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Childhood growth in math and reading differentially predicts adolescent non-ability-based confidence: An examination in the SECCYD

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ABSTRACT

Non-ability-based confidence is one of the most pervasive human psychological biases. It is a part of a family of confidence judgments, including overconfidence and metacognitive calibration accuracy, defined by a discrepancy between self-perception of ability and actual ability. Across many domains, most people exhibit some degree of miscalibration in their confidence. Some people may be overconfident and others are underconfident. Despite the prevalence of non-ability-based confidence, relatively little research has investigated how non-ability-based confidence develops and why some people are more or less confident than others despite sharing the same level of ability. We use a longitudinal dataset to explore the childhood predictors of adolescent non-ability-based confidence. Achievement growth in math and reading in childhood was modeled and used to predict adolescent non-ability-based confidence in math and reading. Results show that the initial level of achievement predicts lower non-ability-based confidence in math. On the other hand, a faster rate of achievement growth across childhood predicts greater non-ability-based confidence in reading. These results highlight how previous experiences inform people's self-perceptions over and above their true abilities. Discussion focuses on the factors that shape non-ability-based confidence over the lifespan and the limitations of the current findings.

1. Introduction

Non-ability-based confidence refers to the tendency to believe one's ability is higher or lower than it is in reality. Many people demonstrate some degree of calibration error in their confidence. They can be overconfident, underconfident, or accurately calibrated in their confidence. People claim to be better than most other people in a variety of domains, including intelligence (Alicke et al., 1995), job performance (Harrison & Shaffer, 1994), morality and "goodness" (Allison et al., 1989), friendliness (Alicke et al., 1995), humor (Kruger & Dunning, 1999), grammar (Kruger & Dunning, 1999), physical health (Taylor & Brown, 1988, 1994), and driving ability (Svenson, 1981). On the other hand, individuals faced with having to estimate their likelihood of experiencing rare events, both positive (such as graduating with a 4.0 GPA) and negative (such as receiving a disappointing work evaluation), tend to downplay their skills relative to reality (Kruger & Burrus, 2004). Imposter syndrome reflects a case of underconfidence that is widely observed (especially in academia, Jaremka et al., 2020). Individuals driven by perfectionism experience high levels of anxiety and low levels of self-esteem and confidence, even though they are highly skilled (Cowie et al., 2018; Reis, 1987).

Despite the ubiquitous experience of non-ability-based confidence, there is relatively little research on how non-ability-based confidence emerges developmentally and what makes some individuals generally overconfident and others underconfident. Here, we use high-quality assessments of achievement in the demographically diverse, longitudinal National Institute of Child Health and Development (NICHD) Study of Early Child Care and Youth Development (SECCYD) dataset to investigate the extent to which growth in math and reading across childhood predicts non-ability-based confidence in adolescence.

1.1. What is non-ability-based confidence?

Non-ability-based confidence refers to the discrepancy between a person's confidence in their ability and their actual ability level. Non-ability-based confidence is part of a family of confidence judgments in which a person displays a level of confidence that is not expected given their ability level. Due to the ubiquity of miscalibrated confidence, the phenomenon is well studied across multiple disciplines, albeit with differing names.

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The social psychology and economics literatures generally refer to this discrepancy as overconfidence. In this framework, a person is overconfident when they are more confident than is justified by their actual ability. In this case, overconfidence is driven by biased self-perceptions that are not grounded in actual ability levels. Evolutionary biologists and psychologists who focus on the fitness advantages of overconfidence refer to positive self-views as a part of a suite of self-deception behaviors. The educational psychology literature generally refers to this discrepancy as calibration accuracy within the domain of metacognition. In this literature, five variants of calibration accuracy have been discussed – absolute accuracy, relative accuracy, bias, scatter, and discrimination (see Schraw, 2009 for an overview). Of these five calculations of calibration, absolute accuracy and bias are the ones most closely related to overconfidence and our conceptualization of non-ability-based confidence. Absolute accuracy is the discrepancy between a person's confidence judgment and performance on a specific task in absolute value (i.e., distance from accuracy). Bias refers to the raw magnitude of the discrepancy and can take on positive and negative values, with positive values generally indicating that one is overconfident.

Due to the various labels applied to the construct across disciplinary domains, we use the term non-ability-based confidence to refer to a generic discrepancy between one's confidence and ability. In particular, we model the extent to which individuals report being more or less confident in math or reading than we would expect given their performance in those subjects.

1.2. How is non-ability-based confidence assessed?

Discrepancies, like the one between confidence and ability, can be measured in different ways (Zumbo, 1999). Non-ability-based confidence can be measured as a simple difference score. One value (in this case, ability) is subtracted from another (confidence) to calculate the difference between those two values. In this approach, a positive difference score indicates that an individual's confidence level is higher than their ability level (i.e., overconfident), and a negative difference score indicates that an individual's confidence level is lower than their ability level (i.e., underconfident). For example, individuals could be asked how many visual pattern puzzles they expect to be able to solve in a given period of time to assess their confidence, and ability could be assessed by actually completing the task (Duttle, 2016). If an individual expects to solve 9 problems, but only solves 8, then they are overconfident by 1 problem.

Alternatively, differences can be measured using a residual approach in which one value (confidence) is regressed on the other value (ability). The discrepancy between the two variables is reflected in the residuals. In this approach, positive residuals indicate that an individual has higher confidence than what would be predicted from their ability level, and negative residuals indicate that an individual has lower confidence than what would be predicted from their ability level. The predicted level of confidence is determined based on data from the entire sample of peers. Continuing with the example of solving visual pattern puzzles, participants could report their confidence using a Likert-style scale to respond to questions about their ability to solve these puzzles. In this design, it is not obvious what a confidence score of 4 on a 5-point scale would translate to in terms of correct items. However, regressing the confidence ratings on performance gives the expected confidence given each level of ability.

There are some key interpretive nuances of the two approaches. When using difference scores, it is possible for all individuals to be overconfident or underconfident. Everyone could indicate they will solve many more or many fewer items then they actually can. The sum of the difference could be any number. In contrast, due to the statistical properties of ordinary least squares regression, residuals sum to zero. This mathematical requirement means that some individuals will have positive residuals indicating that confidence is higher than predicted given ability, and some individuals will have negative residuals indicating that confidence is lower than predicted given ability. Both approaches identify non-ability-based confidence as the discrepancy between confidence and performance. They differ in that the difference score approach is often anchored to the objective number of items completed, whereas the residual approach is anchored to the relative confidence of similarly performing individuals.

In this paper, we assess the discrepancy between confidence and ability as the extent to which an individual expresses higher or lower confidence than similarly achieving peers using the residual approach. In the current dataset, confidence and ability were measured on different metrics. Specifically, the confidence items were not anchored by a reference point. The confidence items assess confidence in math and reading generally, rather than in the context of a specific test. Because of this, we cannot directly compare the confidence measure to the performance score. This prevents the assessment of the extent to which confidence exceeds performance on a test as a simple difference score, and hence represents a departure from much existing work on metacognitive judgments. Instead, here we aim to understand why two people with the same level of ability differ in their level of confidence (i.e., one person thinks they are awesome and the other thinks that they are just OK). Although difference scores are the basis of the calculation of absolute accuracy and bias in the educational psychology literature, residual scores are commonly used to assess overconfidence in the social and organizational psychology literatures (Anderson et al., 2012; John & Robins, 1994).[1] We extend the residual approach to a latent variable residual approach with multiple indicators of ability and confidence. Such an approach has been recently suggested as a way to more accurately sample the confidence and ability space (Murphy et al., 2017). Rather than using just one confidence judgment and just one ability measurement, our latent variable residual approach allows for the opportunity to assess confidence in a more multidimensional way and ability in a more comprehensive manner. For example, instead of having the number of math problems that you think you can solve represent your confidence in math and the number of problems that you actually solve represent your ability in math, several confidence judgments and several achievement measurements indicate latent confidence and ability in math. In using latent variables, this approach covers a fuller content domain than previous work.

1.3. Nomological network of non-ability-based confidence

Much of the previous work on the family of confidence judgments to which non-ability-based confidence belongs has focused on the behavior consequences associated with miscalibrated confidence. For example, evolutionary biologists have sought to understand the puzzling prevalence of overly positive self-views (Schwardmann & Weele, 2019; Trivers, 2011; von Hippel & Trivers, 2011). This work proposes that self-deception into higher confidence may have been favored by natural selection to facilitate other-deception and competition over contested resources. Economists, on the other hand, have focused extensively on the effects of overconfident actors on investment decisions and market dynamics (Biais et al., 2005; Glaser & Weber, 2007; Malmendier & Tate, 2008). Organizational behavior scholars, who extend this interest in outcomes to social domains, have found that confidence confers greater perceived social status and leadership potential (Anderson et al., 2012;

[1] As defined here, non-ability-based confidence and over- or under-confidence are distinct, but related, constructs. In the current work, we lack performance metrics to measure the degree to which an individual's confidence is higher or lower than warranted by their true ability, and are thus unable to precisely capture over- or under-confidence (see Methods below). However, conceptually there is likely a great deal of overlap between these related constructs, which are likely to share much of the same links with real-world constructs. Thus, here we discuss prior work on overconfidence.

