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EMPIRICAL ARTICLE

CHILD DEVELOPMENT

The interplay between investment traits and cognitive abilities: Investigating reciprocal effects in elementary school age

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Abstract

Based on investment theories and guided by Mussel's (2013) intellect model, the present study investigated reciprocal relations over 1 year (2021–2022) between investment traits (need for cognition, achievement motives, epistemic curiosity) and fluid and crystallized cognitive abilities in 565 German elementary school children (298 girls; M_{age} = 8.40, SD = 0.59; 59.5% with immigration background). Children's fluid and crystallized abilities increased over time, whereas fear of failure and curiosity decreased. Investment traits barely predicted change in cognitive abilities. However, mathematical ability predicted change in most investment traits ($.14 \leq |\beta| \leq .20$), even after accounting for control variables. Results largely contradict investment theories but support the role of crystallized abilities for the development of investment traits in elementary school age.

General cognitive ability is the ability to reason, understand complexity, learn quickly and lastingly, and use these competencies to solve complex problems (e.g., Gottfredson, 1997). As such, it has outstanding importance for individuals' lives, as illustrated by its eminent predictive power for various life outcomes such as academic and vocational success, socio-economic status, longevity, and health (e.g., Deary et al., 2004). Against this background, investigating factors that impact intellectual development is an important endeavor. In fact, ever since the beginnings of intelligence research, it has been a central question what determines intellectual development. Research has already identified factors such as biological maturation and cognitive stimulation individuals receive during their socialization by parents, the educational system, or intensive extracurricular long-term programs (e.g., Cahan & Cohen, 1989; Plomin & Spinath, 2004; Schmiedek et al., 2014; von Stumm & Plomin, 2015). By contrast, individual determinants such as personality traits driving individuals to engage in cognitive challenges (i.e., investment traits) have rarely been investigated, although investment theories attribute a central role to them (see Ackerman, 1996; Cattell, 1987; Ziegler et al., 2012). Moreover, theoretically plausible reciprocal effects between investment traits and intelligence (Chamorro-Premuzic & Furnham, 2004; Ziegler et al., 2012) have scarcely been examined up until now.

In the present study, we investigated the impact of five major investment traits (need for cognition (NFC), the achievement motives hope for success (HS) and fear of failure (FF), epistemic curiosity motivated by interest, and epistemic curiosity motivated by deprivation) on intelligence as defined by the hierarchical model of fluid (Gf) and crystallized (Gc) abilities (Cattell, 1963). According to this model, Gf is a general cognitive ability that is primarily comprised of basic processing capacities (especially reasoning ability), whereas Gc reflects the amount of culture-specific knowledge. In addition, we inspected effects of Gf and Gc on investment traits. As the elementary school years are a decisive phase for both intellectual and motivational development, we focused on elementary school children.

Abbreviations: BIC, Bayesian information criterion; CFI, comparative fit index; CFT, Culture Fair Intelligence Test; FF, fear of failure; Gc, crystallized intelligence; Gf, fluid intelligence; HS, hope for success; LCSM, latent change score model; NFC, need for cognition; RMSEA, root mean square error of approximation; SRMR, standardized root mean square residual.

Intellectual and motivational development in elementary school age

Elementary school age is a formative phase for both intellectual and motivational development. At this age, the predictive validity of intelligence test scores for later school and vocational success as well as for intelligence test scores in adulthood sharply increases (McCall, 1977). Thus, the elementary school years strongly contribute to the foundations for an individual's future developments in intelligence and performance. At the same time, intelligence is still comparatively malleable, which is an important prerequisite for investigating determinants of its change. Although it can already be reliably assessed in this phase, intelligence undergoes more change in elementary school than at any later ages. Rindermann (2011), for example, documented average yearly gains of 8.18 IQ points between ages 6 and 9, which was markedly more than between ages 10 and 14 (5.77 IQ points) and ages 15 and 18 (2.73 IQ points). Similar absolute change has been reported for crystallized abilities such as reading and math skills (e.g., Bloom et al., 2008). In addition, environmental influences on intelligence are stronger in elementary school than at any later ages (e.g., Plomin & Spinath, 2004), which might make the role of investment traits for intellectual development especially salient.

At the same time, elementary school children undergo strong changes in their motivation. Right after school entry, most children have overoptimistic views on their abilities and show strong motivation to learn (e.g., Jacobs et al., 2002). However, as children begin to differentiate between effort and ability and to understand ability as a person's characteristic, motivational constructs such as ability self-concepts and intrinsic motivation decline during the elementary school years (e.g., Jacobs et al., 2002; Spinath & Steinmayr, 2008; Weidinger et al., 2018; see also Stipek & Mac Iver, 1989). The intellectual and motivational trajectories during elementary school make these years a particularly suitable phase for the investigation of reciprocal effects between cognitive abilities and investment traits.

A systematization of investment traits: The intellect model by Mussel (2013)

A multitude of investment traits have been suggested, all of which have notable theoretical and empirical overlap (e.g., Mussel, 2010). Previous studies on the relation between investment traits and cognitive abilities have always picked one or two investment traits (e.g., Bergold et al., 2023; Bergold & Steinmayr, 2016; Hülür et al., 2018; Lechner et al., 2019). This practice did not only imply making a rather arbitrary choice but also fell short of the complex field of investment traits and gave rise to the risk of missing effects exhibited by unconsidered investment traits. Given their myriad, it is not possible to include all investment traits in one study. Therefore, we drew on Mussel's (2013) intellect model to make a theory-driven choice of prototypical investment traits that best reflect the broad field of investment traits.

In his framework, Mussel (2013) structured the field of investment traits according to two *processes* and three *operations*. The process dimension targets the motivation behind the investment trait and comprises the two facets *seek* and *conquer*. Seek investment traits motivate individuals to seek out for cognitive challenges. As such, they have a pronounced affective component and determine the quantity with which persons encounter challenges. For example, individuals with high seek investment traits seek out for many challenges, because they are interested in them and like to deal with them. Conquer investment traits, on the contrary, motivate individuals to succeed in a challenging task once it has been encountered. As such, they are tied to achievement motivation and determine the quality with which individuals handle challenges. For example, individuals with high conquer investment traits show much effort and persistence in accomplishing the challenge. Seek and conquer can be related to three operations, namely *think*, *learn*, and *create*. Whereas the latter corresponds to creativity (and is therefore not relevant for our study), both think and learn relate to intelligence. Think relates to Gf, as it represents the preference to reflect upon complex and abstract issues and to solve complex problems. Learn represents the desire to acquire new knowledge and thus relates to Gc. Combining the two processes with the two relevant operations reveals the four facets *seek think*, *seek learn*, *conquer think*, and *conquer learn*.

Mussel (2013) validated his model in three studies and empirically confirmed the theoretical position of several investment traits within the framework. *Seek think* investment traits reflect the tendency to seek out for cognitive challenges that require abstract thinking, because the individual enjoys thinking. A typical seek think investment trait is NFC, that is, the relatively stable intrinsic motivation to search for cognitively challenging tasks and to engage in thinking and problem solving, because thinking is perceived as fun (Cacioppo & Petty, 1982). *Seek learn* investment traits reflect the tendency to seek out for learning opportunities, because the individual has an inherent desire to gain new knowledge. An example for this kind of investment trait is epistemic curiosity driven by the joy of learning new information (curiosity as a feeling of interest, I-type curiosity; Litman & Jimerson, 2004).

Conquer think investment traits represent the tendency to invest effort and persistence in accomplishing cognitively challenging tasks to achieve a performance target (i.e., to master a challenge). A prototype of this facet is the achievement motive with its subdimensions HS and FF (McClelland et al., 1953). Individuals high in HS have the desire to accomplish a challenging task to experience positive emotions such as pride. Therefore, they do not only seek achievement-related situations but also invest a lot of effort when working on the challenge and show high persistence especially when faced with obstacles (e.g., Elliot & Church, 1997). Individuals high in FF, by contrast, primarily aim to avoid failure and related negative emotions such as shame. Therefore, they not only try to avoid achievement-related situations but also show low effort and low persistence when working on challenging tasks in order to protect their self in the case of failure (Elliot & Church, 1997). *Conquer learn* investment traits represent the tendency to invest effort and persistence in acquiring new knowledge to reduce a perceived lack of knowledge. An example for this kind of investment trait is epistemic curiosity driven by the need to terminate an aversive state of uncertainty (curiosity as a feeling of deprivation, D-type curiosity; Litman & Jimerson, 2004).

Investment traits as determinants of intellectual development

In his investment theory, Cattell (1987) proposed that individuals invest their Gf to accumulate Gc. However, individuals likely differ in the degree to which they actually convert their Gf to Gc. As already Cattell (1987) pointed out, this individual difference might be a matter of personality and motivation. Ackerman (1996) elaborated on Cattell's (1987) theory and suggested that investment traits (personality and interests) determine how and how often individuals engage in opportunities to acquire new knowledge, whereas Gf determines how much individuals learn from each of those opportunities. Other authors added that investment traits might also impact Gf. In their Openness-Fluid-Crystallized-Intelligence model, Ziegler et al. (2012) proposed that investment traits such as openness to experience might also influence the development of Gf, because more learning experiences might promote Gf in the long run (environmental enrichment hypothesis).

