Growth in reading and math ability: A behavioral genetic analysis

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Abstract

Background: Research shows that mathematics and reading abilities are associated, and while there is evidence showing that individual differences in reading growth are due to environmental influences, this is the first study to examine the genetic and environmental influences on the growth of math ability, and whether or not they are similar to growth in reading ability.

Methods: Participants were drawn from the Western Reserve Reading and Math Project, a study of 314 twin pairs based in Ohio. Twins were assessed at three annual home visits at approximately ages 10, 11, and 12. Assessments included two measures of mathematics performance from the Woodcock Johnson Tests of Achievement III: Calculation and Fluency. Measures were analyzed using a quantitative genetic latent growth curve model. **Results:** Just as was found for growth in reading ability, genetic and shared environmental influences were significant on initial performance (latent intercept) for all three math measures. Shared environmental influences on growth were significant for Fluency and Calculation, while there was no significant influence attributable to genetics. Finally, none of the observed outcomes showed significant genetic or environmental overlap between the intercept and slope.

Conclusions: Genetic influences are important for initial performance, but are not related to growth in mathematics performance. The significant growth observed for Calculation was due to environmental influences. This matches exactly with what was found for reading growth, implying that the two abilities may share influences and should be further studied as such.

Keywords: Growth, mathematics, twin, genetics, environment

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Background

Mathematic skills are important to success in our increasingly technological society (Fuchs, et al., 2008; Geary, 2010; Landerl, Bevan, & Butterworth, 2004; National Mathematics Advisory Panel, 2008). Despite an apparent understanding of the increasing importance of mathematics skills, research has revealed poor average performance in many countries, with extremely low enrollment in math subjects after age 16 (Mazzocco &Myers 2003; Smith 2004). However, mathematics literature has recently begun to grow in breadth and depth, from research on prevention and detection of math disability (Fuchs, 2005) to math' relationship with cognitive ability (Geary, 2004), showing that although having high math ability is related to achievement in other areas, there is a need for more math research.

There is also increasing work on the genetics of mathematics (Petrill, et. al., 2010; Raghubar, Barnes, & Hecht, 2010). This research is able to identify influences on math ability in twin models using a basic understanding of genetic variation in identical and non-identical twins. Identical (monozygotic; MZ) twins share 100% of their additive genetic variance while non-identical (dizygotic; DZ) twins share 50%, on average. Genetic influences on ability are implied if MZ twin resemblance is greater than in DZ twins. Shared environmental influences are suggested to the extent that DZ/MZ resemblance is similar. Nonshared environment (including error) is implied if MZ twins are not perfectly correlated. In particular, twin and adoption studies allow for the examination of the proportion of variance attributable to genetic influences (or heritability; h^2), shared environmental influences (nongenetic influences making siblings more similar; c^2), and nonshared environmental influences (nongenetic influences making siblings different; e^2).

Furthermore, multivariate twin models can be employed to examine genetic and environmental influences on the covariance among math ability and other abilities (i.e. general cognitive ability, reading, and language). Knopik, Alarcon, and DeFries (1997), found a genetic correlation between reading and mathematics performance measures, which helped lay the groundwork in observed mathematics ability as compared to reading ability from a behavioral genetics standpoint (see also, Thompson et al., 1991). Genetic effects on mathematical ability also appear to extend to other learning and cognitive abilities (Docherty, et. al., 2009). For example, multivariate genetic analyses in the TEDS sample out of the UK yielded a genetic correlation of 0.79 between National Curriculum teacher ratings of Mathematics and English; 0.76 between online tests of mathematics and general cognitive ability; and 0.52 between online tests of mathematics and reading comprehension (Docherty, et. al., 2009). Additionally, Hart, Petrill, Thompson, & Plomin (2009) examined the covariance of math with reading ability and general cognitive ability. These researchers observed significant overlap between math problem solving, general cognitive ability, and reading decoding. The authors also demonstrated that mathematics fluency (the ability to compute math facts and problem solve with automaticity and confidence) overlaps with reading fluency and general cognitive ability, as well as evidence that mathematics has influences which are unique from reading and deserve to be studied separately.

