Who Flourishes in School?
An Integrative Examination of Student Personality and Academic Self-Concepts across Learning Environments

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Danksagung

Is the time coming, when I can endure
to read my own writing in print without blushing
– shivering and wishing to take cover?

Virginia Woolf

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Table of Contents

Summary **9**

1. Theoretical Background **13**

1.1 Only the Young: Developmental Perspectives on Academic Performance in Adolescence 14

1.2 This Is Me Trying: Individual Self-Perceptions Contributing to Academic Success 19

1.3 So High School: Contextual Conditions Contributing to Academic Performance and Individual Development 27

1.4 Research Desiderata 33

2. Who Flourishes in School? The Interplay of Academic Self-Concept and Personality and its Role for Academic Performance in Middle Adolescence **39**

3. Becoming as Open-Minded and Organized as my Classmates? Peer Effects on Self-Reported Personality Trait Development in the Classroom **103**

4. Exploring the Roots: The Role of Perceived Teaching Behavior and Student Personality in Adolescents' Academic Self-Concept Development **143**

5. General Discussion **193**

5.1 Central Findings 193

5.2 Theoretical Implications 197

5.3 Methodological Implications 201

5.4 Practical Implications 203

5.5 Limitations and Outlook for Future Research 206

5.6 Conclusion 209

References **211**

Declarations **247**

Summary

Education has been integral to human societies throughout history, and successful education benefits both individuals and communities. Educational success is especially critical throughout the developmental phase of adolescence. Adolescents face age-specific developmental tasks that refer to academic performance and individual development. Theoretical perspectives emphasise that (academic) development results from transactions between individual characteristics and contextual conditions. Accordingly, individual self-perceptions such as student personality and academic self-concept contribute to academic performance. At the same time, contextual conditions including student sociodemographic characteristics, classroom peers, and teachers shape students' individual development of self-perceptions. Along these lines this dissertation integrated theoretical perspectives from developmental, personality, motivational, and educational psychology and studied the role of student personality and academic self-concept in academic performance and their development within the school context. Thereby, it addressed three overarching research aims. First, it examined how student personality and academic self-concepts relate to each other and jointly contribute to academic performance. Second, it investigated the role of individual self-perceptions in social inequalities relating to individual sociodemographic characteristics. Third, it inspected how peers and teachers shape the development of individual self-perceptions.

To address these overarching aims, this dissertation comprises three studies that took different perspectives on the role of individual self-perceptions in education. Study 1 integrated student personality and academic self-concepts and examined their role in social inequalities. More specifically, it tested the interrelations between and conjoint predictivity of student personality and academic self-concepts, as well as their moderating role in social inequalities. To do so, it applied latent moderated regression models to two large-scale samples of German secondary school students with diverse sociodemographic compositions. Study 2 addressed whether classroom peers shape the development of student personality. It provides a thorough investigation of how the classroom personality composition contributes to students' individual personality development by applying three different strategies of estimating multilevel structural equation models. Lastly, Study 3 applied (moderated) conditional latent growth curve models to predict academic self-concept development by student personality, teaching behaviour, and their respective interplay. Altogether, the three studies provide comprehensive insights into the role of student personality and academic self-concepts within the school environment, as well as the complexity of transactions between students and the school environment. Specifically, results support the interrelatedness and indicate interactive effects of the two self-perceptions on academic performance, while also revealing important differences across academic domains. Moreover, student personality and academic self-concepts potentially reinforce social inequalities. Lastly, the results support interactions between student personality and teaching behaviour in predicting academic self-concept (development), while pointing toward the need for further research on the role of classroom peers in individual personality development.

This dissertation contributes to our understanding of the role of individual self-perceptions in educational success and provides three overarching implications. First, it corroborates the utility of integrating different theoretical perspectives on the role of individual self-perceptions in education as an interdisciplinary perspective best reflects the complex interactive relations between individual self-perceptions and with contextual conditions. Second, it illustrates the impact of methodological aspects such as the specific measures used, sample composition, and modelling strategies, and elucidates how methodological diversity can contribute to a differentiated understanding of individual self-perceptions in education. Lastly, this dissertation substantiates the crucial role of teachers by illuminating their role in social inequalities and in shaping students' academic self-perceptions. Accordingly, teachers are valuable targets for educational policies and interventions, as their behavior can contribute to reducing social disparities and supporting individual student development. Nevertheless, future research should aim for further refinements by implementing advanced research designs across various educational systems that tap into the causality of associations, incorporate multi-method measures, and disentangle inter- and intraindividual variations in developmental trajectories.

1. Theoretical Background

Education and successful learning have been integral to human societies throughout history, shaping individuals and communities alike. Nelson Mandela once considered *“education […] the most powerful weapon which you can use to change the world”,* emphasizing its transformative potential. The transformative potential of education is evident in the connection between educational success and positive individual life outcomes (e.g., Buecker et al., 2018; Roth et al., 1996; Van Iddekinge et al., 2024) as well as in its impact on critical societal issues such as social mobility, equity, and justice—topics of great relevance in today’s society (cf. OECD, 2019). In accordance with a transactional perspective (e.g., Baltes et al., 2006; Eccles & Roeser, 2009; Eccles & Wigfield, 2020; Neyer et al., 2014; Rauthmann, 2021), this dissertation conceptualizes educational success as the outcome of a dynamic interaction between the individual and the contextual conditions of the learning environment. Along these lines, developmental task frameworks (e.g., Havighurst, 1948; Hurrelmann & Quenzel, 2018) emphasize the importance of educational success and individual development throughout the developmental phase of adolescence. Adolescence, spanning from ages 10 to early 20s, is a time during which individuals devote significant time to school (Rutter, 1979) and experience various developmental changes, both academically and personally (Lerner & Steinberg, 2009). Therefore, understanding the factors that contribute to differences in educational success during this age period is particularly important.

Taking a transactional perspective on academic development in adolescence, the stage-environment fit theory (Eccles et al., 1993) considers academic performance as one indicator of educational success, while also emphasizing that individual development is another crucial outcome of successful education (OECD, 2015). Importantly, it again highlights the importance of an integrated examination of both individual and contextual predictors. Taking a look at individual factors, research underscores the predictivity of different self-perceptions including personality traits (i.e., general tendencies to think, feel, and behave) and academic self-concepts (i.e., more specific beliefs about academic abilities) for academic performance (Mammadov, 2022; Möller et al., 2020). Despite theoretical frameworks suggesting an interrelatedness among different self-perceptions (Kandler et al., 2014; McAdams, 1995), limited understanding remains of how student personality and academic self-concept relate to each other and conjointly contribute to academic success.

Taking a look at contextual factors, schools represent the primary learning environment during adolescence (Eccles & Roeser, 2011). In line with a hierarchical conceptualization of the school environment (Eccles et al., 1993; Eccles & Roeser, 2009), I look into sociodemographic characteristics reflecting the individual's position within the broader societal context and, thus, impacting academic performance at school. Beyond sociodemographic characteristics, this dissertation focusses on the immediate classroom environment. Within classrooms, peers provide essential social interaction, while teachers serve as key socializers. Consequently, characteristics of both classroom peers and teachers are known as critical contextual predictors of academic performance (e.g., Hattie, 2002; Kunter & Voss, 2013). Nevertheless, the specific impact of these contextual factors on the development of individual self-perceptions is still underexplored.

By evaluating both individual and contextual characteristics, this dissertation aims to close this gap and adopt an integrative perspective on individual predictors of academic performance and their development in adolescence. Specifically, I examined how personality traits and academic self-concepts relate to each other and jointly contribute to academic performance within the German education system. Additionally, I investigated the role of individual self-perceptions in social inequalities associated with the individual sociodemographic background. Lastly, I accounted for transactions between individual and contextual characteristics and investigated how peers and teachers shape the development of individual self-perceptions. The subsequent chapters will unfold as follows: First, I will introduce theoretical perspectives on the developmental phase of adolescence. Second, I will provide a comprehensive overview of existing theoretical considerations and empirical evidence regarding individual self-perceptions as predictors of academic performance. Third, I will elaborate on theoretical considerations that integrate individual self-perceptions with contextual conditions of the learning environment. Thereby, I will identify gaps in the existing literature to inform my research questions. Lastly, I will briefly summarize the three studies I conducted to address these questions.

1.1 Only the Young: Developmental Perspectives on Academic Performance in Adolescence

While education and learning are considered as life-long processes (UNESCO Institute for Lifelong Learning, 2022), developmental perspectives on education highlight the importance of the life phase of adolescence (Havighurst, 1948; Hurrelmann & Quenzel, 2018). In general, the developmental phase of adolescence marks the transition from child- to adulthood. It spans from the onset of puberty to the transition into adult roles, including work and parenthood (Arnett, 2000; Lerner & Steinberg, 2009). Adolescents experience a multitude of rapid biological, cognitive and social changes requiring them to adapt their socioemotional characteristics accordingly (Lerner & Steinberg, 2009). Due to the extent and intensity of the experienced changes, the phase of adolescence has been divided into three subphases: early adolescence (10-13 years), mid-adolescence (14-16 years), and late adolescence (17-19 years; Lerner & Steinberg, 2009; Smetana, 2006). However, there is considerate interindividual variation in the timing of the specific changes of each subphase, thus, these age-based classifications are considered to be only approximate (Steinberg, 2020).

In line with a transactional perspective (e.g., Baltes et al., 2006; Eccles & Roeser, 2009; Eccles & Wigfield, 2020; Neyer et al., 2014; Rauthmann, 2021), developmental task frameworks view individual development as the result of transactions between individual characteristics and age-related societal expectations, understood as key contextual conditions (Havighurst, 1948; Hurrelmann & Quenzel, 2018; Hutteman et al., 2014). Such theories link the attainment of academic qualifications to the developmental stage of adolescence (Grob & Jaschinski, 2003; Hurrelmann & Quenzel, 2018). Consequently, it is important to understand underlying factors of academic performance within this life phase. Focusing specifically on academic development in adolescence, the stage–environment fit theory (Eccles et al., 1993; Eccles & Roeser, 2009) considers schools as crucial developmental contexts in adolescence and provides specific assumptions on how school characteristics shape adolescent development.

In the following, I further elaborate on the developmental tasks associated with adolescence and deduce the importance of considering both academic performance and the development of individual self-perceptions as important outcomes within this life phase. Subsequently, I introduce the core assumptions of the stage-environment fit theory and outline important considerations regarding schools as developmental contexts when looking into academic performance and the development of individual self-perceptions in adolescence.

Developmental Task Frameworks

According to developmental task frameworks, each life phase is characterized by its own normative age-graded developmental tasks (Erikson, 1959; Havighurst, 1948). Havighurst (p. 2, 1948) defined "[a] developmental task [as] a task which arises at or about a certain period of life of the individual, successful achievement of which leads to […] happiness and to success with later tasks, while failure leads to unhappiness in the individual, disapproval by the society, and difficulty with later tasks." Accordingly, fulfilling developmental tasks that arise from the interplay of biological changes, individual norms and values, and age-related societal expectations prepares the individual to successfully advance to later developmental stages (Havighurst, 1948). Building on the work of Havighurst (1948) various developmental theorists reinforced the concept of developmental tasks (Erikson, 1968; Grob & Jaschinski, 2003; Havighurst, 1972; Hurrelmann & Quenzel, 2018). The specific developmental tasks allocated to adolescence differ across theories in accordance with changes in the societal expectations throughout the years. Despite these differences in conceptualizations, more recent approaches share an emphasis on successful academic qualification and the formation of stable self-perceptions as central developmental tasks in adolescence (Grob & Jaschinski, 2003; Hurrelmann & Quenzel, 2018). The relevance of these central developmental tasks substantiates the importance of both academic performance and the development of individual self-perceptions as central indicators of educational success.

Obtaining an *academic qualification* can be considered the most societally-expected and context-dependent developmental task of adolescence. Academic qualification serves as a key precursor to future development, providing the foundation for increasing independence, a sense of competence, and opportunities for social mobility (Grob & Jaschinski, 2003; Hurrelmann & Quenzel, 2018). Moreover, the quality and kind of the school diploma obtained in adolescence significantly shapes the opportunities that young people have later in life. The kind of diploma that students obtain, to a large extent, depends on their academic performance at the secondary school level (grades 5 to 12). Consequently, academic performance becomes increasingly important across these grade levels, as the respective scholastic results become more directly linked to the kind and quality of diploma and consequently to the potential career paths that can be pursued. The quality of academic performance is reflected both in the grades that students earn in school and the acquired academic abilities measured by standardized ability tests (York et al., 2015). Accordingly, the current dissertation focusses on academic performance reflected both in grades and standardized test scores and its predictors across the secondary school level.

Looking at potential individual performance predictors in adolescence, it is crucial to contemplate a second central developmental task: the *formation of stable self-perceptions*[1]. Forming stable self-perceptions prepares adolescents for the decisions they need to make in young adulthood such as selecting a fitting profession. The formation of stable self-perceptions within the rather unstable life phase of adolescence comprises the reorganization and restructuring of the individual sense of self (Steinberg, 2020). While different disciplines have focused on specific aspects of the self, such as personality traits, motivation, or individual identities, integrative theoretical perspectives share a hierarchical ordering of these aspects (Ackerman, 1997; Graziano et al., 1997; Kandler et al., 2014; McAdams, 1995; McCrae, 2009; Zhang & Ziegler, 2016). McAdams and others (Graziano et al., 1997; 1995; McAdams &

[1] Stable self-perceptions are commonly also referred to as self-concepts. To ensure a clear differentiation between the term self-perceptions and the academic self-concept as one specific self-perception under investigation, I will use the term self-perceptions throughout this dissertation. Specifically, whenever I use the term self-perceptions I refer to both personality self-concepts and academic self-concepts.

Olson, 2010) proposed that an individual’s self-perceptions are organized in three levels: the first level consists of *general dispositions* that can be considered broad, decontextualized, and relatively nonconditional. The second level comprises *characteristic adaptations* that are contextualized in time, place, or role and subsume a variety of motivational, developmental, or strategic constructs. The third level refers to one’s *identity* as an inner story of the self that integrates perceptions of the past and present with anticipations of the future. As one’ narrative identities develop only throughout young adulthood (McAdams & Olson, 2010), this dissertation focuses on individual performance predictors at the first and second level of the self that are already evident in adolescence. Due to the developmental changes in these individual self-perceptions during adolescence, it also examines their development over time.

In summary, developmental task frameworks emphasize that development—the fulfilment of developmental tasks—results from an interplay of the individual with the environment and its demands. Consequently, successful education leads them to their academic qualification but also supports individuals in forming stable self-views. This dissertation addresses both the academic performance in secondary school as the main prerequisite of academic qualification and the individual development of self-perceptions at the two first levels of the self.

Stage-Environment Fit: Student-Context Transactions as Drivers of Adolescent Development

The *stage-environment fit theory* (Eccles et al., 1993; Eccles & Roeser, 2009) applies a transactional perspective to schools as developmental contexts. Building on more general ideas of person-environment transactions (e.g., Hunt, 1975; Lerner, 1991) and self-determination theory (Deci & Ryan, 2002), it proposes that student-environment fit shapes a student’s behavioral, cognitive, and socioemotional development. Based on three core assumptions, it provides a theoretical framework that allows for a structured investigation of student-environment transactions in school. First, it proposes that school environments have to fit the developing needs of adolescents. Whenever the school environment does not fit the developmental changes in students’ needs for competence, relatedness, and autonomy, the resulting incongruence leads to less school engagement and satisfaction (Osterman, 2000; Ratelle & Duchesne, 2014). The probability for such misfits is especially high in adolescence as rapid individual changes are accompanied by important *educational transitions* (Wang & Eccles, 2012). Thereby, stage-environment fit theory emphasizes the importance of investigating the secondary school years (grades 5/7 to 12/13) that in Germany are characterized by such transitions (Becker et al., 2017; KMK, 2021).

Second, the stage-environment fit theory adapts the *hierarchical ordering of contextual levels* evident in Bronfenbrenner's ecological systems theory (1979) to emphasize the complexity of the school environment. It introduces hierarchically ordered levels spanning from the societal level, to the most immediate contextual level of the classroom. At the most distal level, Eccles and Roeser (2009) propose that characteristics of the society and the positions of schools and the individual therein affect an individual's development within school. Regarding the intermediate contextual levels, the allocation of specific features of the school environment to the different levels largely varies with educational policies. For example, the allocation of resources is usually regulated by more distal education authorities, while the specific timetables are more often in the hands of the individual schools. The immediate classroom characteristics constitute the most specific contextual level that is also mostly generalizable across educational systems. Because of this broad applicability, my research addresses both ends of the contextual spectrum: individual sociodemographic characteristics related to social inequalities as an aspect of the most distal and the classroom at the most immediate level. At the same time, it recognizes the influence of intermediate- or cross-level factors such as tracking and school transitions.

Third, Eccles and Roeser (2009) propose that student-environment fit manifests in *interpersonal, instructional,* and *organizational* regulatory processes that occur at each level or even across levels, are dynamic in nature, and change with educational transitions. These processes consequently shape a student's individual development. While organizational processes mostly involve different and higher levels of the educational context, there are interpersonal and instructional processes that specifically take place at the immediate classroom level. Instructional processes mostly involve characteristics of the teacher (e.g. attitudes, behaviors, and instruction) that shape the concrete learning opportunities. Interpersonal processes involve social interactions with teachers and classmates that shape an individual's behavioral, cognitive, and socioemotional development. Accordingly, this dissertation focusses on interpersonal and instructional processes at the most immediate classroom level. Interpersonally, classroom peers are of special importance in adolescence (Havighurst, 1972; Hurrelmann & Quenzel, 2018). Instructionally, the teacher can be considered as a primary socializer that shapes the individual educational development (Eccles & Roeser, 2009; Eccles & Wigfield, 2020; Wigfield & Eccles, 2000).

Based on these three core assumptions of stage-environment fit theory, this dissertation considers the importance of student-environment fit for academic performance and individual development. Due to its applicability to different educational systems, my research focusses on individual sociodemographic characteristics reflecting the relevance of society as the most distant contextual level and the classroom as the most immediate contextual level. Specifically, I look into social inequalities, as well as the role of teachers and peers that shape instructional and interpersonal aspects of the classroom.

1.2 This Is Me Trying: Individual Self-Perceptions Contributing to Academic Success

Focusing on the individual, researchers have increasingly acknowledged that beyond cognitive abilities other individual characteristics further qualify academic performance (Borghans et al., 2016; Mammadov, 2022; McAbee & Oswald, 2013). From a theoretical viewpoint (Ackerman, 1996; Cattell, 1986; Ziegler et al., 2012), such non-cognitive individual characteristics can shape knowledge gains by explaining where, when, and how an individual seeks learning opportunities and, thereby, acquires academic abilities. In line with theoretical elaborations differentiating general dispositions and characteristic adaptations as two levels of the self (Ackerman, 1997; Graziano et al., 1997; Kandler et al., 2014; McAdams, 1995; McCrae, 2009; Zhang & Ziegler, 2016), this dissertation considers two individual self-perceptions at different levels. More specifically, it looks into personality traits at the level of general dispositions and academic self-concepts at the level of characteristic adaptations. In line with the introduced developmental task frameworks (Grob & Jaschinski, 2003; Hurrelmann & Quenzel, 2018; Hutteman et al., 2014) current educational policies (OECD, 2015) underscore that self-perceptions are not only important predictors of academic performance but also developmental outcomes in educational contexts themselves.

In the following, I describe both self-perceptions in more detail and present theoretical and empirical considerations on their prediction of academic performance and development in adolescence. Closing this chapter, I present arguments for integrating personality traits and academic self-concept, outline different approaches of doing so and identify important research gaps.

General Dispositions: Personality Traits Contributing to Academic Behavior

Personality psychology conceptualizes an individual’s general dispositions as a blend of stable traits that reflect consistent patterns in thinking, feeling, and behaving—their personality (Roberts et al., 2006). Over the last decades, personality researchers have adopted the *Big Five* taxonomy as a shared trait framework to describe interindividual differences in personality (cf. John, 2021)[2]. The Big Five include the traits of openness, conscientiousness, extraversion, agreeableness, and neuroticism (John, 2021). *Openness* pertains to the breadth,

[2] Given that they continue to dominate the field of personality research, I will focus on the Big Five within this dissertation, while acknowledging that there are other theoretical models comprising different numbers of broad traits (e.g., Ashton & Lee, 2007; DeYoung, 2015; van der Linden et al., 2010). Henceforth, whenever I refer to student personality, I am referring to their Big Five personality traits.

depth, originality, and complexity of an individual's mental and experiential life. *Conscientiousness* describes socially prescribed impulse control that facilitates task- and goal-directed behaviors. *Extraversion* is characterized by an energetic approach to the social and material world. *Agreeableness* reflects a prosocial and communal orientation, with associated characteristics such as cooperativeness and trust. *Neuroticism* entails negative emotionality and emotional instability. Previous research has established the applicability of the Big Five traits to adolescence (e.g., Brandt, Becker, et al., 2020; Soto et al., 2008) and across different cultures (Schmitt et al., 2007, 2008; Yamagata et al., 2006). Accordingly, the Big Five framework offers an efficient and comprehensive means of explaining variations in students' behavior within and beyond the school context. Thereby, it in turn allows for the prediction of academic performance (e.g., Buecker et al., 2020; Luo et al., 2023; Oshio et al., 2018; Poropat, 2009; Roberts et al., 2007).

Theoretical perspectives specifically indicate the relevance of openness and conscientiousness for academic performance (Trautwein et al., 2019; Ziegler et al., 2012). Students who score high in openness are often intellectually curious, creative, and open-minded. Accordingly, theoretical considerations propose a central role of openness in knowledge acquisition (Ziegler et al., 2012). Individuals high in conscientiousness are typically organized, productive, and responsible, displaying persistent task orientation, goal-setting, and behavioral control (Bidjerano & Dai, 2007). Such characteristics correlate positively with homework effort and compliance (Trautwein et al., 2006), suggesting that conscientiousness is advantageous in academic settings and thus a strong predictor of academic performance. Due to their focus on social and emotional aspects (K. Harris & Vazire, 2016; Mund et al., 2016), theoretical considerations on the associations of extraversion, agreeableness, and neuroticism with academic performance are less specific. There are arguments highlighting that the emotions, behaviors and cognitions related to these traits may support (Miller et al., 2003; Tetzner et al., 2020; Vermetten et al., 2001), but also interfere with performance (Bidjerano & Dai, 2007; Brandt, Lechner, et al., 2020; Tetzner et al., 2020).

Empirical findings match this picture: meta-analyses indicate that students high in openness and conscientiousness tend to show better academic performance (Mammadov, 2022; O'Connor & Paunonen, 2007; Poropat, 2009). Importantly, openness shows stronger associations with standardized ability tests, whereas conscientiousness relates more strongly to student's grades (Borghans et al., 2016; Spengler et al., 2016). Extraversion, agreeableness, and neuroticism show more inconsistent empirical associations with academic performance. Research, including meta-analyses, supports a small positive associations of agreeableness and inconsistent associations of extraversion and neuroticism with academic performance (Mammadov, 2022; O'Connor & Paunonen, 2007; Poropat, 2009). Importantly, findings indicate that the strength and direction of theses association may vary depending on educational levels and contextual factors (Brandt, Lechner, et al., 2020; Israel et al., 2019; Mammadov, 2022; Tetzner et al., 2020).

In summary, the Big Five traits offer a suitable framework to describe general dispositions contributing to an individual's academic performance. While openness and conscientiousness consistently correlate with better academic performance, the relationships involving extraversion, agreeableness, and neuroticism are less clear and require further investigation. Further, empirical results point towards the importance and considering contextual variables when studying personality-performance associations.

Characteristic Adaptations in Academic Contexts: Academic Self-Concepts Specifically Relating to Academic Performance

At the level of characteristic adaptations, motivational psychology highlights the crucial role of competence beliefs for academic performance (e.g., Marsh et al., 2006; Trautwein et al., 2009). While there are different conceptualizations of such beliefs present within the literature, this dissertation focusses on the academic self-concept.[3] The academic self-concept refers to affective and cognitive evaluations of one's own academic abilities and can thus be distinguished from non-academic self-concepts such as general self-esteem (Shavelson et al., 1976). Structurally, researchers have proposed different models of the academic self-concept (cf. Arens et al., 2021). While the models differ in their specificities, most share two important aspects: They propose, 1) a *multidimensionality* of the academic self-concept and, 2) a *hierarchical order* of its components. The multidimensionality is reflected in distinct domain-specific self-concepts that are specifically predictive for academic performance in corresponding domains (Arens et al., 2021). The hierarchical order of the academic self-concept refers to the distinction between lower-order domain-specific self-concepts and superordinate higher-order factors[4]. While some models suggest a single higher-order factor called general academic self-concept (Shavelson et al., 1976), other suggest two higher-order factors, namely

[3] There are different conceptualizations of competence beliefs, such as self-efficacy beliefs (cf. Bandura, 1997) and self-concepts of academic abilities (cf. Shavelson et al., 1976). While both constructs conceptually overlap, they can be considered distinctive of each other. That is, academic self-efficacy is more task-, context- and situation-specific than academic self-concepts and academic self-concepts compriss both affective and cognitive evaluations of academic abilities (Huang, 2012). Accordingly, this dissertation focusses on the broader conceptualization referred to as academic self-concept.

[4] Some models include not only academic but also emotional, physical, and social self-concepts (Shavelson, 1976). However, this dissertation focusses on the academic self-concepts given its specific relevance in educational contexts.

the verbal and math self-concept (Marsh & Shavelson, 1985). This dissertation focuses on the role of the verbal and math self-concept as they provide the advantage of reflecting both the multidimensionality of the academic self-concept while being located at an at least intermediate level of hierarchy.

Theoretically, expectancy-value theory (Eccles & Wigfield, 2020; Wigfield & Eccles, 2000) emphasizes the central role of the academic self-concept for academic performance. It suggests that students with a more positive academic self-concept are confident about their academic abilities and have higher expectations of success when confronted with academic challenges. Consequently, they are more likely to engage in such challenges and show better academic performance. Considering the domain-specificity of the verbal and math self-concept further suggests their domain-specific predictivity (Marsh, 1986; Marsh & Craven, 2006). For instance, an individual may have high confidence in domains requiring verbal abilities and thus demonstrate strong verbal performance, yet hold a negative academic self-concept in areas demanding mathematical skills, leading to lower math performance. At the same time, theoretical elaborations highlight the reciprocity of associations between academic self-concepts and academic performance (Marsh & Craven, 2006).

Empirical research supports the domain-specificity of academic self-concepts (Arens et al., 2021) and their respective relations to academic performance (Marsh, 1986; Marsh et al., 2006; Möller et al., 2020; Trautwein et al., 2009). More specifically, verbal and math self-concepts are only slightly related to each other and show, on the one hand, positive associations with corresponding performance measures, and, on the other hand, negative relations with non-corresponding performance measures (Arens et al., 2021). Accordingly, this dissertation considers the verbal and math self-concept as central self-perceptions that act as context-specific self-perceptions predicting academic performance in related domains. Importantly, academic self-concepts also are predictive of later academic pathways (Jansen et al., 2021; Musu-Gillette et al., 2015; Von Keyserlingk et al., 2020) and, hence, education should support their positive development.

Altogether, academic self-concepts are important self-perceptions within educational contexts. Domain-specific academic self-concepts are specifically predictive of (domain-specific) academic performance but also later academic choices. Given their importance, it is important to identify the factors contributing to their positive development in educational contexts.

The Development of Self-Perceptions Across Adolescence

In line with the introduced developmental task frameworks (Grob & Jaschinski, 2003; Hurrelmann & Quenzel, 2018; Hutteman et al., 2014) current educational policies (OECD, 2015) underscore that individual self-perceptions are not only important predictors of academic performance but also developmental outcomes in educational contexts themselves. In other words, they are expected not only to shape knowledge gains but also to develop over the course of an individual's learning experiences.

