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Personality, intelligence, and academic achievement: Charting their developmental interplay

Lisa Bardach[1] | **Nicolas Hübner**[2] | **Benjamin Nagengast**[1,3] | **Ulrich Trautwein**[1] | **Sophie von Stumm**[4]

[1]Hector Research Institute of Education Sciences and Psychology, University of Tübingen, Tübingen, Germany

[2]Institute of Education, University of Tübingen, Tübingen, Germany

[3]Department of Education and the Brain & Motivation Research Institute (bMRI), Korea University, Seoul, Republic of Korea

[4]Department of Education, University of York, York, UK

Correspondence
Lisa Bardach, Hector Research Institute of Education Sciences and Psychology, University of Tübingen, Walter-Simon-Straße 12, Tübingen 72072, Germany.
Email: lisa.bardach@uni-tuebingen.de

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Abstract

Objective: Although intelligence and personality traits have long been recognized as key predictors of students' academic achievement, little is known about their longitudinal and reciprocal associations. Here, we charted the developmental interplay of intelligence, personality (Big Five) and academic achievement in 3880 German secondary school students, who were assessed four times between the ages 11 and 14 years (i.e., in grades 5, 6, 7, and 8).

Method: We fitted random intercept cross-lagged panel models (RI-CLPs) to investigate reciprocal within-person associations between (a) academic achievement and intelligence, (b) academic achievement and personality, as well as (c) intelligence and personality.

Results: The results revealed negative within-person associations between Conscientiousness and Extraversion assessed at the first wave of measurement and intelligence assessed at the second wave. None of the reciprocal personality–achievement associations attained statistical significance. Academic achievement and intelligence showed reciprocal within-person relations, with the strongest coefficients found for achievement longitudinally predicting intelligence.

Conclusions: Our work contributes to developmental theorizing on interrelations between personality, intelligence, and academic achievement, as well as to within-person conceptualizations in personality research.

KEYWORDS

academic achievement, Big Five, intelligence, personality, random intercept cross-lagged panel model

1 | INTRODUCTION

Academic achievement during the school years has pervasive, long-term influence on people's life outcomes, mainly because it regulates the access to higher education. A key question in psychological research is therefore why some students excel at school, whereas others struggle academically. A large body of empirical research has shown that intelligence and personality are key predictors of academic achievement (e.g., Krapohl et al., 2014; McAbee & Oswald, 2013; Poropat, 2009; Roth et al., 2015; von Stumm & Ackerman, 2013). Yet, longitudinal research on the developmental interplay of intelligence, personality, and academic achievement at school is scarce. This omission is particularly striking because childhood and adolescence are known to be accompanied by significant intellectual and social–emotional changes, such as personality development (e.g., Soto & Tackett, 2015), that are likely to affect concurrent and later development across domains.

Prior studies on intelligence–personality associations have predominantly relied on cross-sectional observational studies that suggested intelligence and personality are largely independent domains (e.g., Ackerman & Heggestad, 1997; Zeidner, 1995). An exception is so-called investment personality traits, for example, Openness to Experience or curiosity, which are thought to predict where, when, and how individuals invest their cognitive abilities to acquire knowledge and grow intellectually (von Stumm & Ackerman, 2013). However, the empirical evidence for the benefits of investment traits for academic achievement is mixed and weak at times (e.g., Poropat, 2009; Richardson et al., 2012). By contrast, the personality trait Conscientiousness has been repeatedly demonstrated to be a powerful predictor of academic achievement, although its association with intelligence is thought to be null, with some studies even showing small negative relations (Poropat, 2009; von Stumm et al., 2011).

Individual differences in intelligence, personality, and academic achievement are relatively stable (e.g., Deary et al., 2013) but within-person changes occur in all three domains (e.g., Borghuis et al., 2020; Ziegler et al., 2012, 2015). Moreover, deviances from one's trait-like characteristics that are captured by within-person analyses are thought to be particularly critical for personality change and likely play a role in individuals' intellectual and achievement-related development as well (e.g., Roberts & Jackson, 2008; Roberts, 2018; Wrzus & Roberts, 2017; see also Brandt et al., 2019). Investigating longitudinal within-person associations is therefore key for theorizing on the developmental interplay between personality, intelligence, and academic achievement. Nonetheless, such research is scarce, mainly because few longitudinal data sets exist with repeated measures over time of all three constructs. Here, we, therefore, utilize data from a longitudinal study of secondary school students who were assessed annually for 4 years (Jonkmann et al., 2013) and apply random intercept cross-lagged panel models (RI-CLPMs, Hamaker et al., 2015) to investigate reciprocal within-person associations between personality, intelligence, and academic achievement.

2 | INTELLIGENCE AND ACADEMIC ACHIEVEMENT

Intelligence or cognitive ability is defined as “a very general mental capability that, among other things, involves the ability to reason, plan, solve problems, think abstractly, comprehend complex ideas, learn quickly and learn from experience” (Gottfredson, 1997, p. 13). Academic achievement, on the other hand, refers to performance outcomes in different domains taught at schools, universities, or other educational settings (e.g., Spinath, 2012). Academic achievement can be measured using teacher-assigned grades or standardized achievement test scores. Grades provide important information typically based on student work closely tied to the curriculum but have also been criticized for being subjective. Standardized achievement tests draw on uniform questions, administration, and scoring systems and thus, on more objective processes (e.g., Bowers, 2011; Koretz, 2002, for a comprehensive discussion of different indicators of academic achievement and their characteristics, see Hübner et al., 2023). The present study relies on standardized test scores as a measure of academic achievement.

Intelligence provides the basis for the development of academic achievement, with academic achievement resulting from the interplay between intelligence and cultural experiences, such as education (e.g., Cattell, 1987; Peng et al., 2019). In fact, intelligence is one of the most potent predictors of academic achievement. For example, a 5-year longitudinal study of 70,000+ English children found a correlation of .81 between children's general intelligence at age 11 and their academic achievement across 25 subjects at age 16 (Deary et al., 2007). A recent meta-analysis reported average correlations between intelligence (assessed with nonverbal reasoning tasks) and mathematics and reading performance of $r = .41$, and $r = .38$, respectively (Peng et al., 2019).

Although most prior studies have conceptualized intelligence as an antecedent of academic achievement, intelligence, and academic achievement are likely to influence each other. According to the mutualism model, reciprocal correlations between different aspects of human cognition—including intelligence and academic achievement—emerge as a result of their mutually beneficial interactions (Van der Maas et al., 2006). Individuals use their intelligence to learn and perform academic tasks while going through education also serves to train intelligence (Martinez, 2000; Peng et al., 2019; Ritchie & Tucker-Drob, 2018). A recent meta-analysis of longitudinal studies found that intelligence predicted long-term gains in reading and mathematics performance after controlling for initial differences in reading and mathematics performance (Peng et al., 2019). Conversely, reading and mathematics performance also predicted growth in intelligence, after initial intelligence differences were taken into account (all meta-analytic r's around .20; Peng et al., 2019).