It is also necessary to understand the genetic and environmental effects on math ability at or across different time points in our academic development. Genetic and environmental factors are known to contribute to the variance in mathematics ability at each specific time point. Genetic and environmental factors also contribute to the rate at which children make gains in mathematics ability. The degree to which these factors play a role in growth is not necessarily related to their contribution to variance in math ability at each time point, as ability and growth are different constructs. It is also important to show the degree to which the genetic and environmental factors influencing the rate of growth in mathematics ability are independent from those influences on the original level of mathematics ability. For example, Kovas, et. al. (2007) found that genetic factors were important for the stability of mathematics performance across measurement times. However, mathematics performance stability is not the same as development of mathematics performance over time.

Previous literature has also showed evidence for what extent genetic and environmental influences on a given skill (e.g. reading comprehension and language) changes over time (Kovas, Haworth, Dale, & Plomin, 2007; Hart, et. al., 2009; Hart, et. al., 2010; Petrill, et. al., 2010). Petrill et al., 2010, examined genetic and environmental influences on development found that with reading performance in early childhood, both genetic and environmental influences were important to initial performance. However, shared environmental influences were significant for development in reading performance over time. This means that the rate of reading growth over time was significantly influenced by shared environmental influences above and beyond the environmental influences which were acting upon initial performance (Petrill, et al., 2010).

Based on the evidence from the Petrill, et. al. (2010) study, as well as previous work in mathematics performance, the current study aims to be the first to examine the factors influencing growth in mathematics ability in a behavioral genetics framework, using two tasks which measure different aspects of mathematics skill: Calculation and Fluency (Woodcock, McGraw, & Mather, 2001, 2007). Furthermore, this study aims to show evidence for similar genetic and environmental contributions to both reading and math growth. The analyses determine initial status and growth in mathematics performance, then identify the proportion of initial status and growth that are due to genetic and environmental effects, and finally examine how the covariance between intercept (initial status) and slope (growth or change over time) are influenced by genetic and environmental effects. In keeping with the idea that reading and math growth are similar in etiology, it is expected that both genetics and environment will be important for initial mathematics performance, but environmental influences will be important factors in the growth or development of mathematics performance over time.

Method

Participants

The participants for this study were drawn from the Western Reserve Reading and Math Project (WRRMP; Petrill, et. al., 2006; Hart, et. al., 2009), which collects data on twin pairs in Ohio. Twins were recruited into the study during kindergarten or first grade and assessed annually 8 times. The analyses for the Petrill, et. al., (2010) paper were based on a sample of the twins' reading data collected annually over 3 years and beginning when they were approximately 6 years old.

The current analyses were based on a sample of the same twins' math data collected at three annual home visits when the twin pairs were approximately 10, 11, and 12 years old (referred to in this paper as assessments 1, 2, and 3). In this sample, there were 222 monozygotic and 318 dizygotic twins, for a total of 270 pairs of twins. Zygosity was determined using buccal swabs for most families, although some did not consent to genotyping and therefore assessed zygosity through a parent questionnaire (Goldsmith, 1991). Parental permission and child assent were obtained at the time of each home visit. The demographics of this sample indicate that most parents are either married or cohabiting (92%), and most were White (92% of mothers, 94% of fathers). Furthermore, data collected from the parent report of their educational attainment shows that 12% completed high school or less, 18% completed some college, 30%

hold a bachelor's degree, 24% had some postgraduate education or degree, and 5% did not specify.