Regarding *personality*, theoretical elaborations on the development are diverse but not specific to personality development in adolescence (cf. Baumert et al., 2017; Specht et al., 2014). Adult personality development has been described by two overarching principles: 1) the *cumulative continuity principle* referring to the increasing rank-order stabilities of personality traits across life (Roberts & DelVecchio, 2000) and 2) the *maturity principle* describing the mean-level increase of socially desirable traits including conscientiousness and agreeableness, and decrease of neuroticism (cf. Bleidorn et al., 2013). Moreover, many theories share a transactional perspective and emphasize that interindividual differences in personality development result from interactions between the individual and contextual conditions (Baltes et al., 2006; Lerner, 1991; Neyer et al., 2014; Rauthmann, 2021). Empirical research highlights that in adolescence personality traits exhibit the lowest rank-order stabilities except for childhood (Bleidorn et al., 2022; Roberts & DelVecchio, 2000). Stability estimates vary across traits and are comparably higher for conscientiousness compared to agreeableness or openness (Borghuis et al., 2017). Regarding mean-level changes, empirical results show relevant inconsistencies: Replicating the maturity principle across adult years (Bleidorn, 2015), some studies report increases in conscientiousness and agreeableness, as well as decreases in neuroticism (Branje et al., 2007; Klimstra et al., 2009). At the same time, other studies find only minimal mean-level changes (De Fruyt et al., 2006; Hill et al., 2013) or even longitudinal developments in the opposite direction (Borghuis et al., 2017; Gillespie et al., 2024; Luan et al., 2017). Consequently, the *disruption hypothesis* has been introduced to explain such temporal dips in conscientiousness and agreeableness accompanied by temporal highs in neuroticism during early or mid-adolescence (Soto & Tackett, 2015). The inconsistency and small size of mean-level changes indicates that personality developments may not occur consistently across individuals and contexts (Hill & Edmonds, 2017) and, thereby, imply the need to study predictors of such inconsistencies.

Regarding students' *academic self-concepts*, expectancy-value theory provides a comprehensive framework for understanding the development of academic self-concepts and potential predictive characteristics (Eccles & Wigfield, 2020; Wigfield & Eccles, 2000). Besides essential associations with previous performance experiences, it proposes a diverse set of individual and contextual predictors that may account for interindividual differences in students' change trajectories. Previous research on adolescent developmental trajectories of academic self-concepts produced four central findings: First, the differentiation between verbal and mathematical self-concepts becomes more pronounced as students progress through school (Wan et al., 2021). Second, the stability patterns of academic self-concepts are comparable to those of other self-perceptions like personality, which are characterized by both stability and change (Rieger et al., 2017). Third, sample average mean-level changes illustrate that academic self-concepts decline from childhood throughout adolescence (Nagy et al., 2010; Postigo et al., 2022; Wigfield et al., 2015). Fourth, adolescents differ considerably in their amount and pattern of change (e.g., Archambault et al., 2010; Nagy et al., 2010; Postigo et al., 2022), pointing toward the importance of understanding factors contributing to these individual differences in change trajectories.

To summarize, the development of students' self-perceptions across adolescence is characterized by both stability and change. Moreover, empirical results indicate that individuals differ in their development and, thereby, point towards the importance to identify the factors contributing to the development. Identifying such factors enables education to support a more adaptive individual development of students' self-perceptions. In line with transactional perspectives on adolescent development, such resources and vulnerabilities reside both within the individual and within the environmental conditions they encounter.

Integrating Self-Perceptions: The Interplay of Personality and Academic Self-Concepts

Stemming from distinct research disciplines, student personality and academic self-concepts have been studied rather independently for a long time. Nevertheless, different theoretical perspectives from personality and motivational psychology assume an interrelatedness of different self-perceptions(Eccles & Wigfield, 2020; Graziano et al., 1997; Kandler et al., 2014; McAdams, 1995; McAdams & Olson, 2010; McCrae, 2009; Zhang & Ziegler, 2016). Importantly, these theoretical perspectives assume that more general dispositions such as the Big Five personality traits are related to more specific characteristic adaptations such as the academic self-concept (Kandler et al., 2014; McCrae, 2009). General dispositions were originally proposed to be more cross-temporally stable than characteristic adaptations (McCrae, 2009). Current perspectives, however, suggest that this may not always be the case, and the distinction between general dispositions and characteristic adaptations may be less clear-cut, particularly regarding stability (Bleidorn et al., 2010; Henry & Mõttus, 2020;

Kandler & Rauthmann, 2022). Consequently, there are different theoretical and empirical approaches to integrate domain-general dispositions and context-specific characteristic adaptations. In the following, I will elaborate on three different integration approaches and deduce important research gaps from the respective empirical evidence on student personality and academic self-concepts.

A first integrative approach is investigating the *nomological network* of the respective constructs by exploring their specific cross-sectional associations and, thereby enhance construct clarity (Cronbach & Meehl, 1955). Importantly, this approach treats different self-perceptions as equally relevant aspects of the self (Fleeson & Jayawickreme, 2015). Nevertheless, more general dispositions such as personality traits can guide the investigation of more specific characteristic adaptations such as the academic self-concept. Studying the nomological networks of self-perceptions is particularly important in adolescence, given their ongoing differentiation and the amount of developmental changes in this life phase (Soto et al., 2008; Van Der Linden et al., 2010). Empirically, the Big Five personality traits relate to different characteristic adaptations of relevance in academic settings in terms of a nomological network (Brandt et al., 2021; Judge & Ilies, 2002; Marsh et al., 2006). Regarding the nomological network of student personality and academic self-concepts, research supports their interrelatedness both in young adults (Brandt et al., 2021) and in adolescence (Marsh et al., 2006). Specifically, the results of Marsh and colleagues (2006) indicated that the verbal self-concept shows stronger relations to the student personality compared to the math self-concept. Especially, openness and conscientiousness were closely related to the verbal self-concept and the math self-concept, respectively. Yet, these first findings remain to be replicated.

A second approach is investigating the *conjoint predictivity* regarding important developmental outcomes such as academic performance. The conjoint predictivity refers not only to the incremental validity (i.e., the association of one predictor controlled for another predictor) but also to potential interactive effects. Along these lines, theoretical elaborations propose an interplay of specific personality traits (i.e. openness and conscientiousness) and students' characteristics adaptations (i.e. their academic interest) in predicting academic performance (Trautwein et al., 2019; Ziegler et al., 2012). While this assumption has not yet been applied to academic self-concepts, it appears reasonable to assume an interactive interplay when examining the conjoint predictivity of student personality and academic self-concepts. To illustrate, a student who is confident of their abilities in mathematics and, thus, has a high math self-concept may be more likely to read books that deal with mathematical topics (high openness), which might lead to particularly beneficial academic outcomes (synergistic effect).

At the same time, a student who is less convinced of their abilities in mathematics and, thus, has a low math self-concept may be particularly invested in their homework and studying time in mathematics (high conscientiousness), which might still lead to beneficial academic outcomes (compensatory effect). Empirically, Marsh and colleagues (2006) addressed the conjoint predictivity of Big Five traits and various (academic) self-concepts. The verbal and math self-concept emerged as the strongest and most consistent predictors of academic performance. Beyond students' domain-specific academic self-concepts, openness and conscientiousness incrementally predicted their verbal and math performance, respectively. Spengler and colleagues (Spengler et al., 2016) replicated these cross-sectional results and extended them by showing that longitudinal predictive patterns were less consistent regarding the incremental effects of openness and conscientiousness. Importantly, neither of these studies examined potential interactive effects, highlighting the need for research that tests this assumption.

Lastly, a third approach addresses the *sequential ordering* of dispositional traits and characteristic adaptations. This approach considers self-perceptions as developmental outcomes and addresses their longitudinal interrelatedness. Some theories assume that characteristic adaptations develop through interactions of an individual's general dispositions (i.e. their Big Five traits) and their environment (Kandler et al., 2014; McCrae, 2009) and, thereby, propose that personality traits precede characteristics adaptations. At the same time, other theories propose an opposite sequential ordering and conceptualize motivational adaptations as drivers of a self-regulated personality development (e.g., Denissen et al., 2013; Specht et al., 2014). Theories focusing at academic contexts in adolescence (Eccles & Wigfield, 2020; Zhang & Ziegler, 2016) generally align with the first assumption and suggest that student personality precedes student's academic self-concepts. Empirically, there is support for longitudinal relations between personality and academic self-concepts (Brandt et al., 2021; Zhang & Ziegler, 2016, 2018). Specifically addressing adolescents in academic settings, Zhang and Ziegler (2016, 2018) showed that domain-specific academic self-concepts mediate the effects of personality traits (i.e., openness and conscientiousness) on academic performance in a sample of Chinese adolescents. Therefore, their results suggest that personality traits precede academic self-concepts and potentially contribute to their development in adolescence. However, no studies have specifically examined the role of student personality in the development of academic self-concepts or tested the applicability of these initial findings to German samples.

Taken together, empirical evidence supports an interrelatedness of student personality and academic self-concepts, the incremental validity of openness and conscientiousness beyond domain-specific self-concepts, and a mediating role of academic self-concepts in the relation between personality and academic performance. However, the few studies providing this evidence leave three important questions unanswered: First, can these findings be replicated? Second, is there an interactive interplay in predicting academic performance? And third, does the finding that student personality precedes academic self-concepts also apply to German adolescents? Consequently, this dissertation aims at integrating student personality and academic self-concepts.

1.3 So High School: Contextual Conditions Contributing to Academic Performance and Individual Development

According to transactional perspectives from developmental, educational, and personality psychology, learning depends not only on the individual but also the learning environment that provides demands and opportunities for trait expression (Eccles & Roeser, 2009; Lerner, 1991; Lewin, 1951; Tett & Burnett, 2003). The school environment is a context specifically providing students with learning opportunities during adolescence. In line with stage-environment fit theory (Eccles et al., 1993; Eccles & Roeser, 2009), this dissertation recognizes the importance of sociodemographic characteristics relating to a distal contextual level. Moreover, it focusses on interpersonal and instructional processes at the most immediate classroom level. In the following, I will further elaborate on theoretical considerations and empirical evidence regarding the impact of sociodemographic characteristics on individual academic performance, as well as the role of classroom peers and teaching behaviors in shaping the development of individual self-perceptions.

Social Inequalities: The Impact of Individual Sociodemographic Characteristics

Stage-environment fit theory (Eccles et al., 1993; Eccles & Roeser, 2009) highlights the importance of societal conditions that affect student learning within schools. In this sense, sociological and educational theories emphasize social inequalities that are reflected in different opportunities and expectations for learning and academic performance and depend on sociodemographic characteristics (Boudon, 1974; Bourdieu, 1990; Wigfield & Eccles, 2000)[5]. According to sociological perspectives on social inequalities (Boudon, 1974; Bourdieu, 1990), students' family background contributes to their individual academic development, while personal dispositions and beliefs shape how sociodemographic characteristics influence them. Integrating perspectives from personality and motivation psychology, some researchers have

[5] While sociodemographic characteristics can also be seen as individual characteristics, they only gain significance when viewed in the broader social context. Since the resulting social inequalities can already be seen as a transaction between the individual and the context, this dissertation conceptualizes sociodemographic characteristics as distal contextual conditions.

suggested two types of interactions between sociodemographic characteristics and individual self-perceptions: compensatory interactions, in which socioemotional characteristics buffer social inequalities (Ayoub et al., 2018; Damian et al., 2015; Lechner et al., 2021; Ross & Mirowsky, 2006; Shanahan et al., 2014) and synergistic interactions, in which socioemotional characteristics reinforce social inequalities (Judge & Hurst, 2007; Merton, 1968). Empirical findings support the existence of social inequalities in academic performance. International educational studies and meta-analyses have repeatedly shown that an individual's parental socioeconomic status, immigrant background, and gender are relevant predictors of academic performance (OECD, 2019; Sirin, 2005; Voyer & Voyer, 2014).

With regard to students' personality, research on interaction effects has produced contradictory results: Studies focusing on *socioeconomic status* indicate compensatory interaction effects in international adult samples (Ayoub et al., 2018), but a reinforcement of inequalities by students' level of conscientiousness in a German adolescent sample (Lechner et al., 2021). Focusing on social inequalities related to students' *immigrant background*, there is some support for an interplay regarding economic outcomes in adults (Brenzel & Laible, 2016), while other findings point towards the absence of interaction effects or a reinforcement of social inequalities by students' level of conscientiousness in adolescence (Israel et al., 2022). Regarding inequality related to students' *gender,* some studies indicate the absence of interaction effects with personality traits (Spinath et al., 2014; Steinmayr & Spinath, 2008), while others support an interactive interplay between students' gender and their level of extraversion and neuroticism (Nguyen et al., 2005; Spinath et al., 2010).

Concerning academic self-concepts, first results do not support interaction effects with students' parental *socioeconomic status* (Li et al., 2020) but rather a mediating role of academic self-concept in the associations of socioeconomic status with performance (Chevalère et al., 2023; Li et al., 2020; Steinmayr et al., 2012). Along these lines, most studies illustrate a slightly positive association of parent socioeconomic status with students' academic self-concepts (Becker & McElvany, 2018; Li et al., 2020; Marsh & Parker, 1984; Muijs, 1997). Regarding *students' immigrant background*, research on potential interaction effects is scarce. However, some empirical research indicates differential associations with domain-specific self-concepts: While students with an immigrant background report lower or similar verbal self-concepts, they report similar or even more positive math self-concepts compared to native students when controlling for actual performance (Lilla et al., 2021; Schöber et al., 2015; Shajek et al., 2006; Siegert & Roth, 2020). Regarding *gender*, differences in academic self-concepts are well established, with meta-analytic findings showing that girls tend to hold a more positive verbal self-concept, whereas boys tend to hold a more positive math self-concept (Wilgenbusch & Merrell, 1999). Moreover, first findings indicate interaction effects insofar that boys show stronger associations between academic performance and self-concept than girls (Denissen et al., 2007).

Taken together, substantial evidence links social inequalities in academic performance to students' parental socioeconomic status, immigrant background, and gender. Although theoretical perspectives suggest an interactive interplay between individual self-perceptions and their sociodemographic characteristics, initial studies have produced inconsistent findings, highlighting the need for further research, particularly with adolescent samples. Consequently, I examined how student personality and academic self-concepts contribute to social inequalities.

Peer Composition Effects on Academic Performance and Individual Self-Perceptions

At the classroom level, peer relationships constitute important interpersonal factors contributing to an individual's development (Eccles et al., 1993; Eccles & Roeser, 2009; Hattie, 2002). Consequently, classroom peers most likely play a vital role in shaping students' academic behavior and individual development. Within educational contexts, peer effects have mostly been addressed in terms of *composition effects* (e.g., Hattie, 2002). Composition effects propose that the average characteristics of an entire school or class are linked to an individual student's learning outcomes and development. Theoretical foundations of composition effects are diverse (Wilkinson et al., 2000). Organizing these diverse theoretical foundations, Wilkinson (2000) summarized four kinds of peer processes involved in classroom composition effects, namely normative, comparative, instructional, and direct peer-interaction processes. *Normative* processes arise by the internalization of group norms by the individual consequently guiding their learning-related behavior. *Comparative* processes involve the comparison to the classroom peers as a crucial reference group for an individual and their academic self-perceptions. *Instructional* peer processes assume that teachers adapt their instructions in accordance with the respective composition to the classroom. Lastly, *peer-interaction* processes refer to effects arising in direct dyadic or group interactions within the classroom potentially also contribute to classroom composition effects. Various theoretical elaborations, that I describe in more detail below, provide more specific assumptions on how these processes shape individual academic performance, student personality and academic self-concept.

Regarding an *individual's academic performance*, theoretical elaborations have focused on normative and instructional processes that explain how the classroom composition potentially contributes to an individual's academic performance (cf. D. N. Harris, 2010).

Regarding students' *academic self-concept (development),* theoretical elaborations highlight the importance of social comparison processes for the development of academic self-concepts and termed such comparison effects as the Big-Fish-Little-Pond effect (Marsh, 1986, 1987). Along these lines, theory suggests that students, regardless of their actual abilities, develop less positive academic self-concepts if they are outperformed by their classmates and peers. Empirically, many studies have addressed peer composition effects on academic performance (e.g., Becker et al., 2022; Dicke et al., 2018; Hanushek et al., 2003; Harker & Tymms, 2004; Stäbler et al., 2017; Van Ewijk & Sleegers, 2010b) and academic self-concepts (Fang et al., 2018). Results indicate that the class composition regarding previous performance (Becker et al., 2022; Harker & Tymms, 2004; Stäbler et al., 2017) and socioeconomic status (Harker & Tymms, 2004; Van Ewijk & Sleegers, 2010b) relates to individual academic performance. Importantly, research supports such associations mainly in cross-sectional (e.g., Van Ewijk & Sleegers, 2010b, 2010a) but also longitudinal settings (e.g., Becker et al., 2022; Becker & Neumann, 2018; Hanushek et al., 2003; Von Keyserlingk et al., 2019).

Regarding *student's personality (development)*, however, classroom composition effects are not well studied. Theoretical elaborations rather suggest a crucial role of dyadic peer-relationships and peer-groups in personality development (Reitz et al., 2014). At the dyadic level, the personality and social relationships (PERSOC) framework (Back et al., 2011) argues that social interaction processes affect individual personality development and vice versa. At a group level, researchers have argued that the assessment of personality self-perceptions involves social comparison processes and, thus, depends on the kind of reference group used in such comparisons (Credé et al., 2010; Lenhausen, Bleidorn, et al., 2023; Lenhausen, Hopwood, et al., 2023). Moreover, group socialization theory (J. R. Harris, 1995) argues that normative socialization processes lead to an increasing similarity of peer group members across time. Accordingly, there are different theoretical approaches underlining the relevance of peer characteristics for individual personality development in adolescence that suggest the involvement of diverse peer processes.

Empirically, adolescents' levels of extraversion, agreeableness, and neuroticism proved to be important predictors of social relationship characteristics across different social situations and relationships types in non-academic and academic contexts (e.g., Deventer et al., 2019; Lösch & Rentzsch, 2018; Parker et al., 2012; Van Der Linden et al., 2010; J. Wagner et al., 2014). Moreover, there is accumulating evidence that peer-relationships and interactions likewise shape individual adolescent personality development (Deventer et al., 2019; Neyer et al., 2014; Wieczorek et al., 2025). Additionally, research on personality assessment supports the relevance of social comparisons to same-aged peers for adult personality self-perceptions (Lenhausen, Bleidorn, et al., 2023; Lenhausen, Hopwood, et al., 2023). At the same time, studies on personality composition effects in university contexts tend to support normative peer processes in the development of academically relevant traits such as openness and conscientiousness (Shan & Zölitz, 2022). Yet, the relevance of classroom peers for individual personality development in adolescence has not been studied so far.

Taken together, theoretical perspectives and empirical evidence underscore the importance of classroom peers for both academic performance and the development of academic self-concept. Although peers also appear relevant for personality development, few studies have examined this influence at the class level within educational contexts. Hence, this dissertation aims fill this empirical gap.

Teaching Behaviors Contributing to Academic Performance and Individual Performance Predictors

Besides interpersonal processes relating to classroom peers, stage-environment fit theory (Eccles et al., 1993; Eccles & Roeser, 2009) suggests the importance of instructional processes shaping an individual's (academic) development. Within classrooms, teachers are the ones who provide students with instruction and, thus, can be considered an important contextual influence on student's development (Hamre & Pianta, 2010). Consequently, teachers' instructional quality characterizes the learning opportunities within classrooms (Kunter & Voss, 2013). According to the COACTIV model (Kunter & Voss, 2013), teacher's instructional quality is reflected in three aspects of teaching behavior—namely emotional support, classroom management, and cognitive activation. *Emotional support* refers to the emotional and motivational support teachers provide their students and is expressed through respectfulness, patience, and being approachable. Effective *classroom management* refers to the optimal use of available time and thereby reflects an effective handling of classroom disturbances. *Cognitive activation* describes properties of the given tasks and their potential to contribute to goal-oriented cognitive activities in learners. Subsequently, I will present theoretical assumptions and empirical evidence on how these teaching behaviors relate to students' academic performance, Big Five personality, and academic self-concepts in adolescence.

Regarding individual *academic performance*, the stage-environment theory (Eccles et al., 1993; Eccles & Roeser, 2009) and the COACTIV model (Kunter & Voss, 2013) propose direct effects of teaching behavior on academic performance. Empirical studies show a positive association between students' perceptions of effective classroom management and cognitive activation and academic performance at the class level (Kunter et al., 2013; Kunter & Baumert, 2007; Kunter & Voss, 2013). Regarding perceived emotional support, empirical findings are less supportive of a direct association with academic performance at the class-level (Kunter et al., 2013; Kunter & Voss, 2013). Rather, findings suggest that teachers' emotional support indirectly relates to academic performance by contributing to individual self-perceptions (e.g., Jensen et al., 2019). Regarding student *personality development*, there is only limited theoretical and empirical research addressing the role of teaching behaviors therein. Nevertheless, researchers have highlighted the interrelatedness of individual personality development with social interactions and relationships (e.g., Back et al., 2011). Accordingly, the overall quality of the student-teacher relationship which might be reflect in teachers' emotional support has been the focus of research addressing the role of teachers in individual personality development. Only recently, teaching behavior has been discussed as one factor contributing to students' individual personality development (Israel et al., 2019). While first research indicates associations of teaching behaviors including teacher emotional support with student personality (Israel et al., 2022; Mammadov & Avci, 2024), these associations seem to become less pronounced in higher grades of secondary school (Israel et al., 2019). Accordingly, the role of the teaching behavior in student personality is not the focus of the current dissertation.

Regarding students' *academic self*-concepts, expectancy-value theory specifies that a student's perceptions of primary socializers' beliefs, attitudes, and behaviors contribute to their formation (Eccles & Wigfield, 2020; Wigfield & Eccles, 2000). Accordingly, teachers emotional support, classroom management and cognitive activation should contribute to individual academic self-concepts. Empirically, all three teaching behaviors relate to differences in (domain-specific) academic self-concepts (Jensen et al., 2019; Lazarides & Ittel, 2012; Skaalvik & Skaalvik, 2013; W. Wagner et al., 2016). Besides cross-sectional associations, however, only one study controlled for initial levels of the general academic self-concept when testing the effects of teaching behaviors on later academic self-concept (W. Wagner et al., 2016). Results indicate that longitudinal associations follow the same direction, but are comparatively small. Moreover, most studies focused on singular teaching behaviors, thereby, not allowing to evaluate their differential contribution to academic self-concepts.

Taken together, theoretical perspectives highlight the crucial role of teaching behaviors in shaping students' academic performance. However, less is known about their importance for individual development. However, there are specific propositions regarding how teaching behaviors relate to students' academic self-concepts and their development. This dissertation aims to test these propositions empirically and importantly, addresses them in longitudinal settings.

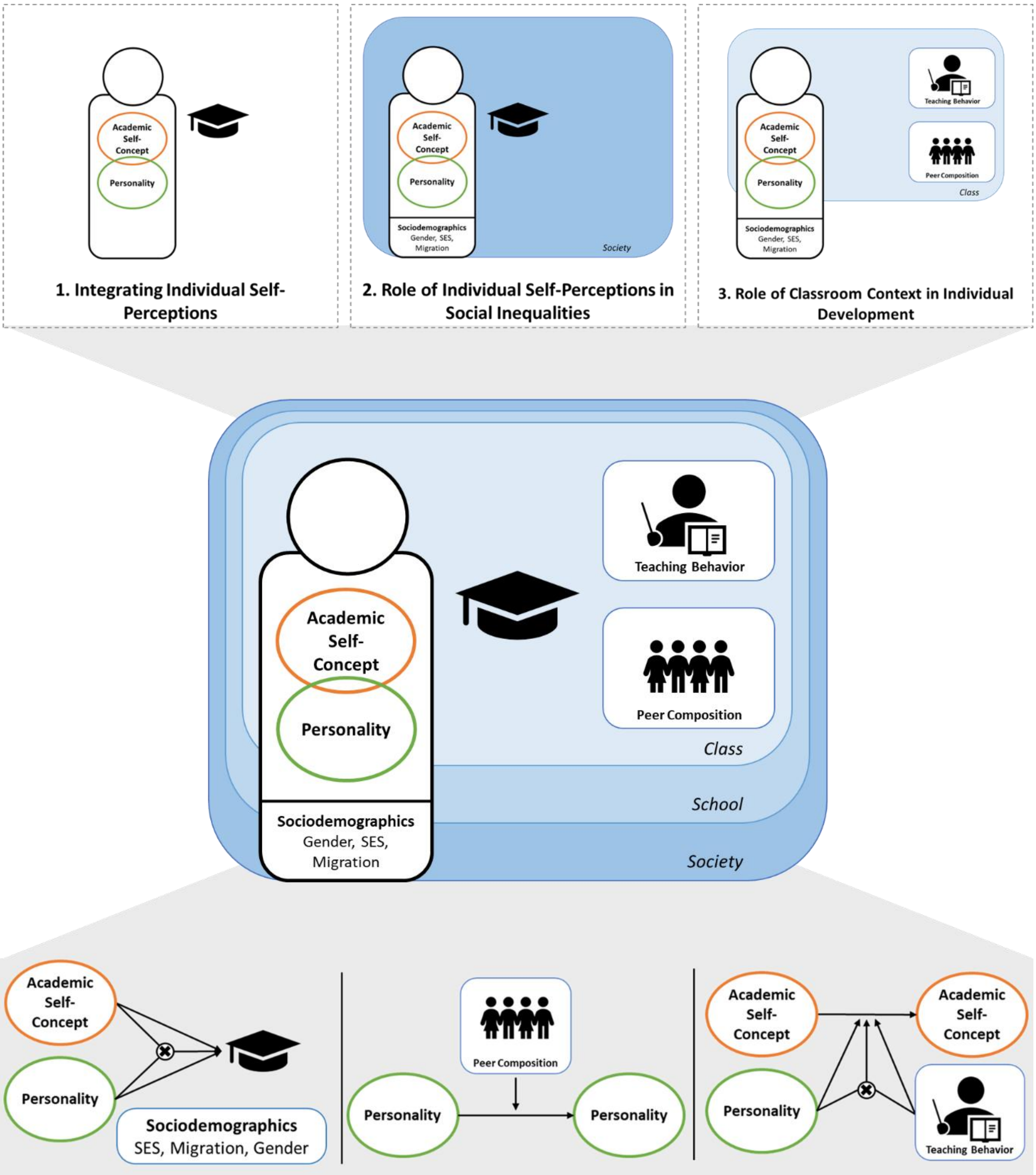
1.4 Research Desiderata

Based on the importance of academic performance in adolescence for future life paths, the overarching objective of this dissertation is to gain a better understanding of individual predictors of academic performance and their development within the school environment. To achieve this objective, this dissertation takes on a transactional perspective and follows an integrative approach (see Figure 1). That is, it integrates students' personality and academic self-concepts as two crucial self-perceptions situated at different levels of the self. Furthermore, it adopts a context-sensitive perspective on these two individual predictors of academic performance and examines how societal conditions, as well as interpersonal and instructional aspects of the classroom environment, influence their development during adolescence. Building on the research gaps outlined above, this leads to the following research questions: First, in what way do different self-perceptions (i.e. personality and academic self-concept) relate to each other and academic performance in adolescence? Secondly, how do individual self-perceptions differentiate social inequalities in adolescent academic performance? And third, how do self-perceptions and their development in adolescence vary with classroom peers and teachers' behaviors?