3 | PERSONALITY AND ACADEMIC ACHIEVEMENT

Students' personality—often referred to as relatively enduring patterns of thoughts, feelings, and behaviors (e.g., Roberts & Jackson, 2008)—accounts for a substantial amount of variance in their academic achievement (e.g., Poropat, 2009, 2011; Schneider & Preckel, 2017). The most widely used personality taxonomy, the Big Five framework, covers five basic dimensions of personality: Extraversion (e.g., active, assertive social), Openness (e.g., open-minded, curious, cultured), Agreeableness (e.g., altruistic, tender-minded, cooperative), Conscientiousness (e.g., self-controlled, following norms and rules, organized), and Neuroticism (e.g., worried, anxious) (John et al., 2008; McCrae & Costa, 1999). Conscientiousness and Openness have been identified as the Big Five personality domains most relevant to academic achievement (Hübner et al., 2022; Poropat, 2009; von Stumm et al., 2011).

Conscientiousness comprises self-regulation, achievement-striving, and organization (Costa & McCrae, 1995; Digman, 1989). Students, who score high on Conscientiousness, tend to, for example, invest more effort in their homework (e.g., Trautwein et al., 2006) and show fewer counterproductive academic behaviors (e.g., absenteeism, low effort; Cuadrado et al., 2021). Conscientiousness correlates about .25 with measures of academic achievement across studies and educational settings (Poropat, 2009; Richardson et al., 2012; see also, e.g., Andersen et al., 2020). In secondary school students, a meta-analytic correlation of $r = .21$ has been reported, which remained unchanged after controlling for intelligence (Poropat, 2009).

Openness has been empirically linked to adaptive approaches to learning and learning motivation (e.g., Komarraju et al., 2011), which possibly underlies the positive effects of Openness on academic achievement. Moreover, Openness has been described as "investment trait." Intellectual investment theories propose that investment traits—among those Openness—determine when, where, and how individuals invest their time and effort in their intellect, and this investment, in turn, contributes to individual differences in cognitive growth, including academic attainment (von Stumm & Ackerman, 2013). Individuals scoring high on Openness actively seek out to and enjoy a wealth of learning opportunities and prefer intellectually stimulating environments, which positively affects their intellectual development (e.g., von Stumm, 2017; von Stumm et al., 2011; Ziegler et al., 2012). Meta-analytical findings have indicated a small correlation between Openness and academic achievement (measured mostly via course grades and students' GPA) at the secondary school level ($r = .12$), which reduced slightly when controlling for intelligence ($r = .09$) (Poropat, 2009).

Evidence for the influence of the other Big Five traits on academic achievement tends to be less consistent (for an overview see De Raad & Schouwenburg, 1996; Poropat, 2009; Poropat, 2015). Students high on Neuroticism have been suggested to be more anxious and worrying, which diverts their attention from academic tasks, thus impairing their performance. Students characterized by high levels of Extraversion may have greater energy, which should be conducive to learning and academic achievement; at the same time, they may be more easily distracted or prefer spending time socializing rather than studying, which could interfere with their learning (e.g., Bidjerano & Yun Dai, 2007). Agreeable students may reap academic benefits, because they are more likely to engage in cooperative behavior, comply with teachers' instructions, and stay out of trouble (e.g., Miller et al., 2003; Vermetten et al., 2001). Notwithstanding these theoretical foundations for associations, nonsignificant and close-to-zero meta-analytic correlations have been reported between secondary school students' academic achievement and emotional stability ($r = .01$), extraversion ($r = -.03$), and Agreeableness ($r = .05$; Poropat, 2009).

Even though it has often been assumed that personality traits, especially Conscientiousness and Openness, give rise to higher academic achievement, the reverse direction of effects is also possible. Success or failure at school is a key influence on adolescents' identity development and personality maturity (e.g., Israel et al., 2019). Hence, academic achievement could involve a feedback loop, with higher academic achievement reinforcing achievement-related behaviors and personality tendencies (i.e., Openness and Conscientiousness). One prior study found in a large sample of 4355 German secondary school students, who were assessed twice, that, overall, personality was associated with change in achievement, and achievement was also related to change in personality. Nonetheless, the corresponding effect sizes were small and sometimes contradictory (Israel et al., 2019). These results evidence the importance of reciprocal effects between academic achievement, intelligence, and personality but the inconsistency of prior findings makes it difficult to derive specific hypotheses.

4 | PERSONALITY AND INTELLIGENCE

Intelligence captures intellectual potential or what an individual *can do*, whereas personality traits describe typical behavioral tendencies or what an individual is *most likely to do* (Cronbach, 1949; von Stumm et al., 2011). The interplay of these two core pillars of individual differences can be viewed from one of three perspectives (von Stumm et al., 2011; Zeidner, 1995). The first suggests the conceptual and empirical independence of intelligence and personality: both are seen as separate psychological entities. This perspective has received some empirical support (e.g., Ackerman & Heggestad, 1997; Reeve et al., 2006). The second perspective proposes associations on the measurement level in that certain personality traits affect individual's intelligence test performance. For example, higher levels of anxiety and worry of emotionally instable individuals (e.g., von der Embse et al., 2018) may impair their intelligence test performance (e.g., Zeidner & Matthews, 2000). The third approach focuses on intelligence–personality associations on a conceptual and developmental level; this approach also informs theoretical foundations of the current study.

A prominent conceptual and developmental approach are so-called investment theories of intelligence (von Stumm et al., 2011; von Stumm, 2017, see also the considerations on the link between Openness and academic achievement in the previous section). Openness to Experience has been frequently studied as a proxy of an intellectual investment trait (e.g., Ackerman & Heggestad, 1997; Chamorro-Premuzic & Furhnam, 2006; Lechner et al., 2019; von Stumm, 2017; von Stumm et al., 2013). Openness correlates moderately with general intelligence (e.g., r = .22 in Judge et al., 2007; r = .33 in Ackerman & Heggestad, 1997), with some of its facets correlating even more strongly with crystallized intelligence (up to meta-analytic r = .58 in von Stumm & Ackerman, 2013). The link between Openness and intelligence is also the focus of the Openness-Fluid-Crystallized-Intelligence (OFCI) model (Ziegler et al., 2012, 2018). Akin to investment theories, the OFCI model argues that Openness leads individuals to select themselves into richer environments that, in turn, exert positive influences on the development of their fluid intelligence (environmental enrichment hypothesis). The OFCI model further specifies that Openness affects crystallized intelligence via fluid intelligence. Individuals higher in Openness more often encounter new situations, but simply experiencing such situations is not sufficient to accumulate crystallized intelligence: Employing fluid abilities is an essential prerequisite to make sense of the situation (Ziegler et al., 2018).

Beyond the effects of Openness on intelligence, reverse influences of intelligence and Openness also seem reasonable (see von Stumm & Ackerman, 2013; Ziegler et al., 2012). For instance, intelligence could precede investment traits, as higher levels of intelligence enable individuals to better engage with and pursue learning experiences (e.g., Silvia & Sanders, 2010), which, in turn, benefit their investment trait development (von Stumm & Ackerman, 2013). The OFCI model proposes that individuals with higher levels of fluid intelligence are more likely to successfully master challenging new tasks, which then makes them more likely to seek out similar tasks or situations in the future (environmental success hypothesis). These processes are thought to ultimately manifest in altered levels of Openness (Ziegler et al., 2018; see also von Stumm & Deary, 2013).