Procedures and measures

Two trained testers assessed the twins separately on several measures of mathematics performance via three annual home visits (assessments 1, 2, and 3). As part of each visit, we collected Woodcock Johnson III Tests of Achievement: Calculation and Fluency (Woodcock, et. al., 2001, 2007). The Calculation subtest measures the ability to perform mathematical computations with no time limit on items including addition, subtraction, multiplication, division, combinations of these basic operations, as well as some geometric, trigonometric, logarithmic, and calculus operation. Fluency also measures the child's ability to solve addition, subtraction, and multiplication problems, but with a 3-minute time limit. Published median reliabilities for these tests are .85, .89, and .92, respectively (Woodcock, et. al., 2001).

Results

Descriptive Statistics

Descriptive statistics for each measure are presented in Table 1. Standardized means and standard deviations for each measure suggest that this sample is slightly higher than the population mean of 100 and the standard deviations were slightly lower than the population standard deviation of 15. Furthermore, w-scores are presented for each mathematics assessment (Table 1). W-scores were developed by the test publisher using item response theory to provide an index of ability with equal intervals between each variable. This is in contrast to raw variables, where equal intervals cannot be assumed. W-scores show that there is improvement over each annual home assessment for both math measures, suggesting general growth in mathematics performance over time.

Growth Curve Model

Next, a latent growth curve model (Reynolds, et al., 2005) was fit to the data. Linear growth was estimated from this model using the 3 assessment points. Figure 1 shows the model using the calculation measure as an example. Calculation W-scores during each home assessment were loaded on a latent intercept and a latent slope. In order to estimate individual differences among the children in levels of initial mathematics performance, all assessment points were loaded onto the latent intercept (shown as 1's on the model paths), but the intercept was centered at the assessment 1 (when the twins were age 10). The latent slope estimated individual differences in the rate of linear growth (shown as 0, 1, and 2 on the model paths from assessments 1, 2, and 3 to the latent slope). The model estimated a regression equation for each child which included the initial level of mathematics performance (latent intercept) and rate of growth in mathematics performance across the 3 assessments (latent slope). Age at assessment 1 was utilized as a definition variable in the model to account for any age differences with the assessments (Neale, et al., 2002). Definition variables account effect of age on both the variance and the covariance among a set of variables. This strategy is consistent with the Petrill, et al., (2010) study of reading growth.

Table 2 presents the data from Petrill, et. al. (2010), shows that while genetics (h^2 intercept) and shared environment (c^2 intercept) are significantly influencing initial reading performance, only shared environment (c^2 slope) is significantly influencing reading growth over 3 annual assessments.

As presented in Table 3, results exhibit findings similar to those from the reading growth study (Petrill, et. al., 2010). The latent intercept (initial math performance) shows significant genetic and environmental influence, while the latent slope (math growth) shows only significant shared environmental influence (as well as nonshared environmental influence for the Fluency measure).

Additionally, Table 4 was included to show that because the latent slope scores are positive, there was growth across the assessments. Calculation exhibits more growth (mean slope = 32.41) than Fluency (mean slope = 6.92). These scores indicate that while the twins' Fluency scores (*m* = 462.53 at assessment 1) increased by 6.92 points with each annual assessment, Calculation (*m* = 399.90 at assessment 1) increased by 32.41 points with each annual assessment. The w-score means listed in Table 1 show the same pattern of growth, giving support for these findings.

Multivariate Analyses

In addition to examining univariate effects of genetic and environmental influences on latent intercept and slope, this model also examined whether genetic, shared environmental, and/or nonshared environmental sources of variation on the growth of mathematics performance (latent slope) were correlated with or independent from initial mathematics performance (latent intercept). This is demonstrated in Figure 1. The pathways from Factors A, C, and E to the latent slope overlap between intercept and slope, whereas the pathways from Factors a, c, and e to the latent slope do not, and so explain unique sources of variation on the slope. The results of the model for each outcome measure are presented in Table 5. The overlap between the latent intercept and latent slope for each variable was nonsignificant for all 3 pathways; A(genetic), C(shared environmental), and E(nonshared environmental), while the unique pathways for a, c, and e were significant. Because these correlations between intercept and slope are all nonsignificant, it suggests that the genetic and environmental factors influencing the intercepts for each variable are unique from the genetic and environmental factors influencing the slopes for each variable.