To answer the outlined research questions, I conducted three preregistered empirical studies focusing on student personality, academic self-concepts, their interplay and development across time. Within the three studies, I used data from diverse adolescent samples with different backgrounds to account for the relevance of sociodemographic characteristics and contextual conditions. Specifically, I applied sophisticated statistical models to (longitudinal) data spanning varying time frames across secondary school. The used datasets stem from one original and two large-scale panel studies: The SEED study (J. Wagner et al., 2024), the National Educational Panel Study (NEPS; cf. Blossfeld & Rossbach, 2019), and the EIKA study (Entwicklung und Implementierung eines neuen Konzeptes zur Eingliederung Jugendlicher in die Berufs- und Arbeitswelt in Schulen mit erhöhtem Förderbedarf, 2005). This dissertation's first study addresses the first and second overarching question, the second study focusses on the third research question, and the third study provides additional insights regarding the first and third research question (see right side of Figure 1). Within the next section, I shortly describe the respective focus and specific methodology of each of the three studies.

Figure 1

Schematic Representation of the Research Aims, Theoretical Framwork and Conducted Studies of This Dissertation



Note. The top part illustrates the three overarching research aims. The middle part reflects the overall transactional and integrative theoretical perspective of this dissertation. The bottom part presents the respective research foci of the three conducted studies.

SES = socioeconomic status.

Study 1: The Interplay of Academic Self-Concept and Big Five Personality

Focusing on the integration of different self-perceptions while considering individual sociodemographic characteristics as distal contextual conditions, Study 1 addresses the first and second overarching research aim. To this end, Study 1 builds on theoretical notions assuming an interrelatedness of student personality as general dispositions and academic self-concepts as characteristic adaptations (McAdams, 1995; Trautwein et al., 2019; Ziegler et al., 2012) and pursued three specific research questions: first, addressing their interrelatedness within a nomological net, I examined the cross-sectional associations between student personality and academic self-concepts. Second, I tested the conjoint predictivity for academic performance levels and changes in terms of main and interaction effects. Finally and based on the importance of sociodemographic characteristics for educational success (OECD, 2019; Sirin, 2005; Voyer & Voyer, 2014), the third aim was to examine potential interaction effects between individual self-perceptions and key sociodemographic characteristics.

Regarding the first question, I expected the verbal self-concept to relate positively to openness, conscientiousness, extraversion, and negative association with neuroticism (H1a), while I hypothesized the math self-concept to relate positively to conscientiousness and negatively to neuroticism (H1b). Regarding the second research question, I assumed a positive association of domain-specific academic self-concepts (H2a), positive associations of openness and conscientiousness (H2b) with academic performance, and interaction effects of domain-specific academic self-concept with openness and conscientiousness in predicting academic performance (H2c). I tested the same associations concerning changes in academic performance (H2d-f). Concerning the last research question addressing the moderating role of sociodemographic characteristics, I expected interactions between students' gender and domain specific academic self-concepts (H3a), students' immigrant background and conscientiousness regarding German grades (H3b), and parental socioeconomic status and conscientiousness (H3c). Beyond, these hypotheses I examined all associations not explicitly included in my hypotheses by means of exploratory analyses.

To test my hypotheses, I applied latent moderated regression models in two large samples of German 9th graders. First, I used data from the EIKA project (Entwicklung und Implementierung eines neuen Konzeptes zur Eingliederung Jugendlicher in die Berufs- und Arbeitswelt in Schulen mit erhöhtem Förderbedarf, 2005) including a comparatively high proportion of families with low SES and immigrant backgrounds, allowing for a thorough examination of the differential effects of sociodemographic characteristics on academic performance. Second, I used longitudinal data of the NEPS (Blossfeld & Rossbach, 2019), which allowed for two important extensions: first, the investigation of the generalizability of the results in a representative student population and, second, the consideration of effects of personality and academic self-concept on changes in academic performance. Consequently, Study 1 shed light on the nomological network and conjoint predictivity of student Big Five personality traits and domain-specific academic self-concepts, as well as potential interactive effects with individual sociodemographic characterstics.

Study 2: Peer Effects on Personality Development in Classrooms

Within Study 2, I addressed the third overarching research aim by investigating how the personality composition of classroom peers relate to the self-reported development of student personality among secondary school students. Following first results obtained based on an university sample (Shan & Zölitz, 2022), I hypothesized that class-level averages of openness (H1a) and conscientiousness (H1b) positively relate to an individual students' reported development of these traits. Given the lack of previous results, I exploratively tested potential classroom composition effects regarding the remaining three traits.

To address this research question, the study used data of German secondary students stemming from the existing NEPS (*N* = 5,470; Blossfeld & Rossbach, 2019) and the self-collected SEED study (N = 788; J. Wagner et al., 2024). Given my interest in the effects of average classroom characteristics I estimated multilevel structural equation models (multilevel SEM). The primary focus was on the average classroom personality effects, called a composition effect (Lüdtke et al., 2008). A composition effect exists if the aggregated classroom-level personality variable is related to individual personality at the second measurement (T2) beyond the influence of personality at the first measurement (T1). Accordingly, the estimated models included three main components: Student personality at T2 was predicted by individual personality at T1, the average classroom personality at T1, and additional covariates. To examine the robustness of the composition effect estimates, I used three modeling strategies (Lüdtke et al., 2008; Marsh et al., 2009): 1) doubly-latent contextual models, 2) manifest-latent contextual models, and 3) Bayesian estimation of double-latent models (Depaoli, 2021; Zitzmann et al., 2016). Thereby, Study 2 contributes to our understanding of how classroom peers potentially affect individual personality development across secondary school years.

Study 3: Individual and Contextual Predictors of Academic Self-Concept Development

Study 3 addressed the first and third overarching research aim by integrating individual student personality with academic self-concepts, and teaching behaviors as contextual conditions. Building on theoretical assumptions of expectancy-value theory (Eccles &

Wigfield, 2020; Wigfield & Eccles, 2000), it explored the role that student personality and perceived teaching behaviors play in the development of students’ academic self-concepts. Specifically, Study 3 had four aims: First, I examined changes in academic self-concepts and hypothesized a decline in individual verbal (H1a) and math self-concepts (H1b) across 10th grade. Second, testing predictive effects of perceived teaching behaviors on academic self-concept development, I expected higher levels of perceived emotional support from German teachers to be associated with a more positive development of students' verbal self-concepts beyond initial levels (H2a) and explored the associations of classroom management and cognitive activation. Concerning math self-concept development, I hypothesized higher levels of perceived emotional support, classroom management, and cognitive activation from math teachers to relate to a more positive development of students' math self-concepts beyond initial levels (H2b). Third, I tested if student personality traits predict the development of academic self-concepts in different subject domains. I expected higher individual levels of openness and conscientiousness, along with lower levels of neuroticism to relate to a more positive development of students’ verbal self-concepts (H3a), independent of initial levels. Moreover, I hypothesized higher conscientiousness and lower neuroticism to relate to a more positive development of students’ math self-concepts beyond initial levels (H3b). Again, I explored the associations with the remaining traits. Fourth, I explored the potential interplay between teaching behaviors and student personality regarding academic self-concept development.

To test these hypotheses, I applied conditional second-order latent growth models to an original longitudinal sample of a total of N = 1,131 German students (J. Wagner et al., 2024) in the transition from grade 10 to 11. More specifically, I first tested for measurement invariance of the verbal and math self-concept across time. Second, I analyzed interindividual differences in intraindividual changes in academic self-concepts utilizing second-order latent growth models (Sayer & Cumsille, 2001). Third, I estimated two sets of conditional second-order latent growth models to address the predictive research questions. Considering predictors as latent time-invariant variables, I separately included each perceived teaching behavior and student Big Five trait in the models. Fourth, I addressed the conjoint contribution and potential interplay of my predictors by estimating moderated conditional second-order latent growth models and including latent interaction effects in the models. Thereby, Study 3 contributed to the integration of student personality and academic self-concepts by tapping into their sequential ordering and, additionally, addressed the role to teaching behavior in academic self-concept development.

2. Who Flourishes in School? The Interplay of Academic Self-Concept and Personality and its Role for Academic Performance in Middle Adolescence

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Abstract

Why are some students more successful than others? We combined motivational and personality predictors and jointly examined the relevance of subject-specific academic self-concepts and Big Five personality traits for academic performance. Based on data from two independent studies of German 9th graders (Study 1: N = 1,508, M_{age} = 14.98 years, 51% female, 38% immigrant background; Study 2: N = 19,783, M_{age} = 15.10 years, 50% female, 36% immigrant background), we, first, estimated latent bivariate correlations to investigate the nomological net between these socioemotional characteristics. Second, using latent moderated regression models we examined the role of the main and interaction effects of both characteristics for academic performance levels and changes assessed by grades and test scores. Finally, we tested whether the relevance of socioemotional characteristics for academic performance differed across sociodemographic characteristics. Five findings stand out: First, we established widely consistent nomological nets between the academic self-concepts and Big Five traits, especially regarding the German self-concept. Second, the domain-specific self-concepts were consistent predictors of different academic performance measures in the respective subject. Third, beyond the established main effects of openness and conscientiousness, all Big Five traits contributed to performance in some way. Fourth, despite some inconsistencies, socioemotional characteristics formed only synergistic interaction effects. Fifth, students' sociodemographic background was likewise important illustrating main effects on performance and foremost synergistic interaction effects with socioemotional predictors. Our results highlight the complex interplay between motivation, personality, and sociodemographic variables in predicting academic achievement and underline the need to be mindful of this interactive nature.

Keywords: academic self-concept; big five personality; academic achievement; adolescence; interactions

Who Flourishes in School? The Interplay of Academic Self-Concept and Personality and its Role for Academic Performance in Middle Adolescence

Why are some students more successful in school than others? The answer to this question is of key interest to both researchers and practitioners (Kuh et al., 2006; Organisation for Economic Cooperation and Development [OECD], 2019; Spinath et al., 2014). Yet, it appears to be a different one across different research traditions: Motivational and personality psychology proposed a wide array of socioemotional characteristics as relevant. Most importantly, an individual's academic self-concept (Möller et al., 2020; Wu et al., 2021) and Big Five personality traits (Mammadov, 2022; McAbee & Oswald, 2013; Poropat, 2009, 2014) are substantially related to academic performance. Although findings suggest that the academic self-concept and Big Five personality traits are parts of the same nomological network (Brandt, Israel, et al., 2021; Marsh et al., 2006), studies have mainly addressed either their singular effects (Mammadov, 2022; Wu et al., 2021) or their incremental validity above each other (Marsh et al., 2006; Spengler et al., 2016). Recent theoretical and empirical developments move beyond this consideration (e.g., Trautwein et al., 2019; Ziegler et al., 2012), suggesting that motivational constructs and personality traits interact in predicting academic performance and its development. Extending this idea, the present work examines the cross-sectional interplay between academic self-concepts and Big Five personality traits and their predictive power for academic performance levels and changes.

Extant work in educational psychology has pointed toward social inequalities regarding academic performance (OECD, 2019; Sirin, 2005; Spinath et al., 2014; Voyer & Voyer, 2014). That is, academic performance differs according to a person's sociodemographic characteristics. As sociodemographic key variables, a student's sex (Voyer & Voyer, 2014), immigrant background (OECD, 2019; Olczyk, Seuring, et al., 2016), and parental socioeconomic status (SES; Sirin, 2005) relate to academic behavior and performance. These sociodemographic characteristics also relate to differences in socioemotional characteristics (Lechner et al., 2021; Lilla et al., 2021; Spinath et al., 2014; Wilgenbusch & Merrell, 1999). Therefore, researchers have argued that fostering socioemotional characteristics can compensate for social disadvantages and, by this means, reduce social inequalities (Ayoub et al., 2018; Damian et al., 2015; Lechner et al., 2021; Lilla et al., 2021). We address this assumption by testing for moderating effects of sociodemographic characteristics in the association between socioemotional predictors and academic performance levels and changes.

Taken together, the present study has three research aims: First, we examine the cross-sectional associations between academic self-concepts and Big Five personality traits in a nomological net. Second, we test the role of both main effects and their interaction for academic performance levels and changes. Third, we explore whether the relevance of socioemotional characteristics for academic performance differs by sociodemographic characteristics. To do so, we apply structural equation modeling to two large samples of German 9th graders. In the first study, we focus on students attending schools in disadvantaged communities (EIKA, 2005). This first sample includes a comparatively high proportion of families with low SES and immigrant backgrounds, allowing for a thorough examination of the differential effects of sociodemographic characteristics on academic performance. The second study focuses on longitudinal data of a representative German sample (Blossfeld et al., 2011), which allows for two important extensions: first, the investigation of the generalizability of the results in a representative student population and, second, the consideration of effects of self-concept and personality on levels and changes in academic performance.

Determinants of School Success: The Role of Socioemotional Characteristics

School success can refer to a diverse set of student outcomes but is most frequently assessed by academic performance measures such as grades and standardized achievement tests (York et al., 2015). Research indicates that these outcome measures differentially relate to individual predictors of academic performance (e.g., Borghans et al., 2016): Beyond general cognitive abilities as a well-established precursor of academic performance, researchers specifically acknowledge the role of socioemotional characteristics in explaining academic performance variations (Borghans et al., 2016; Mammadov, 2022; McAbee & Oswald, 2013). The term socioemotional characteristics refers to a wide array of "individual capacities that (a) are manifested in consistent patterns of thoughts, feelings, and behaviors, (b) can be developed through formal and informal learning experiences, and (c) influence important socioeconomic outcomes throughout the individual’s life" (OECD, 2015, p. 34). Thus, it particularly important to study socioemotional characteristics as they may not only predict school success—a central determinant of later socioeconomic outcomes—but also serve as potential targets of educational interventions (Ayoub et al., 2018; Damian et al., 2015; Lechner et al., 2021; Lilla et al., 2021). So far, research in motivational and personality psychology has focused on different socioemotional characteristics as predictors of interindividual differences in school success (Möller et al., 2020; Poropat, 2009, 2014). Accordingly, the current research focuses on two sets of socioemotional characteristics stemming from these research traditions, namely the academic self-concept and Big Five personality traits.

The relevance of socioemotional characteristics varies with the measures used to assess academic performance (Borghans et al., 2016). Research shows that socioemotional characteristics such as academic self-concept and Big Five personality more closely relate to school grades than to standardized test scores (Borghans et al., 2016; Lechner et al., 2017; Möller et al., 2020; Spinath et al., 2010). Such differential associations are due to diverging characteristics of the two measures: First, unlike the more objective standardized tests, school grades contain the teacher's subjective assessment of student learning and behavior (Spengler et al., 2013). Second, standardized achievement tests represent performance in a one-time testing situation, thus, more likely to represent maximum performance capacities. In contrast, grades capture performance over extended periods of time; thus, they are more likely to reflect general tendencies in performance related behaviors. Third, school grades and achievement tests differ regarding their relevance to the student because the former are directly relevant to students' school careers (Hübner et al., 2022). Thus, we consider grades and standardized test scores to obtain a comprehensive picture of the relationship between socioemotional characteristics and academic performance. While many studies support cross-sectional associations of socioemotional characteristics with academic performance, only few have utilized longitudinal designs. Initial studies testing longitudinal associations between socioemotional characteristics and changes in academic performance indicate that not all cross-sectional associations are transferable to longitudinal analyses (Israel et al., 2019, 2023; Wu et al., 2021). Thus, with our study we extend findings by examining the relevance of socioemotional characteristics not only for performance levels, but also for changes therein.

The Role of the Academic Self-Concept

Motivational psychology highlights the central role of academic self-concepts defined as an individual's beliefs about their capacity for learning and academic performance (Marsh et al., 2006, 2018; Trautwein et al., 2009). Expectancy-value theory (Wigfield & Eccles, 2000) emphasizes that students with a strong belief in their abilities are more likely to succeed in school as they are more willing to engage in the learning opportunities offered by their learning environments. Theoretical specifications suggest that academic self-concepts are domain-specific (Marsh & Craven, 1996). To specify, domain-specific academic self-concepts, such as the belief to be good in math, reflect a student's self-perception of their own academic abilities across different academic tasks within a given school subject[6]. Empirically, domain-specific self-concepts are most predictive of academic performance in corresponding domains (Marsh et al., 2006; Marsh & Craven, 1996; Shavelson et al., 1976; Trautwein et al., 2009). That is, students' beliefs about their math competencies – their mathematical self-concepts – should be

[6] For an in-depth discussion of similarities and differences between the academic self-concept and other self-belief constructs see Huang (2012).

more strongly associated with their math performances but less so with their performance in verbal subjects and vice versa.

A variety of empirical studies support the role of domain-specific academic self-concepts and their respective relations to academic performance (Marsh, 1986; Marsh et al., 2006; Möller et al., 2009, 2020; Trautwein et al., 2009). Specifically, meta-analyses indicate that the mathematical and the verbal self-concept show moderate to strong positive associations with corresponding achievement measures but small negative links with noncorresponding achievement measures. In addition, they are only weakly associated with each other (Möller et al., 2009, 2020; Wu et al., 2021). Moreover, the meta-analytic associations of academic self-concepts with performance are stronger for grades than for test scores. According to meta-analytic integrations of several longitudinal studies, associations of academic self-concepts with subsequent academic performance often generalize but appear to be smaller as compared to cross-sectional associations (Wu et al., 2021).

The Role of the Big Five Personality Traits

Within personality psychology, the Big Five personality traits (Costa & McCrae, 1992a; John, 2021) are the most established conceptualization for describing relatively stable individual differences in how people think, act, and feel (Roberts, 2009). Accordingly, the Big Five traits offer the opportunity to comprehensively explain differences in students' typical learning behavior and academic performance (O'Connor & Paunonen, 2007; Poropat, 2009, 2014). Empirical studies indicate that the Big Five conceptualization can be sufficiently applied to adolescents' personality while likewise highlighting that the five traits are more closely interrelated and become increasingly differentiated across adolescence (Soto et al., 2008). Focusing on academic performance, the Big Five traits of conscientiousness and openness have received considerable attention (Mammadov, 2022). Both traits are associated with favorable skills in educational settings (Bidjerano & Dai, 2007; Poropat, 2009; Ziegler et al., 2012), suggesting that high conscientiousness and openness should be generally beneficial for academic performance. Moreover, given that conscientiousness is associated with observable everyday behavior in class such as persistent task orientation, homework effort, and compliance (Bidjerano & Dai, 2007; Trautwein et al., 2006), high levels of conscientiousness should be generally advantageous for academic performance, especially when considering teacher-rated performance measures (i.e., grades; Brandt, Becker, et al., 2021). In contrast, openness shows robust associations with cognitive skills and behaviors such as intelligence, autonomy, and academic interest (Geisler-Brenstein et al., 1996; Ziegler et al., 2012). Thus, openness should be particularly beneficial for performance in standardized performance measures (i.e., test scores). Empirically, meta-analyses on personality-performance associations support these associations: Students high in conscientiousness and, to a lesser extent, those high in openness show better academic performance levels (Mammadov, 2022; O'Connor & Paunonen, 2007; Poropat, 2009, 2014). While conscientiousness is more strongly associated with school grades, openness is more closely related to standardized achievement tests (Borghans et al., 2016; Spengler et al., 2016). The few existing longitudinal studies, show somewhat less consistent associations. That is, while initial conscientiousness shows fairly consistent positive links with subsequent academic performance, the association of openness with changes in academic performance varies from being slightly negative to insignificant to slightly positive across studies (Israel et al., 2019, 2023; Spengler et al., 2016).

Regarding the other three traits, associations with academic performance are yet more inconsistent. Regarding agreeableness, findings partly support small positive associations with performance levels (Mammadov, 2022; O'Connor & Paunonen, 2007) but also indicate that the strength and even the direction of this association might depend on the educational level (Mammadov, 2022; Poropat, 2009) and other contextual factors (Brandt et al., 2020; Israel et al., 2022; Tetzner et al., 2020). First studies considering the link between agreeableness and changes in academic performance reveal null or only small positive associations (Israel et al., 2019, 2023). Regarding extraversion and neuroticism, hypotheses and findings about their associations with academic performance are even more ambiguous. So far, meta-analyses revealed only weak associations of extraversion and neuroticism with academic performance levels (Mammadov, 2022; O'Connor & Paunonen, 2007; Poropat, 2009, 2014). Moreover, these associations again varied with contextual factors (Brandt et al., 2020; Israel et al., 2022; Mammadov, 2022; Tetzner et al., 2020). First results on associations with changes in academic performance are also inconsistent varying in strength and even direction (Israel et al., 2019, 2023). Given these inconsistencies in previous studies, we included all Big Five traits in our analyses.

The Interplay of Academic Self-Concept and Big Five Personality Traits

Traditionally, the academic self-concept and the Big Five personality traits have been studied separately, with a focus on their individual or additive effects on academic performance, rather than examining their combined contribution (Möller et al., 2020; Poropat, 2009, 2014). However, contemporary perspectives emphasize the need to integrate motivational and personality variables (e.g. Brandt et al., 2021; DeYoung, 2015; Fleeson & Jayawickreme, 2015; Trautwein et al., 2019). Specifically, two recent theoretical models, namely the Conscientiousness × Interest Compensation model (Trautwein et al., 2019) and the Openness-

Fluid-Crystallized-Intelligence model (Ziegler et al., 2012), suggest that an individual's level of interest, as one key motivational variable (Eccles & Wigfield, 2002), moderates the established association between personality traits with academic performance. Interestingly, while the Conscientiousness × Interest Compensation model specifies the interaction between interest and conscientiousness to be compensatory, the Openness-Fluid-Crystallized-Intelligence model provides no specific assumption on the type of interaction between interest and openness.

Transferring such ideas, we argue for an interplay between the academic self-concepts and Big Five personality traits, that is, between a student's perceived capacities in a specific field and their typical (learning) behavior in predicting academic performance. Theoretically, (at least) two types of interaction effects are plausible. On the one hand, there might be a synergistic interaction: Students with a high academic self-concept benefit even more from high levels of academically favorable personality traits. More specifically, students might display their typical thoughts, feelings, and behaviors, that is, their personality, even more regularly in areas where they are confident of their abilities. To illustrate, a student who is assertive in their abilities in mathematics and, thus, has a high math self-concept may be more invested in their homework in mathematics (high conscientiousness) and potentially more likely to read books that deal with mathematical topics (high openness). On the other hand, there could be a compensatory interaction: Students with a high academic self-concept might compensate for lower levels of academically favorable personality traits. For example, a student with low levels of conscientiousness might show less organized behaviors such as careless completion of homework but still perform well in a particular subject given their confidence in this area (i.e., high math self-concept). As a third possibility, the interplay of academic self-concepts and Big Five personality could also be even more complex. For instance, the interaction could depend on the specific combination of academic self-concepts and personality traits or the type of achievement measures under investigation. Given these different possibilities how an interplay between academic self-concepts and Big Five personality could take form and the lack of empirical studies, we aim to gain first insights into how the two sets of socioemotional characteristics interact and jointly contribute to levels and changes in academic performance.

Differentiating School Success: Sociodemographic Variables as Moderators

Besides socioemotional characteristics, educational theories highlight the role of differential opportunities and expectations for learning and academic performance that depend on demographic characteristics and educational contexts (Brandt et al., 2020; Cattell, 1987; Eccles et al., 1983; Wigfield & Eccles, 2000; Ziegler et al., 2012). More specifically, according to the expectancy-value model (e.g., Wigfield & Eccles, 2000), an individual's ability beliefs (e.g., academic self-concept) are shaped by several influential factors including gender role and cultural stereotypes. Therefore, an individual's sex, immigrant background, and parental SES have been identified as relevant predictors of achievement motivation and academic performance (Lilla et al., 2021; OECD, 2019; Sirin, 2005; Spinath et al., 2014; Voyer & Voyer, 2014; Wilgenbusch & Merrell, 1999).

Regarding sex, meta-analytic findings indicate differences in academic performance and domain-specific academic self-concept (Voyer & Voyer, 2014; Wilgenbusch & Merrell, 1999). That is, girls slightly outperform boys on average (Voyer & Voyer, 2014) and tend to have a more positive self-concept in languages, while boys tend to have a more positive math self-concept (Wilgenbusch & Merrell, 1999). Concerning students' immigrant background, research indicates a disadvantage for students with an immigrant background regarding their academic performance (OECD, 2019), which might be qualified by differences in their academic self-concepts (Lilla et al., 2021). Furthermore, research suggests that, particularly in Germany, academic performance is highly contingent on the individual's SES (OECD, 2019; Sirin, 2005): Having parents with higher incomes and educational backgrounds is associated with better academic performance.

Given these findings, researchers have argued that fostering socioemotional characteristics can compensate for social disadvantages and thereby reduce social inequalities (Ayoub et al., 2018; Damian et al., 2015; Lechner et al., 2021; Lilla et al., 2021). However, first findings on interaction effects partly contradict this assumption indicating that in already advantaged groups of students associations between performance and socioemotional characteristics are even stronger (Brandt & Wagner, 2024). That is, conscientiousness showed weaker associations with academic performance in students with an immigrant background (Israel et al., 2022) and low parental SES in Germany (Lechner et al., 2021). Moreover, the association between academic self-concept and performance seems to be stronger in boys than girls (Denissen et al., 2007). Addressing these inconsistencies, the current research investigates the degree to which these sociodemographic characteristics moderate the association between the academic self-concept, Big Five personality traits, and their cross-sectional interplay for levels and changes in academic performance.

The Present Study

Is there a joint contribution of academic self-concept and Big Five personality traits to academic performance? Addressing this research question, the present study has three major aims: First, we examined the cross-sectional association between academic self-concept and

Big Five personality traits in a nomological net. We thereby build on findings regarding the interrelatedness of academic self-concept and Big Five personality traits (Marsh et al., 2006; Spengler et al., 2016). Second, we tested the role of the main and interaction effects of socioemotional characteristics for academic performance levels and changes. Previous studies have yielded mixed results on the incremental validity of academic self-concepts and personality (Marsh et al., 2006; Spengler et al., 2016). Based on theoretical notions (Trautwein et al., 2019; Ziegler et al., 2012), we extend previous research by testing the main and exploring the interaction effects of academic self-concepts and personality traits on academic performance assessed by grades and test scores. Third, we examine whether the relevance of socioemotional characteristics for academic performance differs across key sociodemographic characteristics. Given the importance of sex, immigrant background, and parental SES in educational contexts (Lilla et al., 2021; OECD, 2019; Sirin, 2005; Spinath et al., 2014; Voyer & Voyer, 2014; Wilgenbusch & Merrell, 1999), we assume that these sociodemographics moderate the association between socioemotional predictors and academic performance. Specifically, to answer this third research question, we based our first study on a largely socioeconomically disadvantaged sample to learn more about potentially underprivileged groups. In our second study, by contrast, we use a large-scale representative sample that allows us to replicate the results of our first study and extend them by additionally testing predictive effects on changes in academic performance across time. Table 1 gives an overview of our preregistered research aims and hypotheses.[7]

[7] The online supplemental material (OSM) shows an extended version indicating the empirical support of these hypotheses within our studies (Table S1; https://osf.io/sptve/).

Table 1

Overview of Research Questions, Hypotheses, and Studies

Research aim and hypotheses	Study
RQ 1. Cross-sectional interplay	
H1a: We expect German self-concept to be positively associated with openness, conscientiousness, and extraversion and negatively with neuroticism.	1 + 2
H1b: We hypothesize math self-concept to be positively related to conscientiousness and negatively to neuroticism.	
We refrain from making assumptions regarding the associations between both subject-specific self-concepts and the remaining Big Five personality traits and examine them exploratively.	
RQ2. Explaining academic performance	
H2a: We expect a positive association of subject-specific academic self-concept with levels of academic performance in the respective subject. Associations are more pronounced for school grades than for test scores.	1 + 2
H2b: We hypothesize a positive association of conscientiousness and openness with levels of academic performance. Associations are more pronounced for conscientiousness with school grades and openness with test scores.	
H2c: We expect an interaction effect between subject-specific academic self-concept with conscientiousness and with openness in predicting levels of academic performance.	
H2d: We expect a positive association of subject-specific academic self-concept with change in academic performance in the respective subject. Associations are more pronounced for school grades than test scores.	2
H2e: We hypothesize a positive association of conscientiousness and openness with changes in academic performance. Associations are more pronounced for conscientiousness with changes in school grades and for openness with changes in test scores.	
H2f: We expect an interaction effect of subject-specific academic self-concept with conscientiousness and with openness in predicting changes in academic performance.	
We will additionally explore the association of academic self-concept, the remaining Big Five traits, and their interaction effects with levels of and changes in academic performance.	
RQ 3. Moderating role of socio-demographic characteristics	
H3a: We expect a moderating effect of sex on the association of academic self-concept with academic performance levels and changes with a stronger association in boys.	1 + 2
H3b: We expect a moderating effect of immigrant background on the relation of conscientiousness and German school grades with stronger associations in students with an immigrant background.	
H3c: We expect a moderating effect of parental socio-economic status on the association of conscientiousness and academic performance with stronger associations in students with high parental socio-economic status.	
As previous results on the remaining possible moderation effects are scarce, we will test them exploratively.	