A further conceptual and developmental perspective on intelligence–personality associations involves Conscientiousness and relates to the notion of compensation. It has been proposed that less intelligent individuals become more conscientious over time, as they compensate for their lower cognitive ability, whereas more intelligent individuals can afford being less organized and dutiful and still excel (e.g., Chamorro-Premuzic & Furnham, 2005; von Stumm et al., 2011). Although Conscientiousness and intelligence have often been shown to be independent, some studies have found modest negative correlations (e.g., Lechner et al., 2017; Moutafi et al., 2006; Poropat, 2009; Rammstedt et al., 2016).

5 | RESEARCH GOALS AND HYPOTHESES

The present study charted the interplay between intelligence, personality, and academic achievement over the course of adolescence. We capitalized on longitudinal data from 3880 German secondary school students, who were assessed four times when they were on average age 11, 12, 13, and 14 (i.e., in grades 5, 6, 7, and 8) on intelligence, the Big Five, and academic achievement. Academic achievement was operationalized in terms of standardized achievement test scores in mathematics. Mathematics is typically among the subjects that students find most difficult, which should elicit distinctive relations to intelligence and personality that may not occur in situations of low challenge. Furthermore, making progress in mathematics requires building on previously learned materials. Accordingly, deficits in mathematics competencies are likely to accumulate over time, resulting in long-term differences in mathematics achievement trajectories (Blackwell et al., 2007; Peixoto et al., 2017). In addition, mathematics represents a subject that is taught in all countries, which makes the results better comparable with findings from other studies. We applied RI-CLPMs (Hamaker et al., 2015) to focus on developmental relations at the within-person level.

Developmental processes occurring within persons play a central role in theories of human development (e.g., Baltes & Nesselroade, 1979) and underlie personality changes (e.g., Roberts & Jackson, 2008; Wrzus & Roberts, 2017; see also Brandt et al., 2019).

Three research questions were addressed, each focusing on relations on the within-person level. Please note that these associations always concern associations between *deviations* from one's trait-like characteristic or behavior; hence, if construct 1 positively and longitudinally predicts construct 2 on the within-person level, this means that scoring higher than average on construct 1 positively predicts a higher-than-average score on construct 2 at the subsequent wave (Hamaker et al., 2015; see also Brandt et al., 2019).

First, how is intelligence longitudinally associated with academic achievement? We predict that intelligence and academic achievement will show reciprocal within-person associations, with intelligence positively predicting academic achievement and vice versa (e.g., Deary et al., 2007; Peng et al., 2019).

Second, how are the Big Five personality domains longitudinally related to academic achievement? We expect that Conscientiousness and Openness will positively predict academic achievement. Likewise, we assume that within-person effects of academic achievement on Conscientiousness and Openness occur. By contrast, we hypothesize that the other three Big Five dimensions (Agreeableness, Emotional Stability, and Extraversion) will not be significantly and reciprocally related to academic achievement. Yet, we will still test their cross-lagged associations to add to the current body of knowledge on reciprocal within-person relations between Big Five personality domains and academic achievement.

Third, how are intelligence and personality dimensions longitudinally related? Following investment trait theories (e.g., von Stumm et al., 2011) and the environmental enrichment hypothesis (e.g., Ziegler et al., 2018), we expect within-person effects of Openness on intelligence over time. In line with the environmental success hypothesis (Ziegler et al., 2018), we furthermore propose that there will be significant cross-lagged paths from intelligence to Openness. We will also test if there are compensatory effects between Conscientiousness and intelligence in that low intelligence may prompt students to become more conscientious over time (e.g., von Stumm et al., 2011). We predict that the other Big Five domains will not play a significant role in the development of adolescents' intelligence or be affected by intelligence.

All hypotheses and methods were preregistered at the Open Science Framework (OSF, https://osf.io/74nj5/).

6 | METHOD

6.1 | Sample

Data came from a large-scale longitudinal German study (TRAIN), hosted by the Hector Research Institute of Education Sciences and Psychology at the University of Tübingen in Germany. The sample includes 3880 secondary school students from 136 classes in nonacademic track schools from two German federal states (Baden-Württemberg, 66.0%, and Saxony, 34.0%), for whom data from at least one of four measurement points were available. Across all measurement points, 45.2% of the students identified as females and they were, on average, 14.20 years old at the fourth measurement point ($SD = 0.65$). A total of 43.2% of the students attended the academically least demanding track ("Hauptschule") and 22.7% attended the intermediate track ("Realschule"). All students from Saxony (34.0%) attended "Mittelschule," which combines "Hauptschule" and "Realschule." The assessments of intelligence, personality, and achievement took place 6 weeks after the start of the respective school year when students were on average 11 (grade 5), 12 (grade 6), 13 (grade 7), and 14 (grade 8) years old.

Several studies on personality using TRAIN data have already been published (Göllner, Damian, et al., 2017; Göllner, Roberts, et al., 2017; Israel et al., 2022; Rieger et al., 2017; Trautwein et al., 2015). The study most closely related to the current one is the study by Israel et al. (2022), who focused on multiple school experiences, among those academic achievement, and personality. However, intelligence was only included as a control variable and only the intelligence assessment from the first wave was used. Overall, none of the existing studies based on TRAIN data has investigated joint longitudinal within-person associations between personality, intelligence, and academic achievement.

6.2 | Missing data

Missing data in the present study resulted from nonresponse and attrition. A total of 628 students (16.19%) participated in one, 709 students (18.09%) in two, 335 students (8.63%) in three, and 2208 students (56.91%) in all four waves of measurement. We conducted a series of Welch's tests with Benjamini-Hochberg correction (Benjamini & Hochberg, 1995) to test for mean differences between the students who participated in all waves of data collection and those who missed at least one wave. Results revealed no statistically significant differences for Openness at all waves, Extraversion at all waves, Agreeableness at waves 1–3, and Conscientiousness at wave 1 (Cohen's d ranging between −0.11 and 0.08). There were statistically significant differences for intelligence test scores at all four waves (Cohen's d ranging between 0.19 and 0.35), mathematics achievement at all four waves (Cohen's d ranging between 0.11 and 0.34), Conscientiousness at wave 2–4 (Cohen's d ranging between 0.11 and 0.12), and Agreeableness at wave 4 (Cohen's $d = 0.12$), with higher scores for those present at all waves. Statistically significant differences were also found for neuroticism at all four waves (Cohen's d ranging between −0.12 and −0.22, with lower scores for those present at all waves). Full information maximum likelihood estimation (FIML; Enders, 2010) was used to handle missing data and to reduce possible bias in the parameter estimates.

