**
<i>(c) Correlations among WJ Age Percentiles between Subjects</i>											
	WJ Age Percentiles of Reading Ach.										
7y	.655**	.563**	.550**	.513**	.526**	.530**	.497**	.487**	.487**	.465**	.475**
8y	.624**	.613**	.559**	.541**	.553**	.576**	.538**	.485**	.521**	.497**	.439**
9y	.592**	.596**	.583**	.573**	.528**	.568**	.521**	.444**	.501**	.474**	.410**
10y	.519**	.533**	.510**	.555**	.526**	.551**	.541**	.513**	.483**	.500**	.378**
11y	.563**	.606**	.592**	.602**	.579**	.577**	.581**	.543**	.510**	.509**	.394**
12y	.589**	.606**	.596**	.615**	.596**	.632**	.609**	.611**	.572**	.547**	.529**
13y	.555**	.590**	.553**	.582**	.590**	.620**	.649**	.599**	.605**	.581**	.512**
14y	.558**	.562**	.542**	.575**	.564**	.587**	.637**	.605**	.587**	.632**	.556**
15y	.592**	.608**	.611**	.638**	.639**	.696**	.705**	.667**	.616**	.658**	.596**
16y	.531**	.548**	.579**	.578**	.587**	.629**	.658**	.639**	.627**	.630**	.588**
17y	.534**	.564**	.582**	.610**	.562**	.617**	.600**	.598**	.558**	.602**	.563**

Notes: "y" stands for years; "Ach." stands for achievement.
 ***p* < .01.

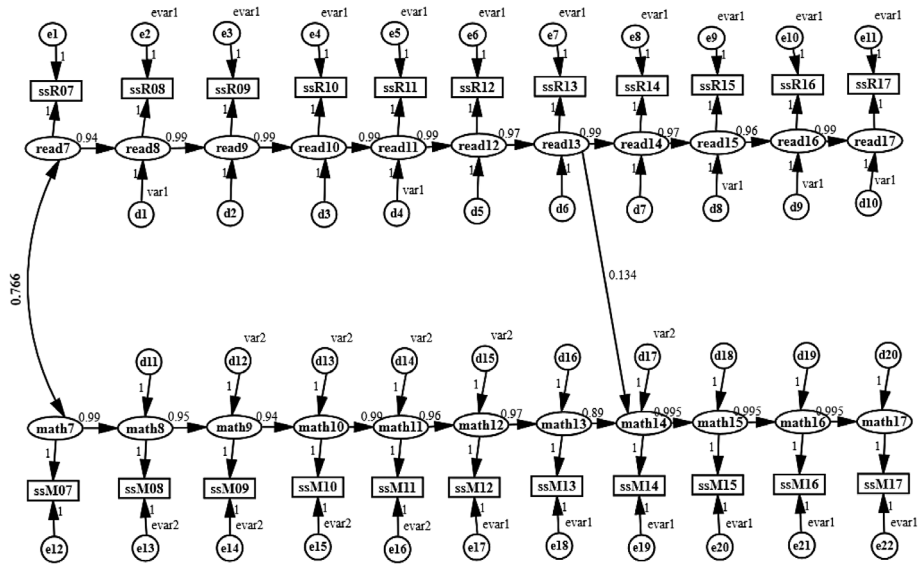


Figure 3. Diagram of the CLPA model of achievement. All the path coefficients are standardized.

age 13 and age 14, which was allowed to freely vary); (2) the error variances in reading achievement across the 11 time points and the error variances in math achievement from age 12 to age 17 were constrained to be equal, and the error variances in math achievement from age 8 to age 11 were constrained to be equal; (3) the disturbance variances of latent reading achievement at age 8, age 11, and from 15 through 17 years old were constrained to be equal. The disturbance variances of latent math achievement at age 14 and from nine through 12 years old were also constrained to be equal. Figure 3 depicts the final CLPA structural model with all these constraints, which exhibited adequate model fit ($\chi^2(234) = 338.6$; RMSEA = .06, CFI = .97, TLI = .97). In contrast, the model that included all of the cross-lagged paths had a χ^2 of 317.9 with 217 degrees of freedom (RMSEA = .06, CFI = .97, TLI = .97). Therefore, the fit of the model with the trimmed cross-lagged paths was not statistically significantly worse than the fit of the model that included all cross-lagged paths (Chi-square difference = 20.7 with 17 degrees of freedom). Therefore, the trimmed model was favored.