Note. RQ = research question; H = hypothesis.

Sample Size Rationale

It has been shown to be difficult to detect interaction effects in nonexperimental research (Aiken & West, 1991; McClelland & Judd, 1993). This is largely due to the small to moderate effect sizes of such effects in observational studies and a potential amplification of measurement error from the two individual predictors in the interaction effect. The literature emphasizes that two characteristics help to avoid Type II errors (i.e., not finding the interaction effect although it does exist) in such contexts, that is, large sample sizes and reliable measures. Our study is equipped with two large independent samples, and we address measurement error by using latent variable modeling.

To further manifest the applicability of the latent interaction models to our data, we conducted a Monte Carlo simulation[8] of the simple model including two latent predictors and their latent interaction to simulate the power to find small latent interaction effects in both samples. The results of these simulations illustrate that we generally have sufficient power to find latent interaction effects of small size (.10) in Study 1 (power = .78) and in Study 2 (power = 1.00) when being accompanied with small to medium main effects.

Study 1

Method

In Study 1, we analyzed data from the German multicohort study “Entwicklung und Implementierung eines neuen Konzeptes zur Eingliederung Jugendlicher in die Berufs- und Arbeitswelt in Schulen mit erhöhtem Förderbedarf” (EIKA, 2005). The project based in Bremen (Germany) aimed to investigate the predictors of academic achievement and individual adjustment focusing on students’ ethnic and socioeconomic differences. In order to ensure comparability across studies, we use data obtained in 9th grade, that is, from the third study cohort of EIKA. Data collection took place in 2004 and 2005 via a paper-pencil format. For further information on the data collection procedure, see EIKA (2005).

Transparency and Openness

The present study is considered a secondary analysis of existing (fully anonymized) data and ethical approval for the study was approved by the Senate Department for Education in Bremen. We preregistered our hypotheses and analytic strategy in the Open Science Framework (OSF; https://osf.io/fg7y2) before data analysis, documented all deviations from the preregistration in in additional online Table S2 (https://osf.io/vam7n), provided a comprehensive additional online material. The data set and analyses codes to reproduce the

[8] We conducted this power simulation post hoc as part of the revision process. Given the complexity of the simulation and the limited available literature (Preacher et al., 2016), the many parameters that need to be specified in these models can only be regarded as an approximation to our models.

presented results, as well as the additional online materials, are uploaded in the OSF project page (https://osf.io/sptve/). We did not exclude any data points from the analyses, and report how we determine the sample size and all study measures. We prepared all data in R (4.2.1; R Core Team, 2022) and subsequently estimated the structural equation models (SEMs) testing our research questions in Mplus (8.5.; Muthén & Muthén, 2021) by means of the MplusAutomation package (1.1.0; Hallquist & Wiley, 2018). We follow Journal Article Reporting Standards for quantitative research in psychology (Appelbaum et al., 2018) in reporting our results. The present study is not classified as a replication or registered report.

Sample

The sample consists of all *N* = 1,508 ninth graders collected within the first assessment wave that all met our preregistered inclusion criteria. That is, participants filled out at least one valid personality item, one valid academic self-concept item, or one valid achievement indicator, and had an existing class ID[9]. Students came from 11 secondary schools in Bremen (Germany). The majority of the participants (77.1%) attended vocational-track schools, which prepare students for further vocational education, while the remaining 22.9% attended academic-track schools, which prepare students for university education. Since all schools served disadvantaged communities, the sample included comparably high percentages of families with low SES and immigrant backgrounds. Specifically, at data collection, students were on average 14.98 years (*SD* = 0.78) old, there was an equal distribution of girls and boys (50.5% female), and 38.1% of the students reported having an immigrant background. The parental SES (*M* = 41.99, *SD* = 14.06, Range 16 to 88) was medium to low on average. For more details about the sample composition, please see EIKA (2005).

Measures

Academic Performance. We included two measures of academic performance in German and math. First, we used the self-reported grades from the previous school report (8th grade). Grades in Germany range from 1 (*very good*) to 6 (*insufficient*). We inverted grades so that higher values reflect higher academic performance. Second, achievement tests for reading and mathematics were assessed based on established measures used in large national and international school achievement studies (e.g. Baumert et al., 2000; Baumert & Lehmann, 1997). All items were multiple-choice questions. Students had to select the one correct answer from either four or five possible solutions. For both subjects, we used maximum likelihood estimates anchored on grade-specific results of the Programme for International Student

[9] We used the class ID instead of the preregistered school ID to account for clustering within our data and therefore changed the inclusion criterion to participants with an existing class ID.

Assessment that are derived from item response theory models and were directly provided in the EIKA data. More information on the tests and scaling procedures is provided in the study documentations (EIKA, 2005).

Academic self-concept. Students reported their academic self-concept by rating five items (e.g. “I am particularly good in mathematics.”; Jerusalem, 1984; Jopt, 1978) on a 4-point scale ranging from 1 (*agree*) to 4 (*disagree*) with higher scores corresponding with a higher self-concept. The German and math self-concept scales showed good reliability based on the measurement-model-based reliability index ω ($\omega_{German} = .90$, $\omega_{math} = .91$).

Big Five Personality Traits. Big Five personality traits were assessed with the 40-item Ostendorf scale (Ostendorf, 1990), a well-established personality instrument for this age group (for details, see Asendorpf & Van Aken, 2003). Each trait was indicated by students’ ratings of eight pairs of adjectives (e.g., *extraversion: ”quiet – talkative”*) on a 5-point scale ranging from 1 (e.g., *very quiet*) to 5 (e.g., *very talkative*). For each trait, there were three to five negatively worded items, which we reverse-coded for the analyses. The Big Five personality scales were sufficiently reliable ($\omega_{openness} = .78$, $\omega_{conscientiousness} = .84$, $\omega_{extraversion} = .85$, $\omega_{agreeableness} = .76$, $\omega_{neuroticism} = .77$).

Demographic Characteristics. Regarding the sociodemographic characteristics, students’ sex was included as a dichotomous variable (0 = male; 1 = female). Moreover, we categorized *students’ immigrant backgrounds* into a dichotomous variable (0 = students without immigrant background; 1 = students with immigrant background). Additionally, parents’ highest International Socio-Economic Index of Occupational Status (HISEI; Ganzeboom et al., 1992) served as an indicator of students’ *SES.* The HISEI, which ranges from 16 (e.g., cleaners) to 90 (e.g., judges), reflects the income and required education level of occupations, with lower values indicating lower occupational status.

Control Variables. We controlled all models for two variables: fluid intelligence and school track. Fluid intelligence was measured by a subset of 46 questions from Cattell’s Culture Fair Intelligence Test (CFT 20; Weiß, 1998). All items are language-free multiple-choice questions in which adolescents had to select one correct answer from five possible solutions. We used z-standardized test scores as a manifest control variable. Second, we included the attended school track as a dichotomous variable (0 = nonacademic track; 1 = academic track).

Statistical Analyses

We applied SEMs based on latent variable models of the two key types of independent variables, that is, the two self-concepts as well as the Big Five personality traits. The latent self-concept variables were based on five manifest indicators each. Regarding the Big Five personality traits, three parcels per trait served as manifest indicators. These parcels, which were based on two or three items, were established based on the item-to-construct balancing technique (Little et al., 2002). To identify the measurement models of the latent independent variables, we used the marker-variable method (Little et al., 2006).

To test our first research question on the nomological network, we estimated bivariate latent correlations for each of the self-concept–personality combinations. To address our second research question, we fitted a series of latent moderated regression models (Klein & Moosbrugger, 2000), each including one subject-specific academic self-concept and one of the Big Five personality traits as well as subsequently their latent interaction as predictors of academic performance. To address our third research question, we extended the final models from the second step by including the three demographic characteristics, that is, sex, parental SES, and student's immigrant background, modeled as additional manifest predictors of academic performance and finally tested for interaction effects in previously established models[10]. In all reported models, we controlled for fluid intelligence and school track.

We prepared all data in R (4.2.1; R Core Team, 2022) and subsequently estimated the SEM models testing our research questions in M*plus* (8.5.; Muthén & Muthén, 2021) by means of the M*plus*Automation package (1.1.0; Hallquist & Wiley, 2018). In all our analyses, we used the robust maximum likelihood estimator and included all available data by using the full information maximum likelihood algorithm. To control for the nested structure of our data (students nested in classrooms), we implemented the type = complex option in M*plus* to estimate robust standard errors.

Following conventional guidelines (Hu & Bentler, 1999; Schermelleh-Engel et al., 2003), we evaluated model fit based on several criteria: the confirmatory fit index (CFI > 0.95 or at least > 0.90), root mean square error of approximation (RMSEA < 0.05 or at least < 0.08), and standardized root mean square residual (SRMR < 0.05 or at least < 0.10). In models with latent interaction terms, no overall model fit in terms of CFI, RMSEA, or SRMR can be estimated (Klein & Moosbrugger, 2000), but we computed $\Delta\chi 2$ values based on the loglikelihood-values and scaling correction factors (see Cheung et al., 2021). To account for the number of models and estimates in our analytic procedure, we only interpreted findings as being significant on the $p < .01$ level. We also report exact p-values and 99% confidence intervals to provide the reader with complete information.

Results and Discussion

[10] Due to missing data patterns in our data, we estimated all interaction effects including manifest variables, i.e., demographic variables, using the Montecarlo integration implemented in M*plus*.

We first present bivariate latent correlations for each of the combinations of self-concept and personality to investigate the nomological net. Second, we report latent moderated regression models predicting academic outcomes, and finally, we include sociodemographic characteristics in these models. All presented latent variable models control for the two covariates fluid intelligence and school track[11] (for uncontrolled models, see additional online Tables S3-S10: https://osf.io/vam7n), and we only present standardized results. Descriptive information and manifest correlations between all study variables are shown in Table 2.

Cross-sectional Associations of Academic Self-Concepts and Big Five Personality

All latent bivariate correlation models fit the data well (CFI ≥ .95, RMSEA ≤ .06, SRMR ≤ .03; see additional online Table S1: https://osf.io/vam7n). As for the German self-concept, latent bivariate correlations with all Big Five traits were statistically significant (see Table 3). In line with and extending our hypothesis H1a, students with higher German self-concept had higher levels of openness, conscientiousness, extraversion, agreeableness, and lower levels of neuroticism. As for math self-concept, there were only significant positive correlations with openness and conscientiousness (see Table 3). In line with and extending our hypothesis H1b, students with higher math self-concepts showed higher levels of openness and conscientiousness. Contrary to hypothesis H1b, the negative association between the math self-concept and neuroticism did not reach statistical significance.

[11] Covariates showed consistent associations across the different latent models. Specifically, fluid intelligence was associated with higher math self-concept ($\beta = .26$, $p < .001$) and openness ($\beta = .16$, $p = .001$). Attending an academic track school related to higher levels of openness ($\beta = .12$, $p = .006$) and lower levels of neuroticism ($\beta = -.14$, $p = .001$). As for the outcome variables, fluid intelligence related to all performance indicators: German ($.09 \leq \beta \leq .10$, $p \leq .002$) and math grades ($.14 \leq \beta \leq .15$, $p < .001$), German ($.37 \leq \beta \leq .42$, $p < .001$) and math test scores ($.40 \leq \beta \leq .42$, $p < .001$). The school track was associated with all performance indicators except math grades: German grades ($.14 \leq \beta \leq .15$, $p \leq .001$), German ($.23 \leq \beta \leq .25$, $p < .001$), and math test scores ($.34 \leq \beta \leq .36$, $p < .001$).

Table 2

Study 1 – Descriptive Statistics of Academic Performance Indicators, Academic Self-Concepts, Big Five Traits, Socio-Demographic Characteristics and Covariates

Variable	*M*	*SD*	*N*	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15
1. German Grade	3.65	0.83	1,430															
2. Math Grade	3.48	1.02	1,407	**.31**														
3. German Test	2.62	1.07	1,388	**.29**	**.15**													
4. Math Test	1.70	0.84	1,409	**.16**	**.30**	**.59**												
5. German Self-Concept	2.86	0.79	955	**.32**	**−.14**	**.14**	−.06											
6. Math Self-Concept	2.58	0.88	970	.02	**.52**	.05	**.26**	−.07										
7. Openness	3.59	0.59	909	**.17**	**.12**	**.23**	**.17**	**.23**	**.15**									
8. Conscientiousness	3.45	0.66	914	**.17**	**.11**	.05	.03	**.23**	**.15**	**.57**								
9. Extraversion	3.71	0.72	918	.07	−.07	**.10**	.02	**.21**	−.00	**.47**	**.40**							
10. Agreeableness	3.46	0.61	916	**.12**	.02	**.09**	.04	**.18**	.08	**.44**	**.51**	**.38**						
11. Neuroticism	2.51	0.63	913	**−.11**	−.07	**−.20**	**−.18**	**−.21**	**−.12**	**−.48**	**−.43**	**−.53**	**−.36**					
12. Sex	0.51	0.50	1,471	**.25**	**−.09**	.05	**−.17**	**.19**	**−.19**	.00	**.16**	**.17**	**.21**	−.02				
13. Immigrant Background	0.41	0.49	1,397	**−.11**	.00	**−.29**	**−.16**	**−.09**	.01	−.03	.07	−.06	−.06	**.09**	−.03			
14. HISEI	41.99	14.06	1,032	.06	.07	**.24**	**.23**	−.00	.03	.08	−.07	.01	−.01	−.02	−.03	**−.21**		
15. Fluid Intelligence	0.22	0.97	1,403	**.15**	**.27**	**.50**	**.59**	−.03	**.22**	**.16**	−.00	.04	.08	**−.12**	−.02	**−.14**	**.18**	
16. School track	0.23	0.42	1,508	**.20**	**.12**	**.42**	**.52**	.01	.03	**.13**	.05	.07	**.09**	**−.11**	.05	**−.09**	**.24**	**.39**

Note. Significant correlations ($p < .01$) are in bold. Sample sizes vary across correlations from 1471 to 804. Ranges of maximum likelihood estimates for the test scores are: German: −2.88 to 7.37; math: −1.57 to 5.01. Sex is dummy coded with 1 = female. Immigrant background is dummy coded with 1 = immigrant background. Fluid intelligence score was *z* standardized. School track is dummy coded with 1 = academic track. HISEI = highest International Socio−Economic Index of Occupational Status.

Table 3

Study 1 − Latent Bivariate Correlations between Academic Self-Concepts and Big Five Personality

Trait	German Self-Concept			Math Self-Concept		
	β	*p*	99% CI	β	*p*	99% CI
Openness	**0.31**	< .001	[0.21, 0.40]	**0.14**	.001	[0.03, 0.26]
Conscientiousness	**0.28**	< .001	[0.17, 0.39]	**0.18**	< .001	[0.07, 0.30]
Extraversion	**0.23**	< .001	[0.12, 0.35]	−0.02	.557	[−0.13, 0.08]
Agreeableness	**0.24**	< .001	[0.13, 0.36]	0.07	.103	[−0.04, 0.18]
Neuroticism	**−0.24**	< .001	[−0.37, −0.12]	−0.11	.012	[−0.22, 0.00]

Note. N = 1,508. Significant parameters (p <.01) are in bold. All estimates are controlled for fluid intelligence and school track. CI = confidence interval.

Predicting Academic Performance

Results of latent regression analyses predicting academic performance in German are presented in Table 4. All latent regression models fit the data well (CFI ≥ .96, RMSEAs ≤ .04, SRMR ≤ .03; see additional online Table S12: https://osf.io/vam7n). As expected, students with a higher German self-concept showed better academic performance in German, and this association tended to be stronger for grades than for test scores as indicated by the non-overlapping confidence intervals (Cumming, 2014)[12] of the parameter estimates in three out of the five models (see Table 4, Model 1 for detailed results). As for the Big Five, three traits proved to be significant predictors: Students with higher levels of conscientiousness reported better German grades, and students with higher levels of openness and lower levels of neuroticism reported higher German test scores. The models explained at least 16.2 % of the variance in German grades and about 33.5 % in German test scores.

Results on academic performance in math are presented in Table 5. The latent regression models again fit the data well (CFI ≥ .95, RMSEA ≤ .05, SRMR = .03; see additional online Table S13: https://osf.io/vam7n). As expected, math self-concept consistently predicted math grades and test scores across all models. More specifically, students with a higher math self-concept showed better academic performance in math, and this association was again stronger for grades than for test scores as indicated by the nonoverlapping confidence intervals

[12] Methodological recommendations suggest that confidence intervals can be used as descriptive evaluations and for the comparison of parameter estimates (Cumming, 2014; Cumming & Fidler, 2009). In most cases, this descriptive evaluation is regarded as an even more strict procedure as compared to chi-square equivalence testing of parameters.

(Cumming, 2014) of the parameter estimates across models. As for the Big Five, only two traits were statistically significant predictors. Students with lower levels of extraversion reported better math grades, and students with lower levels of neuroticism scored higher on math tests. The models explained at least 33.3 % of the variance in math grades and 46.7 % in math test scores.

Next, we extended these models by including the latent interaction between the academic self-concept and the respective Big Five personality trait. Again, all models fit the data well (see additional online Tables S12 and S13: https://osf.io/vam7n). All reported main effects remained stable after adding the latent interaction effect with the exception of the main effect of conscientiousness on German grades, which did not remain statistically significant. There were no substantial interaction effects on standardized test scores, but we found statistically significant interactions with regard to German and math grades.

For German grades, the interactions of German self-concept with agreeableness and neuroticism proved statistically significant (see Figures 1a and 1b for an illustration and Table 4, Model 2 for results). Higher levels of agreeableness (+1 SD) strengthened the association between German self-concept and German grades. Thus, high agreeableness seems to be a resource for better German grades in students with a higher German self-concept, indicating synergistic effects. In contrast, a higher level of neuroticism (+1 SD) weakened the association between German self-concept and German grades. The interaction effects explained an additional 2.2% and 2.0% of the variance in German grades, respectively.

For math grades, the interactions of math self-concept with conscientiousness and agreeableness proved to be statistically significant (see Figures 1c and 1d for an illustration and Table 5, Model 2 for detailed results). For students with higher levels of conscientiousness and agreeableness (+1 SD), the association between math self-concept and math grades was stronger than for those with lower levels of these traits (−1 SD). Thus, again conscientiousness and agreeableness seemed to strengthen the association between math self-concept and math grades, acting as resources. These interaction effects accounted for an additional 2.3% and 1.6% of the variance in math grades, respectively.

Table 4

Study 1 − Latent Regression Model Parameters predicting German Performance by German Self-Concept, Big Five Personality, and Socio-Demographic Characteristics

	Openness			Conscientiousness			Extraversion			Agreeableness			Neuroticism		
	β	*p*	99% CI	β	*p*	99% CI	β	*p*	99% CI	β	*p*	99% CI	β	*p*	99% CI
Predictors							**German Grades**								
Model 1															
German Self−Concept	**0.31**	< .001	[0.21, 0.42]	**0.30**	< .001	[0.20, 0.41]	**0.34**	< .001	[0.24, 0.44]	**0.32**	< .001	[0.21, 0.44]	**0.33**	< .001	[0.22, 0.43]
Personality	0.08	.104	[−0.05, 0.21]	**0.12**	.009	[0.00, 0.24]	−0.01	.884	[−0.11, 0.10]	0.06	.175	[−0.05, 0.16]	−0.05	.285	[−0.16, 0.07]
Model 2															
German Self−Concept	**0.32**	< .001	[0.21, 0.42]	**0.31**	< .001	[0.20, 0.42]	**0.34**	< .001	[0.24, 0.45]	**0.34**	< .001	[0.22, 0.45]	**0.34**	< .001	[0.23, 0.44]
Personality	0.08	.114	[−0.05, 0.21]	0.11	.013	[−0.00, 0.23]	−0.01	.741	[−0.12, 0.09]	0.05	.236	[−0.06, 0.15]	−0.05	.277	[−0.16, 0.07]
GSC × P	0.06	.089	[−0.03, 0.14]	0.08	.012	[−0.00, 0.17]	0.08	.047	[−0.02, 0.19]	**0.12**	.001	[0.03, 0.21]	**−0.11**	.009	[−0.22, −0.00]
Model 3															
German Self−Concept	**0.27**	< .001	[0.16, 0.38]	**0.27**	< .001	[0.16, 0.38]	**0.30**	< .001	[0.20, 0.41]	**0.31**	< .001	[0.19, 0.43]	**0.30**	< .001	[0.18, 0.41]
Personality	0.10	.055	[−0.03, 0.22]	0.11	.024	[−0.01, 0.23]	−0.04	.367	[−0.14, 0.07]	0.01	.805	[−0.10, 0.12]	−0.05	.274	[−0.16, 0.06]
GSC × P										**0.11**	.002	[0.02, 0.21]	**−0.11**	.009	[−0.22, −0.00]
Sex	**0.19**	< .001	[0.12, 0.25]	**0.17**	< .001	[0.10, 0.24]	**0.18**	< .001	[0.12, 0.26]	**0.17**	< .001	[0.10, 0.24]	**0.18**	< .001	[0.11, 0.24]
Immigrant Background	−0.06	.064	[−0.14, 0.02]	−0.07	.033	[−0.15, 0.01]	−0.06	.070	[−0.14, 0.02]	−0.05	.122	[−0.13, 0.03]	−0.05	.096	[−0.13, 0.03]
HISEI	−0.00	.915	[−0.09, 0.08]	0.01	.830	[−0.07, 0.09]	0.00	.993	[−0.08, 0.08]	0.00	.930	[−0.08, 0.08]	−0.00	.971	[−0.08, 0.08]
							German Test Scores								
Model 1															
German Self−Concept	0.09	.012	[−0.00, 0.19]	**0.14**	< .001	[0.04, 0.23]	**0.13**	< .001	[0.04, 0.22]	**0.13**	< .001	[0.04, 0.22]	**0.11**	.002	[0.02, 0.20]
Personality	**0.15**	.001	[0.04, 0.27]	0.01	.735	[−0.08, 0.10]	0.04	.318	[−0.07, 0.15]	0.02	.547	[−0.07, 0.11]	**−0.14**	< .001	[−0.22, −0.05]
Model 2															
German Self−Concept	**0.09**	.009	[0.00, 0.19]	**0.14**	< .001	[0.04, 0.23]	**0.13**	.001	[0.03, 0.23]	**0.14**	< .001	[0.05, 0.22]	**0.11**	.003	[0.01, 0.20]
Personality	**0.19**	< .001	[0.07, 0.30]	0.01	.751	[−0.07, 0.10]	0.05	.337	[−0.08, 0.18]	0.01	.680	[−0.07, 0.10]	**−0.14**	.001	[−0.26, −0.03]
GSC × P	−0.13	.119	[−0.35, 0.09]	0.01	.909	[−0.13, 0.14]	−0.03	.681	[−0.25, 0.18]	0.04	.430	[−0.08, 0.15]	0.02	.839	[−0.30, 0.35]
Model 3															
German Self−Concept	0.07	.069	[−0.03, 0.16]	**0.11**	.002	[0.02, 0.20]	**0.11**	.001	[0.02, 0.20]	**0.11**	.001	[0.03, 0.20]	**0.09**	.009	[0.00, 0.17]
Personality	**0.15**	< .001	[0.05, 0.26]	0.04	.268	[−0.05, 0.12]	0.03	.467	[−0.07, 0.13]	0.01	.748	[−0.08, 0.10]	**−0.12**	< .001	[−0.21, −0.04]
Sex	0.03	.163	[−0.02, 0.08]	0.01	.432	[−0.04, 0.06]	0.01	.439	[−0.04, 0.06]	0.02	.394	[−0.03, 0.07]	0.02	.256	[−0.03, 0.07]
Immigrant Background	**−0.19**	< .001	[−0.25, −0.12]	**−0.19**	< .001	[−0.25, −0.12]	**−0.18**	< .001	[−0.25, −0.12]	**−0.18**	< .001	[−0.25, −0.12]	**−0.17**	< .001	[−0.24, −0.11]
HISEI	**0.07**	.007	[0.00, 0.14]	**0.08**	.003	[0.01, 0.15]	**0.08**	.003	[0.01, 0.15]	**0.08**	.002	[0.01, 0.15]	**0.09**	.001	[0.02, 0.16]

Note. N = 1,508. Models were estimated for each Big Five trait separately. Significant predictors ($p < .01$) are in bold. All models are controlled for fluid intelligence and school track. Sex is dummy coded with 1 = female. Immigrant background is dummy coded with 1 = immigrant background. CI = confidence interval. Personality = Big Five personality trait examined in the respective model, as indicated in the column headings. GSC × P = Interaction between the German Self-Concept and the respective Big Five trait.