Seek investment traits as determinants of intellectual development

As seek think and seek learn investment traits motivate individuals to seek out for cognitive challenges and learning opportunities, respectively, they should promote both Gf and Gc in the long run. In line with this proposition, seek investment traits correlate with both Gf and (especially) Gc (see Ackerman & Heggestad, 1997; Anglim et al., 2022; Liu & Nesbit, 2023; von Stumm & Ackerman, 2013, for meta-analyses). This is also true for elementary school age (Luong et al., 2017; Preckel & Strobel, 2017). However, longitudinal studies predicting change in intelligence (which would hint toward causal relations) are scarce. Most of the longitudinal studies investigated whether seek investment traits buffer cognitive decline in late adulthood. Their findings are inconclusive. Whereas some studies found such an effect (Ziegler et al., 2015), others did not (e.g., von Stumm & Deary, 2013), and still others found it for Gc but not for Gf (Wettstein et al., 2017). Two other studies focused on early adulthood or adolescence, respectively. Ziegler et al. (2012, Study 2) investigated 172 participants from age 17 to 23 and found that openness predicted change in Gf (and in Gc as mediated by Gf). Hülür et al. (2018) followed 112 adolescents for 2 years and did not find any indications that typical intellectual engagement predicts change in either Gf ($\beta = .03$) or Gc ($\beta = .11$). However, as also the authors noted, this study—albeit valuable—was not sufficiently powered to detect small effects (i.e., $.10 \leq \beta < .30$). Furthermore, by adolescence intellectual growth has already decelerated (e.g., Bloom et al., 2008; Rindermann, 2011), which makes it harder to identify its determinants. In a study with a large sample of adolescents (focusing on the prediction of Gc), interest (but not openness) predicted change after 2 years in both reading and math skills (Lechner et al., 2019). To sum up, empirical evidence on the possible effects of seek investment traits on intellectual development is scarce and inconclusive and studies did not focus on elementary school children. Thus, whether seek investment traits predict change in Gf and Gc in elementary school age is unknown.

Conquer investment traits as determinants of intellectual development

Intellectual development should not only depend on the number of cognitive challenges or learning opportunities encountered ("seek") but also on how intensely they are used for intellectual exercise ("conquer"). The more effort and persistence are invested the more likely success on, and learning from, the task (and thus, intellectual growth) will become. Consequently, HS as a conquer think construct should promote the development of both Gf and Gc, whereas high FF should hamper the development of both Gf and Gc. In addition, D-type curiosity (conquer learn) motivates individuals to show effort and persistence in closing knowledge gaps, which should promote especially Gc.

Cross-sectional studies found correlations between conquer investment traits and intelligence (Ackerman & Heggestad, 1997; von Stumm & Ackerman, 2013). However, the role of conquer investment traits in predicting intellectual development has even been less investigated than the role of seek investment traits. Bergold and Steinmayr (2016) examined the effect of HS and FF on Gf by following 157 first graders for 9 months. FF negatively predicted change in Gf, whereas HS had no effect on Gf. However, this zero effect might have been caused by the unrealistically high expectations of success children in the early phase of elementary school typically hold (e.g., Stipek & Mac Iver, 1989). In general, the evidence on the role of conquer investment traits for intellectual development is very limited.

Reciprocal effects between investment traits and cognitive abilities

It is also plausible to hypothesize an effect of cognitive ability on investment traits (environmental success hypothesis). Ziegler et al. (2012) argue that individuals with higher ability experience more success on achievement-related tasks than do individuals with lower ability. More success might promote ability self-concepts and achievement-related emotions (e.g., Pekrun et al., 2017; Weidinger et al., 2018) and therefore also investment traits. Other authors made similar claims (Cattell, 1987; Chamorro-Premuzic & Furnham, 2004; Schmiedek et al., 2014). As effects of performance on ability self-concepts seem especially to apply to elementary school students (e.g., Weidinger et al., 2018), effects of cognitive ability on investment traits might be especially salient in elementary school age.

However, most of the few previous studies investigated adults and revealed inconsistent findings. Focusing on late adulthood, von Stumm and Deary (2013) identified effects of verbal fluency (an indicator of Gc) on openness, and Wettstein et al. (2017) even found effects of both Gf and Gc on openness. Jackson et al. (2012) corroborated these findings. In their study, a cognitive training improved not only inductive reasoning but also openness. Ziegler et al. (2015), however, found no effect on openness, as was also the case for their study with young adults (Ziegler et al., 2012, Study 2). Bergold et al. (2023) found that Gf (but not Gc) predicted growth in adolescents' NFC. To our knowledge, only Bergold and Steinmayr (2016) focused on elementary school children. In this study, Gf tended to predict change in HS (but not in FF) with $\beta = .20$, but this effect missed statistical significance, possibly because of the small sample. Thus, the question of whether there is a reciprocal relation between investment traits and intelligence in elementary school age is still unanswered.

The present study

Previous studies on the relation between investment traits and intelligence have mostly been cross-sectional and the few longitudinal studies predicting change have largely neglected the elementary school years, although these are an especially important phase in both intellectual and motivational development (McCall, 1977; Rindermann, 2011; Spinath & Steinmayr, 2008). In addition, previous longitudinal studies often focused on the environmental enrichment hypothesis (investment traits → intelligence), neglecting potential reciprocal relations; investigated just one or two arbitrarily selected investment traits; or were underpowered. Therefore, we investigated the reciprocal longitudinal relation between investment traits and fluid and crystallized abilities in a sample of 565 German elementary school children as predetermined in an a priori power analysis. Thereby, we captured established investment traits that cover the four main facets of Mussel's (2013) intellect model, namely NFC (seek think), I-type curiosity (seek learn), the achievement motives HS and FF (conquer think), and D-type curiosity (conquer learn). When investigating the relations for Gc, we additionally differentiated between the domains reading and mathematics, as numerous studies have shown that the nomological network differs between, for example, verbal and mathematical indicators of Gc (e.g., Lauermann et al., 2020).

In addition, we considered control variables that might affect the development of intelligence or investment traits. In particular, cognitive stimulation and other variables related to parents' socio-economic status promote intellectual growth (e.g., von Stumm & Plomin, 2015) and might likewise affect investment traits. Thus, we used cognitive stimulation experienced at home, parental education, and number of books in the home as control variables. We also considered immigration background and specific learning disorders. Children with an immigration background or with dyslexia might have slower growth in reading, whereas children with dyscalculia might have slower growth in mathematical ability. In addition, younger children tend to have steeper intellectual growth than older ones (e.g., Rindermann, 2011), and some studies found different intellectual or motivational development for boys and girls (Jacobs et al., 2002; von Stumm & Plomin, 2015). Therefore, we also controlled for age and gender.

As we aimed to avoid the problem of unrealistically high levels (and very low variance) in the investment traits as found at the beginning of elementary school (e.g., Bergold & Steinmayr, 2016; Stipek & Mac Iver, 1989), we followed students from third to fourth grade. This phase should bring about the optimal combination of increasingly realistic values in investment traits and sufficient amount of intellectual growth. Furthermore, fourth grade is a critical stage in Germany's school system, because afterward students change over to secondary schools organized in a tracked system. The transition to either the academic or vocational track strongly depends on students' school performance and ability in fourth grade.

Most parts of our study were confirmatory. We expected that NFC, HS, and both types of curiosity would positively predict change in Gf and Gc; that FF would negatively predict change in Gf and Gc; that both Gf and Gc would positively predict change in NFC, HS, and both types of curiosity; that both Gf and Gc would negatively predict change in FF. We also aimed to examine the uniqueness of seek and of conquer investment traits in the prediction of cognitive abilities. As seek investment traits rather tap the quantity of cognitive challenges, whereas conquer investment traits rather tap the quality of their use, we expected that both types of investment traits would have unique effects on change in both Gf and Gc. As for the exploratory part of our study, we explored the differential strengths of the relations between different investment traits and cognitive abilities. On one hand, one might expect that the predictive value of the investment traits would be stronger for Gc than for Gf, given that the correlations with Gc are usually stronger than those with Gf (Ackerman & Heggestad, 1997; Anglim et al., 2022; von Stumm & Ackerman, 2013). On the other hand, it is also conceivable that the reciprocal relations between investment traits and intelligence facets routed in the same operation (think and Gf; learn and Gc) are stronger than the relations between investment traits and intelligence facets routed in different operations (think and Gc; learn and Gf).

METHOD

Participants

Students

We conducted a priori Monte Carlo studies (Muthén & Muthén, 2002) to determine required sample size. Based on the only available study that investigated reciprocal relations between investment traits and intelligence in elementary school children (Bergold & Steinmayr, 2016), we based the power analysis on a small to medium effect ($|\beta|=.20$). Minimum power was set at 80% and α error likelihood at 5%. We considered students being nested in classrooms and assumed a 20% dropout rate from t_1 to t_2. The power analyses revealed a required sample size of 526 students. Detailed information on the power analyses and their results can be found on pp. 5–7 in Supporting Information.