As seen in Figure 3, the correlation between latent math and reading achievement at age 7 (the first data collection point for standardized achievement data) is .77, which indicates that reading and math achievement are strongly related in early elementary school. Students with high reading achievement are likely to exhibit high math achievement as well, and vice versa. The standardized auto-regressive path coefficients represent the stabilities of achievement over time within a given subject. In general, the stabilities of both reading and math achievement are very high. The stabilities in reading range from a low of .94 (for the autoregressive path from reading at age 7 to reading at age 8) to a high of .99 (for 6 of the 10 standardized autoregressive paths in reading.) Five of the

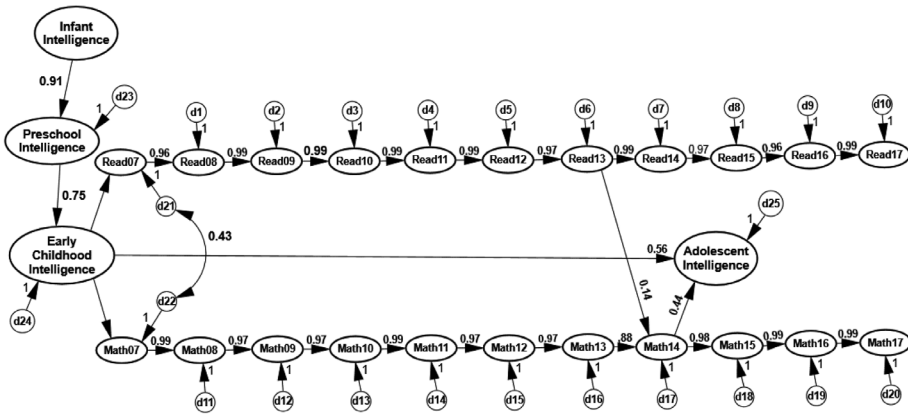


Figure 4. Diagram of the mixed model of intelligence and achievement.

10 stabilities in math were .99 or above as well. These high stability coefficients indicate that achievement can be almost perfectly predicted by achievement from the prior year's achievement.

There is one exception to the pattern of near perfect stabilities across time: the stability of math achievement between ages 13 and 14 is .89. Concurrently, the only statistically significant cross-lagged path occurs during this time period: the cross-lag path from reading achievement at age 13 to math achievement 14 is .134. Math at age 14 is predicted by both age 13 math and (to a much lesser extent) age 13 reading achievement (after controlling for prior math scores). Given the high stabilities, it is no surprise that most cross-lagged paths are generally near 0; there is very little variance that is not explained by the preceding achievement in the same subject area. Not coincidentally, the only cross-lagged regression path occurs at the occasion with the lowest stability. The combination of the autoregressive path and the cross-lagged path explain nearly all of the variance in math achievement at age 14.

The integrated CLPA model of intelligence and achievement

After fitting the first CLPA model to investigate the parallel processes of the development in math and reading achievement across time, we built a SEM model to explore the longitudinal relations between intelligence and achievement. This integrated model of intelligence and achievement investigated whether prior intelligence or achievement could explain additional variance in the other construct after controlling for preceding status. Figure 4 depicts the CLPA model of latent intelligence and latent achievement at four developmental periods: infancy, pre-school, childhood, and adolescence and latent achievement from ages 7 to 17. For ease of explanation, we have named these intelligence factors based on the developmental period in which the measures were obtained. As mentioned earlier, infant intelligence includes indicators from the Bayley infant scales, pre-school

intelligence includes indicators from the McCarthy scale, childhood intelligence includes the measures of the WISC in early childhood, and adolescent intelligence includes WISC and WAIS scores in adolescence.