Table 5

Study 1 - Latent Regression Model Parameters predicting Math Performance by Math Self-Concept, Big Five Personality, and Socio-Demographic Characteristics

	Openness			Conscientiousness			Extraversion			Agreeableness			Neuroticism		
	β	*p*	99% CI	β	*p*	99% CI	β	*p*	99% CI	β	*p*	99% CI	β	*p*	99% CI
Predictors								**Math Grades**							
Model 1															
Math Self-Concept	**0.52**	< .001	[0.45, 0.59]	**0.52**	< .001	[0.44, 0.59]	**0.52**	< .001	[0.45, 0.59]	**0.52**	< .001	[0.45, 0.60]	**0.52**	< .001	[0.45, 0.60]
Personality	0.00	.991	[−0.09, 0.09]	0.03	.425	[−0.07, 0.14]	**−0.09**	.003	[−0.16, −0.01]	−0.03	.393	[−0.12, 0.06]	0.01	.834	[−0.09, 0.11]
Model 2															
Math Self-Concept	**0.52**	< .001	[0.45, 0.59]	**0.52**	< .001	[0.45, 0.59]	**0.52**	< .001	[0.44, 0.59]	**0.52**	< .001	[0.45, 0.59]	**0.52**	< .001	[0.45, 0.60]
Personality	0.00	.995	[−0.09, 0.09]	0.03	.457	[−0.07, 0.12]	**−0.08**	.003	[−0.16, −0.01]	−0.02	.540	[−0.11, 0.07]	0.01	.852	[−0.09, 0.11]
MSC × P	0.03	.329	[−0.05, 0.11]	**0.15**	< .001	[0.07, 0.22]	0.01	.785	[−0.06, 0.07]	**0.13**	< .001	[0.05, 0.21]	−0.03	.421	[−0.11, 0.06]
Model 3															
Math Self-Concept	**0.52**	< .001	[0.44, 0.60]	**0.51**	< .001	[0.44, 0.59]	**0.52**	< .001	[0.44, 0.60]	**0.52**	< .001	[0.44, 0.60]	**0.52**	< .001	[0.44, 0.60]
Personality	−0.00	.984	[−0.09, 0.09]	0.03	.387	[−0.07, 0.13]	**−0.09**	.002	[−0.16, −0.01]	−0.02	.581	[−0.11, 0.07]	0.01	.862	[−0.09, 0.11]
MSC × P				**0.15**	< .001	[0.07, 0.23]				**0.14**	< .001	[0.06, 0.23]			
Sex	0.01	.665	[−0.06, 0.08]	0.00	.898	[−0.07, 0.08]	0.03	.280	[−0.04, 0.10]	0.02	.503	[−0.05, 0.09]	0.01	.649	[−0.06, 0.08]
Immigrant Background	0.02	.506	[−0.05, 0.08]	0.01	.661	[−0.05, 0.07]	0.01	.656	[−0.05, 0.07]	0.02	.511	[−0.05, 0.08]	0.01	.534	[−0.05, 0.08]
HISEI	0.03	.296	[−0.05, 0.11]	0.03	.274	[−0.04, 0.10]	0.03	.310	[−0.05, 0.11]	0.03	.320	[−0.05, 0.10]	0.03	.292	[−0.04, 0.10]
								Math Test Scores							
Model 1															
Math Self-Concept	**0.15**	< .001	[0.07, 0.22]	**0.15**	< .001	[0.08, 0.23]	**0.15**	< .001	[0.08, 0.23]	**0.16**	< .001	[0.08, 0.23]	**0.14**	< .001	[0.07, 0.22]
Personality	0.06	.054	[−0.02, 0.14]	−0.00	.874	[−0.09, 0.08]	−0.01	.600	[−0.08, 0.06]	−0.05	.186	[−0.14, 0.04]	**−0.10**	.001	[−0.17, −0.02]
Model 2															
Math Self-Concept	**0.14**	< .001	[0.07, 0.22]	**0.16**	< .001	[0.08, 0.23]	**0.15**	< .001	[0.08, 0.23]	**0.16**	< .001	[0.08, 0.23]	**0.15**	< .001	[0.07, 0.22]
Personality	0.06	.052	[−0.02, 0.14]	−0.01	.844	[−0.09, 0.07]	−0.01	.604	[−0.08, 0.06]	−0.04	.176	[−0.13, 0.04]	**−0.09**	.001	[−0.17, −0.02]
MSC × P	0.02	.628	[−0.07, 0.11]	0.03	.430	[−0.07, 0.13]	0.01	.717	[−0.07, 0.09]	0.07	.048	[−0.02, 0.16]	0.04	.313	[−0.06, 0.14]
Model 3															
Math Self-Concept	**0.12**	< .001	[0.05, 0.19]	**0.12**	< .001	[0.04, 0.20]	**0.13**	< .001	[0.06, 0.20]	**0.13**	< .001	[0.05, 0.21]	**0.12**	< .001	[0.04, 0.19]
Personality	0.06	.037	[−0.01, 0.14]	0.04	.200	[−0.04, 0.12]	0.01	.622	[−0.05, 0.08]	−0.01	.853	[−0.10, 0.09]	**−0.10**	< .001	[−0.18, −0.03]
Sex	**−0.15**	< .001	[−0.20, −0.10]	**−0.16**	< .001	[−0.21, −0.10]	**−0.15**	< .001	[−0.20, −0.10]	**−0.15**	< .001	[−0.20, −0.09]	**−0.15**	< .001	[−0.21, −0.10]
Immigrant Background	**−0.07**	.001	[−0.12, −0.01]	**−0.07**	.001	[−0.12, −0.02]	**−0.07**	.001	[−0.12, −0.01]	**−0.07**	.001	[−0.12, −0.01]	**−0.06**	.005	[−0.11, −0.00]
HISEI	0.06	.052	[−0.02, 0.13]	0.06	.031	[−0.01, 0.13]	0.06	.036	[−0.01, 0.13]	0.06	.038	[−0.01, 0.13]	0.06	.019	[−0.01, 0.13]

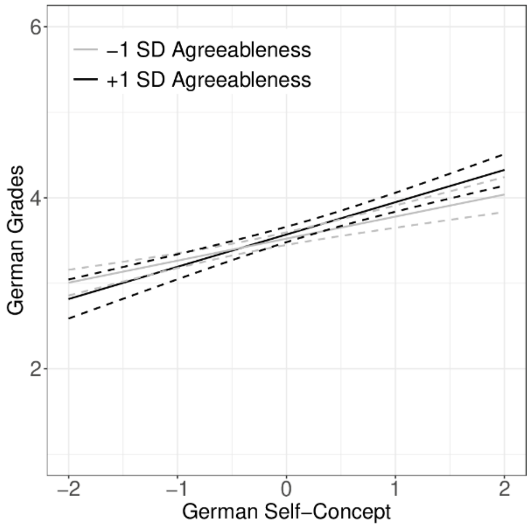
Note. N = 1,508. Models were estimated for each Big Five trait separately. Significant predictors ($p < .01$) are in bold. All models are controlled for fluid intelligence and school track. Sex is dummy coded with 1 = female. Immigrant background is dummy coded with 1 = immigrant background. CI = confidence interval. Personality = Big Five personality trait examined in the respective model, as indicated in the column headings. MSC × P = Interaction between the Math Self-Concept and the respective Big Five trait.

1

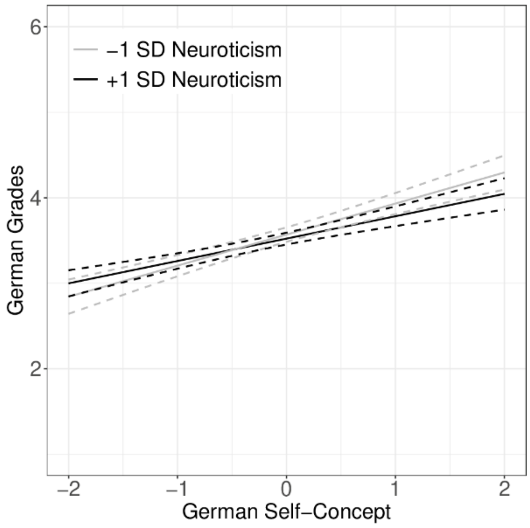
Figure 1

Latent Interaction Effects between Self-Concept and Personality Predicting Grades in German (a-b) and math (c-d)

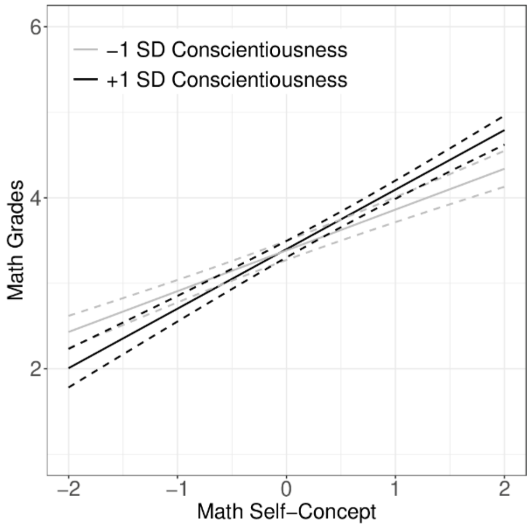
a) Interaction between German self-concept and agreeableness



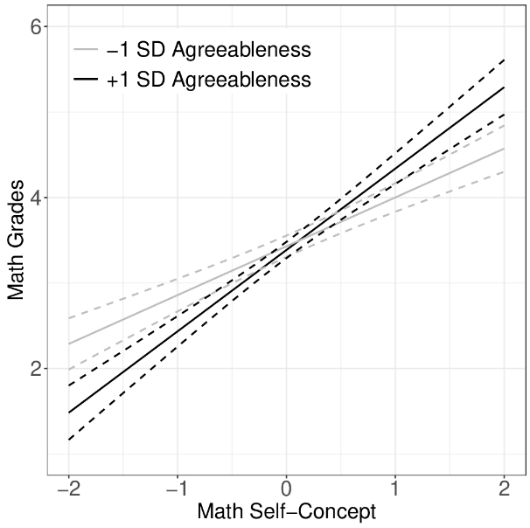
b) Interaction between German self-concept and neuroticism



c) Interaction between math self-concept and conscientiousness



d) Interaction between math self-concept and agreeableness



Note. Grades are reverse-coded, so that higher values represent higher academic performance. Panel (a) Interaction between German self-concept and agreeableness. Panel (b) Interaction between German self-concept and neuroticism. Panel (c) Interaction between math self-concept and conscientiousness. Panel (d) Interaction between math self-concept and agreeableness. Black lines = +1 SD of the respective Big Five trait; grey lines = −1 SD of the respective Big Five trait; Solid line = estimated regression graph; dashed lines = confidence bands.

The Role of Sociodemographic Characteristics

To address our third research question, we extended the best-fitting models from the previous analyses, either with or without latent interactions included, and added the main effects of the sociodemographic variables: participants' sex, parental SES, and immigrant background (see additional online Tables S12 and S13 for model fit: https://osf.io/vam7n). Parameter estimates are presented in Tables 4 and 5 in Model 3. As illustrated in these tables, all main and interaction effects found in the previous models remained stable.

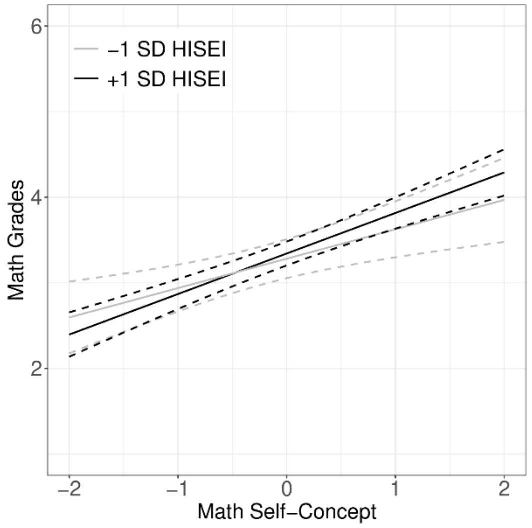
As for academic performance in German, girls reported better German grades than boys. Students with an immigrant background scored lower on the German test than students without an immigrant background, and students with a higher parental SES scored higher on the German test. Adding the sociodemographic variables led to an increase of at least 3.0 % in the explained variance for German grades and 4.0% in test scores. As for academic performance in math, none of the sociodemographic characteristics related to differences in math grades, but boys scored higher in math tests than girls, and students with an immigrant background scored lower in math tests. Adding the sociodemographic main effects led to an increase in explained variance for math test scores of at least 2.8%.

Finally, we tested all possible two-way interactions between the two main predictors of self-concept and Big Five traits and each sociodemographic variable, respectively (see additional online Table S14 for all tested interactions: https://osf.io/vam7n, and additional online Table S15 for model fit: https://osf.io/vam7n). Regarding academic performance in German, there were no statistically significant interaction effects. Regarding math performance, we found three statistically significant interaction effects predicting math grades but none regarding test scores. First, there was a robust interaction effect between the math self-concept and the parental SES ($0.06 \leq \beta \leq 0.07$, $p \leq .009$, $.003 \leq \Delta R^2 \leq .005$; see Figure 2). To illustrate, students with higher parental SES benefited even more from a high math self-concept regarding their math grades, indicating a synergistic effect. The main effect of the math self-concept remained significant but decreased in size in all five models ($0.24 \leq \beta \leq 0.29$, $p \leq .002$). Second, the expected (Hypothesis H3a) interaction effect between the math self-concept and participants' sex ($\beta \leq 0.08$, $p \leq .003$, $.002 \leq \Delta R^2 \leq .003$; see Figure 2b) emerged. However, it was in the opposite direction, indicating that girls benefited more from a high math self-concept. The main effect of the math self-concept remained significant but decreased slightly ($\beta = 0.43$, $p < .001$). Importantly, this effect only proved to be statistically significant in three (openness, neuroticism, extraversion) out of the five models. Third, there was a negative interaction between participants' sex and neuroticism ($\beta = -.12$, $p = .002$, $\Delta R^2 = .02$; see also Figure 2c), demonstrating that higher levels of neuroticism were beneficial for math grades in boys, while the opposite was true for girls. The formerly reported main effects remained stable in this model. Importantly, all significant interaction effects were of small size. This should be considered when interpreting these effects.

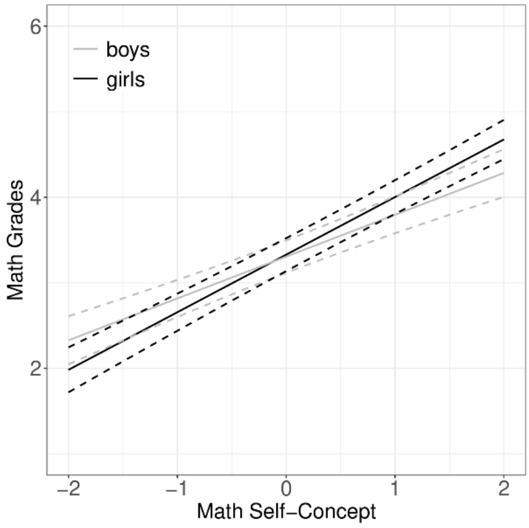
Figure 2

Significant Interaction Effects between Socio-Emotional and Socio-Demographic Variables Predicting German Test Scores

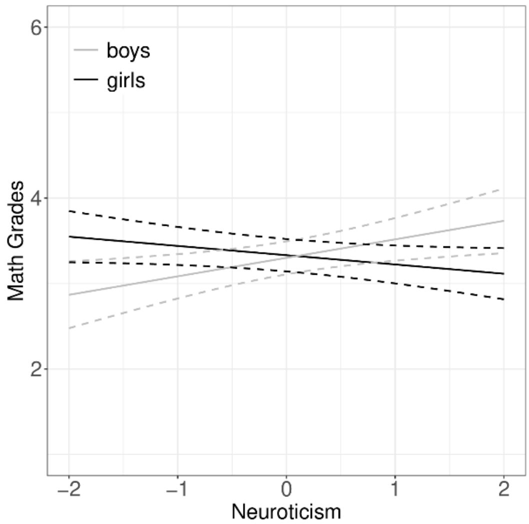
a) Interaction between math self-concept and parental socio-economic status



b) Interaction between math self-concept and participants' sex



c) Interaction between neuroticism and participants' sex



Note. Grades are reverse-coded, so that higher values represent higher academic performance. Panel (a) Interaction between math self-concept and parental socioeconomic status. Panel (b) Interaction between math self-concept and participants' sex. Panel (c) Interaction between neuroticism and participants' sex. Black lines = +1 SD HISEI/girls; grey lines = −1 SD of HISEI/ boys; Solid line = estimated regression graph; dashed lines = confidence bands; HISEI = highest International Socio-Economic Index of Occupational Status.

Altogether, the results of Study 1 illustrated three main findings: First, academic self-concepts and Big Five traits could be integrated into a nomological net. That is, particularly the German self-concept showed consistent associations with personality traits. Second, in line with expectations, both self-concepts demonstrated predictive power for academic achievement outcomes, but in addition, both personality trait effects and specific latent interactions emerged. Specifically, results indicated that openness, conscientiousness, and agreeableness are beneficial, while extraversion and neuroticism can compromise academic performance. That is, they were either directly associated with performance differences or enhanced/reduced the beneficial effect of academic self-concepts. Third, despite their general robustness, SES and sex moderated some main effects. Along these lines, it is important to consider the specific characteristics of our sample, which comprised students from vulnerable communities (e.g., a higher percentage of immigrant backgrounds and lower parental SES). Addressing this constraint on generalizability, we aimed to replicate the findings in a representative sample in Study 2.

Study 2

Method

In Study 2, we analyzed publicly available data from the National Educational Panel Study (NEPS; Blossfeld & Rossbach, 2019). The NEPS is carried out by the Leibniz Institute for Educational Trajectories (Germany) in cooperation with a nationwide network. Further information on the NEPS data is available at https://www.neps-data.de/Mainpage. It provides representative longitudinal data from German samples across six different age cohorts. Given our interest in students from Grade 9 to Grade 12, we were able to use data from two starting cohorts, that is, Cohort 3 (NEPS Network, 2021a) and Cohort 4 (NEPS Network, 2021b) and combined these two cohorts to form one sample. Within both cohorts, the variables relevant for this article were identically assessed in 9th and 12th grade, subsequently referred to as T1 and T2. To be precise, data assessment in 9th grade actually spread across two measurement points with the first taking place during 9th grade and the second taking place at the end of the school year of 9th grade. Again, this was true for both combined starting cohorts in our Study 2. The first measurement point during 9th grade assessed all relevant variables of our study except for the reading competence test. This test was administered only at the end of the school year. Nevertheless, given that all assessments took part during 9th grade, we combined these two assessment points into our T1.

Transparency and Openness

The present study is considered a secondary analysis of existing (fully anonymized) data. The ongoing NEPS study (Study 2) is conducted under the supervision of the German Federal Commissioner for Data Protection and Freedom of Information (BfDI) and all procedures are approved by the data protection unit of the Leibniz Institute for Educational Trajectories. We preregistered our hypotheses and analytic strategy in the OSF (https://osf.io/fg7y2) before data analysis, documented all deviations from the preregistration in additional online Table S2 (https://osf.io/vam7n), and provided a comprehensive additional online material. Analyses codes to reproduce the presented results, as well as the additional online materials are uploaded in the OSF project page (https://osf.io/sptve/). As the NEPS project provides open-source data, data for Study 2 are available on the NEPS project page (https://www.neps-data.de/Data-Center/Data-Access). More specifically, we used the scientific use files of starting Cohorts 3 (NEPS Network, 2021a) and 4 (NEPS Network, 2021b). We excluded participants that did not meet our preregistered inclusion criteria (available data for at least one item of interest and available class identifier) from our analyses. We report how we determined the sample size and all study measures. We prepared all data in R (4.2.1; R Core Team, 2022) and subsequently estimated the SEMs testing our research questions in Mplus (8.5.; Muthén & Muthén, 2021) by means of the MplusAutomation package (1.1.0; Hallquist & Wiley, 2018). We document deviations from the pre-registration in Table S2 in the OSM. We follow Journal Article Reporting Standards (Appelbaum et al., 2018) in reporting our results. ethical approval was not required for our research. The present study is not classified as a replication or registered report.

Sample

Integrating the two starting cohorts of the NEPS data, Study 2 is based on a total sample of N = 19,783 ninth graders meeting the same inclusion criteria as in Study 1[13][14]. Most participants attended vocational-track schools (59.7%), which prepare for vocational training, while the remaining 40.3 % attended academic-track schools, which prepare students for

[13] Again, we used the class ID instead of the preregistered school ID to account for clustering within our data and therefore changed the inclusion criterion to participants with an existing class ID.

[14] Participants included in our study were significantly older (Cohen's d = 0.47), more likely to attend an academic track school (d = 0.20), and scored higher on fluid intelligence (d = 1.22) than those who were excluded (n = 3,605). Concerning socio-emotional predictors, participants meeting our inclusion criteria reported a lower German self-concept (d = 0.07), higher levels of openness (d = 0.07), conscientiousness (d = 0.14), and extraversion (d = 0.08), as well as lower levels of neuroticism (d = 0.07). As for the socio-demographic predictors, included participants were more likely to be female (d = 0.10) and to have a higher SES (d = 0.15). Regarding the outcome variables of interest, participants included in our study reported higher math grades (d = 0.10), scored lower on German (d = 0.64) and math tests (d = 0.66). See Table S16 in the OSM for detailed results of the selectivity analysis.

university education. On average, students were 15.10 (*SD* = 0.67) years old at T1, with an equal distribution of girls and boys (49.9% female). Looking at the SES of parents, the average HISEI was 54.60 (*SD* = 20.29) ranging between 11.74 and 88.96. An immigrant background was reported by 36.3% of the participants.

Measures

Academic Performance. We included two measures of academic performance in both German and math. First, we used the self-reported grades from the T1 assessment.[15] Grades in Germany range from 1 (*very good*) to 6 (*insufficient*). We inverted grades so that higher values reflect higher academic performance. Second, participants took standardized achievement tests for reading (Gehrer et al., 2012) and mathematics at T1 and T2. Tests were administered individually in a paper-pencil mode and were limited to approximately 30 min. The test for reading skills in German comprised at least 30 items at T1 and 22 items at T2. The reliabilities of the tests were reported as good (weighted likelihood estimate [WLE] reliability = .75 - .80; Gnambs et al., 2017; Haberkorn et al., 2012; Kutscher & Scharl, 2020; Scharl et al., 2017). The mathematical skill test comprised at least 21 items at T1 and T2. The reliabilities of the tests were reported as good across both measurements in both starting cohorts (WLE reliability = .74−.81; Duchhardt & Gerdes, 2013; Fischer et al., 2017; Petersen et al., 2021; Van Den Ham et al., 2018).

For both subjects, we used WLEs from item response theory models provided by the NEPS. Due to our longitudinal analyses of competency gains, we used the WLE scores that are linked across waves based on item difficulty parameters. This allows for competence comparisons of adjacent waves and analyses of change across secondary schooling. More information on the tests and scaling procedures is provided in the competency assessment documentations for reading skills in German (Gnambs et al., 2017; Haberkorn et al., 2012; Kutscher & Scharl, 2020; Scharl et al., 2017), and for mathematical skills (Duchhardt & Gerdes, 2013; Fischer et al., 2017; Petersen et al., 2021; Van Den Ham et al., 2018).

Academic self-concept. Within the NEPS, students reported their academic self-concept in German and math based on three parallel worded items per subject (e.g., “I get good grades in German [/mathematics]”) that have been retrieved from the PISA study (Kunter, 2002). All items were rated on a fully labeled 4-point scale ranging from 1 (*does not apply at all*) to 4 (*does completely apply*). We included self-concept measures from T1 in our analyses.

[15] Deviating from our preregistration, we did not include grades obtained at T2 in our analyses, due to the huge amount of missing data.

The German and math self-concept scales showed good reliability based on the measurement-model-based reliability index ω (ω_{German} = .83, ω_{math} = .90).

Big Five Personality Traits. Big Five personality traits were measured using the ten item version of the Big Five Inventory (BFI-10; Rammstedt & John, 2007). The BFI-10 measures the Big Five dimensions with two items each, one of which is reverse-keyed to control for acquiescent responding. Following the suggestion of Rammstedt and John (2007), NEPS included a third agreeableness item to improve the reliability and bandwidth of the agreeableness scale of the BFI-10. We used these three agreeableness items in our analyses. All personality items were rated on a fully labeled 5-point scale ranging from 1 (*does not apply at all*) to 5 (*fully applies*). We included personality measures from T1 in our analyses. In line with other studies (Brandt et al., 2020; Brandt & Lechner, 2022) and due to the low number of items for such broad constructs, the split-half reliabilities of the manifest scales were relatively low (r_{openness} = .45, $r_{\text{conscientiousness}}$ = .53, $r_{\text{extraversion}}$ = .63, $r_{\text{agreeableness}}$ = .36, $r_{\text{neuroticism}}$ = .42). However, the test–retest reliability of the BFI-10 is sufficient as reported in previous research in Germany. Moreover, it shows high convergent validity with longer Big Five scales and the overall criterion validity is comparable to longer inventories (Rammstedt & John, 2007; Thalmayer et al., 2011). To account for the unreliability of the observed items, we used latent variable models for all Big Five traits.

Demographic Characteristics. Regarding the sociodemographic characteristics, we included students' sex as a dichotomous variable (0 = male; 1 = female). Concerning *students' immigrant status*, the NEPS data provide differentiated information (Olczyk, Will, et al., 2016), which we in line with Study 1 integrated into a dichotomous variable (0 = students without immigrant background; 1 = students with some form of immigrant background) and *socioeconomic status* was indicated by parents' highest International Socio-Economic Index of Occupational Status (HISEI; Ganzeboom et al., 1992).

Control Variables. We controlled all models for the same two variables as in Study 1: fluid intelligence and school track. Fluid intelligence was measured by the 12-item NEPS matrices test (NEPS-MAT). NEPS-MAT is similar to Raven's Standard Progressive Matrices and was developed and validated specifically for the NEPS (for further information, see Brunner et al., 2014). We used the sum scores of these items in three sets of four binary items each as manifest indicators for a latent variable identified by the marker variable approach. Second, we included the attended school track as a dichotomous manifest covariate (0 = nonacademic track; 1 = academic track).

Statistical Analyses

We used a nearly identical analysis strategy as in Study 1: We again followed a SEM approach based on latent variable models of the two key groups of independent variables. The two self-concept variables were based on three manifest indicators, while for the Big Five traits, there were two indicators for all traits except agreeableness which was estimated based on three indicators. Deviating from the first study and given the small number of items for personality, we used the effect coding method (Little et al., 2006) to identify the latent personality traits and the estimablity of all models. We again addressed our three research questions by estimating bivariate latent correlations and latent moderated regression models (Klein & Moosbrugger, 2000). Given the longitudinal nature of this study, we extended the latent regression models to additionally predict changes in academic performance by estimating Latent Change Score Models (McArdle, 2009) based on the two assessment waves of academic achievement. We used the same procedure reported in Brandt and Lechner to specify our models (2022, see also our open code at the OSF).

Results and Discussion

We first present bivariate latent correlations for each of the combinations of self-concept and personality to investigate the nomological net. Second, we report latent moderated regression models predicting academic outcomes, and third, include socio-demographic characteristics in these models. Extending the results of Study 1, our final models predicted changes in academic performance. All reported latent models control for covariates[16] and are standardized. For results without covariates, see additional online Tables S17-S24 (https://osf.io/vam7n). Descriptive information and manifest correlations between all study variables are presented in Table 6.

[16] In line with Study 1, consistent associations with covariates emerged. Fluid intelligence was again associated with higher math self-concept ($.26 \leq \beta \leq .28$, $p < .001$) and openness ($.12 \leq \beta \leq .13$, $p < .001$). Additionally, in Study 2 fluid intelligence was associated with lower levels of conscientiousness ($-.09 \leq \beta \leq -.08$, $p < .001$) and extraversion ($-.09 \leq \beta \leq -.08$, $p < .001$), as well as higher levels of agreeableness ($\beta = .05$, $p < .001$). Attending an academic track school was again related to higher levels of openness ($.04 \leq \beta \leq .05$, $p < .001$) and, additionally, to lower levels of conscientiousness ($-.09 \leq \beta \leq -.08$, $p \leq .001$) in Study 2. Fluid intelligence was again associated with all performance indicators: German ($.07 \leq \beta \leq .08$, $p < .001$) and math grades ($.06 \leq \beta \leq .08$, $p < .001$), German ($.24 \leq \beta \leq .25$, $p < .001$) and math test scores ($.14 \leq \beta \leq .16$, $p < .001$). The school track was likewise associated with all performance indicators: German ($.11 \leq \beta \leq .12$, $p < .001$) and math grades ($.09 \leq \beta \leq .10$, $p < .001$), German ($.34 \leq \beta \leq .36$, $p < .001$) and math test scores ($.45 \leq \beta \leq .46$, $p < .001$).