Anderson & Kilduff, 2009; Kennedy et al., 2013; Tenney et al., 2019). Psychologists, with their focus on the intra-personal consequences of confidence, have likewise revealed a range of mental and physical health benefits (Schunk, 1991; Taylor et al., 2000; Taylor & Brown, 1988) as well as potential costs (Kruger & Dunning, 1999; Robins & Beer, 2001). Educational psychologists have focused on calibration accuracy because of its role in children's learning and success in school. Importantly, children's level of calibration is part of their self-regulation of learning and helps them "monitor their knowledge or skills, establish their own goals for learning, develop plans to achieve their goals, control the deployment of those plans, monitor the progress of their plans, further control the plan if necessary, and judge when they have been achieved" (Hacker et al., 2008, p. 432).

In addition to examining the effects of non-ability-based confidence, work in psychology and related fields has devoted substantial attention to predicting non-ability-based confidence from stable individual difference characteristics. For example, researchers have identified a higher propensity towards inflated self-assessments among men (relative to women) (Barber & Odean, 2001; Dahlbom et al., 2011; Murphy et al., 2015; Murray et al., 2017; Niederle & Vesterlund, 2011) and narcissistic individuals (Campbell et al., 2004; Grosz et al., 2017; Macenczak et al., 2016; Meisel et al., 2016; Paulhus et al., 2003). Additionally, individuals who are tolerant of and take more risks tend to be more overconfident (Broihanne et al., 2014; Nosić & Weber, 2010; Odean, 2002). Similarly, extraversion is associated with greater overconfidence (Schaefer et al., 2004).

Work in the educational and developmental psychology literature has investigated non-ability-based confidence in childhood. Across a number of domains, many studies have demonstrated that children can be overconfident (Lipko et al., 2009; Ozsoy, 2012; Rinne & Mazzocco, 2014). However, this literature rarely discusses the individual difference precursors in the development of non-ability-based confidence. As in adults, gender is a significant predictor of non-ability-based confidence in children with boys having greater levels of calibration bias than girls (Boekaerts & Rozendaal, 2010; Gutierrez & Price, 2017). Maternal education level has also been shown to be a predictor of metacognitive knowledge in childhood (Grammer et al., 2011). Although less studied, there is some evidence that early individual differences predict subsequent non-ability-based confidence. For example, Lockl and Schneider (2007) found that age 3 theory of mind predicted subsequent metacognitive knowledge.

Whereas these associations with non-ability-based confidence were with stable characteristics, we are interested in the development of individual differences that might predict non-ability-based confidence. For example, does the pace of growth in theory of mind, rather than simply performance at age 3, predict non-ability-based confidence? It seems likely that the development of non-ability-based confidence would be guided at least in part by the growth of individual differences related to achievement. Age is a dynamic variable that has been identified as a factor predicting calibration accuracy, though with differing results regarding whether it increases or decreases with age (Flavell et al., 1970; Worden & Sladewski-Awig, 1982). In this paper, we posit that non-ability-based confidence is a developmentally emergent psychological dimension that unfolds in response to individual differences in ability growth.

1.4. A developmental perspective on non-ability-based confidence in education

A better understanding of how and why some people have higher or lower non-ability-based confidence can be gained by examining the period of the lifespan in which people are developing their abilities. A person can have non-ability-based confidence in many different ability domains, such as intelligence, driving, comedy, sports, among many others. In the current work, we assess non-ability-based confidence in academic achievement, specifically in the domains of math and reading. Confidence judgments have been studied in many areas of academic achievement (for a review, see Hacker et al. (2008)).

In general, high achieving students tend to have greater accuracy in their confidence. In the domain of reading, Maki et al. (2005) found that college students with low verbal abilities (as determined by SAT scores, not performance on the ability test) were overconfident about their performance on a highly difficult GRE reading comprehension passage. Conversely, those with medium or high abilities were calibrated in their confidence. When a different set of students was presented with a similar, but less challenging, passage, all of the students, regardless of verbal ability level, were overconfident. The pattern replicates in the domain of math – as a student's achievement level (as measured by overall math grade, not the test on which confidence accuracy was assessed) decreases, overconfidence increases (Lingel et al., 2019). Similarly, a higher percentage of low achieving students were overconfident in math compared to high achieving students (García et al., 2016). Furthermore, in the domain of math, greater calibration has been shown to yield more success. When students have an accurate perception of their own abilities, they are better able to use those abilities to solve the problem (Rinne & Mazzocco, 2014).

Building on this past work showing the link between achievement level and calibration accuracy, we explore growth in achievement as a factor in the development of non-ability-based confidence. Individuals may get to the same level of ability in very different manners. One individual may simply start out at a given level of ability, compared to a peer who was initially much lower in ability, but increased rapidly across schooling. It may be the case that starting at a higher level of ability relative to peers instills a sense of confidence, and this confidence persists even in the face of growth among peers. On the other hand, individuals may be sensitive to the rate of change in their abilities. Some students may increase less rapidly in achievement relative to their peers, a particularly salient experience of childhood. Growth in confidence may simply lag behind the actual growth in achievement. Of course, both of these processes may potentially operate to some extent at the same time. In fact, self-concept (or confidence) and academic ability have been shown to interact with each other in a reciprocal manner. Early self-concept informs later academic achievement, and early academic achievement informs later self-concept to varying degrees (Guay et al., 2003; Marsh et al., 2005; Marsh & Craven, 2006; Marsh & Yeung, 1997). In the current work, we combine self-concept and academic achievement into one construct representing the discrepancy between the two, and explore the developmental process of academic achievement as a precursor to that discrepancy.

Math and reading skills develop rapidly between ages 4 and 8 (Burchinal et al., 2002; Krinzinger et al., 2009). However, within this broad pattern of growth, Burchinal et al. (2002) find that there are significant individual differences in both children's initial level of achievement and their rate of growth in math and reading. During this time of academic growth, children experience significant life changes as they move from a preschool, daycare, or home environment with few achievement-based expectations to elementary school with daily achievement-based expectations. As children interact with teachers and peers in this new environment, they quickly develop their self-concepts and confidence for their individual achievement. Children have a general sense of self-concept and confidence by kindergarten that develops and becomes more domain-specific (e.g., specific to math and reading) as children continue through school (Marsh et al., 1991). Similarly, by first grade, children have a strong sense of how good they are at certain subjects and how well they expect to do in those subject (Eccles et al., 1993). However, children's beliefs about their competence in math and reading, among other domains, decrease between grades 1 and 5 (Eccles et al., 1993; Wigfield et al., 1997).

Wigfield and Eccles (2000) suggest that the development of and changes in these domain-specific self-concepts and expectancy values may also result from children's greater understanding of how to interpret academic feedback and evaluations from teachers, as well as comparison and competition with peers. Therefore, self-concept, or confidence, may not be based exclusively on the child's own accurate perception of their ability level leading to some level of non-ability-based confidence. The development of academic ability and self-concept in childhood, and, consequently, non-ability-based confidence is part of a complex schooling process involving experiences with parents, teachers, and peers.

In this study, we investigate one potential source of non-ability-based confidence, achievement growth. We measure the impact of early achievement and growth on the later expression of non-ability-based confidence. For example, if Jimmy started out at a very high achievement level early in childhood, and Jane started out at a lower level of achievement but had the experience of rapid growth and passing her peers – how much non-ability-based confidence would Jimmy and Jane develop later in adolescence?

Achievement growth may influence non-ability-based confidence if children are aware of inter-individual differences in performance and use this knowledge to update their self-concepts. There is mixed evidence as to how accurately children recognize their own achievement level across childhood. In kindergarten and Grade 1, children's ratings of their own ability and their teacher's (or mother's) ratings are only weakly related, but by second and third grade, these ratings are significantly correlated (Helmke, 1999; Stipek, 1981), indicating increasing accuracy as they age. In fact, by the end of third grade, the relationship between self-ratings of achievement and teacher-ratings of achievement become strongly correlated (Helmke, 1999). The correspondence between self-concept and academic achievement increases consistently with age (Bouffard et al., 1998; Eshel & Kurman, 1991; Guay et al., 2003;), such that by age 10 and 11, children's self-perceived competence in math and reading are moderately to strongly related to their achievement in those domains ($rs = 0.39$–0.56; Stringer & Heath, 2008). This age is around the time that students begin to regularly take standardized tests, at least in the United States which is the context for the current study. Thus, it may be the case that, upon receiving direct information and feedback regarding their abilities from test scores, students gain a more accurate sense of their abilities compared to their peers taking the same tests.