6.3 | Measures

6.3.1 | Personality

Personality traits were assessed using the German version (Lang et al., 2001) of the Big Five Inventory (John et al., 1991). The items were rated on a 5-point rating scale ranging from 1 (*strongly disagree*) to 5 (*strongly agree*). Negatively worded items in this instrument had a low item-total correlation (all rs < .22) and were therefore excluded (Rieger et al., 2017). Five items assessed Conscientiousness (e.g., "I see myself as someone who preserves until the task is finished"), five items for Openness (e.g., "I see myself as someone who is original, comes up with new ideas"), four items for Agreeableness (e.g., "I see myself as someone who is helpful and unselfish with others"), five items for Neuroticism (e.g., "I see myself as someone who is depressed, blue"), and four items for Extraversion (e.g., "I see myself as someone who is outgoing, sociable").[1] Cronbach's alpha coefficients for waves 1, 2, 3, and 4, respectively, were .77, .80, .80, and .81 for Conscientiousness; .78, .81, .81, and .81 for Openness; .67, .67, .66, and .67 for Agreeableness; .70, .67, .67, and .69 for Neuroticism; and .72, .72, .74, and .75 for Extraversion. Table S1 shows all items.

6.3.2 | Intelligence

A test of figural intelligence—figural analogies—from the intelligence test battery KFT 4–12+ R (Heller & Perleth, 2000), which is an adapted version of the Cognitive Abilities Test by Thorndike and Hagen (1971), was used. Item and person parameters for students' intelligence have previously been estimated with longitudinal, multidimensional two-parameter item response theory models (Rose et al., 2013), and we relied on weighted likelihood estimators (WLEs) of students' figural intelligence test scores (Warm, 1989). Reliabilities of the WLEs for the four waves were estimated using the TAM package (Robitzsch et al., 2021) in R (R Core Team, 2022) and amounted to .87, .86, .82, and .84, respectively.

6.3.3 | Academic achievement

A standardized mathematics test was created from the item pool designed to test standards in education ("Bildungsstandards") in Germany and prior large-scale assessment studies (e.g., BIJU, Baumert, Gruehn, et al., 1997, ELEMENT, Lehmann & Nikolova, 2005, and TIMSS, Baumert, Lehmann, et al., 1997). Depending on the wave, the test contained 74–87 items spanning the areas (a) numbers, (b) measuring, (c) geometry, (d) functions, and (e) probability and statistics. Item and person parameters for students' mathematics achievement have previously been estimated with longitudinal, multidimensional two-parameter item response theory models (Rose et al., 2013). As for intelligence, we used WLEs of students' mathematics achievement test scores (Warm, 1989). Reliabilities of the WLEs for the four waves were .76, .72, .71, and .77, respectively.

6.4 | Analytic approach

We performed all analyses with Mplus Version 8.4 (Muthén & Muthén, 2017) using the robust maximum likelihood estimator (MLR). Personality dimensions were modeled as latent variables. For the standardized mathematics achievement WLEs and for intelligence, we employed a single-indicator (SI) approach (e.g., Hoyle, 2012). Specifically, to implement the single-indicator approach, we fixed the residual variance of the respective scores (standardized test achievement) to (1-reliability) * sample variance.

We specified RI-CLPMs (Hamaker et al., 2015) to investigate longitudinal reciprocal relations between personality, intelligence, and academic achievement. Unlike the "traditional" CLPM, the RI-CLPM divides the variance of constructs into variance between persons (between-person level) and variance within persons (i.e., fluctuations over time; within-person level). Hence, the RI-CLPM accounts for trait-like, time-invariant stability (person-specific mean) through the inclusion of a random intercept (a factor with all loadings constrained to 1). As this random intercept partials out time-invariant differences between-persons, the lagged relationships in the RI-CLPM pertain to within-person relations (Hamaker et al., 2015). The RI-CLPM, therefore, relaxes some of the assumptions of the traditional CLPM; however, it is important to note that it does not control for time-varying unobserved confounding (Usami et al., 2019). We set up five RI-CLPMs, each of them included a different Big Five personality dimension, with all of them additionally including intelligence and academic achievement (see Figure 1).

We conducted the RI-CLPMs in two steps to test for longitudinal measurement invariance (Mulder & Hamaker, 2021). First, we set up the RI-CLPMs with freely estimated factor loadings (Model 1, configural invariance). Second, we re-estimated the RI-CLPMs and constrained the factor loadings to be equal across time (Model 2, metric invariance). It is important to note that for comparing cross-lagged and autoregressive parameters, as we did in the present study, metric invariance is sufficient. However, for comparing means over time, scalar invariance would be required (Hamaker, 2018). We assessed the goodness of fit of all models using the comparative fit index (CFI), the Tucker–Lewis Index (TLI), and the root mean square error of approximation (RMSEA). Typical cutoff scores taken to reflect appropriate fit to the data will be considered: (a) CFI and TLI >.95; (b) RMSEA <0.05 (e.g., Hu & Bentler, 1999). The evaluation of longitudinal invariance assumptions was based on the recommendations of Chen (2007) and Cheung and Rensvold (2002). Accordingly, we considered drops in CFI >0.01 and increase in RMSEA >0.015 as indicative of meaningful changes in model fit, which make assumptions of measurement invariance not tenable. To answer our research questions, we were particularly interested in the reciprocal within-person relations between (a) intelligence and achievement, (b) personality and achievement, and (c) personality and intelligence. In the RI-CLPM, the cross-lagged coefficients reflect within-person associations rather than between-person associations. This makes it possible to, for example, estimate associations of the *deviances* of a person's trait-like personality with deviances of person's trait-like academic achievement and intelligence (Hamaker et al., 2015; see also Brandt et al., 2019). Moreover, whereas the autoregressive coefficient in the "traditional" CLPM indicates the stability of the rank order of individuals from one occasion to the next, the autoregressive coefficient in the RI-CLPM represents the amount of "within-person carry-over effect": For example, if it is positive, this implies that occasions on which one scored above one's expected score are likely to be followed by occasions on which one still scores above the expected score again, and vice versa (Hamaker et al., 2015; see also Hamaker, 2012; Kuppens et al., 2010). To account for the hierarchical data structure, with students nested in classes, we conducted