Table 6

Study 2 – Descriptive Statistics of Academic Performance Indicators, Academic Self-Concepts, Big Five Traits, Socio-Demographic Characteristics and Covariates

Variable	*M*	*SD*	*N*	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15
1. German Grade	4.18	0.82	18,227															
2. Math Grade	4.05	1.01	18,163	**.38**														
3. German Test	0.29	1.36	17,845	**.33**	**.21**													
4. Math Test	0.41	1.39	18,915	**.26**	**.37**	**.64**												
5. German Self-Concept	2.94	0.62	18,482	**.55**	**.06**	**.20**	**.08**											
6. Math Self-Concept	2.52	0.92	18,427	**.05**	**.65**	**.05**	**.31**	**−.07**										
7. Openness	3.45	0.95	18,509	**.12**	**−.02**	**.09**	−.00	**.15**	**−.07**									
8. Conscientiousness	3.13	0.86	18,540	**.19**	**.15**	**−.07**	**−.10**	**.23**	**.11**	**.09**								
9. Extraversion	3.40	0.88	18,448	**.05**	**−.07**	**−.04**	**−.07**	**.13**	**−.07**	**.07**	**.02**							
10. Agreeableness	3.44	0.66	18,400	**.04**	.02	−.02	**−.04**	**.06**	−.00	**.14**	**.22**	**−.05**						
11. Neuroticism	2.79	0.86	18,521	.00	**−.04**	.01	**−.06**	**−.06**	**−.13**	.01	**.02**	**−.27**	.02					
12. Sex	0.50	0.50	19,700	**.21**	**−.06**	**.11**	**−.13**	**.18**	**−.25**	**.21**	**.19**	**.02**	**.13**	**.23**				
13. Immigrant Background	0.36	0.48	17,380	**−.07**	**−.08**	**−.14**	**−.16**	−.02	**−.05**	**.06**	.02	**.04**	**.02**	.02	**.03**			
14. HISEI	54.60	20.29	11,732	**.19**	**.15**	**.33**	**.34**	**.10**	**.07**	**.07**	**−.05**	**.04**	−.02	**−.04**	.01	**−.14**		
15. Fluid Intelligence	10.38	3.67	19,502	**.08**	**.14**	**.10**	**.08**	**.07**	**.13**	**.11**	**.04**	.01	**.19**	**−.04**	**.03**	**−.09**	**.11**	
16. School Track	0.40	0.49	19,563	**.21**	**.13**	**.47**	**.52**	**.11**	**.03**	**.07**	**−.10**	**.03**	**−.02**	−.02	**.07**	**−.08**	**.41**	**.19**

Note. Significant correlations ($p < .01$) are in bold. Sample sizes vary across correlations from 10,384 to 19,700. Ranges of weighted likelihood estimates for the test score: German: −4.75 to 6.33; math: −4.37 to 6.88. Sex is dummy coded with 1 = female. Immigrant background is dummy coded with 1 = immigrant background. Fluid intelligence score was z standardized. School track is dummy coded with 1 = academic track. *N* = number of observations; HISEI = highest International Socio-Economic Index of Occupational Status.

Cross-Sectional Associations of Academic Self-Concepts and Big Five Personality

All latent bivariate correlation models fit the data well (CFI ≥ .93, RMSEA ≤ .05, SRMR ≤ .06; see additional online Table S25: https://osf.io/vam7n). As in Study 1, the latent bivariate correlations between the German self-concept and all Big Five traits were statistically significant (see Table 7). Students with higher German self-concept had higher levels of openness, conscientiousness, extraversion, and agreeableness and lower levels of neuroticism. As for the math self-concept, there were statistically significant correlations with all Big Five traits except agreeableness (see Table 7). Contrary to Study 1, openness was negatively related to the math self-concept. This is most likely due to the different item content across the two questionnaires. We elaborate on this in the General Discussion. The correlation with conscientiousness pointed in the same direction and was at a comparable size. In addition, the correlations with extraversion and neuroticism proved to be statistically significant in Study 2. That is, higher levels of extraversion and neuroticism were related to a lower math self-concept. In summary, the results of Study 2 replicated large parts of the results from Study 1 but also extended and refined our understanding regarding the nomological net between self-concepts and personality traits.

Table 7

Study 2 – Controlled Latent Bivariate Correlations between Academic Self--Concepts and Big Five Personality

Trait	German Self-Concept			Math Self-Concept		
	β	*p*	99% CI	β	*p*	99% CI
Openness	**0.25**	< .001	[0.21, 0.28]	**−0.15**	< .001	[−0.18, −0.12]
Conscientiousness	**0.34**	< .001	[0.31, 0.37]	**0.19**	< .001	[0.16, 0.21]
Extraversion	**0.18**	< .001	[0.15, 0.21]	**−0.07**	< .001	[−0.11, −0.03]
Agreeableness	**0.16**	< .001	[0.13, 0.19]	−0.02	.132	[−0.05, 0.01]
Neuroticism	**−0.10**	< .001	[−0.12, −0.06]	**−0.15**	< .001	[−0.18, −0.12]

Note. N = 19,781. Significant parameters (p <.01) are in bold. Estimates are controlled for fluid intelligence and school track. CI = confidence interval.

Predicting Academic Performance

Results of the latent regression analyses predicting academic performance in German are presented in Table 8. Again, all latent regression models fit the data well (CFI ≥ .98, RMSEAs: .02 to .03, SRMRs: .01 to .03; see additional online Table S25: https://osf.io/vam7n). Consistent with the findings of Study 1, German self-concept predicted German grades and German test scores, and, similar to Study 1, the association was stronger for grades as indicated by the nonoverlapping confidence intervals (Cumming, 2014; see Table 8, Model 1 for detailed results). As for the Big Five, three traits proved to be statistically significant predictors of German grades. Consistent with the results of Study 1, students with a higher level of conscientiousness reported better German grades. Additionally, lower levels of extraversion and higher levels of neuroticism were associated with better German grades. As for the effects on German test scores, we found four trait effects: Consistent with Study 1, students with higher levels of openness gained higher German test scores. In contrast to Study 1, students with lower levels of conscientiousness and extraversion and higher levels of agreeableness also achieved higher German test scores, while students' levels of neuroticism were unrelated to their German test performance. The models explained about 41% of the variance in German grades and about 30 % in German test scores.

Results on academic performance in math are presented in Table 9 and the latent regression models again fit the data well (CFI ≥ .97, RMSEA ≤ .05, SRMR ≤ .03; see additional online Table S26: https://osf.io/vam7n). As expected and consistent with Study 1, math self-concept consistently predicted math grades and test scores across all models and this association was again stronger for grades as indicated by the nonoverlapping confidence intervals (Cumming, 2014). As for the Big Five, four traits proved statistically significant for each performance measure. Consistent with Study 1, students with lower levels of extraversion reported better math grades. Extending Study 1, this was also true for students with higher levels of conscientiousness, agreeableness, and neuroticism. Contrary to Study 1, students with lower levels of openness, conscientiousness, extraversion, and agreeableness scored higher on math tests. The models explained about 48% of the variance in math grades and 38 % in test scores.

We extended these models by including the latent interaction between the academic self-concept and the respective Big Five personality trait. All models fit the data well (see additional online Tables S26 and S27: https://osf.io/vam7n). Interestingly, the main effects were somewhat less robust in Study 2: Including the latent interaction decreased the main effect of the German self-concept in the models with openness, conscientiousness, and agreeableness. Although the main effect remained statistically significant in the models predicting grades, it did not significantly predict test scores anymore. In contrast, all reported main effects of the Big Five traits remained stable after adding the interaction effect. We found six statistically significant interactions: three on German grades, one on German test scores, and one on each of the two mathematics achievement measures.

For German grades, the interactions of German self-concept with openness, conscientiousness, and neuroticism proved statistically significant (see Table 8, Model 2 for results and additional online Figures S1a-c for an illustration: https://osf.io/vam7n). Supporting results from Study 1, higher levels of neuroticism (+1 SD) weakened the association between German self-concept and German grades. Supporting our Hypothesis 2c, higher levels of openness and conscientiousness (+ 1 SD) strengthened the association between German self-concept and German grades, suggesting synergistic effects with high levels in both traits as a resource in students with a high German self-concept. The interaction effects were generally small, explaining an additional 0.2%, 0.4%, and 0.2% of the variance in German grades, respectively. For test scores, the German self-concept interacted with openness only (see Table 8, models 2 for results and Figure S1d for an illustration). Supporting our hypothesis, higher levels of openness (+1 SD) strengthened the association between German self-concept and test scores, thereby indicating a synergistic interaction. The interaction effect explained an additional 0.1% of the variance in German test scores.

For academic performance in math, two latent interaction effects of math self-concept with openness and extraversion emerged (see additional online Figures S2a and S2b for an illustration: https://osf.io/vam7n and Table 9, Model 2 for detailed results). Supporting our hypothesis, for students with higher levels of openness (+1 SD), the association between math self-concept and math grades was again stronger. Openness strengthened the association and acted as a resource (synergistic effect). For students with higher levels of extraversion (+1 SD), the association between math self-concept and math test scores was weaker. Thus, higher levels of extraversion acted as a risk factor. These interaction effects accounted for an additional 0.1% and 0.2% of the variance in math grades and test scores, respectively.

Table 8

Study 2 – Controlled Cross-Sectional Latent Regression Model Parameters predicting Academic Performance in German

	Openness			Conscientiousness			Extraversion			Agreeableness			Neuroticism		
	β	*p*	99% CI	β	*p*	99% CI	β	*p*	99% CI	β	*p*	99% CI	β	*p*	99% CI
Predictors	**German Grades**														
Model 1															
German Self-Concept	**0.60**	< .001	[0.58, 0.62]	**0.57**	< .001	[0.55, 0.59]	**0.61**	< .001	[0.59, 0.63]	**0.60**	< .001	[0.58, 0.62]	**0.61**	< .001	[0.59, 0.63]
Personality	−0.00	.603	[−0.03, 0.02]	**0.09**	< .001	[0.06, 0.12]	**−0.04**	< .001	[−0.06, −0.02]	0.02	.012	[0.00, 0.03]	**0.05**	.001	[0.01, 0.10]
Model 2															
German Self-Concept	**0.38**	< .001	[0.22, 0.54]	**0.41**	< .001	[0.30, 0.52]	**0.58**	< .001	[0.47, 0.69]	**0.52**	< .001	[0.36, 0.68]	**0.75**	< .001	[0.60, 0.90]
Personality	−0.01	.379	[−0.04, 0.02]	**0.08**	< .001	[0.06, 0.11]	**−0.04**	< .001	[−0.06, −0.02]	0.02	.014	[−0.00, 0.04]	**0.06**	< .001	[0.03, 0.10]
GSC x P	**0.04**	< .001	[0.01, 0.07]	**0.03**	< .001	[0.01, 0.06]	0.01	.482	[−0.02, 0.03]	0.01	.168	[−0.01, 0.03]	**−0.03**	.009	[−0.06, −0.00]
Model 3															
German Self-Concept	**0.47**	< .001	[0.38, 0.56]	**0.40**	< .001	[0.29, 0.52]	**0.58**	< .001	[0.57, 0.60]	**0.58**	< .001	[0.56, 0.60]	**0.76**	< .001	[0.60, 0.91]
Personality	−0.02	.027	[−0.04, 0.00]	**0.07**	< .001	[0.04, 0.10]	**−0.04**	< .001	[−0.06, −0.02]	0.00	.892	[−0.02, 0.02]	**0.06**	< .001	[0.03, 0.09]
GSC x P	**0.03**	.001	[0.01, 0.04]	**0.03**	< .001	[0.01, 0.05]							**−0.03**	.005	[−0.06, −0.00]
Sex	**0.10**	< .001	[0.08, 0.12]	**0.08**	< .001	[0.06, 0.10]	**0.10**	< .001	[0.08, 0.11]	**0.10**	< .001	[0.08, 0.11]	**0.07**	< .001	[0.05, 0.09]
Immigrant Background	**−0.04**	< .001	[−0.05, −0.02]	**−0.04**	< .001	[−0.05, −0.02]	**−0.04**	< .001	[−0.05, −0.02]	**−0.04**	< .001	[−0.05, −0.02]	**−0.04**	< .001	[−0.06, −0.02]
HISEI	**0.08**	< .001	[0.06, 0.10]	**0.08**	< .001	[0.06, 0.10]	**0.08**	< .001	[0.06, 0.10]	**0.08**	< .001	[0.05, 0.10]	**0.08**	< .001	[0.06, 0.10]
	German Test Scores														
Model 1															
German Self-Concept	**0.16**	< .001	[0.14, 0.19]	**0.20**	< .001	[0.18, 0.23]	**0.19**	< .001	[0.16, 0.21]	**0.17**	< .001	[0.15, 0.19]	**0.18**	< .001	[0.15, 0.20]
Personality	**0.04**	< .001	[0.01, 0.07]	**−0.08**	< .001	[−0.11, −0.05]	**−0.08**	< .001	[−0.10, −0.05]	**0.03**	< .001	[0.01, 0.05]	0.03	.013	[−0.00, 0.07]
Model 2															
German Self-Concept	0.01	.926	[−0.15, 0.16]	0.12	.011	[−0.00, 0.24]	**0.21**	< .001	[0.10, 0.33]	0.10	.087	[−0.05, 0.25]	**0.23**	< .001	[0.13, 0.32]
Personality	**0.04**	< .001	[0.01, 0.07]	**−0.08**	< .001	[−0.11, −0.05]	**−0.08**	< .001	[−0.11, −0.05]	**0.03**	< .001	[0.01, 0.05]	**0.03**	.001	[0.01, 0.06]
GSC x P	**0.03**	.008	[0.00, 0.06]	0.02	.070	[−0.01, 0.04]	−0.01	.545	[−0.03, 0.02]	0.01	.219	[−0.01, 0.03]	−0.01	.164	[−0.03, 0.01]
Model 3															
German Self-Concept	0.06	.101	[−0.04, 0.16]	**0.18**	< .001	[0.16, 0.21]	**0.17**	< .001	[0.14, 0.19]	**0.15**	< .001	[0.13, 0.17]	**0.16**	< .001	[0.14, 0.18]
Personality	−0.02	.019	[−0.04, 0.00]	**−0.10**	< .001	[−0.13, −0.08]	**−0.08**	< .001	[−0.10, −0.05]	0.02	.028	[−0.00, 0.04]	**0.05**	< .001	[0.02, 0.08]
GSC x P	0.02	.012	[0.00, 0.04]												
Sex	**0.07**	< .001	[0.05, 0.09]	**0.09**	< .001	[0.07, 0.11]	**0.07**	< .001	[0.05, 0.09]	**0.07**	< .001	[0.05, 0.09]	**0.05**	< .001	[0.03, 0.07]
Immigrant Background	**−0.06**	< .001	[−0.09, −0.04]	**−0.07**	< .001	[−0.09, −0.04]	**−0.06**	< .001	[−0.09, −0.04]	**−0.07**	< .001	[−0.09, −0.04]	**−0.07**	< .001	[−0.09, −0.04]
HISEI	**0.14**	< .001	[0.11, 0.16]	**0.13**	< .001	[0.10, 0.16]	**0.14**	< .001	[0.11, 0.16]	**0.13**	< .001	[0.11, 0.16]	**0.14**	< .001	[0.11, 0.16]

Note. N = 19,781 – 19,783. Models were estimated for each Big Five trait separately. Significant predictors (p < .01) are in bold. All models are controlled for fluid intelligence and school track. All variables included in these cross-sectional analyses were obtained at the first time point (T1). Sex is dummy coded with 1 = female. Immigrant background is dummy coded with 1 = immigrant background. CI = confidence interval. Personality = Big Five personality trait examined in the respective model, as indicated in the column headings. GSC × P = Interaction between the German Self-Concept and the respective Big Five trait.

Table 9

Study 2 – Controlled Cross-Sectional Latent Regression Model Parameters predicting Academic Performance in Math

	Openness			Conscientiousness			Extraversion			Agreeableness			Neuroticism		
	β	*p*	99% CI	β	*p*	99% CI	β	*p*	99% CI	β	*p*	99% CI	β	*p*	99% CI
Predictors							**Math Grades**								
Model 1															
Math Self-Concept	**0.66**	< .001	[0.65, 0.68]	**0.63**	< .001	[0.62, 0.65]	**0.66**	< .001	[0.64, 0.68]	**0.66**	< .001	[0.65, 0.68]	**0.67**	< .001	[0.66, 0.69]
Personality	0.02	.016	[−0.00, 0.04]	**0.12**	< .001	[0.10, 0.15]	**−0.02**	< .001	[−0.04, −0.01]	**0.04**	< .001	[0.02, 0.06]	**0.07**	< .001	[0.05, 0.10]
Model 2															
Math Self-Concept	**0.54**	< .001	[0.44, 0.65]	**0.59**	< .001	[0.50, 0.69]	**0.64**	< .001	[0.56, 0.71]	**0.57**	< .001	[0.41, 0.74]	**0.69**	< .001	[0.58, 0.80]
Personality	0.02	.018	[−0.00, 0.04]	**0.12**	< .001	[0.10, 0.15]	**−0.03**	< .001	[−0.04, −0.01]	**0.04**	< .001	[0.02, 0.06]	**0.07**	< .001	[0.05, 0.10]
MSC x P	**0.02**	.003	[0.00, 0.04]	0.01	.268	[−0.01, 0.03]	0.00	.438	[−0.01, 0.02]	0.01	.155	[−0.01, 0.03]	−0.00	.730	[−0.02, 0.02]
Model 3															
Math Self-Concept	**0.62**	< .001	[0.56, 0.69]	**0.66**	< .001	[0.64, 0.68]	**0.68**	< .001	[0.67, 0.70]	**0.68**	< .001	[0.67, 0.70]	**0.69**	< .001	[0.67, 0.70]
Personality	−0.01	.060	[−0.03, 0.00]	**0.10**	< .001	[0.07, 0.12]	**−0.03**	< .001	[−0.04, −0.01]	0.02	.019	[−0.00, 0.04]	**0.05**	< .001	[0.02, 0.07]
MSC x P	0.01	.011	[0.00, 0.03]												
Sex	**0.11**	< .001	[0.09, 0.13]	**0.07**	< .001	[0.05, 0.09]	**0.10**	< .001	[0.09, 0.12]	**0.10**	< .001	[0.08, 0.12]	**0.09**	< .001	[0.07, 0.11]
Immigrant Background	**−0.03**	< .001	[−0.04, −0.01]	**−0.03**	< .001	[−0.05, −0.01]	**−0.03**	< .001	[−0.04, −0.01]	**−0.03**	< .001	[−0.05, −0.01]	**−0.03**	< .001	[−0.05, −0.01]
HISEI	**0.06**	< .001	[0.04, 0.08]	**0.06**	< .001	[0.04, 0.09]	**0.06**	< .001	[0.04, 0.08]	**0.06**	< .001	[0.04, 0.08]	**0.06**	< .001	[0.04, 0.08]
							Math Test Scores								
Model 1															
Math Self-Concept	**0.25**	< .001	[0.23, 0.27]	**0.28**	< .001	[0.25, 0.30]	**0.25**	< .001	[0.23, 0.27]	**0.25**	< .001	[0.23, 0.28]	**0.25**	< .001	[0.23, 0.27]
Personality	**−0.05**	< .001	[−0.07, −0.02]	**−0.10**	< .001	[−0.13, −0.07]	**−0.06**	< .001	[−0.09, −0.04]	**−0.03**	.004	[−0.06, −0.00]	−0.01	.117	[−0.04, 0.01]
Model 2															
Math Self-Concept	**0.20**	.001	[0.04, 0.36]	**0.38**	< .001	[0.27, 0.50]	**0.41**	< .001	[0.31, 0.52]	**0.43**	.001	[0.10, 0.75]	**0.35**	< .001	[0.17, 0.53]
Personality	**−0.04**	< .001	[−0.08, −0.01]	**−0.10**	< .001	[−0.13, −0.08]	**−0.07**	< .001	[−0.09, −0.05]	**−0.04**	.007	[−0.07, −0.00]	−0.02	.076	[−0.05, 0.01]
MSC x P	0.01	.425	[−0.02, 0.04]	−0.02	.014	[−0.05, 0.00]	**−0.03**	< .001	[−0.06, −0.01]	−0.02	.165	[−0.06, 0.02]	−0.02	.153	[−0.06, 0.02]
Model 3															
Math Self-Concept	**0.23**	< .001	[0.21, 0.25]	**0.25**	< .001	[0.23, 0.27]	**0.39**	< .001	[0.29, 0.49]	**0.23**	< .001	[0.21, 0.25]	**0.23**	< .001	[0.21, 0.25]
Personality	**−0.02**	.005	[−0.03, −0.00]	**−0.08**	< .001	[−0.10, −0.05]	**−0.07**	< .001	[−0.09, −0.05]	0.00	.990	[−0.02, 0.02]	0.02	.016	[−0.00, 0.05]
MSC x P							**−0.04**	< .001	[−0.06, −0.01]						
Sex	**−0.09**	< .001	[−0.11, −0.07]	**−0.07**	< .001	[−0.09, −0.05]	**−0.09**	< .001	[−0.11, −0.07]	**−0.09**	< .001	[−0.11, −0.07]	**−0.10**	< .001	[−0.12, −0.08]
Immigrant Background	**−0.07**	< .001	[−0.10, −0.06]	**−0.08**	< .001	[−0.10, −0.06]	**−0.07**	< .001	[−0.09, −0.05]	**−0.08**	< .001	[−0.10, −0.06]	**−0.08**	< .001	[−0.10, −0.06]
HISEI	**0.12**	< .001	[0.10, 0.15]	**0.12**	< .001	[0.10, 0.15]	**0.13**	< .001	[0.10, 0.15]	**0.12**	< .001	[0.10, 0.15]	**0.12**	< .001	[0.10, 0.15]

Note. N = 19,781 – 19,783. Models were estimated for each Big Five trait separately. Significant predictors ($p < .01$) are in bold. All models are controlled for fluid intelligence and school track. All variables included in these cross-sectional analyses were obtained at the first time point (T1). Sex is dummy coded with 1 = female. Immigrant background is dummy coded with 1 = immigrant background. CI = confidence interval. Personality = Big Five personality trait examined in the respective model, as indicated in the column headings. MSC × P = Interaction between the Math Self-Concept and the respective Big Five trait.

The Role of Sociodemographic Characteristics

To address our third research question, we again extended the best-fitting models from the previous analyses, either with or without latent interactions included, and added the main effects of the sociodemographic variables: participants' sex, parental SES, and immigrant background (see additional online Tables S25 and S26 for model fit: https://osf.io/vam7n). Parameter estimates are presented in Tables 8 and 9 in Model 3, respectively. In the models predicting German and math grades, all main and interaction effects in previous models remained stable. Regarding math test scores, only the main effect of agreeableness was not statistically significant anymore. In the models predicting German test scores, the effects were overall less stable. Specifically, in the model including openness, neither the main effects nor the interaction effect remained statistically significant, whereas in the model including agreeableness, the main effect of agreeableness was no longer statistically significant. Finally, the regression weight of neuroticism became statistically significant in this final most complex model.

As for academic performance in German, girls reported better German grades and gained higher German test scores than boys. Students with an immigrant background reported lower grades and scored lower on the German test than students without an immigrant background, and students with a higher parental SES reported better grades and scored higher on the German test. All effects support those of Study 1 but were more consistent across performance indicators. The sociodemographic variables increased the amount of explained variance by about 1.6 and 2.6% for German grades and test scores, respectively. As for academic performance in math, again all sociodemographic characteristics were similarly associated with academic performance. The only difference between b German and math was that, while girls again reported better grades, in line with Study 1boys scored higher than girls on the math test. Adding the sociodemographic variables again led to an increase in the amount of explained variance of 0.9 to 1.6% for math grades and 2.6 to 3.2% for test scores.

Finally, we also tested all possible two-way interactions between the two main predictors of self-concept and Big Five traits and each sociodemographic variable, respectively (see additional online Table S27 for all tested interaction effects: https://osf.io/vam7n). In line with our hypothesis H3c, the association between students' level of conscientiousness and their German academic performance (grades/ test scores) was stronger for students with a higher parental SES (β = 0.05/0.04, p <.001, ΔR^2 = .002/.002). Extending on our hypotheses, the association between students' German self-concept and their academic performance was likewise stronger for students with a higher, as compared to a lower, SES (β = 0.04/0.03, p <

.001, $\Delta R^2 \leq .001$). Moreover, the positive association of openness with German test scores was stronger for girls than boys ($\beta = 0.04$, $p < .001$, $\Delta R^2 < .001$). Additionally, an immigrant background weakened the positive association of agreeableness with German grades ($\beta = -0.02$, $p = .005$, $\Delta R^2 < .001$).

As for math achievement and again in line with our hypothesis H3c, students with higher parental SES benefited more from higher levels of conscientiousness regarding their math grades ($\beta = 0.03$, $p = .009$, $\Delta R^2 < .001$), indicating a synergistic effect. Second and in line with results on German performance, there was a robust positive interaction effect regarding math test scores between the parental SES and the math self-concept of students ($0.08 \leq \beta \leq 0.09$, $p \leq .001$, $\Delta R^2 \leq .007$), again indicating a synergistic effect. Third, there was a robust negative interaction regarding test scores between the immigrant background and the math self-concept ($\beta = -0.04$, $p < .001$, $.001 \leq \Delta R^2 \leq .002$), demonstrating that students with an immigrant background benefitted less from a higher math self-concept regarding their math test performance. Finally, the negative association between extraversion and math test scores was moderated by parental SES ($\beta = -0.04$, $p \leq .001$, $\Delta R^2 = .002$) and by immigrant background ($\beta = 0.02$, $p \leq .001$, $\Delta R^2 = .001$), illustrating a more pronounced effect for students with a higher parental SES, and a less pronounced effect for students with an immigrant background. Importantly, the small size of all reported interaction effects should be considered when interpreting them.

Predicting Change in Academic Performance

In order to predict changes in academic performance, we extended our latent models by estimating latent change score models (McArdle, 2009) for academic performance based on two assessment waves of German and math test scores.[17] Regarding German test scores, the estimated models fit the data well (see additional online Table S29: https://osf.io/vam7n) and explained at least 24.6% of the variance in the latent change score. In the longitudinal models, the effects on the baseline level remained consistent except for the interaction between the self-concept and openness, which was not statistically significant anymore. As for predicting changes in German test scores, only two statistically significant predictors emerged. The German self-concept was associated with a stronger increase in test scores ($0.04 \leq \beta \leq 0.05$, p $\leq .001$) in two out of the five models. Thus, results only partly support our hypothesis H2d. As for the Big Five traits, increases in German test scores from Grade 9 to 12 were less pronounced for students reporting higher levels of conscientiousness ($\beta = -0.06$, $p < .001$) and extraversion

[17] We refrained from estimating such models predicting grades due to the low number of participants who reported grades at T2.

($\beta = -0.06$, $p < .001$). The effect of conscientiousness contradicts our hypothesis H2e but corroborates the negative cross-sectional effect. In the General Discussion, we will highlight potential reasons for this unexpected pattern of results. Regarding the effect of extraversion, we did not preregister a hypothesis. However, the results were concordant with findings from a younger cohort of the NEPS study (Israel et al., 2019). As for socio-demographic characteristics, a higher parental SES related to more pronounced increase in German test scores over time ($\beta = 0.09$, $p < .001$). The sociodemographic variables explained an additional 1% of the variance in the change in German test performance. Moreover, a statistically significant interaction between the level of conscientiousness and the immigrant background emerged ($\beta = -0.04$, $p = .009$, $\Delta R^2 = .001$). That is, for students with an immigrant background higher levels of conscientiousness were associated with an even smaller increase in test performance, thereby confirming our hypothesis H3b. There were no other statistically significant effects. Thus, there was no support for hypotheses regarding the change in German test scores.

Regarding math test scores, the estimated models fit the data well (see additional online Table S2: https://osf.io/vam7n) and explained at least 37.1% of the variance in the latent change score. Again, all effects on the baseline level remained consistent. As for predicting changes in math test scores, students with a more positive math self-concept demonstrated more pronounced increases in test scores from Grade 9 to 12 ($0.15 \leq \beta \leq 0.38$, $p < .001$), supporting our hypothesis H2d. In addition, and again unexpectedly, students who reported higher levels of conscientiousness showed less pronounced increases in test performance over time ($\beta = -0.05$, $p < .001$). Extending on our hypotheses, higher levels of extraversion ($\beta = -0.04$, $p = .001$) and agreeableness ($\beta = -0.04$, $p = .006$) were related to less pronounced increases in math test performance. As for latent interaction effects between the math self-concept and personality, only one unexpected finding emerged: Students that reported both a more positive self-concept in math and higher levels of extraversion showed a less pronounced increase in math test performance compared to those who reported lower levels of extraversion ($\beta = -0.05$, $p < .001$, $\Delta R^2 = .003$). As for sociodemographic predictors, the longitudinal findings were in line with the cross-sectional results. That is, girls ($-0.14 \leq \beta \leq -0.12$, $p < .001$) and students with an immigrant background ($\beta = -0.04$, $p < .001$) showed less pronounced increases in math test scores from grade 9 to 12, while students with a higher parental SES showed more pronounced increases ($\beta = 0.08$, $p < .001$). The main effects of socio-demographic characteristics explained at least 1.8 % of additional variance in the change score of math test performance. Moreover, we found an unexpected interaction between the students' level of extraversion and parental SES ($\beta = 0.04$, $p \leq .001$, $\Delta R^2 = .001$). For students with a higher parental SES, the negative association of extraversion with the change in math performance was less pronounced indicating a compensatory effect. For an overview of all results of latent regression models predicting the latent change scores see additional online Tables S30 and S34: https://osf.io/vam7n (for uncontrolled results, see additional online Tables S35 to S39: https://osf.io/vam7n).