Together, this previous work suggest that younger children are less accurate in their understanding of their own achievement level, but that there is some degree of accuracy that exists at those younger ages, and this grows with age. Even if children are not actively aware of their ability level such that they can accurately report their achievement level, they still likely have some degree of insight into how their abilities compare to that of their peers. As they progress through formal school and begin to understand the assessment system, their awareness of their own abilities likely heightens, and they are more readily able to accurately report their abilities levels. In addition, they may notice how quickly or slowly they are learning at each grade level, compared to their peers. Given the importance of academic development, it follows that these experiences in early achievement may impact a child's level of confidence later in their development.

1.5. Present study

In the present study, we used data collected as part of the NICHD SECCYD to explore childhood achievement growth as a predictor of adolescent non-ability-based confidence. The primary research question was: Does an individual's initial achievement level and subsequent growth in early to middle childhood predict non-ability-based confidence in adolescence? We approached this question in an exploratory fashion and did not have specific a priori hypotheses. However, because non-ability-based confidence is the extent to which confidence exceeds ability, we anticipated that an individual's initial achievement level, as well as their achievement growth, might influence their development of non-ability-based confidence, in line with the aforementioned developmental work. Adolescent confidence was measured using self-reported confidence in two domains, math and reading, on a Likert-type scale. Adolescent ability was measured (on a different metric) by a combination of standardized achievement assessments and teacher-reported grades for math and reading. To avoid problematic inferences due to not fully sampling the confidence and ability space (Murphy et al., 2017) or weak measurement (Westfall & Yarkoni, 2016), we used a structural equation modeling approach to identity latent non-ability-based confidence for math and reading. Then, we used a latent basis growth curve to identify growth in childhood standardized math and reading achievement test scores over four time points. Finally, we used the identified intercept and slope to predict adolescent non-ability-based confidence.

2. Methods

2.1. Participants

Participants in this study are children who took part in the NICHD SECCYD. Parents of the children were recruited to be part of the study after giving birth at one of 10 hospitals across the United States. All children included in the study were born between January and November of 1991. Children were excluded from participation in the study if the mother was under 18 years old, the family planned to move, the child had known disabilities at birth, or the mother did not speak conversational English. More information on the selection and inclusion criteria of participants can be found in technical reports (NICHD Early Child Care Research Network, 2005). The participants were assessed across fifteen assessment waves broken up into four major phases as identified by the research team. There were 1364 children in the first phase of the study (58% of the children initially contacted after birth), 1226 in the second, 1061 in the third, and 1009 children in the final phase. According to past research from the SECCYD, the attrition from phase one to phase four does not produce substantial bias and, thus, is not discussed in the following analyses (NICHD Early Child Care Research Network, 2005). We received approval from the University of Illinois at Urbana-Champaign Institutional Review Board (protocol #19003) to perform secondary data analyses on this dataset. Informed consent of the children was attained by the SECCYD research team.

2.2. Procedure

After being recruited at the hospital, the study children and their parents were assessed at 1 month, 6 months, 15 months, 24 months, 36 months, 54 months, 1st grade, 2nd grade, 3rd grade, 4th grade, 5th grade, 6th grade, 7th grade, 8th grade, and age 15. Data was collected from 1991, when the study children were born, to 2008. Various measures were administered at different timepoints. Depending on the nature of the questionnaire and the age of the child, measures were completed by the study child, their mother, their father, their caregiver, their teacher, their principal, or a research assistant. We made use of all data relevant to our hypothesis which were available at timepoints 54 months, 1st grade, 3rd grade, 5th grade, and age 15. These measures represent only a small subset of the measures included in the full NICHD SECCYD. A comprehensive table of all measures and the timepoints at which they were collected can be found by downloading the "documentation only" at https://www.icpsr.umich.edu/icpsrweb/ICPSR/studies/21940. A visual timeline of the specific measures used in this paper can be found in Fig. 1.

2.3. Measures

2.3.1. Childhood achievement

Achievement in mathematics and reading was measured objectively using the Woodcock-Johnson Achievement Test of Applied Problems and Woodcock-Johnson Achievement Test of Letter-Word Identification, respectively, at four timepoints. The Woodcock-Johnson

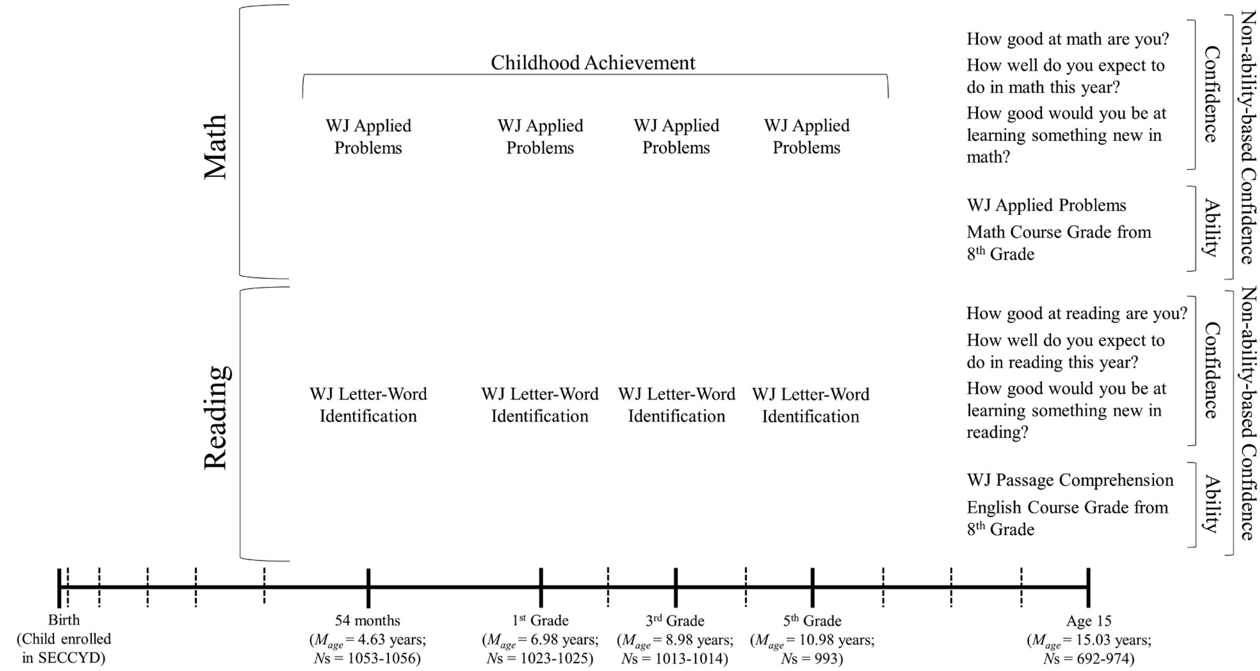


Fig. 1. Timeline indicating the temporal assessment of the childhood achievement measures (that comprise the growth curve model) and the adolescent confidence and ability measures (that comprise the latent residual score model of non-ability-based confidence). The childhood achievement measures were collected at 54 months, 1st Grade, 3rd Grade, and 5th Grade. The adolescent confidence and ability measures were collected at age 15. The non-labeled dashed tick lines represent timepoints when variables not relevant to the goals of this study were measured.

Achievement Tests were administered by a trained research assistant in a lab setting. As participants progress through the test, items increase in difficulty. For the Letter-Word Identification subtest, more difficult items are words that are less common in written English. For the Applied Problems subtest, more difficult items are problems with more difficult calculations. The test continues to get more difficult until the participant fails the six highest difficulty items. Each item on the test is scored as 1 = correct, 0 = incorrect. Raw scores are transformed into W-scores which have a mean of 500, the average test score for a 5th grader. W-scores have the beneficial property of having equal intervals between points on the scale and are appropriate for analyses of developmental growth (Benson et al., 2018).