Figure 4 presents the final integrated SEM model of achievement and intelligence. The final CLPA model of intelligence and achievement also exhibited adequate fit ($\chi^2(542) = 756.0$; RMSEA = .055, CFI = .96, and TLI = .96). Childhood intelligence strongly predicts both math and reading achievement at age seven (approximately the end of the first grade). Childhood intelligence explains over 56% ($r^2 = .75^2 = .56$) of the variance in reading achievement and almost 70% ($r^2 = .83^2 = .69$) of the variance in math achievement at age seven. The pathway between preschool and infant intelligence on initial math and reading achievement is completely mediated by childhood intelligence. In other words, there are no direct effects of infant and preschool intelligence on achievement at age seven, after controlling for childhood intelligence. Moreover, after controlling for prior achievement, childhood and adolescent intelligence do not explain additional variance in either reading or math achievement from ages 8- to 17-years. Thus, the effects of intelligence on subsequent achievement are completely mediated by prior achievement. Put simply, intelligence predicts achievement, prior achievement predicts subsequent achievement, and after accounting for prior achievement, intelligence does not aid in the prediction of subsequent achievement.

Although intelligence does not predict achievement after controlling for prior achievement, math achievement at age 14 predicts adolescent intelligence, even after controlling for childhood intelligence. This relation between math achievement and intelligence in early adolescence is not necessarily causal, but it does suggest that adolescent math reasoning and general cognitive ability in adolescence are related to each other, even after controlling for intelligence during childhood.

Finally, math and reading achievement are strongly correlated with each other. However, generally, reading and math achievement are not predictive of each other after accounting for prior achievement in the same subject area. There is one exception between ages 13 and 14, when prior reading achievement predicts math achievement, although the magnitude of the effect is relatively small ($B = .14$).

Discussion

To address the concern that measurement error has not been adequately addressed in previous studies on this topic, we applied latent variable modeling techniques to examine the longitudinal relations of intelligence and achievement from childhood and adolescence (Hoyle, 2012; Kline, 2015). It appears that intelligence has direct effects on students' performance at the beginning of school; thereafter, students' achievement is stable from elementary school through high school. Childhood intelligence is a strong predictor of initial reading and math achievement, and prior achievement is a strong predictor of subsequent achievement. Given the strong stabilities of the math and reading variables, students with strong math

and reading at age 7 are likely to continue to exhibit strong math and reading achievement throughout their school years. The latent relations between intelligence and achievement are stronger than the average correlations between IQ and achievement test scores reported by previous studies (Sternberg et al., 2001).

Students' reading and math achievement are strongly correlated with each other in early elementary school. In addition, achievement is quite stable throughout the primary and secondary school (from ages 7- to 17-years). Reading achievement revealed greater stability than math achievement at some time periods. Given its high level of stability, reading achievement at one time point can be almost perfectly predicted by preceding reading achievement without knowing anything about earlier reading achievement, math achievement, or intelligence. Additionally, reading achievement at age 7-years explains 64% ($r^2 = .80^2 = .64$) of the variance in reading achievement at the end of high school. Generally speaking, students who are proficient readers at age 7-years tend to maintain their advantage in reading throughout their entire education prior to college. In fact, it also predicts post-secondary educational attainment (Gottfried, Schlackman, Gottfried, & Boutin-Martinez, 2015). Compared with reading achievement, math achievement is slightly less stable. The stability of math achievement is somewhat lower between ages 13 and 14 than it is at any other interval. This time period may correspond to the introduction of more algebraic and abstract reasoning skills in mathematics. Perhaps when students transition from arithmetic to algebra or from intermediate to advanced mathematical content, additional skills and abilities are required to be successful.