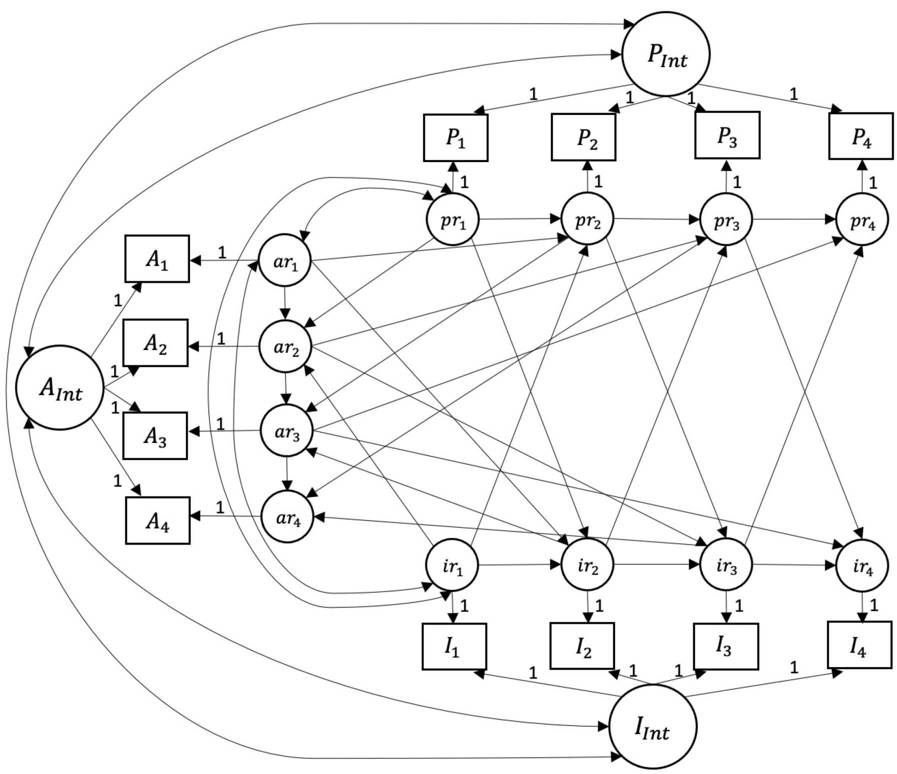

FIGURE 1 Graphical representation of a RI-CLPM estimated in the current study. A = Academic Achievement; I = Intelligence; P = Personality. The random intercepts are represented by the latent variable $P_{Int}/I_{in}t/A_{Int}$, factor loadings are all constrained to 1. For parsimony, residuals and their correlations are not displayed. One model was set up for each personality dimension.

the analyses using cluster-robust standard errors (e.g., McNeish et al., 2017). All significance testing was performed at the .05 level, and we relied on two-tailed tests.

6.5 | Transparency and openness

We described the sample and procedure in detail. There were no data exclusions. All analysis codes and output files are available at OFS (https://osf.io/74nj5/). We deviated in one significant way from the preregistration: We had initially preregistered to also use German achievement test scores in addition to the mathematics ones. However, we encountered persistent model convergence problems for German achievement. We then adopted a different analytical approach by constraining all autoregressive paths as well as the cross-lagged paths to be equal over time (e.g., Orth et al., 2021), which resolved the convergence issues. However, these constrained models are not directly comparable to our preregistered models that fit for mathematics. To be fully transparent, we have uploaded the analysis codes and output files for the models for German achievement to the OSF and included a table reporting all estimates from these models in the Online Supplement. In the paper, we focus on the results from the models including mathematics achievement and only briefly refer to the findings for German because the constrained models for German achievement deviated too much from our preregistered analytical approach.

We furthermore want to point out that the results of our analyses revealed that in some cases the statistical significance between standardized and unstandardized coefficients differed (statistically significant standardized but nonsignificant unstandardized coefficients or vice versa). We therefore based decisions regarding statistical significance for these cases on additional analyses using bias-corrected bootstrapping (5000 bootstraps), and, thus, on whether the 95% CIs included zero (see Table S3 for details).

7 | RESULTS

Descriptive statistics and bivariate correlation coefficients are shown in Table S2 in the Online Supplement. The results from measurement invariance testing are displayed in Table 1. All models showed an excellent fit to the data, and measurement invariance assumptions (metric invariance) were supported for all models. The results from the five RI-CLPMs are reported in Table 2 (standardized coefficients for all autoregressive and cross-lagged coefficients) and Table S3 in the Online Supplement (unstandardized coefficients).

7.1 | Autoregressive paths

Looking at the autoregressive paths showed that for all personality dimensions, scoring higher-than-average (scoring higher than suggested by one's respective personality

TABLE 1 Measurement invariance testing results, and model fit of the configural and metric invariance random intercept cross-lagged panel models

Model	χ^2	*df*	CFI	TLR	RMSEA	SRMR	BIC
Openness							
Configural	1199.734	313	.962	.954	0.027	0.029	189,369.301
Metric	1229.369	325	.961	.955	0.027	0.031	189,302.686
Conscientiousness							
Configural	1242.444	313	.959	.951	0.028	0.032	186,937.052
Metric	1265.392	325	.959	.952	0.028	0.033	186,867.327
Extraversion							
Configural	894.526	215	.962	.951	0.029	0.030	165,077.036
Metric	903.109	224	.962	.953	0.028	0.031	165,014.430
Agreeableness							
Configural	734.980	215	.968	.959	0.025	0.031	168,260.240
Metric	744.473	224	.968	.961	0.025	0.032	168,198.141
Neuroticism							
Configural	924.868	215	.958	.946	0.029	0.031	174,217.030
Metric	934.440	224	.958	.948	0.029	0.031	174,153.217

TABLE 2 Results of the latent random intercept cross-lagged panel models for the five personality dimensions, intelligence, and mathematics achievement: standardized estimates