These measures were administered at 54 months (mean age (M_{age}) = 55.56 months (4.63 years), standard deviation (SD_{age}) = 1.16 months), 1st grade (M_{age} = 83.77 months (6.98 years), SD_{age} = 3.65 months), 3rd grade (M_{age} = 107.87 months (8.98 years), SD_{age} = 3.72 months), and 5th grade (M_{age} = 131.81 months (10.98 years), SD_{age} = 4.01 months). We made use of all timepoints at which the Applied Problems and Letter-Word Identification subtests were administered. None of the Woodcock-Johnson Achievement subtests were administered after 5th grade. We rescaled the W-scores into a metric more familiar to general psychologists, z-scores. In particular, we wanted to center our growth curve on the initial time point of our growth curve, age 54 months. As such, we scaled all W-scores on the basis of the mean and standard deviation of the age 54 months scores. This linear transformation maintains the function of the W-scores. This transformation ensured that longitudinal assessments remained on a similar metric, while enhancing the interpretability of the growth parameters (i.e., in terms of baseline standard deviations). The Woodcock-Johnson Achievement Test of Letter-Word Identification had a Cronbach's alpha of 0.84 at the 54 month timepoint, 0.92 at Grade 1, 0.90 at Grade 3, and 0.88 at Grade 5, indicating high reliability. The Woodcock-Johnson Achievement Test of Applied Problems had a Cronbach's alpha of 0.84 at the 54 month timepoint, 0.83 at Grade 1, 0.81 at Grade 3, and 0.82 at Grade 5, indicating moderately high reliability.

2.3.2. Non-ability-based confidence

Non-ability-based confidence is the extent to which a person's confidence exceeds the level of achievement that is feasible given their actual abilities. Thus, to calculate a non-ability-based confidence score, a measure of confidence and a measure of ability, in this case, math and reading achievement, is needed. We calculate a non-ability-based confidence score for math and reading, separately.

2.3.2.1. Adolescent confidence. Participants' self-rated perceptions of ability in math and reading were assessed at age 15 (M_{age} = 180.31 months (15.03 years), SD_{age} = 1.96 months). The child completed this assessment independently at their home. They were asked to indicate their level of agreement on a 7-point Likert scale (where 1 = not at all good/well, 4 = OK, and 7 = very good/well) with the following three questions:

"How good at math/reading are you?"

"How well do you expect to do in math/reading this year?"

"How good would you be at learning something new in math/reading?"

Participants' raw scores on these confidence items were squared to correct for left skewness. Then, scores were z-score transformed. Following these transformations, we used these items to create latent confidence factors for math and reading separately.

2.3.2.2. Adolescent ability. Separate latent ability factors for math and reading were created from participants' grades in Math and English in 8th grade and their scores on the Passage Comprehension subtest and Applied Problems subtest of the Woodcock-Johnson Achievement Test at age 15 (M_{age} = 180.48 months (15.04 years), SD_{age} = 1.66 months). The Passage Comprehension subtest had a Cronbach's alpha of 0.81 at age 15 and the Applied Problems subtest had a Cronbach's alpha of 0.87. Grades in Math and English were reported by teachers in the Grade 8 Year End Questionnaire (M_{age} = 171.58 months (14.30 years), SD_{age} = 4.57 months). Based on information from participants who

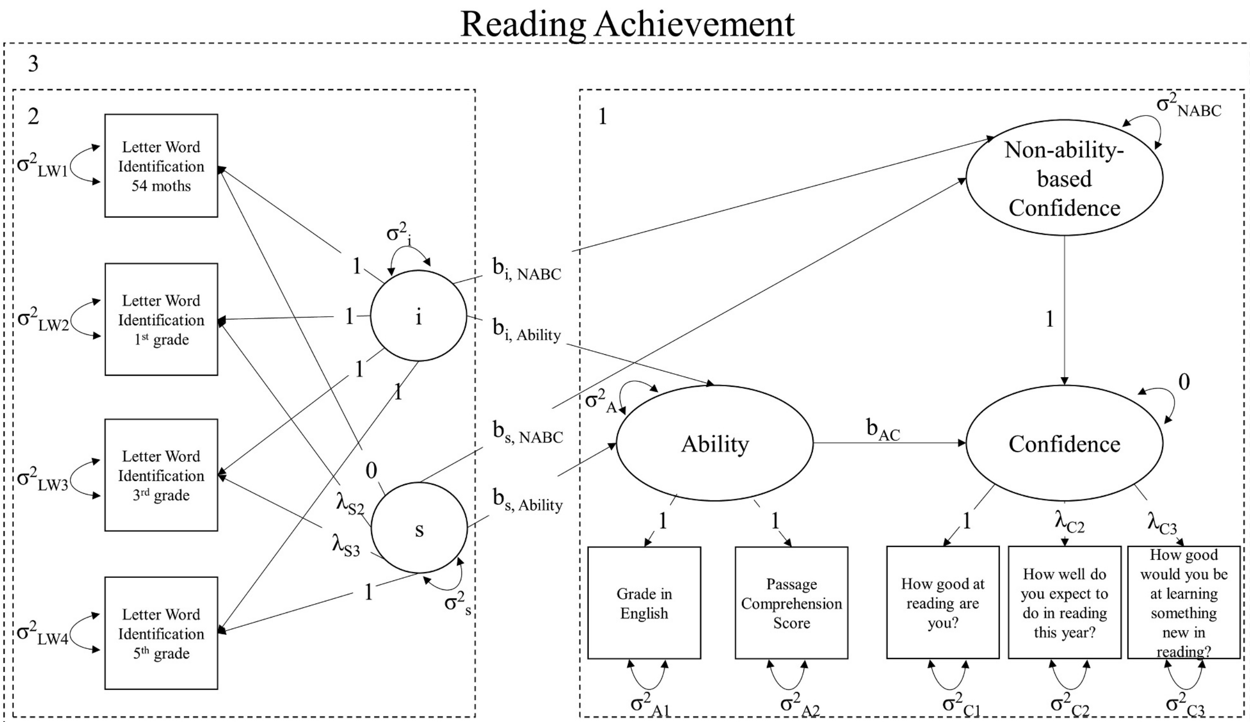


Fig. 2. Example latent residual score model (in box 1 at right) with latent basis growth curve model (in box 2 at left) combined into the full model predicting non-ability-based confidence in reading achievement (box 3).

reported information about their school, we know that there are 511 unique schools. 97% of schools had 3 or fewer children in the study. The greatest number of study participants in one school was 12. Grades were reported in letter grade format; therefore, we converted them into numerical values so they could be used in our analysis. In the conversion, an A+ equaled 98, an A equaled 95, and an A- equaled 92. The scale was similar for Bs, Cs, and Ds, with the first digit replaced by 8, 7, 6, respectively, and an F equaled 58. All variables were z-score transformed.

2.4. Analytic approach

First, to calculate non-ability-based confidence, we used a structural equation modeling approach in which we fixed the pathway from non-ability-based confidence to confidence at 1 and regressed confidence on ability (see Fig. 2, box 1). In this model, the confidence latent factor was identified by three confidence measures (in the order of item presentation in the methods section above). The loading of the first indicator onto confidence in math and confidence in reading was fixed at 1. The loadings of the second and third indicators were freely estimated in the latent residual score model. For ability, there were only two indicators, and their loadings were both fixed at 1 for identification purposes. Typically, latent factors should be indicated by three or more manifest variables. However, there were only two achievement variables for each domain available at the age 15 timepoint. In this latent residual score model, a residual close to 0 indicates that the adolescent reported a confidence level that we would expect given his/her achievement level. A positive residual indicates that the adolescent reported a confidence level greater than what we would expect given the achievement level and a negative residual indicates that the adolescent reported a confidence level lower than what we would expect given the achievement level.

Second, we modeled growth in mathematics and reading achievement using a latent basis growth model to account for the nonlinear increase in achievement. Using children's scores on the same Woodcock Johnson Achievement Test (the Applied Problems subtest to assess math and the Letter-Word subtest to assess reading) administered at 54 months, 1st grade, 3rd grade, and 5th grade, we estimated the intercept and slope of growth separately for each domain. We fixed the 54 month loading of the slope at 0, the 5th grade loading of the slope at 1, and freely estimated the 1st grade and 3rd grade loadings of the slope (Fig. 2, box 2).

Finally, we combined the latent residual score model with the latent basis growth curve model to explore how growth in early achievement predicts later non-ability-based confidence. We regressed non-ability-based confidence from the latent residual score model onto the intercept and slope. These models estimated whether the achievement level at which children start in early childhood predicts their adolescent non-ability-based confidence and whether children's growth in achievement over childhood predicts adolescent non-ability-based confidence. Additionally, we regressed age 15 ability on the intercept and slope of the growth model (Fig. 2, box 3).

In the combined model for math, we also included a regression pathway from the intercept and slope of growth to Applied Problems score at age 15. In the SECCYD dataset, the Applied Problems subtest was the only mathematics-based subtest that was administered at multiple timepoints in childhood (used in the latent basis growth model). It was also the only mathematics-based subtest that was administered at age 15 (used in the latent residual confidence score). It follows that the age 15 Applied Problems score would be related to growth in the Applied Problems score during early childhood over and above the association implied via the latent age 15 ability factor which represents shared variance with end of year grades. This additional regression pathway was not included in the reading model because the same subtest was not used for both the confidence model and the growth model.