Further, reading achievement by the end of middle school is also a positive predictor (standardized path coefficient = .13) of math achievement of the first year at high school after accounting for the math achievement at the end of middle school. Therefore, math achievement at age 14, which typically corresponds with the beginning of high school, is predicted by both reading and math learning outcomes at age 13, which typically corresponds with the end of middle school. This suggests that students who are high achievers in both reading and math by the end of middle school are likely to have slightly higher math achievement in high school than their peers who achieve equally well in math, but who exhibit lower reading scores. In addition, math achievement at age 14 predicts adolescent cognitive ability, after controlling for childhood intelligence. Thus age 14 may represent a turning point. Perhaps as math concepts achievement becomes more abstract in adolescence, they may relate more strongly to traditional measures of cognitive ability. Nevertheless, math achievement appears to be very stable both before and after this transitional period. Math achievement at age 7-years shares 67%³ ($r^2 = .82^2 = .67$) of the variability with math achievement by the end of middle school. Math achievement at the beginning of high school shares 97%⁴ ($r^2 = .97^2 = .985$) of variance in the math achievement at the end of high school, which indicates that students' math achievement at high school can be reasonably well predicted across high school.

Although intelligence does not aid in the prediction of achievement after age 7-years, controlling for prior achievement, math achievement at age 14-years predicts adolescent intelligence. The direction of causality is not known, but such results suggest that adolescent math achievement is a good predictor of adolescent ability after controlling for childhood intelligence. This result may imply that education affects cognitive ability. Previous studies have found strong correlations (>.8) between IQ and years in school (Ceci, 1991; Ceci, Liker, & Glucksberg, 1986). These results may also suggest that math achievement during the later grades are more related to cognitive ability than earlier mathematics achievement is. Given that mathematical concepts become increasingly abstract during high school, it is quite conceivable that math tests in the later grades are more related to ability.

Our findings suggest that after age 7, interventions for talent development, especially those that focus on increasing cognitive skills or abilities, may have less of an impact than they do in early childhood. The high stability of reading and math achievement across elementary and secondary school suggests the importance of early education for a students' educational pathway and eventual achievement. Students who have high initial achievement in elementary school are far more likely to be high achievers in high school. Therefore, early education programs and parents who furnish enrichment experiences that help students to develop cognitive and academic abilities place them at an advantage at the outset of their formal education (see e.g. Gottfried et al., 2015).

Prior studies have demonstrated that as people develop expertise in a domain, prior knowledge, skills and competencies become more important in predicting future knowledge and competencies in that domain, while intelligence becomes less predictive (Detterman, 2014). Our findings indicate that after age 7, intelligence is not predictive of either reading or math achievement after accounting for prior achievement. Despite differences in intelligence, advanced readers continue to be more proficient readers, and higher achieving math students continue achieving higher in math throughout all school years. Although these results may seem obvious, they have important implications. The best way to predict future achievement in math or reading is past performance within the same subject area. Knowing the students' cognitive ability does not necessarily enhance prediction of later achievement. Imagine a scenario in which there is a mismatch between a student's cognitive ability and his/her achievement: a student with high intelligence has low achievement or a student with low intelligence has high achievement. Our results suggest that the achievement level of the student should guide educational interventions. Focusing interventions on increasing academic achievement and the development of academic skills seems more likely to result in long-term academic benefits than attempting to increase cognitive abilities in the hopes that cognitive gains will result in academic improvements.

Intelligence does not contribute to the prediction of later achievement, after controlling for prior achievement. However, it is important to recognize that intelligence does predict later achievement, via the indirect pathway through prior

achievement. Although intelligence does not explain incremental variation in achievement after controlling for prior achievement, intelligence does predict initial achievement, and intelligence and achievement are closely related constructs throughout childhood and adolescence. Therefore, the results of this study affirm the predictive power of intelligence. However, they also suggest that increases in achievement, even in the absence of changes to intelligence or cognitive ability could have meaningful long-term academic benefits. Therefore, interventions that affect early intelligence could have lasting impacts on academic achievement and educational and career success, even if the effects on intelligence dissipate over time.