		Wave (W)		
Model	**Effects**	**2**	**3**	**4**
Openness	Autoregression – personality (W-1) → personality (W)	**0.344** (0.049)	**0.315** (0.062)	**0.271** (0.064)
	Autoregression – intelligence (W-1) → intelligence (W)	**0.135** (0.066)	0.153 (0.130)	**0.260** (0.113)
	Autoregression – achievement (W-1) → achievement (W)	**0.696** (0.138)	**0.603** (0.217)	**0.631** (0.196)
	Cross-lagged relation – personality (W-1) → intelligence (W)	−0.077 (0.046)	−0.080 (0.065)	−0.053 (0.046)
	Cross-lagged relation – personality (W-1) → achievement (W)	−0.045 (0.046)	−0.021 (0.075)	0.013 (0.049)
	Cross-lagged relation – intelligence (W-1) → personality (W)	−0.061 (0.063)	−0.069 (0.071)	−0.001 (0.090)
	Cross-lagged relation – intelligence (W-1) → achievement (W)	0.175 (0.095)	0.233 (0.144)	0.104 (0.135)
	Cross-lagged relation – achievement (W-1) → personality (W)	0.100 (0.120)	0.084 (0.110)	0.044 (0.150)
	Cross-lagged relation – achievement (W-1) → intelligence (W)	**0.435** (0.158)	**0.568** (0.212)	**0.396** (0.155)
Conscientiousness	Autoregression – personality (W-1) → personality (W)	**0.362** (0.050)	**0.384** (0.060)	**0.340** (0.064)
	Autoregression – intelligence (W-1) → intelligence (W)	0.127 (0.073)	0.136 (0.147)	**0.286** (0.134)
	Autoregression – achievement (W-1) → achievement (W)	**0.604** (0.134)	**0.442** (0.217)	**0.531** (0.185)
	Cross- lagged relation – personality (W-1) → intelligence (W)	**−0.099** (0.049)	−0.051 (0.071)	−0.005 (0.052)
	Cross-lagged relation – personality (W-1) → achievement (W)	−0.077 (0.067)	0.074 (0.085)	0.036 (0.058)
	Cross-lagged relation – intelligence (W-1) ➔personality (W)	−0.043 (0.064)	−0.048 (0.064)	−0.089 (0.084)
	Cross-lagged relation – intelligence (W-1) → achievement (W)	0.199 (0.107)	**0.305** (0.142)	0.146 (0.142)
	Cross-lagged relation – achievement (W-1) → personality (W)	0.146 (0.098)	0.013 (0.133)	0.204 (0.104)
	Cross-lagged relation – achievement (W-1) → intelligence (W)	**0.381** (0.169)	**0.566** (0.267)	**0.314** (0.147)
Extraversion	Autoregression – personality (W-1) → personality (W)	**0.362** (0.073)	**0.409** (0.077)	**0.402** (0.072)
	Autoregression – intelligence (W-1) → intelligence (W)	**0.137** (0.063)	0.150 (0.139)	**0.259** (0.129)
	Autoregression – achievement (W-1) → achievement (W)	**0.696** (0.163)	**0.606** (0.243)	**0.644** (0.237)
	Cross-lagged relation – personality (W-1) → intelligence (W)	**−0.090** (0.045)	−0.068 (0.071)	−0.016 (0.052)
	Cross-lagged relation – personality (W-1) → achievement (W)	−0.059 (0.041)	−0.120 (0.065)	0.028 (0.047)
	Cross-lagged relation – intelligence (W-1) → personality (W)	−0.056 (0.073)	0.016 (0.073)	0.044 (0.089)
	Cross-lagged relation – intelligence (W-1) → achievement (W)	**0.177** (0.110)	0.235 (0.156)	0.102 (0.157)
	Cross-lagged relation – achievement (W-1) → personality (W)	0.049 (0.144)	−0.045 (0.118)	−0.058 (0.141)
	Cross-lagged relation – achievement (W-1) → intelligence (W)	**0.460** (0.150)	**0.588** (0.206)	**0.416** (0.187)
Agreeableness	Autoregression – personality (W-1) → personality (W)	**0.366** (0.059)	**0.354** (0.080)	**0.376 (**0.101)
	Autoregression – intelligence (W-1) → intelligence (W)	0.166 (0.090)	0.089 (0.225)	0.323 (0.215)
	Autoregression – achievement (W-1) → achievement (W)	**0.594** (0.227)	0.438 (0.454)	0.507 (0.360)
	Cross-lagged relation – personality (W-1) → intelligence (W)	−0.077 (0.044)	−0.150 (0.132)	−0.018 (0.064)
	Cross-lagged relation – personality (W-1) → achievement (W)	−0.005 (0.046)	−0.033 (0.149)	0.107 (0.094)
	Cross-lagged relation – intelligence (W-1) → personality (W)	−0.089 (0.062)	−0.060 (0.082)	0.009 (0.104)
	Cross-lagged relation – intelligence (W-1) → achievement (W)	**0.236 (0.148)**	0.323 (0.278)	0.186 (0.231)
	Cross-lagged relation – achievement (W-1) → personality (W)	0.039 (0.186)	0.016 (0.135)	0.013 (0.192)
	Cross-lagged relation – achievement (W-1) → intelligence (W)	**0.412** (0.134)	**0.658** (0.331)	0.319 (0.276)
Neuroticism	Autoregression – personality (W-1) → personality (W)	**0.436** (0.081)	**0.593** (0.074)	**0.506** (0.084)
	Autoregression – intelligence (W-1) → intelligence (W)	**0.131** (0.064)	0.150 (0.116)	**0.251** (0.097)
	Autoregression – achievement (W-1) → achievement (W)	**0.766** (0.104)	**0.713** (0.151)	**0.711** (0.148)
	Cross-lagged relation – personality (W-1) → intelligence (W)	−0.066 (0.063)	−0.022 (0.089)	0.014 (0.052)
	Cross-lagged relation – personality (W-1) → achievement (W)	−0.019 (0.038)	0.011 (0.069)	−0.030 (0.041)
	Cross-lagged relation – intelligence (W-1) → personality (W)	0.016 (0.088)	−0.074 (0.086)	−0.119 (0.107)
	Cross-lagged relation – intelligence (W-1) → achievement (W)	**0.158** (0.075)	**0.195 (0.103)**	0.082 (0.101)
	Cross-lagged relation – achievement (W-1) → personality (W)	−0.084 (0.145)	−0.015 (0.120)	0.130 (0.161)
	Cross-lagged relation – achievement (W-1) → intelligence (W)	**0.525** (0.160)	**0.621** (0.167)	**0.485** (0.162)

Note: Standardized estimates (standard errors); Achievement = Standardized achievement test results in mathematics. Statistically significant results at $\alpha = .05$ are in boldface.

trait level) at one wave was related to scoring higher-than-average at the next wave too (i.e., statistically significant autoregressive paths). A similar pattern emerged for the autoregressive paths for academic achievement in mathematics in most models. Higher-than-average intelligence test scores at the first measurement point significantly predicted higher intelligence at the second measurement point in the models for Openness, Extraversion, and Neuroticism, and higher-than-average intelligence scores at the third measurement point significantly predicted higher intelligence at the fourth measurement point in the models for Openness, Conscientiousness, Extraversion, and Neuroticism. (Please note that the significance of autoregressive relations for intelligence and achievement differ in some models, as different personality dimensions were included in each of them).

7.2 | Achievement–intelligence associations

The results indicated that all longitudinal cross-lagged within-person relations between academic achievement in mathematics and intelligence, with achievement positively predicting intelligence at the subsequent wave, were statistically significant in all models except for the path between wave 3 achievement and wave 4 intelligence in the Agreeableness model. Hence, higher-than-average achievement in mathematics longitudinally predicted higher-than-average intelligence test scores.

Intelligence predicted subsequent academic achievement too: In the models for Extraversion, Agreeableness, and Neuroticism, scoring higher-than-average on the intelligence test at wave 1 was associated with higher-than-average mathematics achievement at wave 2. In the models including Neuroticism and Conscientiousness positive cross-lagged within-person relations were further found for wave 2 intelligence predicting wave 3 achievement.

7.3 | Personality–achievement associations

None of the within-person paths from Big Five personality domains to academic achievement were statistically significant. The achievement also did not statistically significantly predict any of the personality domains.

7.4 | Personality–intelligence associations

Most of the cross-lagged intelligence–personality associations failed to reach statistical significance, with two exceptions: Extraversion at the first wave significantly and negatively predicted intelligence at the second wave; thus, being more extraverted than one would on average be at the first wave was related to lower-than-average intelligence test scores at the second wave. Moreover, we obtained a significant negative within-person association between Conscientiousness at the first wave and intelligence at the second wave. Overall, the statistically significant coefficients for personality–intelligence associations were much smaller than those observed for achievement–intelligence associations (see standardized coefficients in Table 2).

7.5 | Additional findings (academic achievement in German)

The results of the analyses for German achievement with constrained autoregressive and cross-lagged paths (see Table S4 in the Online Supplement) revealed significant positive autoregressive paths for all personality dimensions, German achievement, and intelligence in all models. In all models, the cross-lagged paths for achievement and intelligence, with achievement predicting intelligence and vice versa, were statistically significant. In addition, we found a positive longitudinal relation between higher-than-average Agreeableness and subsequent higher-than-average German achievement, and negative longitudinal relations between higher-than-average Neuroticism and subsequent higher-than-average German achievement and intelligence.

8 | DISCUSSION

The goal of this study was to investigate the developmental interplay between personality, intelligence, and academic achievement over the course of adolescence. We focused on reciprocal within-person associations between all three constructs as deviances from one's trait-like behavior or characteristics have been presumed to be particularly critical for personality change and arguably play a role in an individual's intellectual and achievement-related development as well (e.g., Brandt et al., 2019; Roberts & Jackson, 2008; Wrzus & Roberts, 2017). Hence, our work makes an important contribution to prior research, which has, so far, mainly relied on concurrent between-person interrelations between personality, intelligence, and academic achievement.