All analyses were conducted using M*plus* version 8.2 (Muthén & Muthén, 1998). We use structural equation modeling (SEM) with maximum likelihood estimation with robust standard errors (MLR) for all models. SEM is robust to violation of assumptions, especially with large sample sizes like those in the present study. Some of our variables (grades in Math and English and the confidence items, in particular)

Table 1
Descriptive statistics and correlations for observed variables.

	n	*M*	*SD*	*r*																	
				1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18
1. Math grade (age 14.30 years)	695	83.532	10.258	1.000																	
2. English grade (age 14.30 years)	692	84.392	10.544	0.646	1.000																
3. Passage comprehension (age 15 years)	887	520.364	12.475	0.396	0.349	1.000															
4. Applied problems (age 15 years)	887	524.568	16.772	0.395	0.440	0.688	1.000														
5. How good at math are you? (age 15 years)	974	5.191	1.458	0.203	0.377	0.223	0.414	1.000													
6. How good at reading are you? (age 15 years)	974	5.682	1.332	0.147	0.050	0.333	0.162	−0.007	1.000												
7. How well do you expect to do in math this year? (age 15 years)	974	5.371	1.369	0.207	0.330	0.113	0.282	0.745	0.050	1.000											
8. How well do you expect to do in reading this year? (age 15 years)	974	5.653	1.263	0.249	0.112	0.162	0.075	−0.007	0.552	0.166	1.000										
9. How good would you be at learning something new in math? (age 15 years)	974	5.112	1.435	0.189	0.315	0.160	0.347	0.774	0.086	0.737	0.101	1.000									
10. How good would you be at learning something new in reading? (age 15 years)	974	5.575	1.309	0.179	0.039	0.179	0.054	−0.067	0.608	0.023	0.686	0.064	1.000								
11. Applied problems (age 54 months/4.5 years)	1053	424.716	19.272	0.334	0.346	0.518	0.493	0.212	0.146	0.138	0.056	0.142	0.067	1.000							
12. Letter-word identification (age 54 months/4.5 years)	1056	369.363	21.413	0.271	0.240	0.460	0.455	0.141	0.219	0.110	0.087	0.121	0.125	0.560	1.000						
13. Applied problems (age 84 months/7 years)	1023	470.046	15.541	0.310	0.315	0.557	0.638	0.300	0.131	0.180	0.042	0.233	0.071	0.602	0.505	1.000					
14. Letter-word identification (age 84 months/7 years)	1025	452.585	23.990	0.260	0.232	0.485	0.446	0.102	0.295	0.074	0.156	0.079	0.179	0.435	0.562	0.576	1.000				
15. Applied problems (age 108 months/9 years)	1013	497.332	13.187	0.320	0.337	0.564	0.664	0.285	0.132	0.178	0.086	0.201	0.059	0.561	0.452	0.689	0.530	1.000			
16. Letter-word identification (age 108 months/9 years)	1014	493.863	18.730	0.244	0.227	0.596	0.505	0.107	0.391	0.064	0.202	0.066	0.219	0.478	0.510	0.533	0.753	0.612	1.000		
17. Applied problems (age 132 months/11 years)	993	509.825	12.846	0.327	0.354	0.638	0.740	0.315	0.167	0.150	0.063	0.213	0.039	0.558	0.442	0.698	0.502	0.780	0.584	1.000	
18. Letter-word identification (age 132 months/11 years)	993	510.119	17.520	0.273	0.188	0.625	0.521	0.095	0.420	0.030	0.217	0.059	0.245	0.453	0.494	0.516	0.665	0.595	0.863	0.560	1.000

Note: All descriptive statistics were performed using raw data.

were not normally distributed by nature. Using SEM and MLR helps assuage these concerns.

3. Results

Descriptive statistics and correlations among study variables are reported in Table 1. As can be seen, the age 15 ability measures (Math grade, English grade, passage comprehension score, and applied problems score) are moderately to strongly correlated. Similarly, the three age 15 confidence items are highly correlated within domain. The childhood achievement scores for math and reading are strongly correlated within timepoint (e.g., applied problems score at age 54 months and letter word identification score at age 54 months) and within domain (e.g., applied problems score at age 54 months and applied problems score at 1st grade).

3.1. Non-ability-based confidence

Non-ability-based confidence in adolescence was calculated as the portion of confidence that is unexplained by achievement using a latent residual score approach. Non-ability-based confidence in math and reading was calculated separately. The fit statistics of the latent residual score models for math and reading are reported in Table 2. Both models fit relatively well (math: $n = 1009$, $\chi^2(5) = 26.717$, $p < .001$, CFI = 0.985, RMSEA = 0.066; reading: $n = 1008$, $\chi^2(5) = 63.521$, $p < .001$, CFI = 0.940, RMSEA = 0.108).[2] Non-ability-based confidence in math had a variance of 0.513 ($p < .001$) and non-ability-based confidence in reading had a variance of 0.429 ($p < .001$), which, as expected, suggests that adolescents vary in their degree of non-ability-based confidence in math and reading at age 15. In Figs. 3 and 4, we report the standardized loadings and regression coefficients for the reading and math latent residual score models, respectively. The unstandardized loadings and regression coefficients can be found in Table 2.

3.2. Growth curve models

3.2.1. Math

The latent basis growth curve model for achievement in math fit very well ($n = 1154$, $\chi^2(3) = 3.678$, $p = .2984$, CFI = 1.000, RMSEA = 0.014). The freely estimated loadings for the slope of math achievement were estimated at 0.529 for the 1st grade score and 0.851 for the 3rd grade score, suggesting that math achievement grows rapidly in early childhood and then slows down in middle childhood. About 53% of the change in achievement from 54 months to 5th grade occurs from 54 months to 1st grade, 32% of the change occurs from 1st to 3rd grade, and 15% of the change occurs between 3rd and 5th grade. In this model, the intercept of math growth has a mean of -0.014 ($p = .654$) and variance of 0.643 ($p < .001$), which indicates that children differ significantly in their initial level of math achievement at 54 months. The slope of math growth has a mean of 4.431 ($p < .001$) and variance of 0.194 ($p < .001$), which indicates that children's math achievement grows in childhood on average approximately 4 standard deviation units of baseline math variability from 54 months to 5th grade but that children differ in their individual rates of math achievement growth.

3.2.2. Reading

Although the RMSEA value was relatively high, the CFI of the latent basis growth curve model for achievement in reading indicated excellent fit ($n = 1154$, $\chi^2(3) = 98.799$, $p < .001$, CFI = 0.957, RMSEA = 0.166). Examining residuals indicated that the model well captured the mean level trends and majority of error came from covariance structure (Yuan et al., 2019).[3] The freely estimated loadings for the slope of reading achievement were estimated at 0.589 for the 1st grade score and 0.883 for the 3rd grade score. Like math achievement growth, a large proportion of the growth in achievement in reading occurs in early childhood (59% of the change in childhood achievement in reading occurs between 54 months and 1st grade) with relatively less growth occurring in middle childhood (29% of change from 1st to 3rd grade and 12% of change from 3rd to 5th grade). In this model, the intercept of reading growth has a mean of 0.001 ($p = .967$) and variance of 0.739 ($p < .001$), which means that children differ in their initial level of reading achievement at 54 months. The slope of reading growth has a mean of 6.577 ($p < .001$) and variance of 0.029 ($p < .001$), which means that children's reading achievement improves in childhood and that children differ in their individual rates of reading achievement growth. See Fig. 5 for a visual representation of the growth curves for math and reading. In this figure, we plot the applied problems and letter word identification data from 50 randomly chosen individuals overlaid with the model implied trend line. The figure shows that the segment of growth from 54 months to first grade is the steepest for both domains and then the line becomes flatter at each timepoint representing a slowing down of growth.

3.3. Predicting non-ability-based confidence in adolescence from childhood achievement

3.3.1. Math

The model predicting adolescent non-ability-based confidence in math from childhood growth in math achievement had good fit ($n = 1156$, $\chi^2(22) = 76.918$, $p < .001$, CFI = 0.988, RMSEA = 0.046). Non-ability-based confidence in math was significantly negatively predicted by the intercept of achievement in math growth ($\beta = -0.598$, $p = .020$). Children who start out at a higher level of achievement in math at 54 months have lower levels of non-ability-based confidence at age 15 than children who start out at a lower level of achievement. This effect of math intercept on math non-ability-based confidence is considered a large effect size based on commonly used benchmarks (Bosco et al., 2015; Gignac & Szodorai, 2016). Non-ability-based confidence in math was not significantly predicted by the slope of achievement in math growth ($\beta = -0.116$, $p = .538$). Children who grew more quickly in their math achievement over childhood do not seem to have greater levels of non-ability-based confidence than those who grow at a slower rate.