Between the second half of August and the first half of October 2021 (t_1), we collected data from 565 third graders (298 girls, 261 boys, 6 with no gender specified; $M_{\text{age}}=8.40$ years, SD=0.59) from 52 classrooms in 22 elementary schools located in the Rhine-Ruhr area in North Rhine-Westphalia, a federal state in Germany. The elementary schools had been randomly chosen from a ministerial internet database covering all schools in the Rhine-Ruhr area. As expected for this region with its long history of labor immigration, students with immigration background (as indicated by child's or parents' countries of birth or language mostly spoken at home) were overrepresented in relation to the state's population of elementary school students (59.5% vs. 45.0%; Ministry for School and Education of North Rhine-Westphalia, 2022). 20 students had a diagnosed dyslexia, and 5 students had a diagnosed dyscalculia as stated by their parents or teachers (see below).

From the t_1 sample, 445 students (78.76%) also took part at t_2 from August to September 2022. Students with lower Gf, Gc, HS, and I-type curiosity were somewhat more likely to drop out of the study ($.24 \leq d \leq .38$; see Discussion). Attrition was not systematic in any other regard. For details of the attrition analysis, see p. 7 in Supporting Information. We retained the students who dropped out, using the full information likelihood approach in order to preserve as much information as possible. Rates of missing values for students taking part in both measurement occasions were 2.50% at t_1 and 1.61% at t_2. We handled this type of missing data with the full information maximum likelihood approach as well.

Parents and teachers

Overall, 283 mothers ($M_{\text{age}}=38.76$ years, SD=5.14) and 169 fathers ($M_{\text{age}}=42.72$ years, SD=6.41) filled in the parent questionnaire, providing information inter alia on their educational levels, child's cognitive stimulation at home, and child's diagnosis of dyslexia and dyscalculia. Details on the parent sample can be found on pp. 7–8 in Supporting Information. In addition, 39 teachers ($M_{\text{age}}=41.63$ years, SD=10.79) filled in the teacher questionnaire, providing information inter alia on child's diagnosis of dyslexia and dyscalculia.

Measures

In the following, we provide an overview of the measures. Information on the measurement model fits can be found on pp. 8–12 in Supporting Information.

Investment traits

Need for cognition
We used a measure that Preckel and Strobel (2017) had adapted from the original NFC scale (Cacioppo & Petty, 1982) to elementary school age. This adapted and translated scale has been successfully validated (Keller et al., 2019). The scale comprises 14 items (e.g., "I am glad when we get brain teasers in school"). The items—as all items in the student questionnaire—were answered on a 4-point Likert scale (1=*does not apply at all*, 4=*fully applies*). Internal consistency was $\alpha=.85/.86$ (t_1/t_2) and $\omega=.87/.88$. We used the sum score, its reliability and variance to compute a single-indicator latent NFC variable.

Achievement motives
We assessed HS and FF with a German short version of the Achievement Motives Scale (Lang & Fries, 2006).

This version measures both motives with five items each and has been validated for young adults (Lang & Fries, 2006). We adapted the item wordings so that they were appropriate for elementary school children (modified items were, e.g., "I like it when I can find out how good I really am on a task," "If I do not understand a task immediately I start feeling anxious"). We conducted a pilot study with students at the end of second grade to test the psychometric properties of the modified instrument. The analyses revealed good reliability and supported the validity of the measure (see pp. 2–5 in Supporting Information). In the present study, we excluded one HS item, which improved reliability and model fit (see p. 9 and Table S5 in Supporting Information), as well as measurement invariance across time. Internal consistency was $\alpha = .71/.72$, $\omega = .72/.74$ (HS) and $\alpha = .78/.77$, $\omega = .78/.78$ (FF).

Epistemic curiosity

We assessed I-type and D-type curiosity with the German version of the Epistemic Curiosity Scale (Litman & Mussel, 2013). The original scale measures both types of curiosity with five items each. We adapted the item wordings to elementary school children. The pilot study indicated sufficient reliability and supported the validity of the measure but suggested one I-type item to be excluded (see p. 3 in Supporting Information). The same item was excluded from the present study (see p. 9 in Supporting Information). We therefore measured I-type curiosity with four items (e.g., "I find it very exciting to learn new things"; $\alpha = \omega = .65/.73$) and D-type curiosity with five items ("I can spend hours on a difficult task, because I just want to know the answer"; $\alpha = .78/.80$, $\omega = .79/.80$).

Cognitive abilities

Fluid intelligence

We administered the short form of the revised German version of the Culture Fair Intelligence Test (CFT 20-R; Weiß, 2006) as a measure of Gf. This version of the CFT 20-R is comprised of four subtests (series completion, classifications, matrices, and topological reasoning) with overall 56 items presenting figural material ($\alpha = .77/.77$).

Crystallized intelligence

To achieve a broad operationalization of Gc, we administered two tests that cover two core domains in school, namely reading and mathematics. We measured reading comprehension with the text comprehension test from the Reading Comprehension Test for first to seventh graders—Version II (Lenhard et al., 2017). In this test, the children read short texts and answer one to three questions about each text in a single-choice format. There are overall 26 questions ($\alpha = .88/.89$). We coded 1 for correct answers and 0 for wrong or missing answers. To measure mathematical ability, we applied the arithmetic operations module from the Heidelberg Numeracy Test (Haffner et al., 2005). In this module, six subtests measure elementary school children's skills in addition ($\alpha = .91/.89$), subtraction ($\alpha = .93/.92$), multiplication ($\alpha = .91/.91$), division ($\alpha = .94/.95$), supplementing numbers ($\alpha = .86/.89$), and comparing numbers ($\alpha = .93/.94$). Internal consistency of the sum score was $\alpha = .98$ at both t_1 and t_2.

As the math test revealed six subtest scores as opposed to the reading test with only one score, we used the overall sum scores of both tests as indicators to model Gc. In separate analyses for mathematical ability and reading comprehension, we used the six subtests to model mathematical ability as a latent variable and the reading score, its reliability and variance to compute a single-indicator latent reading comprehension variable.

Control variables

Children reported their age and gender and the number of books in the home as an indicator of the family's cultural capital. Graphics placed next to the response options showed different numbers of books. The response options were: 1 = *none or only very few [0–10 books]*, 2 = *enough to fill a shelf-board [11–25 books]*, 3 = *enough to fill one shelf [26–100 books]*, 4 = *enough to fill two shelves [101–200 books]*, 5 = *enough to fill three or more shelves [more than 200 books]*. In addition, we considered students' immigration background and dyslexia or dyscalculia as indicated by the parents or teachers.

Parents reported their highest educational level (1 = *no graduation*, 2 = *Hauptschulabschluss* [lower secondary education], 3 = *Mittlere Reife* [intermediate secondary school certificate], 4 = *Fachabitur* [entrance qualification for university of applied sciences], 5 = *Abitur* [entrance qualification for university]). Parents also filled in two questionnaires from PIRLS and TIMSS 2011 (Martin & Mullis, 2012) on the child's cognitive stimulation at home ("How often do you or someone else at home pursue the following activities with your child?"). One scale assessed literacy activities with 9 items and one assessed numeracy activities with 6 items. Items were answered on a 3-point scale (1 = *never/almost never*, 2 = *sometimes*, 3 = *often*). We calculated the mean of mothers' and fathers' responses for each item to achieve an average cognitive stimulation at home score. As the latent correlation between both scales amounted to $r = .90$, we merged both scales to one representing overall cognitive stimulation at home ($\alpha = \omega = .84$). As cognitive stimulation, books in the home, and parents' educational level intercorrelated only modestly ($.12 \leq r \leq .24$), we considered them as separate control variables.

Procedure

Trained research assistants collected the data during regular classes in the morning. Students first filled in a questionnaire assessing demographics and the investment traits. To make sure that all students would understand how to work on the questionnaire, item examples were given, and students could ask questions. The children were informed that there were no wrong or right answers and that their answers were confidential. The test administrator read all questionnaire items aloud to ensure that all children could follow and answer the items. Subsequently, the students took the CFT 20-R. After a break, the testing session continued with the reading comprehension test. Finally, the students completed the math test. Overall, the testing session took about 90 min. Participation was voluntary; students participated only if their parents had provided informed written consent and if they were not ill or missed school due to other reasons. The final sampling ratio was about 50%.

Analyses

Latent change score models

As a first step, we computed univariate latent change score models (LCSMs) in Mplus 8.5 to inspect latent change in cognitive abilities and investment traits as well as individual differences therein. In a second step, we set up a series of bivariate LCSMs with either Gf or Gc (or mathematical ability or reading comprehension) and either NFC, HS, FF, I-type curiosity, or D-type curiosity (see Figure 1). In these models, the base-level value of each variable served as predictor of the latent difference score of the respective other variable. In addition, we predicted change in both variables from the control variables. In all LCSMs, corresponding residual variances were allowed to correlate over time and corresponding factor loadings and intercepts were constrained to be equal over time. Correlations between all predictors and between the change residuals were also estimated.