The most consistent effects were found for *achievement–intelligence associations*. Interestingly, longitudinal links from achievement to intelligence were not only more often statistically significant, but also generally stronger than links from intelligence to achievement. Hence, intelligence benefits mathematics achievement, but mathematics achievement benefits intelligence even more. The acquisition of complex skills in core subjects, such as mathematics, thus seems to serve as training to improve intelligence to some degree. Being academically proficient may further enable one to engage in increasingly more cognitively stimulating activities, with academic achievement and intelligence then mutually reinforcing each other over time (e.g., Peng et al., 2019; Van der Maas et al., 2006). As such, this finding can also be linked to recent meta-analytic results revealing that years spent in education are correlated with increases in IQ points (Ritchie & Tucker-Drob, 2018). In addition, it makes a valuable extension to the work of Peng et al. (2019), who meta-analyzed longitudinal studies conducted with younger students mostly between ages 6 and 11 and showed that mathematics achievement longitudinally predicted fluid intelligence, partialing out initial intelligence and vice versa. Lastly, the findings regarding mutual achievement–intelligence associations have implications for the large body of (educational and personality psychology) research on academic achievement, which typically only includes intelligence as a covariate, thus failing to account for the intricate interplay between achievement and intelligence.

Regarding *personality–intelligence associations*, we had hypothesized that Openness should be reciprocally related to intelligence. Among the Big Five personality traits, Openness to experience has been described as a primarily "cognitive trait" (e.g., DeYoung et al., 2005), and we had assumed that particularly Openness and intelligence would reveal mutual associations in line with investment trait theories, the environment enrichment hypothesis (Openness predicts intelligence) and the environmental success hypothesis (intelligence predicts Openness) (e.g., von Stumm & Ackerman, 2013; Ziegler et al., 2018). However, none of the cross-lagged relations between Openness and intelligence were statistically significant. One reason for the lack of significant relations could be that the learning environment in secondary school is highly structured, leaving fewer degrees of freedom for exploration and thus the transformation of Openness and intellectual curiosity into intelligence (and vice versa). It may be that longitudinal relations between Openness and other investment personality traits and cognitive development emerge in contexts where self-determined intellectual activities play a more important role and individuals are able to shape their learning environments in line with their personality (e.g., Hülür et al., 2018). We further hypothesized that lower intelligence is associated with increases in Conscientiousness as being self-controlled, organized, and dutiful may aid in compensating for poorer cognitive abilities (compensation mechanisms, e.g., Chamorro-Premuzic & Furnham, 2005; von Stumm et al., 2011). However, the results revealed a significant and negative cross-lagged effect of Conscientiousness on subsequent intelligence test scores. Speaking in "within-person terminology," higher-than-average conscientiousness at wave 1 was related to a lower-than-average intelligence test performance the next year. Although we did not find empirical support for compensation mechanisms between intelligence and Conscientiousness, the results are a noteworthy extension of prior research on negative (mostly concurrent) relations between Conscientiousness and intelligence (e.g., Lechner et al., 2017). Interpreting the finding, we suggest that being conscientious may backfire, as occupying oneself too much with being a "good," always organized, and dutiful (i.e., conscientious) student potentially leaves less time and resources for one's cognitive development. The effect only surfaced at the beginning of secondary school, which points toward the role of context and timing. Specifically, the transition from elementary to secondary school goes along with changes in the school environment and rules, and the nature of academic tasks (e.g., Dent & Koenka, 2016; Jindal-Snape et al., 2020). To better cope with the challenging transition period, adolescents may increase their level of Conscientiousness, with negative side effects on their intellectual development.

Although we had no specific hypotheses for the link between Extraversion and intelligence (see, e.g., Wolf & Ackerman, 2005, for a close-to-zero negative meta-analytic correlation), the results showed a significant negative association between Extraversion at the first wave and intelligence at the second wave. Hence, being outgoing, social, and enthusiastic (or, more precisely, being more outgoing, social, and enthusiastic than expected by one's respective traits) longitudinally predicted lower intelligence test scores. It may be that higher levels of Extraversion diverted adolescents' attention from cognitively simulating activities and led them to primarily focus on their social life, which came at a cost for their intellect. A reason why this pattern of results was only found at the beginning of secondary school, that is, from wave 1 to wave 2, could be that adolescents are confronted with an entirely new peer group after they move to secondary school. Thus, the need—or press—to be socially accepted by one's new peers and make friends, which may manifest in higher-than-average levels of Extraversion, may therefore be particularly pronounced in this period. Moreover, as expected, we did not find significant within-person links between Agreeableness, Neuroticism, and intelligence.

Contradicting the large body of prior research on Conscientiousness and Openness as robust correlates of success at school (e.g., Poropat, 2009) and our hypotheses, none of the *personality–achievement associations* in our study attained statistical significance. One reason could be that more complex dynamics are at work but were not captured by our analytical approach. For instance, personality may rather predict or interact with motivation, which in turn, feeds into higher academic achievement (see, e.g., Lechner et al., 2019; Ziegler et al., 2015). Another potential explanation relates to the measurement of academic achievement. Other measures than standardized achievement test scores, such as evaluations of student performance teachers directly communicate to their students in day-to-day interactions could more strongly inform personality development and be influenced by student personality. Due to the scarcity of research in this area, we based our hypotheses regarding within-person longitudinal associations between personality and academic achievement mostly on prior between-person and often cross-sectional research. Alas, modeling approaches that seek to capture between-person effects (e.g., cross-lagged panel model, CLPM) differ fundamentally from those that test for within-person effects (e.g., RI-CLPM). Accordingly, the conclusion that can be derived from the models' findings differ (Hamaker et al., 2015; Orth et al., 2022): For example, the CLPM allows investigating the cross-lagged effect of individual differences in one construct on individual differences in another construct, while controlling for prior individual differences in the outcome. In the CLPM, a cross-lagged effect of adolescents' personality (e.g., Openness) on achievement would indicate that adolescents with higher levels of Openness are more likely to show higher levels of achievement than adolescents with lower Openness. The RI-CLPM is similar to the CLPM in some regards but includes random intercept factors, which conceptually correspond to trait factors, and which capture stable between-person variance in the constructs across assessments. After removing the stable between-person variance of each construct, the cross-lagged effects are then modeled between the residualized scores. Hence, the RI-CLPM examines the cross-lagged effect of the within-person deviation from the trait level of one construct on the within-person deviation from the trait level of another construct, while controlling for previous within-person deviations from the trait level of the construct that is to be predicted. As effect paths are controlled for autoregressive effects in the deviations, the RI-CLPM examines the change in within-person deviations from the respective trait level. In the RI-CLPM, a cross-lagged effect of Openness on achievement would therefore mean that adolescents who experience higher levels of Openness than on average at a specific time point will show higher-than-average levels of achievement at the following time point. Even though both CLPM and RI-CLPM help address the question of whether a particular construct has a prospective effect on another construct, within-person versus between-person analytical approaches test different effects and focus on conceptually distinct psychological and developmental processes (Orth et al., 2021, 2022). Hence, previously found relations in between-person studies are likely to not pertain to the within-person level of longitudinal links between personality and achievement (see also e.g., Brose et al., 2020; Hamaker et al., 2015; Hübner et al., 2023): Here, we observed nonsignificant within-person links between personality and academic achievement, while the extant literature brims with findings of significant between-person associations between personality and academic achievement (e.g., Andersen et al., 2020; Poropat, 2009; von Stumm et al., 2011). Although the theoretical importance of within-person differences in personality is broadly recognized (e.g., Brandt et al., 2019; Hecht et al., 2022; Wrzus & Roberts, 2017), the respective empirical evidence base is just emerging. Our current results are a first step for contributing to this emerging evidence base for the links between personality and academic achievement.