3.3.2. Reading

The model predicting adolescent non-ability-based confidence in reading from growth in reading achievement over early and middle childhood also had adequate fit ($n = 1156$, $\chi^2(25) = 306.339$, $p < .001$, CFI = 0.928, RMSEA = 0.101). In this model, non-ability-based confidence in reading was significantly predicted by the slope of reading achievement growth over childhood ($\beta = 0.208$, $p = .006$). Children who grew in their reading achievement across childhood faster than others had greater levels of non-ability-based confidence at

[2] Based on the residuals, we correlated the Passage Comprehension score with the response to "How good at reading are you?". This was the largest residual in the model. When we do this, the fit of the model improves ($\chi^2(4) = 7.606$, $p = .107$, CFI = 0.996, RMSEA = 0.030). None of the conclusions differ between the original model and this modified model. Because the modifications were data driven and because the CFI of the original model was good, we decided to retain the initial specification.

[3] Based on the residuals, we correlated Grade 1 and Grade 3 Letter Word scores. This was the largest residual in the model. When we do this, the fit of the model improves ($\chi^2(2) = 19.145$, $p < .001$, CFI = 0.992, RMSEA = 0.086). None of the conclusions differ between the original model and this modified model. Because the modifications were data driven and because the CFI of the original model was good, we decided to retain the initial specification.

Table 2
Model parameters and fit statistics for math and reading models.

	Math						Reading					
	Latent residual score model		Latent basis growth curve model		Latent residual score model + latent basis growth curve model		Latent residual score model		Latent basis growth curve model		Latent residual score model + latent basis growth curve model	
Factor loadings												
Ability												
λ_{A1}	at 1.000		–		at 1.000		at 1.000		–		at 1.000	
λ_{A2}	at 1.000		–		at 1.000		at 1.000		–		at 1.000	
Confidence												
λ_{C1}	at 1.000		–		at 1.000		at 1.000		–		at 1.000	
λ_{C2}	0.933	(0.028)	–		0.933	(0.028)	1.118	(0.052)	–		1.088	(0.053)
λ_{C3}	0.972	(0.028)	–		0.972	(0.027)	1.207	(0.054)	–		1.172	(0.056)
Intercept												
λ_{I1}	–		at 1.000		at 1.000		–		at 1.000		at 1.000	
λ_{I2}	–		at 1.000		at 1.000		–		at 1.000		at 1.000	
λ_{I3}	–		at 1.000		at 1.000		–		at 1.000		at 1.000	
λ_{I4}	–		at 1.000		at 1.000		–		at 1.000		at 1.000	
Slope												
λ_{S1}	–		at 0.000		at 0.000		–		at 0.000		at 0.000	
λ_{S2}	–		0.529	(0.004)	0.530	(0.004)	–		0.589	(0.004)	0.589	(0.004)
λ_{S3}	–		0.851	(0.003)	0.851	(0.003)	–		0.883	(0.002)	0.883	(0.002)
λ_{S4}	–		at 1.000		at 1.000		–		at 1.000		at 1.000	
Regression coefficients												
Confidence on ability												
b_{AC}	0.796	(0.081)	–		1.568	(0.362)	0.425	(0.067)	–		0.265	(0.119)
Non-ability-based confidence on intercept												
$b_{I,NABC}$	–		–		−0.587	(0.2788)	–		–		0.113	(0.101)
Non-ability-based confidence on slope												
$b_{S,NABC}$	–		–		−0.198	(0.324)	–		–		0.202	(0.078)
Means & variances												
Non-ability-based confidence												
M_{NABC}	at 0.000		–		–		at 0.000		–		–	
σ^2_{NABC}	0.513	(0.044)	–		–		0.429	(0.033)	–		–	
Intercept												
M_I	–		−0.014	(0.031)	−0.015	(0.031)	–		0.001	(0.031)	−0.002	(0.031)
σ^2_I	–		0.643	(0.050)	0.653	(0.050)	–		0.739	(0.065)	0.774	(0.065)
Slope												
M_S	–		4.431	(0.026)	4.433	(0.026)	–		6.577	(0.029)	6.580	(0.029)
σ^2_S	–		0.194	(0.038)	0.213	(0.039)	–		0.441	(0.070)	0.495	(0.069)
Correlations												
Intercept with Slope												
r_{IC}	–		−0.239	(0.037)	−0.252	(0.037)	–		−0.263	(0.062)	−0.309	(0.062)
Fit statistics												
χ^2	26.717		3.678		76.918		63.521		98.799		306.339	
df	5		3		22		5		3		24	
CFI	0.985		1.000		0.988		0.940		0.957		0.928	
TLI	0.971		0.999		0.980		0.881		0.914		0.891	
RMSEA	0.066		0.014		0.046		0.108		0.166		0.101	

Note. Unstandardized parameter estimates shown with standard errors in parentheses.

age 15. This effect of reading growth on reading non-ability-based confidence is considered a medium effect size based on commonly used benchmarks (Bosco et al., 2015; Gignac & Szodorai, 2016). However, children's initial level of reading achievement at 54 months did not predict later non-ability-based confidence ($\beta = 0.146$, $p = .251$).

Given the differences in these patterns of results, we also inspected the strength of the relation between non-ability-based confidence in math and non-ability-based confidence in reading. The correlation between non-ability-based confidence in math and non-ability-based confidence in reading was significant ($r = 0.138$, $p = .003$), but fairly small based on commonly used benchmarks of effect size (Bosco et al., 2015; Gignac & Szodorai, 2016). This relatively small correlation suggests that non-ability-based confidence is quite different in the two domains of reading and math. Thus, it is entirely plausible that the predictive relation between early achievement growth and non-ability-based confidence is different in the two domains.

3.4. Gender differences

We ran a gender moderation version of the combined growth and non-ability-based confidence model for each domain. We estimated whether gender moderated the pathways between non-ability-based confidence and the intercept and the slope of achievement. We found no evidence of gender moderation of any path related to non-ability-based confidence (p's > 0.668 for math, p's > 0.631 for reading). This result implies that the associations between non-ability-based confidence and earlier development are similar for boys and girls. However, we did find gender differences in non-ability-based confidence: boys tended to have more non-ability-based confidence in math, but less in reading.

4. Discussion

This study demonstrated that children's individual achievement in early childhood and growth across childhood predicted their later non-

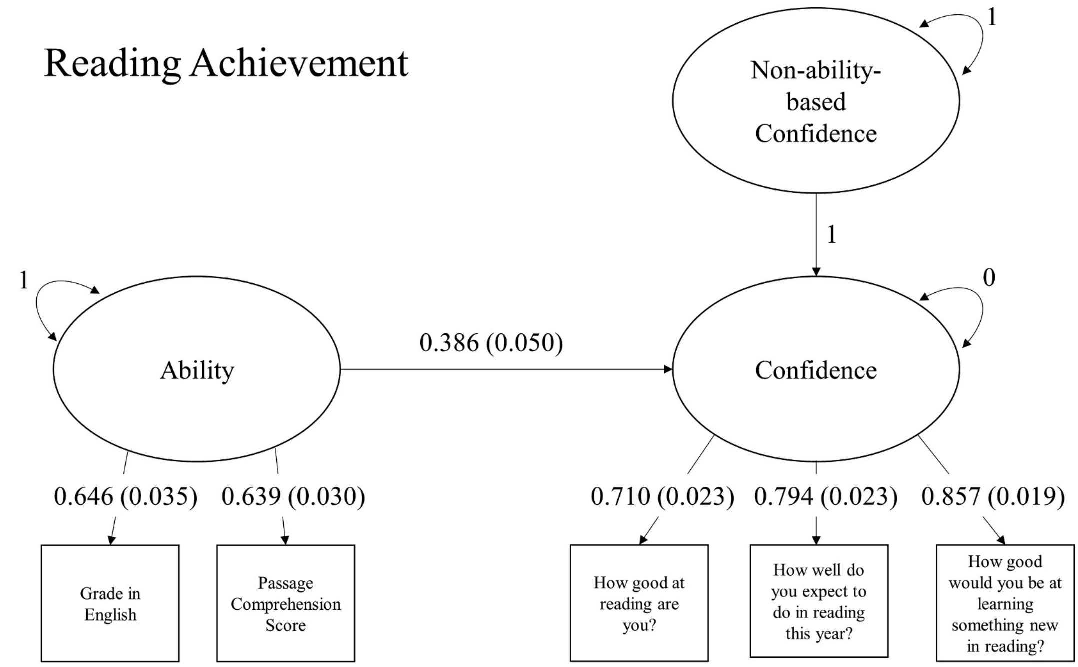


Fig. 3. Latent residual score model of non-ability-based confidence in reading. Standardized parameter estimates shown with standard errors in parentheses.