Discussion

This current study was the first to examine the genetic and environmental influences on the rate of growth of mathematics performance and compare them to influences on reading growth. The initial level of mathematics performance (latent intercept) was estimated, as well as the rate of growth from that initial level of performance (latent slope), and the correlation between intercept and slope. This data was then compared to the data provided by Petrill, et. al., (2010) regarding genetic and environmental influences on initial reading ability and reading growth over 3 time points.

Our research suggested that both genetic and environmental influences were statistically significant for initial performance on Calculation and Fluency. The fact that both genetics and environment are influencing the latent intercept suggests that our ability at the initial assessment is shaped by both genetic and environmental influences, which was originally hypothesized. This is consistent with findings from the Petrill, et. al. (2010) study of reading.

In the case of growth, w-score means and mean slope suggested that very little growth occurred across the three time points for the Fluency measure, but growth was observed for Calculation. Based on the skill sets needed to complete each of these tasks, an assumption can be made that growth in Calculation may be due to the fact that it requires reading and critical application skills, while Fluency emphasizes automaticity and simple computation. Additionally, the calculation measure introduces increasingly difficult math problems, many of which are a direct result of instruction that is still occurring in the classroom. As exhibited by the mean intercept of Fluency (m = 462.53), students at this age may have already gained a firm understanding of addition, subtraction and multiplication, and can do much of it by our initial assessment as fast as they are ever going to get. This could explain why the Fluency measure grows differently than Calculation. This reasoning can also be assumed due to the findings in previous studies comparing mathematics and reading performance, in which the authors found some overlap in genetic and environmental influences on similar measures, but found that overall, specific measures have differing genetic and environmental influences, especially for measures with significant shared environmental influences (Hart, et. al., 2009), which were found for growth of math in this study.

Nonsignificant genetic effects were observed for the latent slope, which suggests that while genetic influences are important for initial math performance, they do not seem to be as important for growth in mathematics ability over time. There was significant shared environmental variance observed for the latent slope of Calculation and Fluency, indicating that influences such as teacher instruction and educational curriculum may be playing a larger role in growth of mathematics performance than a student's genetic makeup. Again, it is important to note that these findings were similar to the study of reading growth (Petrill, et. al., 2010), which provides evidence that reading and math are influenced by the same genetic and environmental factors.

Furthermore, the genetic and environmental influences on the latent intercept are unique from the influences on the latent slope, as there is no significant overlap for any of the measures. This suggests that the environmental influences shaping initial mathematics performance (at age 10) are not the same as those affecting how much we grow over time. Thus, unique environmental influences, such as educators, classes, schools, and home environment, are related to mathematics performance at age 10 and growth in mathematics performance from ages 10-12.

One limitation of this study is that because the sample was assessed at only 3 time points, these data are limited to linear growth estimates. Further analysis with more assessments could provide results for quadratic growth and perhaps enhance these current findings. Future research may also benefit from the inclusion of measures other than the Woodcock Johnson in order to test whether these results are construct or measure specific. Additionally, this model does not allow us to identify the specific genes and shared environmental influences, but simply to estimate them. Another limitation is the lack of any significant genetic and shared environmental results for the slope of applied problems. This may be due to the fact that we are partitioning the variance of something which has already been partitioned into a latent variable. With nonshared environment being a child specific measure not including error, it is possible that the model is picking up some of these issues and causing the .34 for shared environment to be nonsignificant. Finally, although there was less growth found with Fluency compared to Calculation, the significant influences on the latent intercept suggest that Fluency is still an individual differences predictor at each wave, so it remains an important measure to study longitudinally.