In sum, the results of Study 2 replicate and extend the findings from Study 1 in a large, representative sample. That is, results corroborate the interrelatedness of the academic self-concept and Big Five personality, establishing the nomological net. In addition, we refined the insights gained in Study 1 by indicating that the measures used for the Big Five traits, especially openness, might be relevant in considering their effects in Study 2. The latent interaction effects were widely in line with our hypotheses, illustrating synergistic effects from openness and conscientiousness. Furthermore, our results highlight both the robustness of academic self-concept and personality as predictors of academic performance and the essential role of demographic variables for academic success in German students. Finally, extending predictions to changes in test scores across time, the results of Study 2 demonstrate that predicting change is complex and highlight the potential negative effects of high extraversion.

General Discussion

Using two large samples from German 9th graders with diverse sociodemographic composition, this study provides a first empirical test of the interplay between academic self-concepts and Big Five personality and its relevance for academic performance. Integrating the results from Study 1 and Study 2, we highlight five main findings: First and in line with our hypotheses H1a and H1b, associations between academic self-concepts and Big Five traits were widely consistent across studies illustrating a nomological net between these socioemotional variables. Second and in line with our hypothesis H2a, the German and the math self-concept were consistent predictors of academic performance in the respective subject measured by grades and test scores. Third, beyond the established main effects of openness and conscientiousness, all Big Five traits contributed to performance in some way. Fourth, despite some inconsistencies, socioemotional characteristics formed only synergistic interaction effects. Fifth, students' sociodemographic characteristics were consistently associated with interindividual differences in academic performance and showed several synergistic interaction effects with socioemotional predictors of academic performance. Importantly, while some findings were consistent across both studies, we found some differences in other cases. The following section discusses the theoretical and practical implications of the consistent findings and addresses possible reasons for the inconsistencies.

Academic Self-Concepts and Big Five Personality Form a Nomological Net

Following the call for an integration of motivational and personality variables (e.g., Brandt et al., 2021; DeYoung, 2015; Fleeson & Jayawickreme, 2015; Trautwein et al., 2019), our results in line with our hypotheses H1a and H1b support the idea that the academic self-concepts and Big Five personality form a nomological network. Our findings corroborate initial results (Brandt, Israel, et al., 2021; Marsh et al., 2006), demonstrating the interrelatedness of both socioemotional characteristics in adult samples and using different personality measures. Within these consistent patterns, two findings are particularly interesting: First, while some traits (e.g., conscientiousness) were related to a positive self-perception of one's abilities in German and math, others (e.g., agreeableness) differentially related to subject-specific self-concepts. To illustrate, both subjects seem to require organization and productiveness, as higher levels of conscientiousness were consistently associated with a more positive German and math self-concept. In contrast, being more compassionate and trusting, (i.e., high agreeableness) coincides with a positive German concept, while there was no such association with the math self-concept.

Second, the current results shed light on the differential associations across motivational variables. Specifically, the nomological net seemed closer and more consistent regarding the German self-concept and Big Five personality, whereas the associations with the math self-concept appeared less consistent. Specifically, the German self-concept showed consistent positive associations with all Big Five traits (except for neuroticism). In contrast, the math self-concept was only consistently associated with conscientiousness. As illustrated by existing research, previous performance-related experiences and evaluations influence self-concept formation (Denissen et al., 2007; Wigfield & Eccles, 2000). Therefore, the stronger association of the Big Five traits with the German self-concept might result from a higher relevance of Big Five-related experiences and evaluations in German compared to math lessons (Brandt et al., 2020; Meyer et al., 2019).

Motivation and Personality as Determinants of School Success

While previous research demonstrated the importance of singular socioemotional characteristics for academic performance (Borghans et al., 2016; Mammadov, 2022; McAbee & Oswald, 2013; OECD, 2015), we addressed the joint relevance of academic self-concepts and Big Five personality traits as well as their interplay for academic performance. Our findings regarding motivational variables were in line with the expectancy-value theory (Wigfield & Eccles, 2000) and our hypothesis H2a, showing that domain-specific academic self-concepts were consistent predictors of academic performance for the respective subject area.

Additionally, the academic self-concepts were more consistently and more strongly linked to grades than test scores across both samples (Möller et al., 2020; Spinath et al., 2010). Regarding test scores, we could moreover confirm previous findings indicating the relevance of academic self-concept not only for levels but also for changes in performance (Wu et al., 2021), which further highlights its importance as an socioemotional resource in educational contexts. However, previous studies likewise indicate that the academic self-concept is highly dependent on prior educational experiences and performances (Denissen et al., 2007; Wu et al., 2021) and the German and math self-concept refer to rather specific content areas. Therefore, the goal of the present study was to go beyond these specific motivational variables to explore additional, broader socioemotional and individual resources (or potential vulnerabilities) that might moderate these associations.

The Big Five traits offer a broad framework to efficiently and comprehensively explain differences in typical learning behavior and academic performance across subject areas (O'Connor & Paunonen, 2007; Poropat, 2009, 2014). Our results add to the accumulating evidence that, besides openness and conscientiousness, other traits likewise play a role in academic performance (Mammadov, 2022). Moreover, they do so even when simultaneously including the specific predictor of the academic self-concept. Our results further specify that whether personality traits act as a resource (or risk factor) for academic performance is linked to characteristics of both the academic environment and the individual. First, the relevance of Big Five traits seemed to vary across subject areas. That is, the expected associations of openness and conscientiousness were only consistent across samples for academic performance in German, while extraversion emerged as the only consistent predictor of math performance or more specifically math grades. Second, our results emphasize personality effects vary across motivational characteristics, which is illustrated in the complex pattern regarding the interaction effects. Although only one interaction effect itself was consistent across samples, further consistencies in result patterns need a more in-depth discussion.

As a first pattern, our results consistently supported notions of synergistic but not of compensatory interaction effects. That is, when students showed low confidence in their abilities, personality traits such as high conscientiousness could not compensate for such a negative self-belief, but synergistic effects were evident. For example, one consistent, although not hypothesized, synergistic interaction effect occurred for neuroticism indicating that in subjects where they are less confident in their abilities, students appear to also be more likely to show insecure behavior, as associated with higher levels of neuroticism. In contrast, the hypothesized interaction effects regarding openness and conscientiousness were not consistent across studies but results rather (partly) support that students are more likely to express personality traits beneficial for their performance (e.g., higher openness and conscientiousness) in subjects where they are also more confident about their abilities (higher self-concept).

A second consistent finding is that more interaction effects occurred regarding grades than test scores. As grades include a teacher's subjective assessments (Spengler et al., 2013) and capture performance over long periods, previous research has demonstrated that school grades tend to be more strongly related to socioemotional characteristics (Borghans et al., 2016; Lechner et al., 2017; Möller et al., 2020; Spinath et al., 2010). We extend these findings, illustrating synergistic interaction effects between academic self-concepts and Big Five traits. Nevertheless, our results also support the importance of both socioemotional characteristics, not only for grades but also for test scores. Particularly in Study 2, our results illustrate personality links to levels of and changes in test scores beyond motivational characteristics, suggesting that typical learning behaviors shapes academic performance across time.

As a third consistent pattern, we found more interaction effects regarding German than math performance. This pattern fits previous findings showing that language classes allow for more personality expression, as they require and reward oral participation while the requirements in math classes more closely relate to cognitive abilities (Brandt et al., 2020; Meyer et al., 2023). The requirement of oral participation might be especially beneficial for students being confident in their verbal skills explaining the synergistic effects of German self-concept and personality. Moreover, the more cognitive requirements required in math classes might result in a higher relevance of specific abilities and leave less room for personality expression as reflected by the stronger associations of the math self-concept with academic performance.

Finally, across both studies, the interaction effects explained only small amounts of additional variance (0.1−2.8%). This should be considered when interpreting the data. However, small amounts of additional explained variance are not uncommon for interaction effects in observational, non-experimental studies (Chaplin, 1991; McClelland & Judd, 1993). Importantly, the small amount of explained variance does not undermine the theoretical importance of the interaction effects (Funder & Ozer, 2019; Nagengast et al., 2013). Interestingly, in the context of our study, the interaction effects led to similar increases in explained variances as the main effects of the sociodemographic variables that are known to have sustainable effects on educational outcomes across the entire life span (Becker et al., 2019). These effect patterns illustrate that, despite small amounts of explained variance, predictors can be of substantial and long-lasting practical significance. We therefore hope that the consideration of interaction effects will lead to new theoretical and practical insights into the interplay between academic self-concepts and Big Five personality.

Differentiating School Success: The Sociodemographic Variables as Moderators

Our results support the relevance of sociodemographic characteristics. In our study, sex, immigration background, and parental SES emerged as important predictors for academic performance. In line with previous research, girls outperformed boys, especially concerning German grades, while boys gained higher math test scores across both studies (Voyer & Voyer, 2014; Wilgenbusch & Merrell, 1999). Moreover, an immigrant background consistently appeared as a risk factor (Lilla et al., 2021; OECD, 2015), while a high parental SES seemed to be a resource (OECD, 2019; Sirin, 2005), especially when considering test scores as academic performance indicators.

Besides such sociodemographic main effects, researchers have argued that fostering socioemotional characteristics can compensate for sociodemographic disadvantages, thereby reducing social inequalities (Ayoub et al., 2018; Damian et al., 2015; Lilla et al., 2021). Contradicting this assumption, the interaction effects between the socioemotional and the sociodemographic characteristics in our studies largely support the resource-strengthening associations previously found in Germany (Becker et al., 2021; Lechner et al., 2021). Specifically, the SES and immigrant background apparently interact synergistically with socioemotional resources such as academic self-concept and conscientiousness (Lechner et al., 2021). That is, for students from families with high socioeconomic status the positive associations of the academic self-concept and several performance indicators were stronger as compared to students from families with lower SES. Effects were more pronounced in the representative sample of Study 2, whereas in Study 1, the sociodemographic disadvantages were less pronounced pointing toward the importance of considering diverse samples and vulnerable subgroups when it comes to sociodemographic compositions (see also *Beyond Consistency: Important Differences Across Samples* section). Building on previous findings (e.g. Oczlon et al., 2021; Schachner et al., 2021), future research should further our understanding of the potential benefits and challenges of socio-demographically diverse learning environments when it comes to the role of socioemotional characteristics.

Two additional findings stand out: First, there was one exception to the resource-strengthening pattern: the interactions between extraversion and different sociodemographics. For students with a higher parental SES, higher levels of extraversion coincided with even lower academic performance. Furthermore, the negative main effect of extraversion was less pronounced for students with an immigrant background. Second, there were more pronounced interaction effects with sociodemographic characteristics regarding mathematics performance (at least one significant interaction for each sociodemographic characteristic). This result corroborates previous research on the relevance of sex difference in the science, technology, engineering, and mathematics area (Denissen et al., 2007; McCabe et al., 2019; Niepel et al., 2019) and additionally highlights the importance of considering additional sociodemographics when studying the relevance of socioemotional characteristics in this field (Lilla et al., 2021; Oczlon et al., 2021).

Beyond Consistency: Important Differences Across Samples

As an overarching pattern, some inconsistencies across the two studies emerged and we would like to propose some explanations for such inconsistencies. First, the sample was considerably larger in Study 2 resulting in higher power and allowing us to detect small main and interaction effects (see *Sample Size Rationale* section). This might sufficiently explain the emergence of additional significant associations of the math self-concept with extraversion and neuroticism within the investigation of the nomological net, as well as the higher number of significant interaction effects in Study 2. Second, the personality measures differed between samples (see also Limitations) in terms of length and facet representation. Previous research indicates that the facets of the Big Five domains differentially relate to achievement (Bergold & Steinmayr, 2018; Brandt et al., in press). This might have contributed to the negative associations of openness, which is largely a measure of creativity in Study 2, with math self-concept and math test scores. That is, whereas the adjective scale used in Study 1 covers the broadness of the openness trait spanning from intellectual curiosity to aesthetic sensitivity and creativity, the two items in the BFI-10 in Study 2 only assess the latter. However, aspects relating to intellectual curiosity are likely more important in the context of math achievement. Along these lines, we encourage future research to implement broader, multidimensional instead of narrower, short-scale measures of personality to represent each trait in its broadness and to allow for studying single facets.

Third, differences in sample composition might have contributed to differences in our results between studies. To specify, our samples differed regarding their sociodemographic composition. To account for these differences, we addressed the relevance of key sociodemographic characteristics within our third research question. Despite considerable consistency across both studies, there were no effects of immigration status and parental SES on grades in Study 1. Study 1 was based on a sample of schools serving disadvantaged communities and included higher percentages of families with an immigrant background and low SES. The overall reduced variance regarding the SES may have resulted in the insignificance of the associations with grades and the less pronounced interaction effects in Study 1. However, it is also possible that social disadvantages become less salient in more homogeneous learning environments, such as for teachers' grading, which is known to be affected by frame-of-reference effects (Marsh, 1987). As an alternative explanation, students and teachers in Study 1 may benefit from cultural pluralism in their learning environments (Oczlon et al., 2021). Such an argument could be relevant in applied contexts, as it might indicate that the composition of the educational contexts shapes the relevance of socioemotional characteristics for academic performance.

Limitations and future research

Despite using two large samples of 9th-grade students and a combination of self-reports and (longitudinal) test scores, some limitations should be considered when interpreting the results. First, our studies were correlational in design and do not allow causal interpretations. Thus, we cannot determine the direction of the found associations. Future research might apply different statistical approaches to control for the selectivity of observational samples (e.g., using propensity score matching). To adopt a more processoriented perspective, intensive longitudinal designs should complement such large-scale long-term panel studies (Bleidorn et al., 2020).

Second, the measures of the two socioemotional characteristics potentially affected some of the found associations. On the one hand the Big Five traits are a broad conceptualization of personality and the two personality measures in our studies did not allow for a more fine-grained investigation at the facet level. On the other hand, the academic self-concept was assessed at a subject-specific, and thus very fine-grained, level but not as a general self-concept. Therefore, future research may benefit from investigating the relationship between personality, academic self-concept, and academic performance by combining instruments that allow for analyses on a more similar level. That is a more nuanced facet level of personality and/or the broader level of general academic self-concept.

Third, while addressing three key sociodemographic characteristics and demonstrating their relevance to academic performance, our study design did not target specific facets of these characteristics. Therefore, future research could use more differentiated measures of the SES covering educational as well as financial aspects to disentangle potentially differential associations. Likewise, researchers have claimed the need to further differentiate students having an immigrant background as their experiences vary depending on different factors (Lilla et al., 2021).

Fourth, our study was solely based on self-report measures with respect to socioemotional characteristics. Previous research has illustrated that parent and teacher reports can add to the prediction of academic performance (Brandt, Becker, et al., 2021; Israel et al., 2022). Such data might allow for better differentiation of potential reference effects, meaning that future research should incorporate either (or both) teacher and parent ratings of socioemotional characteristics.

Finally, given that we are working with secondary data, we had to use the available assessment scales and the key constructs were not assessed identically across the two studies. On the one hand, this could be regarded as a limitation but, on the other hand, also a strength in a sense of testing the generalizability of results across assessment scales. More specifically, first, when it comes to the measurement of the academic self-concept, the measure in Study 2 included one item referring to "getting good grades" in the specific subject. This reference could have led to inflated associations between the academic self-concepts and the grades as performance outcomes. To address this point, we conducted a sensitivity analysis comparing manifest bivariate correlations with and without these items, which led to largely identical results, that is, for example no substantial differences in associations with grades (cf. additional online Table S40: https://osf.io/vam7n). Given this consistency across the two conceptualizations in Study 2 and across the results in Study 1 and Study 2, we are confident in the generalizability of our results across different measures of the academic self-concept. Second, when it comes to the Big Five, the measure in Study 1 used the Ostendorf Big Five scale. Although this scale might not be as established in the international context, as compared to the BFI-2 (Soto & John, 2017) or the NEO Personality Inventory–Revised (Costa & McCrae, 1992b), it has been used in several German studies with adolescents (e.g., Asendorpf & Van Aken, 2003; Israel et al., 2021; Luan et al., 2017; Sturaro et al., 2008) and, thus, can be regarded as a well-established instrument to assess Big Five personality, particularly in younger cohorts. Furthermore, it is a more comprehensive measure, representing the broad Big Five somewhat better as compared to the reduced assessment with the ultra-short scale used in Study 2. Along these lines, researchers should closely monitor which type of personality measure they use. Third, the two measures of our control variable fluid intelligence also differed between the two studies. That is, while both measures comprise figural reasoning items, the number of items differed. The fluid intelligence scale in Study 2 comprises only 12 items, as compared to 46 items in Study 1. Despite this difference, associations between fluid intelligence and grades and test scores were fairly robust and similar across both studies.

Conclusion

The results of our studies go beyond the consideration of singular effects of the academic self-concept and Big Five personality traits, illustrating a concurrent importance and a complex interplay between the two socioemotional characteristics in shaping academic performance. We additionally considered three sociodemographic characteristics and demonstrated that academic performance of German students is equally dependent on these characteristics and their complex and mostly synergistic interplay with socioemotional predictors. Thus, being a successful student in school appears to be a synergistic function of motivational, personality, and sociodemographic resources, whereas little evidence for compensatory effects occurred across the academic achievement indicators. Future research should be mindful of the interactive nature of individual predictors to obtain a more comprehensive understanding of what helps and hinders students’ academic success.

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3. Becoming as Open-Minded and Organized as my Classmates? Peer Effects on Self-Reported Personality Trait Development in the Classroom

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Abstract

Introduction: How does a student's personality development relate to the personality of their classmates? The school class builds a pertinent comparison group during adolescence that has been identified as a critical factor in students' development of abilities and self-perceptions. This study empirically tests the impact of classroom personality composition on changes in adolescents' Big Five personality traits. We hypothesized positive associations between class-level openness and conscientiousness and the individual development of these traits given their role in academic performance.

Method: To test these hypotheses and explore additional composition effects, we employed three approaches of multilevel structural equation modeling on two large longitudinal samples of German adolescents (N_1 = 5,470; N_2 = 788).

Results: Our analyses yielded two principal findings: First, individual personality levels remained highly stable across different time periods. Second, contrary to our hypotheses, baseline class-level openness and conscientiousness were not positively linked to individual personality development. Instead, there were some indications that higher class-level openness was negatively linked to individual openness to experiences at the second measurement point.

Conclusions: We discuss the absence of systematic composition effects at the classroom level and consider methodological challenges in investigating these effects.

Keywords: adolescence, personality development, classroom peers, composition effect, multilevel structural equation modeling

Becoming as Open-Minded and Organized as my Classmates? Peer Effects on Self-Reported Personality Trait Development in the Classroom

To what degree does the way students see themselves relate to their classmates? How people see themselves is reflected in their personality, defined as relatively stable individual differences in how people think, act, and feel (Roberts, 2009). Often, we use people as informants on their personalities by asking them to self-report their typical behaviors, thoughts, and feelings. However, according to social comparison theories (e.g., Festinger, 1954; Wood et al., 2012), such self-perceptions involve comparisons to others (besides potential other sources; McCrae, 2018). Accordingly, personality self-reports have been found to vary with the given reference group instructions (Credé et al., 2010; Lenhausen, Bleidorn, et al., 2023; Lenhausen, Hopwood, et al., 2023). Specifically, people of the same age appear to form the most relevant reference group for personality self-reports in adulthood (Lenhausen, Hopwood, et al., 2023).

In adolescence, schools and classrooms constitute institutionalized peer groups that are not self-selected and entail frequent social interactions with same-aged peers (Eccles & Roeser, 2011). Therefore, educational contexts allow for a meaningful investigation of peer effects (Marsh et al., 2020). Research on composition effects has argued that peers are not only relevant comparison targets but also mold an individual's academic behaviors and specific self-perceptions (e.g., Fang et al., 2018; Van Ewijk & Sleegers, 2010). That is, the average level of certain peer characteristics within a classroom should be associated with an individual’s development in the same characteristic. To illustrate, a student might adapt their level of diligence and organization across time when being in a classroom with more diligent and organized classmates. While the same student might show and report less diligence and organization within a less organized class. However, so far we know little about the degree to which an adolescent’s Big Five personality development is associated with their classmates’ average personality manifestations—despite the relevance of several personality traits within the educational context (e.g., Israel et al., 2019; Mammadov, 2022).

Building on the relevance of peers for personality self-reports of adults (Lenhausen, Hopwood, et al., 2023) and the established knowledge regarding the relevance of class-average peer characteristics in the school context (e.g., Fang et al., 2018; Van Ewijk & Sleegers, 2010), the current study sets out to integrate these two lines of research to provide a first empirical test of classroom peer effects on adolescents’ Big Five personality self-reports. By applying multilevel structural equation modeling to two samples of N = 5,470 and N = 788 German secondary school students, we test the assumption that the development in self-reported personality traits is associated with the initial average level of personality traits of their classmates.

Reference Group Effects on Personality Self-Reports

As a framework for relatively stable individual differences, the Big Five (Costa & McCrae, 1992) offer a comprehensive conceptualization to describe people's personalities. The assessment of the five personality traits of openness, conscientiousness, extraversion, agreeableness, and neuroticism (or emotional stability) commonly involves self-report scales (e.g., Ostendorf & Angleitner, 2004; Soto & John, 2017). Self-report questionnaires using Likert scales—the typical scale format of (personality) questionnaires—do not objectively capture one's absolute level of a given trait but rather require the respondent to form a self-evaluation of the assessed characteristic (Heine et al., 2002). Social comparison theories have argued that these self-evaluations involve comparisons to reference groups (e.g., Festinger, 1954). For example, there is no objective consensus on a threshold for being considered industrious. Rather the reported level of industriousness depends on comparisons with a given or chosen reference group. Personality research has only very recently considered such reference group effects more closely focusing on the kind of reference groups used when people report their personality (Heine et al., 2002; Lenhausen, Bleidorn, et al., 2023; Lenhausen, Hopwood, et al., 2023).

The first studies on reference group effects on personality self-reports stem from cross-cultural research (e.g., Heine et al., 2002). These studies highlight the relevance of cultural contexts, norms, and expectations for forming self-evaluations assessed with personality self-reports. However, more recent studies on personality assessments also point to the relevance of more specific comparison groups (Credé et al., 2010; Lenhausen, Bleidorn, et al., 2023; Lenhausen, Hopwood, et al., 2023). To illustrate this relevance, Lenhausen and colleagues (2023; 2023) systematically varied their instructions to examine potential reference group effects in adult samples. More specifically, they asked participants to report their personality relative to different reference groups: on a between-person level, participants were asked to compare themselves to people in general, close others, people their age, and people the same gender, whereas, on a within-person level, they were asked to compare themselves to their ideal self and their past self. Furthermore, participants also reported what they believed they most strongly used as a reference group if none was specified. Findings suggest that while most people believed to use *people in general* as a reference, the most influential reference group was people the *same age* as the participants. Thus, same-aged peers form a relevant reference group for personality self-reports in adulthood. However, we know little about *how* people perceive and describe their levels of Big Five personality relative to same-aged peers when it comes to adolescence and the specific context of the school class.

Classrooms as Reference Groups for Personality Development

Investigating the relevance of peers for personality self-reports is particularly interesting in adolescence because adolescents face (among others) two developmental tasks that seem to be important in the context of peer effects on personality (Eccles et al., 1989; Erikson, 1968; Klimstra, 2013). First, adolescents need to develop a stable picture of themselves as a person, whereby personality traits are still comparably unstable during the developmental phase of adolescence (Soto & Tackett, 2015). Second, adolescents expand their networks beyond the family and peer relationships become increasingly relevant (Cillessen & Borch, 2006; Smetana, 2006; Wagner et al., 2014). Moreover, schools and classrooms are the most prevalent developmental contexts in adolescence (Eccles & Roeser, 2011). Classrooms offer frequent peer interactions and constitute clearly defined institutional peer groups (Marsh et al., 2020). This is especially true within the German school system, where classes often are not subject-specific but students in one class regularly go through their entire curriculum together over several years (Becker et al., 2017). Along these lines, classrooms are specifically suitable to address the role of peers in an individual's self-perceptions of personality.

Various disciplines have addressed the relevance of peer composition within educational contexts (cf., Van Ewijk & Sleegers, 2010). As a general proposition, composition effects in education assume that the average characteristic of an entire school class relates to an individual student's learning outcomes and development of this characteristic (Hattie, 2002). Empirically, educational researchers have shown that an individual's performance varies with the composition of schools and classes regarding different peer characteristics, such as socio-economic status (e.g., Van Ewijk & Sleegers, 2010) and performance (Becker et al., 2022). That is, attending a socioeconomically well-positioned school or class is associated with better performance, as is attending a school or class with a higher average performance. Moreover, research indicates that classroom composition is not only linked to students' performance but also their socioemotional characteristics like well-being (Belfi et al., 2012) and ability self-perceptions (Fang et al., 2018). Interestingly, while class-average achievement is positively related to individual achievement and its development (Becker et al., 2022), it shows negative associations with individual ability self-perceptions (Fang et al., 2018). These findings might reflect the different processes involved in composition effects (Dreeben & Barr, 1988; Thrupp et al., 2002). To specify, beyond social comparison processes which suggest a negative association of the class level with individual levels of a specific characteristic, it is likewise possible that students internalize the norms of their peer group and adapt their learning and behavior (in the sense of a socialization process) resulting in a positive link between the class and individual level.

While there is support for the relevance of social comparison processes for personality self-perceptions (Credé et al., 2010; Lenhausen, Bleidorn, et al., 2023; Lenhausen, Hopwood, et al., 2023), there is also a first study supporting peer socialization effects for Big Five trait development (Shan & Zölitz, 2023). This study from the field of economics was based on a higher education sample in small learning groups (four students) and indicates that group-average peer personality positively relates to an individual's personality development (Shan & Zölitz, 2023). Specifically, being randomly assigned to a learning group with more open-minded and conscientious peers increased individual levels of these traits across one semester within the selective academic environment of a Swiss private university. However, due to the highly selective private university setting and the small peer group, it is an open question whether these positive personality peer effects generalize, or whether negative comparison effects similar to those related to ability self-perceptions occur in a more diverse adolescent population and larger classrooms.

Integrating these different lines of research, we expect that the class level is associated with an individual's development of the respective Big Five trait. However, given their differential role in academic outcomes (e.g., Israel et al., 2023; Mammadov, 2022), we expect different associations for specific traits. We argue for a particularly straightforward relevance of classroom peers regarding the two traits of openness and conscientiousness. Research has demonstrated that both traits relate to everyday school behavior and academic performance (e.g., Israel et al., 2023; Mammadov, 2022). Students high in openness and, to a somewhat stronger extent, those high in conscientiousness show better academic performance in the classroom (Mammadov, 2022; Poropat, 2009). Taking up the results from Shan and Zölitz (2023) indicating socialization processes, we argue that students adapt to the typical class-average of open and conscientious behavior within their class. Therefore, self-perceptions of openness and conscientiousness within classrooms should be positively linked to the average level of these traits across all classroom peers. That is, we assume that higher initial class-level averages of openness and conscientiousness are associated with an increase in the individual student level of self-reported openness and conscientiousness across time spent in the classroom. To illustrate, an intellectually less curious student surrounded by many intellectually curious students (higher class level of openness) might adapt and show more intellectually curious behavior. However, the same student surrounded by only a few intellectually curious students (lower class level of openness) might experience a decrease in their self-reported level of openness.