Prior to the main analyses, we inspected the variance proportions at the student level and at the class level. As can be seen in Table 1, some variables (especially the ability measures) displayed considerable between-class variance. Therefore, we specified a multilevel structure for the LCSMs and centered all predictors at the group mean to ensure unbiased estimations of the within-class effects. We used the maximum likelihood estimator with robust standard errors. We evaluated model fit using the Satorra-Bentler corrected χ^2 value, the comparative fit index (CFI), the root mean square error of approximation (RMSEA), and the standardized root mean square residual (SRMR). As the χ^2 value is sensitive to larger sample sizes, we put a special focus on the other fit indices. Following the relatively strict criteria by Hu and Bentler (1999), we considered fit as good

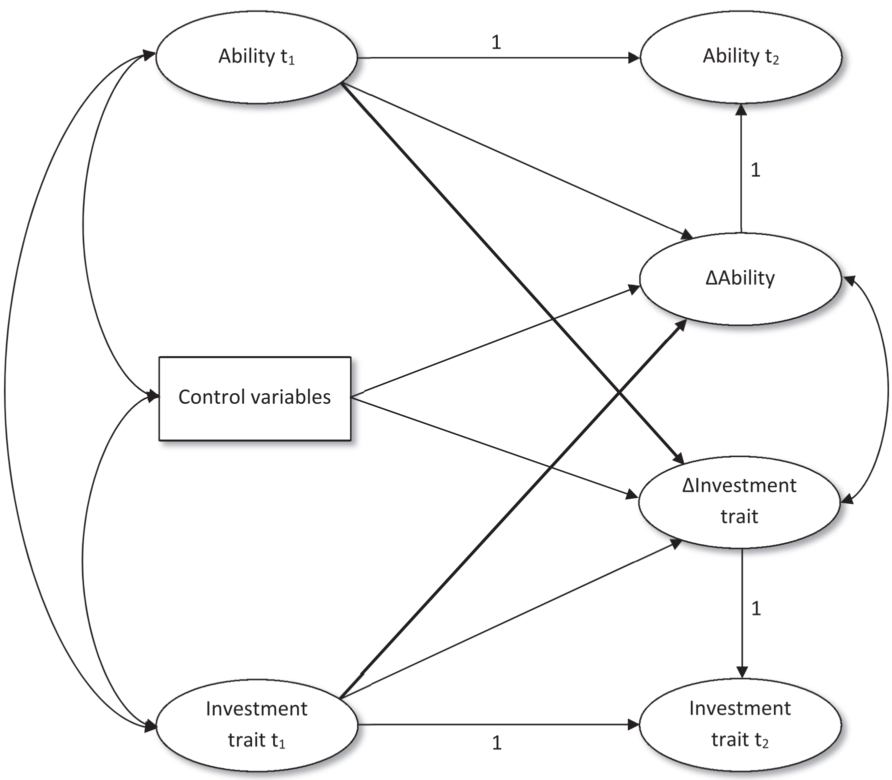

FIGURE 1 Bivariate latent change model. Paths representing reciprocal relations are printed in bold. Indicators of latent variables as well as correlations among corresponding indicators and among control variables are omitted for clarity.

TABLE 1 Means (M), standard deviations (SD), intraclass correlations (ICC), and intercorrelations of the study variables.

Variable	N	M	SD	ICC	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18	19	20	21	22	23
Variables t_1																											
1. Age	544	8.40	0.59		-																						
2. Gender (0=boy, 1=girl)	559	.53	.50		.03	-																					
3. Immigration background	565	.59	.49		**.18**	.01	-																				
4. Cultural capital	552	2.94	1.29		**−.15**	−.08	**−.23**	-																			
5. Parental educational level	273	4.04	1.15		**−.24**	−.02	**−.18**	**.24**	-																		
6. Cognitive stimulation	311	2.18	0.36		**−.16**	−.01	**−.13**	**.22**	**.12**	-																	
7. Dyslexia	459	.04	.19		**.17**	−.08	.03	−.07	−.10	**−.11**	-																
8. Dyscalculia	459	.01	.09		−.03	.05	.00	−.05	−.00	−.03	**.08**	-															
9. Need for cognition	563	3.09	0.56	.09	.04	−.01	**.09**	**.11**	.03	.06	**−.14**	**−.15**	-														
10. Hope for success	563	3.64	0.49	.03	−.05	.07	**−.09**	.07	.03	.06	−.06	**−.12**	**.43**	-													
11. Fear of failure	563	2.46	0.86	.16	.06	**.19**	**.17**	**−.26**	**−.22**	**−.16**	.09	**.10**	−.08	−.03	-												
12. I-type curiosity	561	3.49	0.57	.06	**−.09**	.05	.00	**.16**	.06	.08	**−.11**	−.05	**.51**	**.41**	**−.11**	-											
13. D-type curiosity	562	2.89	0.83	.13	.05	−.03	**.13**	.01	.02	.03	**−.09**	−.03	**.58**	**.26**	**.16**	**.29**	-										
14. Gf	556	23.64	6.43	.09	**−.09**	.06	**−.16**	**.18**	**.31**	**.14**	**−.11**	**−.12**	**.16**	**.17**	**−.25**	**.16**	.01	-									
15. Reading comprehension	478[a]	7.32	4.83	.18	**−.13**	−.04	**−.22**	**.27**	**.35**	**.15**	**−.15**	−.03	**.11**	.08	**−.30**	**.12**	−.07	**.46**	-								
16. Mathematical ability	418[b]	93.98	32.56	.22	**−.15**	**−.22**	**−.12**	**.23**	**.27**	**.20**	**−.18**	**−.18**	**.25**	**.22**	**−.38**	**.12**	.03	**.45**	**.58**	-							
Variables t_2																											
17. Need for cognition	445	3.03	0.55	.06	−.00	−.06	.09	**.22**	**.14**	.10	**−.10**	**−.16**	**.56**	**.25**	−.05	**.33**	**.44**	**.16**	**.17**	**.29**	-						
18. Hope for success	445	3.64	0.46	.06	−.04	−.02	**.10**	**.13**	.02	.05	−.04	**−.21**	**.30**	**.21**	−.05	**.21**	**.26**	**.12**	.09	**.19**	**.55**	-					
19. Fear of failure	445	2.34	0.77	.08	**.15**	**.11**	**.20**	**−.22**	**−.27**	**−.16**	−.00	.03	−.04	−.06	**.39**	−.07	**.11**	**−.20**	**−.27**	**−.36**	**−.13**	−.05	-				
20. I-type curiosity	445	3.34	0.60	.07	−.02	.04	.06	**.21**	.06	.06	**−.16**	**−.17**	**.35**	**.21**	−.07	**.27**	**.34**	**.12**	**.12**	**.19**	**.70**	**.57**	**−.10**	-			
21. D-type curiosity	445	2.75	0.77	.12	−.00	−.08	**.12**	.03	.03	.01	−.07	−.03	**.31**	**.11**	**.10**	**.18**	**.41**	.00	.00	.09	**.59**	**.32**	.06	**.42**	-		
22. Gf	441	28.95	6.43	.12	**−.22**	−.02	**−.22**	**.22**	**.34**	**.13**	−.08	**−.11**	.04	**.11**	**−.21**	.01	−.06	**.60**	**.42**	**.44**	**.18**	**.12**	**−.19**	**.11**	**.17**	-	
23. Reading comprehension	393[a]	11.97	5.15	.25	**−.22**	−.04	**−.29**	**.33**	**.35**	**.22**	**−.23**	.01	**.13**	.09	**−.32**	**.11**	−.02	**.41**	**.75**	**.56**	**.15**	.08	**−.23**	**.16**	**.21**	**.43**	-
24. Mathematical ability	419[b]	118.05	33.08	.24	**−.11**	**−.21**	−.07	**.19**	**.30**	**.23**	**−.17**	**−.17**	**.25**	**.16**	**−.33**	.08	.08	**.39**	**.52**	**.83**	**.31**	**.17**	**−.30**	**.18**	**.32**	**.42**	**.53**

Note: Correlations printed in bold are statistically significant at $p<.05$.

[a]Note that some students misinterpreted the instruction of the reading comprehension test and therefore, we coded their reading test score as missing.

[b]In some classrooms, at least one of the math subtests could not be administered. In most of these cases, the division subtest was not administered, because division had not yet been taught due to the school lockdown during the COVID-19 pandemic. In these cases, we coded the manifest math test sum score as missing.

(satisfactory) when CFI ≥ .97 (≥.95), RMSEA ≤ .05 (≤.08), and SRMR ≤ .05 (≤.08).