Several alternative analytical approaches other than the RI-CLPM exist to investigate longitudinal within-person associations (for overviews and empirical demonstrations, see e.g., Orth et al., 2021; Usami et al., 2019). For example, the Trait–State-Error-Model (STARTS model, Kenny & Zautra, 2001) can be used to examine the same hypotheses as the RI-CLPM (e.g., "When adolescents have higher Openness than on average, they will subsequently show higher-than-average academic achievement."), although the exact model specifications differ between the STARTS model and the RI-CLPM. Specifically, the STARTS model involves complex constraints on the variances and covariances of the residualized variables to impose stationarity, which may not be reasonable to assume in developmental studies (Orth et al., 2021; see also Donnellan et al., 2012). Continuous time models, another approach to study within-person reciprocal associations, have recently started to gain traction in psychology. Continuous time models easily integrate data from flexible longitudinal designs with unequally spaced measurement occasions, facilitate cross-study comparisons, and help exploring the unfolding of cross-lagged effects across different time intervals (Hecht et al., 2022; Hecht & Zitzmann, 2020). The latent curve model with structured residual (LCM-SR, Curran et al., 2014) represents another alternative to model reciprocal within-person relations. However, the hypotheses that can be addressed using this model (e.g., "When adolescents have higher Openness than would be expected from their developmental trajectory in Openness, they will experience a subsequent higher-than-average increase in academic achievement") slightly differ from the ones for the RI-CLPM (Orth et al., 2021). In general, an important advantage of the RI-CLPM over alternative within-person analytical approaches is that, typically, fewer convergence problems occur, and fewer measurement points are needed. In the model comparison study by Orth et al. (2021), the RI-CLPM converged in all the 10 used data sets, whereas other models, among those the STARTS model and the LCM-SR, frequently failed to converge.

Lastly, our paper focused mostly on the results for mathematics achievement, but key findings from the models for German achievement also emerged. First, German achievement and intelligence exhibited significant positive cross-lagged relations, which is aligned with our findings regarding positive cross-lagged relations between mathematics achievement and intelligence (Peng et al., 2019). Second, there was a positive longitudinal relation between Agreeableness and subsequent German achievement. This indicates that when students were more considerate, unselfish, helpful, and kinder than on average, they had subsequently higher-than-average levels of achievement in German, maybe because such behavioral tendencies are valued by teachers and high-achieving classmates who, in turn, provide academic support. Third, we found negative longitudinal relations between Neuroticism and subsequent intelligence and German achievement. Hence, being more emotionally unstable than on average predicted decrements in one's cognitive development, probably because experiencing higher levels of anxiety and worry than on average overloaded limited cognitive resources and was detrimental to deeply engaging with cognitively stimulating activities and tasks conducive to cognitive growth (e.g., De Raad & Schouwenburg, 1996; Sarigiannidis et al., 2020).

8.1 | Limitations and directions for future research

Several limitations of the current study and direction for future work should be noted. First, our study was conducted in German secondary schools. Although we think that the most basic processes linking intelligence, academic achievements, and personality should largely apply to different settings, there is a need to replicate our work in other countries and cultural contexts. Second, the current study yielded important insights into reciprocal associations between personality, intelligence, and academic achievement, but this focus necessarily led to the exclusion of further potentially relevant variables. For instance, other school-related variables than academic achievement, such as motivational orientations (e.g., goals, Bardach et al., 2020), expectancy and value beliefs (e.g., Nagengast et al., 2011), or school-related emotions (e.g., Peixoto et al., 2017) are likely to play a role for personality development in adolescence and are worth targeting in future longitudinal studies. Third, adolescents participating in this research project were followed over an extended period of time; however, it would have been desirable to include even more waves of measurement, ideally spanning different educational levels and developmental stages. Fourth, our study did not test mechanisms, such as specific (learning) behaviors (e.g., Komarraju et al., 2011; Trautwein et al., 2006), that may underlie the investigated within-person relations, and we encourage future research to do so in order to refine the insights gained in our and related previous research.

9 | CONCLUSIONS

The present study revisited associations between personality, intelligence, and academic achievement in adolescence using a longitudinal design and a within-person analytical approach. We found that Conscientiousness and Extraversion negatively predicted intelligence at the within-person level, whereas personality and academic achievement in mathematics were not significantly reciprocally related. Thus, our results regarding personality–intelligence and personality–achievement associations did either not support prominent theoretical assumptions, such as those outlined in investment trait theories (i.e., lack of significant effects for Openness), or suggested adaptations (i.e., for the link between Conscientiousness and intelligence). The results further showed within-person associations between academic achievement and intelligence, underscoring their important reciprocal connections in adolescence. Overall, this study represents an important step towards a more comprehensive understanding of the within-person interplay between personality, intelligence, and academic achievement.

AUTHOR CONTRIBUTIONS

The authors declare the following contributions to this article: LB: conceptualization, data curation, formal analysis, methodology, validation, visualization, writing–original draft, writing–review and editing. NH: conceptualization, data curation, formal analysis, methodology, validation, writing–review and editing. BN: conceptualization, methodology, writing–review and editing, supervision. UT: conceptualization, methodology, writing–review and editing, supervision, funding acquisition. SvS: conceptualization, methodology, writing–original draft, writing–review and editing, supervision.

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ETHICS STATEMENT

This is a secondary data analysis of data from the TRAIN study. The TRAIN study was approved by the state authorities, who, at this time, were responsible for approving studies like this one.

ENDNOTE

[1] When modeling personality dimensions as latent factors, as was done in this study, several problems can arise, such as single items that show a substantially low(er) loading on the latent factors than others, and model fits might not be in line with traditional recommendations (e.g., Hu & Bentler, 1999). In such instances and as outlined in our preregistration, we carefully checked both statistical indicators (e.g., lower loading, worse model fit) and content-related indicators (e.g., a specific item may not "present" the respective personality domain as well as others) and adapted our models to achieve adequate fit. In terms of model fit, we followed typical cutoff scores reflecting appropriate fit to the data, as described in the preregistration: (a) CFI and TLI > .95; (b) RMSEA <0.05 (e.g., Hu & Bentler, 1999). This led us to exclude one of the original five positively worded items for Neuroticism and Extraversion, respectively, and three of the original eight positively worded items for Openness (see Online Supplement Table S1 in the for the items).

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