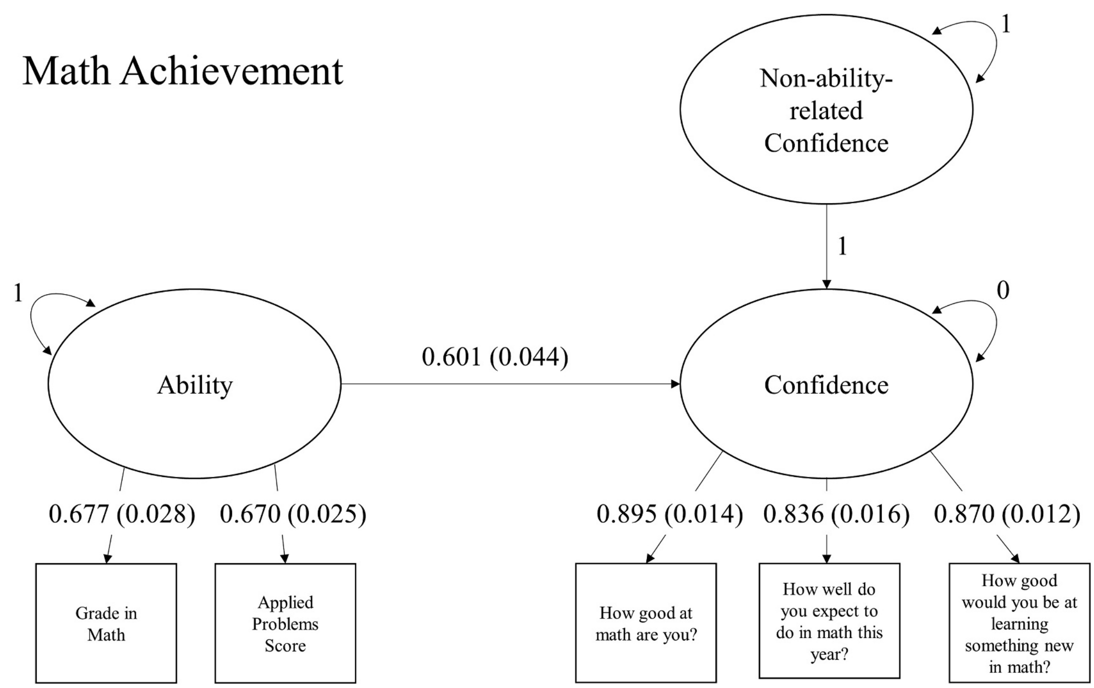
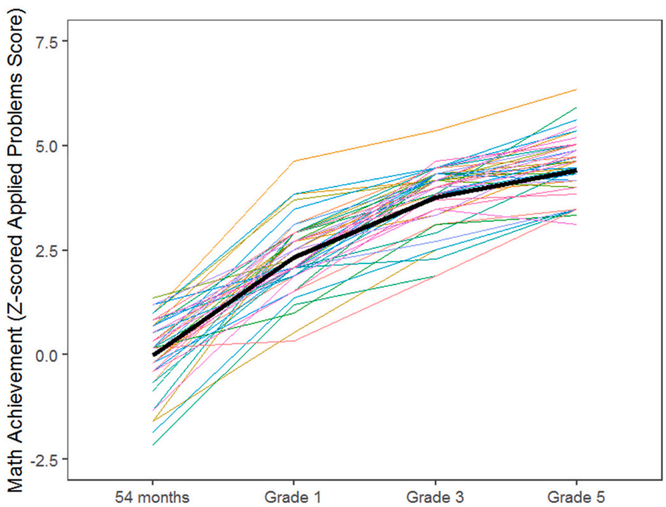


Fig. 4. Latent residual score model of non-ability-based confidence in math. Standardized parameter estimates shown with standard errors in parentheses.

ability-based confidence at age 15, though the pattern differed across domains. In math, children's initial level of achievement negatively predicted adolescent non-ability-based confidence. Children who scored higher on the Woodcock Johnson Applied Problems subtest at 54 months expressed less confidence at age 15 than peers who have the same level of performance. In reading, children's achievement growth over childhood positively predicted adolescent non-ability-based confidence. Children who grew faster in early and middle childhood expressed more confidence than would be expected given their performance at age 15. Interestingly, non-ability-based confidence in math was only correlated modestly with reading, highlighting the unique trajectories of math and reading development.

4.1. Potential explanations of divergent findings for math and Reading

Previous work suggests that although math and reading are significantly and strongly related, they are not perfectly correlated. A recent meta-analysis of over 368,000 individuals showed that the correlation between math and language is only $r = 0.42$ (Peng et al., 2020). In our data, the correlations between math and reading achievement at each wave are slightly higher ($r = 0.560$–0.688; see Table 1); however, they are still not perfectly correlated. The development of language and math skills mutually inform one another; however, they do not grow at the same pace or to the same level of ability. Given that the domains themselves differ, it is not surprising that the development of non-



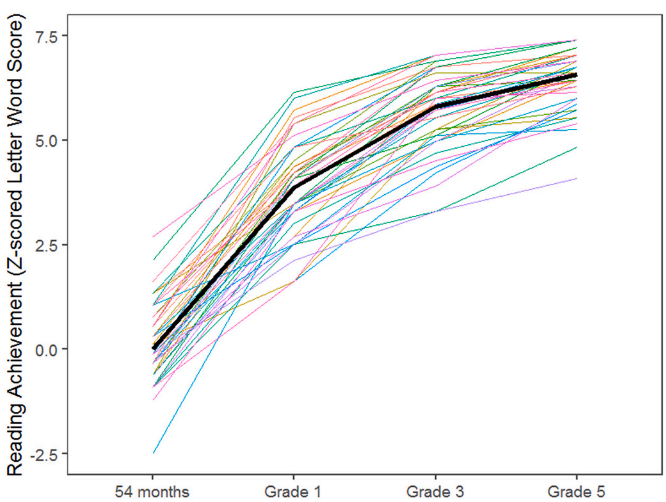


Fig. 5. Growth trajectories for 50 randomly chosen individuals (thin lines), overlaid with the model implied growth curve (thick line) for math (top) and reading (bottom). For most individuals, the slope of the curve is steepest between the 54 month and Grade 1 timepoints, representing the greatest amount of achievement growth in both domains. The slope of the curve becomes flatter at each subsequent timepoint, representing achievement growth slowing down. Note: the y-axis in these figures is standardized based on wave 1 (54 month) means and standard deviations (as specified in the Methods section).

ability-based confidence within those domains differs.

The pattern of results for math shows that kids who start out at higher levels of achievement at 54 months tend to become adolescents with lower levels of non-ability-based confidence. This finding mirrors much of the previous research on overconfidence and calibration. Ghazal et al. (2014) found that individuals who are more numerate (an ability closely related to math ability) are less overconfident. Lingel et al. (2019) demonstrated that students with lower achievement levels in math are more likely to be overconfident in the same domain. Cho (2017) similarly showed that both males and females with higher math ability have lower levels of overconfidence. Each of these studies, however, was cross-sectional and thus, the current paper adds to this body of work by demonstrating a developmental trajectory of achievement that predicts non-ability-based confidence. It is likely that the child's initial level of math achievement at 54 months is an early link in a causal chain that leads to lower non-ability-based confidence later in adolescence. Because some amount of ability is stable, the 54 month assessment is a (weak) proxy for the level of achievement at age 15 ($r = 0.33$ in the current sample), and importantly, throughout earlier schooling. We do not suggest that it is the 54 month assessment alone that yields low non-ability-based confidence 10 years later. Instead, it may be that students who do well in early childhood also tend to be well-liked and are praised by their teachers because of their high abilities. For example, they may be called on to answer more questions and their own questions are answered more frequently, or they may be more often asked to assist other students and practice their skillsets, and consequently have more opportunities to learn. These patterns reinforce the ability differences between students that are relatively stable over time. The children who are high math achievers at age 54 months are likely to also be high math achievers at age 15, at which point the previous cross-sectional literature notes that high math achievement predicts lower non-ability-based confidence in math.

One possible explanation for why high early math achievers have lower levels of non-ability-based confidence at age 15 is that they might have greater awareness of what they do and do not know about math. For example, they may be aware that they know algebra, but do not know geometry, statistics, calculus, etc. This awareness, in turn, may yield a lower level of confidence about how much they know about math that is outpaced by the individual's ability level. In contrast, students who did poorly in math at an early age may believe that they are good at math at age 15 because their first semester of algebra was a breeze relative to their past math experiences, when in reality they are still performing less well than their peers. More research is needed to uncover the mechanisms that link high early math achievement with low later non-ability-based confidence in math.