Finally, for psychologists or educators interested in using intelligence tests during infancy or preschool to predict academic success, we present two relevant findings for reference. First, a latent measure of infant intelligence explains only 32% [$r^2 = (.91 \times .75 \times .83)^2 = .32$] of the variability in math achievement and 26% [$r^2 = (.91 \times .75 \times .75)^2 = .26$] of the variability in reading achievement at the beginning of schooling. Although a latent variable of infant intelligence predicts a latent variable of preschool intelligence, which in turn predicts latent variables of childhood intelligence and achievement, over 2/3 of the variance in math achievement and almost 3/4 of the variance in reading achievement is not explained by infant intelligence. Because infant intelligence measures explain only a small proportion of the variance of later academic achievement, and because infant intelligence measures produce less reliable scores than later IQ tests do, predicting future intellectual and academic performance for a given individual from observed infant cognitive measures is fraught with peril. Similarly, the latent measure of preschool intelligence predicts 38% [$r^2 = (.75 \times .83)^2 = .38$] of the variability in math achievement and 32% [$r^2 = (.75 \times .75)^2 = .32$] of the variability in reading achievement at the beginning of schooling. Thus, preschool intelligence explains a moderate proportion of the variance in elementary school achievement. These results call into question the use of observed scores from early childhood intelligence tests to predict later academic success at the individual level. Further, such results seem very compatible with a talent development framework. Instead of focusing on measuring abilities in early childhood, we should focus on providing enriching environments and multiple opportunities to develop skills and abilities in a variety of academic and non-academic domains.

Educational implications, limitations, and future research

Although intelligence predicts achievement at the beginning of school, academic achievement is impressively stable through the primary and secondary school years, and intelligence plays a much less important role than prior academic performance in predicting subsequent achievement. Students who enter school with strong academic skills tend to maintain their academic advantage throughout primary and secondary education. Likewise, students who enter school at an

academic disadvantage are likely to lag behind their peers throughout elementary and secondary school. Therefore, the educational implications are clear. High-quality early childhood learning experiences for all children are essential for academic success; such programs are particularly important if we hope to narrow achievement gaps among subgroups of students. Furthermore, interventions for improving students' academic achievement should be conducted as early as possible in light of the fact that academic performance is so highly stable across the school years.

A strength of this research pertains to the intensity of measures from infancy through adolescence. Within the longevity of this study, intelligence and achievement were measured repeatedly permitting the analysis of cross-time latent constructs. The constructs were formed by having 13 measures of intelligence spanning from ages 1- through 17-years. Academic achievement was measured from elementary through high school and encompassed 11 annual assessments of reading and math achievement. This allowed for the use of latent variable modeling, which minimizes measurement error and provides a novel perspective on the issues addressed.

However, it worth noting several potential limitations. First, the number of participants was relatively modest. Additionally, the study sample was predominantly white, which represented the demographics in the area at the initiation of the investigation. Future research should seek to determine generalizability of the findings across various populations. However, as noted above, the sample was not restricted to a particular school, school district, or region as the participants resided throughout the United States. Hence, with regard to these aspects, there is apt to be generalizability of these findings.

Future research should investigate other important developmental and educational variables that may play a role in understanding the relation of intelligence and achievement, as well as the stability of achievement itself. Specifically, it is well known that students' intrinsic motivation for learning has considerable stability (i.e. individual differences across time) from elementary through high school (e.g. Gottfried, Fleming, & Gottfried, 2001; Marcoulides, Gottfried, Gottfried, & Oliver, 2008). Perhaps motivation may serve as a factor mediating the stability of achievement and/or cognitive abilities over time. Thus, research should continue to examine the inter-relations among motivational, academic and cognitive variables across the academic life-span using long-term longitudinal designs.

Notes

1. We first calculated z-scores from the age percentile ranks and then rescaled the z-scores into scales scores with the mean of 100 and the SD of 15.
2. The correlation between the reading achievement at age 7 and age 17 was the product of the ten standardized auto-regression path coefficients, which was computed as: $.94 \times .99 \times .99 \times .99 \times .99 \times .97 \times .99 \times .97 \times .96 \times .99 = .80$.

3. The correlation between math achievement at age 7 and age 13 was the product of the six standardized auto-regression path coefficients, which was $.99 \times .95 \times .94 \times .99 \times .96 \times .97 = .82$.
4. The correlation between math achievement at age 14 and age 17 was the product of the three standardized auto-regression path coefficients, which was $.995 \times .995 \times .995 = .985$.

Disclosure statement

No potential conflict of interest was reported by the authors.

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