Measurement invariance

Prior to the main analyses, we first tested for metric (i.e., equality of factor loadings) and then for scalar (i.e., equality of indicator intercepts) invariance. Non-invariance was indicated by a statistically significant ($p < .05$) increase in the Satorra-Bentler corrected χ^2 in combination with its related $\text{RMSEA}_D \geq .10$ (Savalei et al., 2023), $\Delta\text{CFI} \geq -.01$, $\Delta\text{RMSEA} \geq .015$, and $\Delta\text{SRMR} \geq .030$ (≥.010 for scalar invariance; Chen, 2007).

Ethical approval and transparency and openness

This study was approved beforehand by the ethics committee of TU Dortmund University. Its design, hypotheses, and analysis plan were not preregistered but described a priori in the project proposal directed to the German Research Foundation. Data, analysis codes, and research materials are not publicly available. However, interested researchers may email the authors for insights into data, codes, and materials for replication purposes.

RESULTS

Descriptive statistics, correlations, and validity of the intellect model

Means, standard deviations, and intercorrelations of the study variables are displayed in Table 1. The intercorrelations of the investment traits showed expected patterns of convergent and discriminant validity. A nested-factor model representing the factorial structure of the intellect model (except for the operation "create") showed a satisfactory fit to the data, $\chi^2 = 731.76$, df = 413, CFI = .920, RMSEA = .037, SRMR = .044. This model fitted the data better than a model with five correlated factors and a one-factor model (χ^2/df: 1.77 vs. 2.11 vs. 4.36, Akaike information criterion: 43,356.48 vs. 43,565.56 vs. 44,889.37, Bayesian information criterion [BIC]: 43,993.47 vs. 44,024.88 vs. 45,305.36, adjusted BIC: 43,526.82 vs. 43,688.39 vs. 45,000.61). Thus, the validity of the intellect model in the present sample was supported.

All investment traits except for D-type curiosity correlated in the expected directions with cognitive abilities both within and across the measurement occasions. The cognitive abilities were substantially interrelated. Relative stabilities ranged from $r = .21$ to $r = .56$ (investment traits) and from $r = .60$ to $r = .83$ (cognitive abilities).

Measurement invariance

All measures used in the present analyses showed full scalar invariance across time. Detailed results from the invariance tests can be found in Table S6.

Univariate LCSMs

Table 2 shows the latent change (Δ) in cognitive abilities and investment traits. Both Gf and Gc significantly increased. At the same time, there was considerable variance between the children in intellectual growth (σ_Δ). FF and both types of curiosity significantly decreased, whereas there was no significant mean change in NFC and HS. However, the children markedly differed in their change in investment traits.

Bivariate LCSMs

The main results from the bivariate LCSMs can be seen in Tables 3 (Gf), 4 (Gc), 5 (reading comprehension), and 6 (mathematical ability). The intercorrelations of the predictors can be seen in Tables S7–S18. Changes in all investment traits and in most abilities were negatively related to their base levels. Thus, children with lower base-level values showed a stronger increase. Regression to the mean might be responsible for this pattern. We will return to this aspect in the Discussion. The correlations between the change residuals were small ($-.08 \leq r \leq .11$) and not statistically significant. Thus, there was no notable common change above and beyond the cross-lagged effects, the autoregressive effects, and the control variable effects.

Effects on cognitive abilities

Effects of investment traits

Against our expectations (environmental enrichment hypothesis), the investment traits did not predict change in either Gf or Gc. In the separate LCSMs for reading comprehension and mathematical ability, we found no significant effects on change in either ability, with two exceptions: NFC positively predicted change in reading comprehension ($\beta = .16$, SE = .08, $p = .034$) and I-type curiosity negatively predicted change in mathematical ability ($\beta = -.19$, SE = .10, $p = .048$). We also explored effects of the investment traits on cognitive abilities when investigating all investment variables simultaneously (see Tables S19–S23). Results did not change substantially and were hard to interpret due to multicollinearity.

Effects of control variables

Age and gender predicted change in Gf. Younger children and boys had greater increases than older children ($-.24 \leq \beta \leq -.26$) and girls ($-.12 \leq \beta \leq -.15$). No significant

TABLE 2 Latent change in cognitive abilities and investment traits.

	Parameter		Model fit			
Model	**Δ(SE)**	**σ_{Δ}(SE)**	**χ^2(df)**	**CFI**	**RMSEA**	**SRMR**
Cognitive abilities						
Gf (weighted indicators)	0.91 (0.07)***	0.25 (0.06)***	20.23 (21)	1.00	.000	.033
Gc	27.26 (1.48)***	61.72 (25.38)*	1.71 (1)	.999	.036	.015
Reading comprehension[a]	4.41 (0.25)***	7.05 (1.44)***	0 (0)	1.00	.000	.000
Mathematical ability	4.41 (0.26)***	3.95 (0.98)***	145.37 (53)***	.976	.056	.069
Investment traits						
Need for cognition[a]	−0.07 (0.04)	0.19 (0.02)***	0 (0)	1.00	.000	.000
Hope for success	−0.01 (0.03)	0.22 (0.04)***	26.82 (21)	.988	.022	.050
Fear of failure	−0.12 (0.05)*	0.66 (0.09)***	60.48 (45)	.987	.025	.038
I-type curiosity	−0.15 (0.03)***	0.27 (0.05)***	40.50 (21)**	.960	.041	.042
D-type curiosity	−0.14 (0.05)**	0.41 (0.06)***	42.18 (45)	1.00	.000	.033

Note: Unstandardized solution.

Abbreviations: CFI, comparative fit index; Gc, crystallized intelligence; Gf, fluid intelligence; RMSEA, root mean square error of approximation; SRMR, standardized root mean square residual.

[a]Model just identified.

*$p<.05$; **$p<.01$; ***$p<.001$.

effects on Gc were found. However, children with dyslexia had weaker growth in reading comprehension than other children ($-.16 \leq \beta \leq -.19$). By tendency, the same was true for children with dyscalculia regarding mathematical ability, but this effect was not statistically significant. There were no consistent effects of the other control variables.

Effects on investment traits

Effects of cognitive abilities

There was only one significant effect of Gf, namely on change in HS (β=.17, SE=.08, p=.046). In line with the environmental success hypothesis, Gc predicted an increase in NFC (β=.20, SE=.08, p=.007), HS (β=.14, SE=.07, p=.039), and I-type curiosity (β=.18, SE=.07, p=.009), as well as a decrease in FF (β=−.15, SE=.08, p=.049), above and beyond the control variables. The regression weight of D-type curiosity missed the statistical significance level, β=.14, SE=.08, p=.066.

The results of the separate LCSMs for reading comprehension and mathematical ability showed that the Gc effects originated from mathematical ability. Whereas reading comprehension had no effects on the change in investment traits, mathematical ability had (NFC: β=.16, SE=.08, p=.043, HS: β=.16, SE=.06, p=.008, FF: β=−.14, SE=.07, p=.041, I-type curiosity: β=.20, SE=.06, p=.001). Again, the regression weight of D-type curiosity missed the statistical significance level, β=.13, SE=.07, p=.059.

Exploring differential relations between investment traits and mathematical ability, we did not find any indications that mathematical ability predicts learn investment traits (curiosity; $.13 \leq \beta \leq .20$) more than think investment traits (NFC and achievement motives; $.14 \leq |\beta| \leq .16$).

Effects of control variables

Cultural capital predicted change in NFC and I-type curiosity. Children from homes with higher cultural capital had sharper increases in these investment traits ($.14 \leq \beta \leq .19$). Children with an immigration background had a somewhat stronger increase in HS than other children ($.11 \leq \beta \leq .15$). As children with an immigration background started at lower HS levels than the other children, $t(550.71)=2.19$, p=.029, d=.18, regression to the mean might have caused this effect. Interestingly, specific learning disorders predicted a weaker growth in I-type curiosity (dyslexia: β=−.15, SE=.06, p=.011; dyscalculia: β=−.14, SE=.06, p=.028; models with separate abilities). Dyscalculia additionally predicted a weaker growth in HS (β=−.19, SE=.06, p=.001).

DISCUSSION

The causal relation between investment traits and cognitive abilities is a fundamental research question. Especially the elementary school years hold promise for its investigation, as this phase is crucial for both intellectual and motivational development (e.g., Rindermann, 2011; Spinath & Steinmayr, 2008). Most studies on the association between investment traits and cognitive abilities, however, have been cross-sectional and there are barely any longitudinal studies focusing on elementary school children. In addition, most studies neglected reciprocal effects, focused on one or two arbitrarily selected investment traits, or were beset with power problems. The present study examined reciprocal relations, considering several established investment traits derived from Mussel's (2013) intellect model and

TABLE 3 Prediction of latent change in fluid intelligence and investment traits.