Despite these limitations, the study provides the first comparison of the etiology of growth in reading and math ability by providing estimates of the genetic and environmental influences on initial mathematics performance (at age 10) and rate of growth, and the overlap between initial status and growth. This suggests the need for future research in the realm of growth of mathematics and reading performance, as well as research about educational models for reading and mathematics courses. Future studies will attempt to answer specifically whether or not the genetic and environmental influences on reading and math growth are shared, or if these similarities are solely coincidental.

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Tables and Figures

Table 1

Standardized scores, W-scores, and raw scores for each mathematics measure at assessments 1, 2, and 3

Variable	Standardized Mean	Standardized SD	W-score Mean	W-score SD	n
Calculation					
Assessment 1	106.34	13.25	504.43	15.69	564
Assessment 2	106.49	13.71	515.44	15.09	463
Assessment 3	101.53	14.56	519.65	15.50	324
Fluency					
Assessment 1	101.14	14.69	498.42	7.67	560
Assessment 2	101.46	14.88	502.52	8.33	461
Assessment 3	100.67	15.48	505.97	9.29	333
Age*					
Assessment 1			9.81	.98	582
Assessment 2			10.94	.98	476
Assessment 3			12.17	1.03	378

Note: *Standardized measures were not coded for this measure in this study

Note: W-Scores are presented for Calculation, Fluency, and Applied Problems. Age is reported as a raw variable.

Table 2

Genetic (h^2), Shared Environmental (c^2), and non-shared environmental (e^2) components of the latent intercept and latent slope for reading measures (Petrill, et. al., 2010)

Variable	Latent Intercept			Latent Slope		
	h^2 intercept	c^2 intercept	e^2 intercept	h^2 intercept	c^2 intercept	e^2 intercept
Word ID	0.38* [.25-.55]	0.62* [.44-.74]	0.01 [.00-.04]	0.00 [.00-.10]	1.00* [.90-1.00]	0.00 [.00-.12]
Word Attack	0.38* [.18-.65]	0.60* [.34-.78]	0.02 [.00-.08]	0.09 [.00-.75]	0.91* [.25-1.00]	0.00 [.00-.08]

Note: *Statistically significant from zero using 95% confidence intervals, presented in brackets.

Table 3

Genetic (h^2), Shared Environmental (c^2), and non-shared environmental (e^2) components of the latent intercept and latent slope for math measures

Variable	Latent Intercept			Latent Slope		
	h^2 intercept	c^2 intercept	e^2 intercept	h^2 slope	c^2 slope	e^2 slope
Calculation	0.29* [.06-.59]	0.68* [.39-.88]	0.03 [.00-.11]	0.03 [.00-.58]	0.92* [.38-1.00]	0.05 [.00-.24]
Fluency	0.51* [.29-.78]	0.42* [.16-.62]	0.07* [.03-.13]	0.10 [.00-.71]	0.83* [.24-.98]	0.07* [.00-.26]

Note: *Statistically significant from zero using 95% confidence intervals, presented in brackets.

Table 4

Mean intercept, slope, -2log-likelihood (-2LL), and degrees of freedom (df) for the mathematics performance measures

Variable	Mean intercept	Mean slope	-2LL	*df*
Calculation	399.90	32.41	9613.64	1285
Fluency	462.53	6.92	7767.00	1289
Applied Problems	411.17	30.07	9387.61	1207

Table 5

Genetic, Shared Environmental, and Nonshared Environmental contributions to the correlation between latent intercept and latent slope

Variable	Genetic Pathway ($r_{genetic}$)	Shared Environmental Pathway ($r_{shared\ environment}$)	Nonshared Environmental Pathway ($r_{nonshared\ environment}$)
Calculation	0.09 [-.23-.28]	-0.14 [-.37-.18]	0.04 [-.03-.09]
Fluency	0.23 [-.09-.54]	0.20 [-.11-.50]	0.07 [-.01-.13]

Figure 1. Latent growth curve model.