In the reading domain, we found that children who grew faster in their reading achievement developed higher levels of non-ability-based confidence at age 15. These children may be growing so quickly in their reading achievement that they overestimate how quickly they will continue to grow. As reported in the growth curve of reading achievement, growth slows down dramatically between 3rd and 5th grade, compared to growth from 54 months to 1st grade to 3rd grade. Extrapolating from this pattern, we would expect that growth would continue to slow down as children approach adolescence. Thus, an overestimation of growth would yield a discrepancy between what the child/adolescent believes their achievement level will be and what the actual achievement level will be given the trajectory of growth. In this case, non-ability-based confidence develops from rapid, but unsustainable, achievement growth.

More work is needed to better understand the mechanisms that produce divergent trends for math and reading. There are likely many other processes that play a role in the development of a complex outcome like non-ability-based confidence which merit further study.

4.2. Limitations

This study has a number of important strengths: a large sample size, longitudinal design over five timepoints in childhood and adolescence, use of latent variable approaches (Murphy et al., 2017; Westfall & Yarkoni, 2016), and standardized assessments of ability. Of course, there are some important limitations to consider.

This study employed a correlational design. Although our results reveal that higher early math achievement predicts lower non-ability-based confidence and that faster reading growth predicts higher subsequent non-ability-based confidence, we cannot infer causality.

Several limitations arise from our use of a secondary dataset not designed specifically for testing the research questions explored in this paper. In the current study, confidence was measured using subjective 7-point Likert scale ratings on items such as “how good at math/reading are you” and “how well do you expect to do in math/reading this year.” On such items, there is no objective metric for evaluating whether a participant is correct or incorrect in their assessments. This is unlike the case where participants are instead asked “how many questions did you answer correctly on the quiz," for which there is a definitive, objective answer against which to anchor the confidence judgment. Confidence scales such as these included in the SECCYD dataset do not allow for nuance and therefore, may yield imprecise estimates of confidence and subsequently non-ability-based confidence (Lingel et al., 2019). Other work has similarly employed confidence measures that lack objective reference (Lyons et al., 2020). Nevertheless, this is an issue that should be addressed in future work using more refined measures of confidence.

Another limitation that arises from the design of the dataset is that there were only two indicators of adolescent achievement available. Typically, latent factors should be indicated by three or more manifest variables. Because we only had two indicators of achievement, we had to fix the loadings to be equal in order to fit the model. In reality, it is likely that the measured variables load differently onto their latent factor. However, our use of a latent variable approach allowed us to isolate and model the common variance of the achievement measures.

Additionally, in using Math and English grades as one of the indicators of achievement, we made some assumptions about what each letter grade meant numerically. Though we used a standard letter grade to numerical value conversion, it is possible that in some schools the letter grades equaled different numerical values in which case we may be over- or underestimating some students' level of non-ability-based confidence. We should also keep in mind that grades in Math and English, may represent more than just academic ability. Often, grades, especially those earned in early adolescence, include the students' participation in the class and effort on homework assignments. These additional factors represent something in addition to a student's achievement in math or reading – perhaps their conscientiousness (Poropat, 2009). We cannot disentangle achievement from effort and conscientiousness in student grades and thus, we should use caution when interpreting the results.

Our growth curve models are also limited by the data available to use in this secondary dataset. The Woodcock-Johnson Achievement Tests of Applied Problems and Letter-Word Identification, which were the basis of the growth curve models, were only administered at the 54th month, 1st grade, 3rd grade, and 5th grade timepoints. If these assessments had been administered in the middle school years, we may have gotten a more robust picture of how math and reading grow up until the age 15 timepoint at which non-ability-based confidence measured. Furthermore, these additional datapoints, which are closer in time to the non-ability-based confidence outcome, may have a greater impact on the development of non-ability-based confidence and associated behaviors such as choices about classes to take, subjects to major in, and amount of time to study.

Finally, we acknowledge limitations in the fit of the models presented. In all of the models, the chi-square value and *p*-value indicate poor fit. However, this is because the chi-square test is sensitive to large sample sizes like ours, wherein models with more than 400 cases general yield statistically significant chi-square values. Thus, we would not expect a non-significant chi-square statistic given our large sample (Schermelleh-Engel et al., 2003). The RMSEA for the models in the domain of reading also indicated mediocre fit as they exceeded a common rule of thumb of 0.08 (Hooper et al., 2008). However, while the fit of the models could be better by chi-square value and RMSEA in the domain of reading, we have excellent fit by CFI. Rules of thumb for model fit should be interpreted in the context of a specification analysis intended to identify where the misfit occurs in the model (Marsh et al., 2004). Importantly, our sensitivity analyses indicated that our results were not affected by issues of fit.

Beyond the limitations of the data set and resulting models themselves, we also must acknowledge the known limitations about the family of confidence judgments to which non-ability-based confidence belongs. One of those confidence judgments, overconfidence, is susceptible to the hard-easy effect where individuals show greater overestimation on hard tests than on easy tests, on which people generally underestimate their performance (Lichtenstein et al., 1982; Merkle, 2009). This effect is due to an insensitivity to task difficulty. Individuals do not adjust their confidence appropriately when tasks become more or less difficult while achievement on those tasks vary largely. This produces large discrepancies between confidence and ability on difficult tests compared to easy tests. In addition, the metacognitive literature has shown robust underconfidence with practice effects (Koriat et al., 2002). Whereas one would expect that after practice, people become more calibrated in their confidence, in fact, there is effect where the discrepancy between confidence and ability increases in the underconfidence direction after practice. This effect is rather counterintuitive and calls into question how confidence, ability, and learning influence one another. Additionally, researchers have found that, depending on how the data are analyzed, both overconfidence and underconfidence can be demonstrated in the same data set (Erev et al., 1994). In fact, these researchers argue that this finding suggests the possibility that overconfidence and underconfidence are statistical artifacts, not true effects, produced by data analysis choices. However, there is disagreement as other researchers find over- and underconfidence to be true effects, not statistical illusions to be ignored (Ayton & McClelland, 1997; Brenner, 2000). With these cautions in mind, we believe that non-ability-based confidence is a true effect that many individuals experience and thus, understanding the developmental precursors is an important research area.

4.3. Future directions

Future research should continue to explore the childhood predictors of non-ability-based confidence. As demonstrated in this study, both initial achievement and achievement growth in children have important consequences for adolescent non-ability-based confidence. We expect other experiences in childhood, beyond early achievement, to shape adult non-ability-based confidence. The breadth of the NICHD SECCYD dataset offers additional opportunities to explore the childhood predictors of non-ability-based confidence. Of particular interest are experiences with parents, such as the level of autonomy that parents allow their child to have and the level of maturity they expect from their child, and socialization with peers in daycare and school. Moreover, other work has pointed to the role of children's experiences with how their successes are praised or undermined by parents and society at large (Cho, 2017). The current work as well as these proposed future directions paint a more comprehensive picture of the development of non-ability-based confidence beyond just personality differences, which has been the focus of past work.

Future research should also test alternative models for predicting adolescent non-ability-based confidence with variables that are not available in the current dataset. For example, given the abundance of correlational evidence linking overconfidence to personality traits (Broihanne et al., 2014; Campbell et al., 2004; Grosz et al., 2017; Macenczak et al., 2016; Meisel et al., 2016; Nosić & Weber, 2010; Odean, 2002; Paulhus et al., 2003; Schaefer et al., 2004), personality traits may interact with the development of non-ability-based confidence over childhood and adolescence. Similarly, there may be other individual differences that are either present or continue to develop in childhood that may be important for the emergence of non-ability-based confidence in adolescence. In addition, it is important to look at how individuals' non-ability-based confidence, itself, grows or shrinks over childhood, adolescence, and young adulthood as they progress through life stages. The current analysis does not examine the growth of non-ability-based confidence on its own. Unfortunately, due to the use of secondary data, these measures (such as, a version of the Big Five Inventory and repeated measures of confidence paired with concurrent ability measures) are not available to us and thus, we are unable to integrate these variables into our current analysis. Future research using these additional variables will enrich our understanding of the development of non-ability-based confidence.

5. Conclusion

Most people – children, adolescents, and adults alike – display non-ability-based confidence in some domain in their daily lives. However, relatively little is known about the developmental origins of such biased confidence. In this paper, we found that academic growth in math and reading across four timepoints in childhood is associated with non-ability-based confidence in age 15 adolescents. We found that children who start out at a higher level of math achievement at 54 months develop into adolescents with lower levels of math non-ability-based confidence. On the other hand, children who grow faster in their reading achievement from 54 months to 5th grade develop into adolescents with higher levels of reading non-ability-based confidence. Importantly, we do not identify the mechanism underlying the relation between early achievement growth and later non-ability-based confidence; future research should explore why and how early growth predicts later non-ability-based confidence. Together, these findings suggest a dynamic childhood growth process that contributes to the development and expression of non-ability-based confidence later in life.

Declaration of competing interest

None.

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