	Model NFC↔Gf		Model HS↔Gf		Model FF↔Gf		Model I-type curiosity↔Gf		Model D-type curiosity↔Gf	
Predictor	**ΔGf**	**ΔNFC**	**ΔGf**	**ΔHS**	**ΔGf**	**ΔFF**	**ΔGf**	**Δcuriosity**	**ΔGf**	**Δcuriosity**
Investment trait t_1	**−.05 (.09)**	−.43 (.06)***	**.01 (.10)**	−.62 (.06)***	**.08 (.13)**	−.61 (.06)***	**−.17 (.13)**	−.60 (.07)***	**.04 (.08)**	−.54 (.05)***
Gf t_1	−.35 (.13)**	**.04 (.08)**	−.37 (.13)**	**.17 (.08)***	−.34 (.15)*	**.03 (.07)**	−.34 (.13)*	**.08 (.07)**	−.36 (.13)**	**.01 (.08)**
Cognitive stimulation	.05 (.13)	.05 (.05)	.05 (.13)	.06 (.06)	.06 (.13)	−.03 (.07)	.06 (.13)	−.01 (.05)	.05 (.13)	.02 (.06)
Cultural capital	.11 (.09)	.14 (.06)*	.10 (.08)	.07 (.05)	.11 (.09)	.00 (.06)	.13 (.09)	.19 (.06)**	.09 (.08)	.02 (.05)
Parental education	−.03 (.17)	.16 (.08)	−.03 (.16)	−.02 (.06)	−.00 (.17)	−.17 (.09)	−.03 (.16)	.01 (.07)	−.03 (.17)	.11 (.07)
Immigration background	.02 (.08)	.04 (.06)	.01 (.08)	.15 (.04)***	.01 (.08)	.08 (.05)	.02 (.08)	.07 (.05)	.00 (.08)	.02 (.06)
Age	−.20 (.08)*	−.03 (.06)	−.20 (.08)**	.02 (.05)	−.19 (.08)*	.03 (.05)	−.21 (.08)**	.04 (.05)	−.21 (.08)**	−.07 (.06)
Female gender	−.13 (.07)*	−.02 (.06)	−.13 (.06)*	−.04 (.05)	−.15 (.07)*	.06 (.05)	−.12 (.06)	.04 (.05)	−.12 (.06)*	−.06 (.05)
$r_{\text{change residuals}}$	.04 (.06)		−.02 (.09)		−.08 (.07)		.08 (.10)		−.01 (.06)	
Model fit										
χ^2(df)	72.74 (69)		177.02 (174)		230.91 (218)		234.45 (174)**		257.61 (218)*	
CFI	.995		.997		.992		.950		.975	
RMSEA	.010		.006		.010		.025		.018	
SRMR	.030		.036		.038		.039		.038	

Note: Standardized solution. Values in brackets show standard errors. Regression weights indicating reciprocal relations are printed in bold.

Abbreviations: CFI, comparative fit index; FF, fear of failure; Gf, fluid intelligence; HS, hope for success; NFC, need for cognition; RMSEA, root mean square error of approximation; SRMR, standardized root mean square residual (student level).

*$p<.05$; **$p<.01$; ***$p<.001$.

TABLE 4 Prediction of latent change in crystallized intelligence and investment traits.

Predictor	Model NFC ↔ Gc		Model HS ↔ Gc		Model FF ↔ Gc		Model I-type curiosity ↔ Gc		Model D-type curiosity ↔ Gc	
	ΔGc	ΔNFC	ΔGc	ΔHS	ΔGc	ΔFF	ΔGc	Δcuriosity	ΔGc	Δcuriosity
Investment trait t_1	**.13 (.13)**	−.50 (.06)***	**−.00 (.10)**	−.65 (.07)***	**−.18 (.11)**	−.65 (.06)***	**−.15 (.14)**	−.63 (.06)***	**.08 (.12)**	−.57 (.05)***
Gc t_1	−.35 (.18)*	**.20 (.08)****	−.28 (.17)	**.14 (.07)***	−.33 (.19)	**−.15 (.08)***	−.27 (.19)	**.18 (.07)****	−.32 (.16)	**.14 (.08)**
Cognitive stimulation	.02 (.10)	.01 (.05)	.01 (.10)	.04 (.05)	.01 (.11)	−.01 (.07)	.04 (.11)	−.05 (.06)	.02 (.09)	.00 (.06)
Cultural capital	.08 (.08)	.14 (.06)*	.11 (.07)	.07 (.05)	.10 (.08)	.01 (.06)	.16 (.09)	.18 (.06)**	.09 (.07)	.02 (.05)
Parental education	.02 (.12)	.13 (.09)	.03 (.12)	.03 (.04)	.03 (.13)	−.12 (.09)	.02 (.14)	.00 (.08)	.04 (.12)	.09 (.06)
Immigration background	.04 (.06)	.03 (.06)	.06 (.07)	.12 (.04)**	.05 (.07)	.08 (.05)	.06 (.07)	.05 (.05)	.05 (.07)	.01 (.06)
Age	−.12 (.09)	−.03 (.06)	−.09 (.09)	.01 (.06)	−.09 (.10)	.03 (.05)	−.12 (.10)	.04 (.06)	−.11 (.09)	−.06 (.06)
Female gender	−.04 (.11)	.04 (.06)	−.05 (.11)	.02 (.05)	−.02 (.12)	.02 (.05)	−.04 (.12)	.10 (.05)	−.05 (.10)	−.03 (.05)
Dyslexia	−.10 (.10)	−.04 (.09)	−.12 (.11)	.01 (.04)	−.13 (.12)	−.04 (.06)	−.15 (.11)	−.12 (.06)	−.11 (.10)	−.05 (.06)
Dyscalculia	−.06 (.08)	−.11 (.08)	−.07 (.07)	−.19 (.06)**	−.07 (.09)	.00 (.08)	−.06 (.08)	−.14 (.07)*	−.05 (.07)	−.02 (.09)
$r_{\text{change residuals}}$	−.05 (.06)		.01 (.06)		.11 (.06)		.08 (.09)		−.05 (.08)	
Model fit										
χ^2(df)	61.49 (21)***		159.46 (114)**		191.50 (154)*		230.69 (114)***		195.62 (154)*	
CFI	.958		.965		.978		.912		.975	
RMSEA	.058		.027		.021		.043		.022	
SRMR	.038		.042		.038		.046		.040	

Note: Standardized solution. Values in brackets show standard errors. Regression weights indicating reciprocal relations are printed in bold.

Abbreviations: CFI, comparative fit index; FF, fear of failure; Gc, crystallized intelligence; HS, hope for success; NFC, need for cognition; RMSEA, root mean square error of approximation; SRMR, standardized root mean square residual (student level).

*p<.05; **p<.01; ***p<.001.

TABLE 5 Prediction of latent change in reading comprehension and investment traits.

Predictor	Model NFC↔reading comprehension		Model HS↔reading comprehension		Model FF↔reading comprehension		Model I-type curiosity↔reading comprehension		Model D-type curiosity↔reading comprehension	
	Δreading	ΔNFC	Δreading	ΔHS	Δreading	ΔFF	Δreading	Δcuriosity	Δreading	Δcuriosity
Investment trait t_1	**.16 (.08)***	−.43 (.06)***	**.11 (.10)**	−.60 (.06)***	**−.10 (.10)**	−.63 (.06)***	**−.12 (.13)**	−.61 (.06)***	**.10 (.07)**	−.55 (.05)***
Reading t_1	−.40 (.12)**	**.02 (.08)**	−.37 (.12)**	**.06 (.07)**	−.39 (.12)**	**−.09 (.06)**	−.34 (.13)**	**.03 (.04)**	−.37 (.12)**	**.04 (.08)**
Cognitive stimulation	.13 (.08)	.03 (.05)	.15 (.08)	.05 (.06)	.13 (.08)	−.03 (.07)	.15 (.08)	−.03 (.06)	.14 (.08)	.01 (.06)
Cultural capital	.10 (.08)	.14 (.06)*	.13 (.08)	.08 (.05)	.12 (.08)	.01 (.06)	.15 (.08)*	.19 (.06)**	.12 (.08)	.02 (.05)
Parental education	−.06 (.09)	.16 (.09)	−.04 (.09)	.02 (.04)	−.04 (.09)	−.13 (.09)	−.06 (.09)	.04 (.07)	−.04 (.09)	.11 (.06)
Immigration background	−.13 (.07)	.03 (.06)	−.10 (.07)	.13 (.04)***	−.11 (.07)	.07 (.05)	−.10 (.07)	.06 (.05)	−.12 (.07)	.02 (.06)
Age	−.05 (.08)	−.03 (.06)	−.02 (.08)	.03 (.06)	−.02 (.07)	.03 (.04)	−.03 (.08)	.05 (.05)	−.04 (.08)	−.05 (.06)
Female gender	−.03 (.08)	−.02 (.06)	−.05 (.08)	−.03 (.05)	−.02 (.09)	.06 (.05)	−.03 (.08)	.04 (.05)	−.03 (.08)	−.06 (.05)
Dyslexia	−.16 (.08)*	−.06 (.06)	−.17 (.08)*	.01 (.04)	−.18 (.08)*	−.03 (.06)	−.19 (.08)*	−.15 (.06)*	−.17 (.08)*	−.06 (.06)
$r_{\text{change residuals}}$	−.05 (.05)		−.09 (.07)		.07 (.07)		.11 (.08)		−.07 (.05)	
Model fit										
χ^2(df)	0 (0)[a]		72.89 (75)		110.40 (109)		128.88 (75)***		123.07 (109)	
CFI	1.00		1.00		.999		.939		.988	
RMSEA	.000		.000		.005		.036		.015	
SRMR	.000		.029		.032		.036		.031	

Note: Standardized solution. Values in brackets show standard errors. Regression weights indicating reciprocal relations are printed in bold.

Abbreviations: CFI, comparative fit index; FF, fear of failure; HS, hope for success; NFC, need for cognition; RMSEA, root mean square error of approximation; SRMR, standardized root mean square residual (student level).

[a]Model just identified.

*$p<.05$; **$p<.01$; ***$p<.001$.

TABLE 6 Prediction of latent change in mathematical ability and investment traits.

	Model NFC ↔ mathematical ability		Model HS ↔ mathematical ability		Model FF ↔ mathematical ability		Model I-type curiosity ↔ mathematical ability		Model D-type curiosity ↔ mathematical ability	
Predictor	**Δmath**	**ΔNFC**	**Δmath**	**ΔHS**	**Δmath**	**ΔFF**	**Δmath**	**Δcuriosity**	**Δmath**	**Δcuriosity**
Investment trait t_1	**.01 (.11)**	−.49 (.07)***	**−.03 (.09)**	−.66 (.07)***	**−.01 (.09)**	−.65 (.05)***	**−.19 (.10)***	−.62 (.07)***	**.04 (.10)**	−.57 (.05)***
Math t_1	−.23 (.09)*	**.16 (.08)***	−.23 (.09)**	**.16 (.06)****	−.23 (.09)**	**−.14 (.07)***	−.20 (.09)*	**.20 (.06)****	−.24 (.09)**	**.13 (.07)**
Cognitive stimulation	.03 (.09)	.03 (.05)	.03 (.08)	.04 (.05)	.03 (.09)	−.04 (.07)	.04 (.08)	−.03 (.05)	.03 (.08)	.01 (.06)
Cultural capital	.03 (.06)	.14 (.07)*	.04 (.06)	.07 (.06)	.04 (.07)	−.03 (.06)	.07 (.06)	.18 (.06)**	.03 (.06)	.01 (.05)
Parental education	−.02 (.10)	.15 (.09)	−.00 (.09)	.02 (.04)	.01 (.09)	−.16 (.09)	−.01 (.10)	.01 (.07)	.00 (.10)	.10 (.07)
Immigration background	−.01 (.06)	.03 (.06)	−.00 (.06)	.11 (.04)**	−.01 (.06)	.09 (.04)*	.01 (.06)	.05 (.05)	−.01 (.07)	.01 (.06)
Age	−.14 (.08)	−.03 (.06)	−.13 (.08)	.02 (.06)	−.13 (.08)	.05 (.05)	−.14 (.07)	.04 (.05)	−.14 (.07)*	−.06 (.06)
Female gender	−.06 (.09)	.03 (.06)	−.06 (.09)	.03 (.05)	−.06 (.09)	.02 (.05)	−.04 (.08)	.11 (.05)*	−.07 (.08)	−.02 (.05)
Dyscalculia	−.12 (.09)	−.12 (.08)	−.13 (.09)	−.19 (.06)**	−.12 (.09)	−.02 (.09)	−.11 (.10)	−.14 (.06)*	−.12 (.09)	−.03 (.09)
$r_{\text{change residuals}}$	.01 (.05)		.02 (.06)		−.01 (.05)		.09 (.06)		−.01 (.06)	
Model fit										
χ^2(df)	315.26 (143)***		463.30 (278)***		526.40 (332)***		514.80 (278)***		543.18 (332)***	
CFI	.950		.951		.955		.938		.950	
RMSEA	.046		.034		.032		.039		.034	
SRMR	.042		.047		.043		.052		.045	

Note: Standardized solution. Values in brackets show standard errors. Regression weights indicating reciprocal relations are printed in bold.

Abbreviations: CFI, comparative fit index; FF, fear of failure, HS, hope for success; NFC, need for cognition; RMSEA, root mean square error of approximation; SRMR, standardized root mean square residual (student level).

*p<.05; **p<.01; ***p<.001.

using a sample of elementary school children determined by an a priori power analysis.

Effects of cognitive abilities on investment traits

Investment traits are thought to direct our achievement-related appraisals, emotions, motives, and behaviors over long periods of time (Mussel, 2013). Against this background, it is an important question how investment traits develop in a phase of pronounced motivational and cognitive change, namely in the elementary school years, and what might influence this development. We found that, similar to learning motivation and ability self-concepts (e.g., B. Spinath & Steinmayr, 2008), there was a decreasing trend for investment traits that especially pertained to curiosity. Even more important, we found that children strongly differed in that trend and that, in line with the environmental success hypothesis, mathematical ability could partly explain these differences. More precisely, higher mathematical skills predicted a slighter decline in investment traits that motivate individuals to search for intellectual challenges and to persist in working on them. In addition, higher mathematical skills predicted a stronger decline in FF, an investment trait that motivates individuals to avoid intellectual challenges and to withdraw from challenges when obstacles occur (e.g., McClelland et al., 1953).

Higher cognitive abilities might buffer the decline of investment traits (or promote investment traits, respectively), because they might cause positive attitudes toward achievement-related situations. Students with higher cognitive skills are likely to experience more success and more learning progress in achievement-related situations and receive positive feedback via grades (e.g., Steinmayr & Spinath, 2009). Experience of success (e.g., high grades) is likely to enhance children's ability self-concepts (e.g., Weidinger et al., 2018). Higher ability self-concepts, in turn, might motivate students to seek for cognitive challenges and to show persistence when working on tasks, even when obstacles occur (see also Cattell, 1987; Chamorro-Premuzic & Furnham, 2004; Schmiedek et al., 2014). Experience of success also helps students develop positive emotions toward achievement-related situations (e.g., Pekrun et al., 2017). These positive emotions might lead to stronger investment traits, too. Especially seek investment traits have an affective component, as they tap, for example, interest in and enjoyment of thinking and learning (Mussel, 2013). But also HS and FF have an affective dimension tapping hope and pride as well as fear and shame (McClelland et al., 1953). School grades, ability self-concepts, and achievement-related emotions might therefore mediate the effect of mathematical ability on investment traits. Future longitudinal studies might implement at least three measurement occasions to provide suitable conditions for testing such a mediation effect.

The question is, however, why especially mathematical ability predicted the change in the investment traits. Learning mathematics strongly depends on *explicit* learning opportunities provided by school (e.g., Bisanz et al., 1995). Although the developments of reading comprehension and thinking skills also depend on schooling (e.g., Cahan & Cohen, 1989; Crone & Whitehurst, 1999), they might rather happen through *implicit* learning in a wider range of situations than school. For example, promoting thinking skills is no explicit part of school curricula (see Bergold & Steinmayr, 2019), and reading comprehension becomes a matter of automation through exercise, once its precursors (e.g., phonological awareness, letter knowledge) have developed (e.g., Hjetland et al., 2020). Because of their explicit nature, learning progress, success, and failure in mathematics might be much more salient to students than learning progress, success, and failure in reading comprehension and reasoning. Furthermore, performance in mathematics is related to problem solving (e.g., Kretzschmar et al., 2016). Thus, if students solve mathematical problems they might feel more competent in problem solving. As feelings of competency are related to intrinsic motivation and thus to internal enjoyment derived from engaging in these tasks (Deci et al., 1991), increased task-specific intrinsic motivation might generalize to investment traits. This hypothesis is supported by the significant associations between interest and seek and conquer facets of intellect (Rusche & Ziegler, 2022). In addition, students might perceive mathematics as an especially structured and “strict” school subject, where there are clearly right and wrong answers and where grades are especially indicative of cognitive skills, as opposed to other subjects such as languages (Roth et al., 2015). Consequently, mathematical skills might make a stronger impact on investment traits than might reading comprehension or Gf.

Consistent effects of Gf on investment traits might first emerge in late adolescence, as Bergold et al. (2023) found Gf to predict the development of NFC from age 16 to age 19. HS might be a precursor in this process, being the first investment trait affected by Gf (see our finding and the finding by Bergold & Steinmayr, 2016). Given that adolescence comes with rapid cognitive development (e.g., Anderman et al., 2023), older adolescents might become aware of the importance of cognitive ability in our Western societies. In addition, self-evaluations of intelligence become more accurate by adolescence (Demetriou et al., 2020). Both aspects might enhance the predictive power of Gf for the development of a wider range of investment traits. However, results are inconsistent, as Ziegler et al. (2012, Study 2) found no effect of Gf or Gc on openness from age 17 to age 23. Future studies might therefore test whether results systematically vary by investment trait and possibly also by time lag.

No effects of investment traits on cognitive abilities

Investment traits might not only be important for achievement-related attitudes and behavior but also for the development of academic abilities (e.g., Ackerman, 1996; Cattell, 1987). Although the correlations between investment traits and cognitive abilities were in line with both theoretical expectations and previous studies (see Ackerman & Heggestad, 1997; Anglim et al., 2022; Liu & Nesbit, 2023; von Stumm & Ackerman, 2013), there were no effects of the investment traits on change in either Gf or Gc, with the exception of an effect of NFC on reading comprehension. Furthermore, changes in cognitive abilities did not vary with changes in investment traits. Given that the investment traits investigated in this study were quite representative of the range of investment traits (and the investment traits in the present study supported the differentiation proposed by Mussel's, 2013 intellect model), we suppose it is unlikely that there are other investment traits we did not consider that would have exhibited consistent and notable effects. Our finding is also in line with the studies by Hülür et al. (2018) and Lechner et al. (2019) who did not find significant effects of typical intellectual engagement or openness, respectively, on intellectual growth in adolescence. It is also in line with the zero effect of HS found for elementary school children (Bergold & Steinmayr, 2016). However, we could not replicate the negative effect of FF on intellectual growth identified by Bergold and Steinmayr (2016). In this previous study, the effect of FF occurred in a cross-lagged panel model without control variables. By contrast, we accounted for a number of control variables (note, however, that the LCSM without control variables did not reveal a significant effect of FF either).

Our findings together with the findings by Hülür et al. (2018) and Lechner et al. (2019) indicate that there is no consistent effect of (domain-general) investment traits on intellectual development throughout childhood and adolescence. In the same vein, the present findings suggest that the zero effects found in the previous studies were likely not caused by power problems. In addition, we found no consistent effects of cultural capital or cognitive stimulation on intellectual development, which would have been predicted by the environmental enrichment hypothesis. A recent study by Mussel (2022) also revealed that epistemic behavior did not mediate the effect of cognitive ability or curiosity, respectively, on change in grades. This overall picture contradicts the environmental enrichment hypothesis, at least for younger individuals. Maybe children's and adolescents' opportunities to choose their intellectual challenges on their own are so limited that their domain-general investment traits cannot come into effect (see also Hülür et al., 2018). Domain-general investment traits might gain importance as individuals get more options to increase self-determined learning, especially after leaving school (or at the later stages of secondary school, where there are more options to choose classes). The effects of openness on the changes in both Gf and Gc from late adolescence to early adulthood found by Ziegler et al. (2012, Study 2) are in line with this proposition as are the increasing relations between NFC and reasoning or academic achievement, respectively, as students age (Liu & Nesbit, 2023; Luong et al., 2017). Future longitudinal studies might employ fine-grained analyses of when exactly between late adolescence and early adulthood domain-general investment traits emerge as predictors of intellectual development.

Interestingly, Lechner et al. (2019) did find effects of interests on change in reading and math skills. However, these interests were domain-specific. Although constructs related to interest (e.g., intrinsic motivation, intrinsic values) conceptually differ from investment traits, future research might investigate whether domain-specific investment traits such as interests might be more important for intellectual development in childhood and (early and middle) adolescence than domain-general investment traits. Domain-specific investment traits might be especially predictive of domain-specific indicators of Gc such as reading skills or mathematical ability (as opposed to Gf and to more domain-general indicators of Gc such as general knowledge, vocabulary, or verbal fluency). Given that some investment traits originally thought to be domain-general have already been shown to be potentially domain-specific (Sparfeldt & Rost, 2011), future studies might test whether investment traits such as NFC or curiosity might be also be regarded as domain-specific.

Strengths and limitations

Although this study has several strengths (e.g., a sample of elementary school students predetermined by a power analysis, a comprehensive consideration of investment traits derived from an established theoretical model, a longitudinal assessment allowing for testing reciprocal effects), it also has limitations.

We only had two measurement occasions covering 1 year, which is a limitation in several regards. Cross-lagged paths from LCSMs with two measurement occasions equal those from cross-lagged panel models, which have been criticized for mixing up relations within individuals and relations between individuals, potentially producing biased estimates and neglecting the fact that within-person relations are at the core of developmental theories (e.g., Berry & Willoughby, 2017). Nevertheless, the LCSMs allowed us to inspect mean-level change, individual differences in change, and explaining these individual differences with individual differences in cognitive abilities or investment traits, respectively. In addition, a recent simulation study has shown that cross-lagged effects from cross-lagged panel models are unbiased in models with controls for third variable effects in which the correlations between the control variable and the variables of interest remain constant or decrease over time; biases emerged when correlations increased by the factor 2 or 3 (Lüdtke & Robitzsch, 2022). This was barely the case in our study (see Table 1).

The fact that we only had two measurement occasions prevented us from rigorously testing mediation effects. Moreover, regression to the mean might have been at work, given that change in most variables was negatively related to their base levels. It might also be that effects of investment traits occur over longer periods than 1 year. Future studies should therefore implement several measurement occasions over longer periods to address these shortcomings. In addition, the dropout from t_1 to t_2 was slightly systematic. Students with lower abilities, HS, and I-type curiosity were somewhat more likely to drop out of the study. However, this effect was rather small and did not affect the variances of these variables (see the standard deviations shown in Table 1).

A hard look needs to be given at the adapted measure of D-type curiosity. The results for change in D-type curiosity did not match with the results for the other investment traits. In addition, for t_1 the correlation with I-type curiosity was lower than expected and the correlations of D-type curiosity with the ability measures roughly equaled zero. All these findings were against the expectations. Although we had tested this scale in the pilot study and this scale seemed to provide adequate psychometric properties in the present study, too, we cannot completely rule out that the adapted scale did not fulfill its purpose, at least at t_1.

Another potential limitation refers to the generalizability of our findings. The students in our sample performed below average at t_1 as compared to the norm samples of the instruments applied ($43.06 \leq T \leq 47.73$; Haffner et al., 2005; Lenhard et al., 2017; Weiß, 2006). The question is whether this indicates that our sample is so specific that the findings might not be generalizable to other same-aged students. Two reasons might explain the underperformance. The first measurement occasion took place after the summer holidays following the last school lockdown in Germany caused by the COVID-19 pandemic. Before the summer break, students had attended school every other day for 3 weeks and on a regular daily basis for 6 weeks. Recent studies have shown that the school lockdowns impeded learning (e.g., Di Pietro, 2023) and possibly intellectual development (Breit et al., 2023). Another explanation might be that our sample was not representative of the same-aged student population in Germany. It comprised more students with an immigration background as compared to the norm samples, which might have led to a left-handed switch of the distribution (the standard deviations approximated those from the norm samples). However, we believe that these factors do not strongly limit generalizability. First, we were interested in predicting growth in raw scores, not in determining standard values. Whereas the school lockdowns did have effects on learning until the end of the last lockdown, the study by Breit et al. (2023) indicated no unusual patterns in intellectual growth after the school lockdowns, that is, in times when we collected our data. Second, samples with many migrant students will probably become the rule rather than the exception in Germany, as the number of students with an immigration background is rising. In addition, we controlled for immigration background and other demographics. Finally, this investigation together with the few previous studies draws a quite consistent picture questioning the validity of the environmental enrichment hypothesis for both childhood and adolescence, which also speaks for the reliability of the present findings.

Finally, our study was non-experimental. Although we considered a number of control variables, non-experimental designs are always in danger of overlooking potential third variable effects.

CONCLUSIONS

The present study found no consistent effects of investment traits on change in either Gf or Gc in elementary school children despite accurate test power. Although much intellectual development happens in elementary school age, significant others such as teachers and parents might determine the children's learning environments to such degree that children's investment traits cannot exert an influence on intellectual development. Thus, it remains the question whether a practical focus on investment traits would be appropriate in this age range, as promoting investment traits seems not to be an investment in intellectual growth, notwithstanding that it might be an investment in more subjective achievement criteria such as grades (e.g., Liu & Nesbit, 2023). This might change between late adolescence and young adulthood when individuals get more options to actively choose their learning environments. At the same time, this study revealed effects of mathematical ability on investment traits, even when accounting for various control variables. This is an important finding that should be further investigated, for example, regarding mediating effects. In school practice, promoting children's mathematical abilities might serve to buffer their motivational declines. We propose that more experiences of success in a highly valued, highly structured, and explicitly taught subject might increase children's achievement-related emotions, ability self-concepts, self-confidence, and self-efficacy, all of which might motivate them to seek for more cognitive challenges and to show more persistence when working on them. In any case, our finding illustrates a hitherto understudied phenomenon, namely that cognitive skills can shape personality development.

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DATA AVAILABILITY STATEMENT

The data, analytic code, and materials necessary to reproduce the analyses presented here are not publicly accessible. However, interested researchers may email the authors for insights into data, codes, and materials for replication purposes. The analyses presented here were not preregistered. The study design, hypotheses, and analysis plan were described a priori in the project proposal directed to the DFG.

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SUPPORTING INFORMATION

Additional supporting information can be found online in the Supporting Information section at the end of this article.

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