Although extraversion, agreeableness, and neuroticism are less consistently associated with performance indicators in the school context (Meyer et al., 2023), they have been related to positive social interactions in adolescence inside and outside of the classroom (Israel et al., 2023; Wieczorek et al., 2022). High levels of extraversion relate to higher likeability and popularity (De Vries et al., 2020; Hubers et al., 2016; Van Der Linden et al., 2010) and friendship development in the school context (Israel et al., 2023). Higher levels of agreeableness are associated with better peer (and teacher) cooperation (Miller et al., 2003) and larger social networks (De Vries et al., 2020). Higher levels of neuroticism in adolescence are associated with insecurity (Deventer et al., 2019), lower levels of emotional closeness (Wagner et al., 2014), and lower popularity among classmates (Van Der Linden et al., 2010). Along these lines, extraversion, agreeableness, and neuroticism appear to have more of a social as compared to a performance function and, thus, might be less prone to be affected by performance-related peer interactions within classrooms. This might explain the absence of peer effects on these traits within university learning groups (Shan & Zölitz, 2023) that may not serve as much of a social function as the classroom context. Due to the particular importance of social relationships with peers during adolescence and the relevance of social interactions within classrooms, we assume the classroom levels of extraversion, agreeableness, and neuroticism relate to self-reported individual levels of these traits. However, given the lack of previous studies in educational contexts indicating whether social comparison or socialization processes are more relevant for the development of these traits, we investigate the direction of these peer group effects exploratory.

The Present Study

Given the relevance of peers for personality self-reports (Lenhausen, Hopwood, et al., 2023), the established knowledge regarding classroom peers affecting an individual's learning outcomes (Fang et al., 2018; Van Ewijk & Sleegers, 2010), and the relevance of personality within classroom contexts (Israel et al., 2023), the current study sets out to provide a first empirical test of peer composition effects on adolescents' self-reported Big Five personality in the classroom context. Specifically, we assume that the initial class-level average of openness (H1a) and conscientiousness (H1b) relate positively to an individual's development of the respective traits controlling for initial individual levels. We test composition effects on the remaining three traits exploratorily. To test our hypotheses, we apply multilevel SEM to two samples of N = 5,470 and N = 788 of German secondary students.

Transparency and Openness

We pre-registered our hypotheses and analytic strategy at the OSF (https://osf.io/evga9/) before data analysis and provide a comprehensive supplement. All analysis codes, Supporting Information and data of Study 2 are also available on the OSF project page. We prepared all data in R (4.3.3; R Core Team, 2024) and subsequently estimated the MLM models testing our research questions in M*plus* (8.5.; Muthén & Muthén, 2021) by means of the M*plus*Automation package (1.1.0; Hallquist & Wiley, 2018). The analyses were performed in line with our preregistered analysis plan except for some deviations documented in Table S1 at the OSF. We follow JARS (Appelbaum et al., 2018) in reporting our results. We addressed our research questions based on two independent already existing datasets. The dataset of Study 1 stems from the German National Educational Panel Study (NEPS) and data is open source and available on the NEPS project page (https://www.neps-data.de/Data-Center/Data-Access). The dataset of Study 2 is part of the SEED project (Wagner et al., 2024) and is uploaded to the OSF project page.

We determined a lower boundary[18] for power by conducting a series of simulations with the R-packet *simr* (Green & MacLeod, 2016), following the tutorial by Arend and Schäfer (2019). Simulation results suggest that the size of the NEPS sample (N = 5,470 nested in k = 606 classes)[19] provides sufficient power to detect small (b = 0.10) student-level effects and small to medium (b = 0.20) class-level effects. Regarding the SEED sample (N = 788 nested in k = 54 classes), simulation results suggest that the given sample size provides sufficient power to detect small to medium (b = 0.20) student-level effects and medium (b = 0.50) class-level effects.

Study 1: Method

Within Study 1, we used publicly available data from the German National Educational Panel Study (NEPS), starting cohort 3. The NEPS is carried out by the Leibniz Institute for Educational Trajectories (LIfBi, Germany) in cooperation with a nationwide network. Further information on the NEPS data is available at https://www.neps-data.de/Mainpage. It provides representative longitudinal data from German samples across six different age cohorts (for details, see Blossfeld et al., 2011). Given our interest in adolescent personality development, we based our analyses on data from starting cohort 3 (NEPS Network, 2023) as it provides personality data collected in the 7th (T1) and 9th (T2) grades. More specifically, for T1 we took

[18] Given the complexity of assumptions necessary for power simulation for SEM approaches, we used power simulations for manifest models as a lower boundary for the power estimate for our study (Wolf et al., 2013).
[19] We already conducted preliminary power simulations as part of the preregistration (see OSF project page) but updated the simulations based on actual sample sizes during the writing of this manuscript.

wave 3 data, and for T2 we combined waves 5 and 6, which both have been assessed in 9th grade.

Sample

Out of the 7,805 NEPS participants available within starting cohort 3 who attended regular schools, we, first, excluded all participants who did not report any personality data at T1 (n = 1,135), second, all participants for whom there was no class identification available at any time point (n = 660), and, finally, all participants that changed classes in between measurements (n = 540)[20]. The exclusion of a total of n = 2,335 participants resulted in a total sample of N = 5,470 seventh graders nested within 606 classes across 272 schools for Study 1. There were M = 9.02 (SD = 5.90; range[21]: 1−31) participants in each class on average. Participants were equally distributed across vocational-track schools (51.4%), which prepare for vocational training, and academic-track schools (48.6%), which prepare students for university education. On average, students were 12.86 (SD = 0.52) years old at T1, with an equal distribution of girls and boys (48.3% female). Looking at the SES of parents, the average HISEI was 56.79 (SD = 19.84) ranging between 11.74 and 88.96. An immigrant background was reported by 32.0% of the participants.

A selectivity analysis indicated that compared to the n = 2,335 excluded students, the N = 5,470 participants included in our analyses showed higher fluid reasoning scores (t(3636.9) = 7.10, p < .001, d = 0.21), were less likely to have a migration background (t(3923.6) = −3.65, p < .001, d = 0.11), and came from families with higher SES (t(2784.1) = 3.89, p < .001, d = 0.12). There were no significant differences in the personality scale scores at the first measurement between included and excluded participants (all ps > .175).

Measures

Big Five Personality Traits

Big Five personality traits were measured using the BFI-10 (Rammstedt & John, 2007). The BFI-10 measures the Big Five dimensions with two items each, one of which is reverse-keyed to control for acquiescent responding. Following the suggestion of Rammstedt and John (2007), NEPS included a third agreeableness item to improve the reliability and bandwidth of the agreeableness scale of the BFI-10. We used these three agreeableness items in our analyses. All personality items were rated on a fully labeled 5-point scale ranging from 1 (*does not apply at all*) to 5 (*fully applies*). We included personality measures from T1 and T2 in our analyses.

[20] As the class codes available within the NEPS data are not linked across waves, longitudinal class codes were obtained based on the procedure described by Florean and colleagues (2019). Moreover, the exclusion of participants changing classes was not preregistered but necessary based on our interest in class-level personality.
[21] As preregistered, we performed a robustness check excluding all classes with less than five students at T1. Result patterns were identical (cf., OSM, Table S6).

In line with other studies (Brandt et al., 2020; Brandt & Lechner, 2022) and due to the low number of items for such broad constructs, the split-half reliabilities of the manifest scales were relatively low ($r_{\text{opennessT1/T2}}$ = .36/.48, $r_{\text{conscientiousness T1/T2}}$ = .53/.50, $r_{\text{extraversion T1/T2}}$ = .40/.62, $r_{\text{agreeableness T1/T2}}$ = .40/.36, $r_{\text{neuroticism T1/T2}}$ = .33/.44). However, the test–retest reliability of the BFI-10 is sufficient as reported in previous research in Germany (Rammstedt et al., 2020). Moreover, it shows high convergent validity with longer Big Five scales and the overall criterion validity is comparable to longer inventories (Rammstedt & John, 2007; Thalmayer et al., 2011). To account for the unreliability of the observed items, we used latent variable models for all Big Five traits.

Control Variables

Control variables are all considered from T1. *Gender* (0 = male, 1 = female), *fluid reasoning*, and parental *socioeconomic status* served as manifest control variables at the individual level. *School track* (0 = nonacademic; 1 = academic) served as a control variable at the class level. Within the NEPS, fluid reasoning was measured by the 12-item matrices test (NEPS-MAT). NEPS-MAT is similar to Raven's Standard Progressive Matrices and was developed and validated specifically for the NEPS (for further information, see Brunner et al., 2014) and *socio-economic status* was indicated by parents' highest International Socio-Economic Index of Occupational Status (HISEI; Ganzeboom et al., 1992).

Statistical Analyses

Given our interest in effects of average classroom characteristics and to account for the nested structure in our data, that is students (L1) nested in classrooms (L2), we estimated a set of multilevel structural equation models (multilevel SEM). Our multilevel SEMs consisted of three main components: Student personality at the second measurement point (T2) was predicted by personality at T1 (L1), by the average classroom personality at T1 (L2), and by a subsequently added set of covariates (L1 and L2). Given our research question, the main interest is on the average classroom personality effects, which in this modeling approach is called a composition effect (Lüdtke et al., 2008). A composition effect is regarded to be present if the average classroom personality variable on level 2, which is based on the aggregated individual-level personality scores within one classroom, is related to individual personality at T2 over and above the effect of personality at T1. In order to assess the robustness of our estimates of composition effects to different modeling strategies, we decided to apply three modeling strategies (Lüdtke et al., 2008; Marsh et al., 2009): 1) double-latent contextual models 2) manifest-latent contextual models, and 3) the Bayesian modelling approach to estimate double-latent contextual models (Depaoli, 2021; Zitzmann et al., 2016)[22].

First, we estimated doubly latent contextual models (Lüdtke et al., 2008; Marsh et al., 2009) using the robust maximum likelihood estimator (MLR; Yuan & Bentler, 2000). These models allow to control for both measurement error at the individual level and sampling error in the classroom level variable. To control for measurement error, we specified the Big Five traits as latent constructs. More specifically, given the small number of items (two or three items per trait) for personality in the NEPS data, we fixed the loadings within each factor to 1[23]. Furthermore, we allowed for correlated item residuals across time. To control for sampling error, the unobserved group mean is regarded as a latent variable that is measured with a certain amount of precision by the group mean of the observed data (e.g., latent aggregation). Moreover, we accounted for the sampling of classrooms within schools (L3) by correcting the standard-error estimation for the nested data structure (analysis option type = complex two-level in Mplus). To handle missing values, we used the full information maximum likelihood estimation (Enders, 2010).

Second, we exploratively estimated manifest-latent contextual models (Lüdtke et al., 2008; Marsh et al., 2009). To avoid modelling issues referring to the latent measurement of the Big Five traits (i.e., negative error variances), we decided to estimate manifest-latent contextual models. That is, instead of specifying latent measurement models, we used the total scale scores as manifest indicators of each trait, while keeping all other model specifications identical to our first modeling approach. Thus, these models do not control for potential measurement error, however, they, nevertheless, include a latent aggregation of the trait at the class level and thus control for potential sampling error.

Third, we specified double-latent contextual models, but used a Bayesian modeling approach (Zitzmann et al., 2016). Double-latent contextual models have been linked to estimation problems such a inadmissible results (i.e., negative variances) especially in contexts with little information on the group-level (e.g., low ICCs; Zitzmann et al., 2016). According to simulation studies, the Bayesian estimation approach leads to fewer estimation problems and additionally increases the accuracy of the estimates of group-level effects in these cases

[22] We preregistered only the first of the three described modelling approaches. Given we faced some estimation difficulties, we decided to strengthen the confidence in our results by testing the robustness of findings across different modelling approaches. We report all models and estimation procedures in the paper and on our osf page.

[23] In deviation from our preregistration, we were not able to sufficiently estimate the models using the effect-coding approach. Instead, we kept the models more parsimonious by restricting all loadings of the latent factors to 1 (see OSM, Table S1).

(Depaoli, 2021; Zitzmann et al., 2016). We largely followed the approach of Zitzmann and colleagues (2016) and specified our priors accordingly. More specifically, the Bayesian approach allowed us to avoid negative residual variances without having to restrict them to 0 by specifying a weakly informative prior for the between-group level. Detailed model syntax are uploaded at the OSF project page (https://osf.io/evga9/).

Following conventional guidelines (Hu & Bentler, 1999; Schermelleh-Engel et al., 2003), we based our model evaluations for the first and second approach on several criteria: the confirmatory fit index (CFI < 0.95 or at least < 0.90), root mean square error of approximation (RMSEA < 0.05 or at least < 0.08), and standardized root mean square residual (SRMR < 0.05 or at least < 0.10). All variable preprocessing was done with R (R Core Team, 2024) using R-Studio and all multilevel SEMs were estimated using Mplus (Muthén & Muthén, 2021) by means of the *MplusAutomation* package (Hallquist & Wiley, 2018). We standardized all continuous variables across the sample to facilitate the interpretation of the regression coefficients from multilevel SEMs. Please also see our model outputs at the OSF (https://osf.io/evga9/) for complete model syntaxes for all modeling approaches. To account for the number of models and estimates in our analytic procedure, we will only interpret findings being significant on the $p < .01$ level. We also report exact p-values and 99% confidence intervals (credibility intervals for Bayesian estimates) for all parameter estimates to provide the reader with complete information.

Study 1: Results and Discussion

Intraclass correlation coefficients (.01−.03) indicated a low amount of variance in the personality scales scores at T1 being attributable to the class level (see Table 1). To illustrate, an ICC of .03 for the trait of openness suggests that only 3% of the total variance in openness scores can be attributed to the classroom level, while 97% of the variance is due to individual differences between students within the same classes. Thus, across all Big Five personality traits most variance and interindividual differences can be found between students within one classroom but less so between classrooms. Table 2 shows manifest correlations between the Big Five personality traits at both measurement points and all covariates.

Table 1

Study 1 - Intraclass Correlation Coefficients (ICCs) and Cluster Variances for Personality Scales

	ICC	var_{within}	$var_{between}$
Openness T1	0.03	0.89	0.03
Conscientiousness T1	0.02	0.72	0.02
Extraversion T1	0.02	0.60	0.01
Agreeableness T1	0.03	0.41	0.01
Neuroticism T1	0.01	0.68	0.01

Note. T1 = first measurment in 7th grade; var_{within} = variance within classes; $var_{between}$ = variance between classes

In the following, we report and compare the results from the three modeling approaches introduced above: doubly-latent contextual models, manifest latent models, and Bayesian estimation of doubly-latent contextual models. Across modeling approaches, our models with and without covariates fit the data well (see Table S2 for detailed information on model fit). We report all findings with and without covariates (gender, fluid reasoning ability, and socio-economic status at the individual, school track at the class level) and thus, illustrate if our results are robust to the inclusion of covariates.

Regarding the rank-order stability of the Big Five traits at the individual level, results generally showed high stability coefficients. Given the latent variable models control for measurement error, the size of the estimates of the latent modeling approaches (*b*s: 0.60–1.04, *p*s < .001) was expectedly larger compared to the manifest-latent approach (*b*s:0.38–0.51, *p*s < .001). This result pattern remained widely identical once we added the covariates (see Tables S3 and S4 in the OSM). Taken together, personality showed to be relatively stable from 7th to 9th grade.

Table 2

Study 1 - Means, Standard Deviations, Number of Observations, and Correlations of Big Five Traits, Socio-Demographic Characteristics and Covariates

Variable	*M*	*SD*	*N*	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15
1. Openness T1	3.44	0.96	5,382															
2. Openness T2	3.36	0.95	4,332	**.51**														
3. Conscientiousness T1	3.22	0.86	5,381	**.10**	**.05**													
4. Conscientiousness T2	3.05	0.83	4,324	**.05**	**.08**	**.51**												
5. Extraversion T1	3.40	0.79	5,302	**.08**	**.06**	.00	.01											
6. Extraversion T2	3.30	0.85	4,324	.02	**.05**	.03	**.07**	**.49**										
7. Agreeableness T1	3.45	0.65	5,307	**.19**	**.10**	**.30**	**.17**	−.00	−.00									
8. Agreeableness T2	3.44	0.64	4,305	**.09**	**.13**	**.17**	**.18**	−.02	−.02	**.38**								
9. Neuroticism T1	2.83	0.83	5,353	.02	−.01	**−.04**	−.03	**−.23**	**−.19**	−.02	**.05**							
10. Neuroticism T2	2.84	0.85	4,326	**.07**	.03	−.00	−.02	**−.13**	**−.29**	**.04**	.01	**.37**						
11. Female	0.48	0.50	5,466	**.22**	**.21**	**.17**	**.14**	.03	−.02	**.18**	**.13**	**.17**	**.28**					
12. HISEI	56.79	19.84	3,689	**.08**	**.06**	.04	−.00	**.08**	.04	.03	−.00	**−.05**	−.03	.01				
13. Fluid Reasoning T0	7.08	2.58	3,340	**.10**	**.07**	−.04	**−.12**	.00	−.04	−.00	.00	**−.05**	**−.07**	−.04	**.21**			
14. Fluid Reasoning T2	9.19	2.25	3,849	**.10**	**.09**	.01	**−.06**	−.02	−.03	.03	.03	**−.05**	−.03	.01	**.23**	**.50**		
15. Immigration Background	0.32	0.47	3,333	.02	**.06**	.01	.02	.02	.02	.02	−.00	.01	.01	.03	**−.16**	**−.12**	**−.12**	
16. School Track	0.49	0.50	5,450	**.09**	**.06**	.03	**−.07**	**.08**	**.06**	.02	−.02	**−.06**	−.02	**.04**	**.39**	**.37**	**.35**	**−.07**

Note. Significant correlations ($p < .01$) are in bold. Sample sizes vary across correlations from 2453 to 5466 due to missing values. HISEI = parents' highest International Socio-Economic Index of Occupational Status (Ganzeboom et al., 1992). Immigrant background is dummy coded with 1 = immigrant background. School track is dummy coded with 1 = academic track.

Regarding the composition effects, regression coefficients obtained from the different modeling approaches are shown in Table 3. Across modeling approaches there were almost no significant compositions effects. Specifically, there were no composition effects in any of the manifest-latent models and the double-latent models using a Bayesian approach, but there was one composition effect in the double-latent models using the maximum-likelihood approach. That is, the composition effect of openness reached statistical significance ($b = -0.33$, $p = .009$) and this effect was robust for the inclusion of covariates ($b = -0.42$, $p = .008$). Contrary to our hypothesis, the composition effect of openness was negative indicating that a higher class-average of openness at the first measurement point was associated with lower individual levels of openness at the second measurement point. Thus, in classrooms with higher average levels of openness in 7th grade, students reported lower levels of openness two years later in 9th grade controlling for the individual stability.

Regarding the covariates, student's sex robustly predicted individual change in extraversion (*b*s = −0.08, *p*s ≤ .001), agreeableness (*b*s = 0.04−0.13, *p*s ≤ .006), and neuroticism (*b*s = 0.26−0.44, *p*s ≤ .006). Girls reported lower levels of extraversion and higher levels of agreeableness and neuroticism at the second measurement point. Furthermore, the school track emerged as a robustly significant predictor of class level conscientiousness (*b*s = −.20 to −.14, *p*s ≤ .001), indicating that classes at academic track schools reported lower levels of conscientiousness on average compared to classes at nonacademic track schools.

Given the absence of the expected composition effects regarding conscientiousness and the school track differences in class levels of this trait, we decided to further explore the relevance of school track differences regarding the composition effects in our sample. To do so, we set up a series of multigroup models based on the preregistered double-latent modeling approach to test whether the estimates for the composition effects for all Big Five traits varied across school tracks. Replicating our main findings, the composition effect for openness reached significance. Interestingly, this was only the case for academic track schools (*b* = −0.57, *p* = .001), but not for nonacademic track school (*b* = −0.07, *p* = .734). This result pattern remained robust after including the individual level covariates gender, parental socioeconomic status, and fluid reasoning. The expected composition effect regarding conscientiousness again remained insignificant (see Table S5 for detailed results).

Taken together, the results of Study 1 do not support our assumption of the relevance of peer composition effects for personality development in the school contexts. Our results show a relatively high rank-order stability of students' personality from 7^{th} to 9^{th} grade. Against our expectation, the significant composition effect of openness in classrooms was negative, which is contrary to previous findings in university learning groups (Shan & Zölitz, 2023). This opposite direction might indicate that social comparison, as compared to socialization, processes are more pronounced within the classroom context. To illustrate, being constantly surrounded by and learning in a classroom with classmates who report higher levels of intellectual curiosity, read a lot, and regularly visit museums (e.g., high openness), might trigger contrasting social comparison processes that, in the long run, lead to a more negative evaluation of a student's own intellectual curiosity. However, the composition effect regarding openness did not emerge robustly across modeling strategies and, thus, should be interpreted cautiously. At the same time, our exploratory analyses indicate, that composition effects regarding openness might vary across school tracks and are more pronounced in particularly intellectual challenging contexts such as academic track schools.

Despite having a large and diverse sample, at least one limitation characterizes our Study 1. Despite its frequent application particularly in panel studies, the very short personality measure in the NEPS study has the limitations of an incomplete representation of the broadness of the underlying traits and the relatively low reliability coefficients. While we controlled for measurement error by using a diverse set of latent variable approaches, the brevity of the measure limited its validity to a certain extent. Therefore, we aimed to replicate our results in Study 2 using an independent adolescent sample and applying a longer and more reliable personality measure.

Table 3

Study 1 - Composition Effect Estimates Obtained Across Modelling Approaches

	Double Latent			Manifest Latent			Bayesian		
	b	*p*	99% CI	*b*	*p*	99% CI	*b*	*p*	99% CI
				Openness					
Uncontrolled	**−0.33**	.009	[−0.65, −0.00]	0.07	.537	[−0.21, 0.35]	−0.31	.020	[−0.68, 0.08]
Controlled	**−0.42**	.008	[−0.83, −0.01]	−0.05	.748	[−0.42, 0.33]	−0.39	.021	[−0.90, 0.12]
				Conscientiousness					
Uncontrolled	−0.23	.283	[−0.78, 0.32]	0.03	.905	[−0.54, 0.59]	−0.12	.267	[−0.62, 0.38]
Controlled	−0.03	.900	[−0.61, 0.55]	0.22	.339	[−0.37, 0.80]	−0.04	.416	[−0.49, 0.46]
				Extraversion					
Uncontrolled	−0.85	.015	[−1.74, 0.05]	−0.34	.297	[−1.20, 0.51]	−0.52	.014	[−1.17, 0.11]
Controlled	−1.43	.134	[−3.90, 1.03]	−0.65	.356	[−2.47, 1.17]	−0.58	.075	[−1.72, 0.54]
				Agreeableness					
Uncontrolled	−0.11	.509	[−0.52, 0.31]	0.04	.815	[−0.40, 0.48]	−0.09	.290	[−0.49, 0.35]
Controlled	−0.10	.610	[−0.61, 0.41]	0.04	.813	[−0.43, 0.51]	−0.11	.256	[−0.55, 0.34]
				Neuroticism					
Uncontrolled	−0.40	.073	[−0.97, 0.17]	−0.02	.926	[−0.51, 0.47]	−0.38	.031	[−0.91, 0.15]
Controlled	−0.42	.114	[−1.10, 0.26]	−0.09	.685	[−0.67, 0.49]	−0.37	.074	[−1.05, 0.34]

Note. Bold estimates are significant at $p < .01$. Uncontrolled = No covariates included. Controlled = Models include sex, HISEI, and fluid reasoning as individual, and school track as class level covariates.

Double Latent = Maximum likelihood estimation of double-latent contextual models.

Manifest Latent = Maximum likelihood estimation of manifest-latent contextual models.

Bayesian = Bayesian estimation of double-latent contextual models.

Study 2: Method

Within Study 2, we used existing data from the SEED project (Wagner et al., 2024). The SEED study tracked 10th grade students across one school year as well as their transition to 11th grade (upper secondary school). The study included four measurement time points with roughly quarterly intervals. The present paper uses data from the first (T1) and third (which will be called T2 from now on) measurement point only, which were assessed at the beginning/middle (November 2022 to February 2023) and the end (June 2023) of the 10th grade, respectively. More information on the SEED data collection is available at the OSF project page (https://osf.io/xyf8c/).

Sample

Study 2 was based on a total sample of N = 788 tenth graders nested in 54 classes from 12 schools meeting the inclusion criteria of at least one answered personality item at T1 and an available class identification. There were on average M = 14.28 (SD = 5.12, Range: 1[24]–26) participants in each class. The majority of participants attended vocational-track schools (43.9%), which prepare for vocational training, while all other participants attend academic-track schools (56.1%), which prepare students for university education. On average, students were 15.49 (SD = 0.68) years old at T1, with an equal distribution of girls and boys (49.6% female). Most participants reported that at least one parent had an intermediate (49.7%) or high (47.0 %) educational qualification as categorized by CASMIN Educational Classification scheme (Brauns et al., 2003). An immigrant background was reported by 47.3% of the participants.

Measures

Big Five Personality Traits

Within Study 2, Big Five personality was assessed using the well-established and reliable German BFI-2 (Danner et al., 2016) again at T1 and T2. The BFI-2 assesses the Big Five traits with 12 items (4 items per facet) each. All items were rated on a 7-point scale ranging from 1 (*does not apply at all*) to 7 (*fully applies*). We included personality measures from T1 and T2 in our analyses. The reliability of the measurement models was sufficient ($\omega_{\text{openness}\,T1/T2}$ = .81/.86, $\omega_{\text{conscientiousness}\,T1/T2}$ = .87/.87, $\omega_{\text{extraversion}\,T1/T2}$ = .87/.87, $\omega_{\text{agreeableness}\,T1/T2}$ = .82/.86, $\omega_{\text{neuroticism}\,T1/T2}$ = .87/.88). To account for the unreliability of the observed items, we used latent variable models for all Big Five traits.

[24] As preregistered, we performed a robustness check excluding all classes with less than five students at T1. Result patterns were identical (cf., OSM, Table S11).

Control Variables

Control variables are all considered from T1. S*chool track* (0 = nonacademic; 1 = academic) and *gender* (0 = male, 1 = female) served as manifest control variables at the class and individual level, respectively. Moreover, we included *fluid reasoning* assessed with 12 items arranged in 3 sets of 4 items retrieved from the international cognitive ability resource (Condon & Revelle, 2014) as a control variable at the individual level. The sets comprised letter series, matrix, and verbal reasoning tasks. We used the sum score of these items as a manifest covariate. Additionally, the highest parental education which was assessed by two items (for mothers and fathers, separately) served as a manifest indicator of *socioeconomic status* at the class and individual level. Parental education was categorized according to the CASMIN Educational Classification index (Brauns et al., 2003). That is, high education (CASMIN 3) refers to university degrees; intermediate education (CASMIN 2) includes secondary school certificates and comparable qualifications; and low education (CASMIN 1) subsumes no formal qualification as well as lower secondary education. These levels were recoded so that 0 referred to low, 1 to intermediate, and 2 to high education.

Statistical Analyses

We followed an identical modeling approach as described in Study 1 testing three modeling strategies (Lüdtke et al., 2008; Marsh et al., 2009): 1) doubly-latent contextual models, 2) manifest-latent contextual models, and 3) the Bayesian modeling approach to estimate doubly-latent contextual models. There is one difference in model specification regarding the doubly latent models: Given the more extensive personality measure assessed in Sample 2, we specified the Big Five traits again as latent constructs but now follow a content-based parceling approach (e.g.; Matsunaga, 2008). Thus, we used the three facet means as the three indicators for each trait. Model outputs can be found at the OSF project page (https://osf.io/evga9/).

Study 2: Results and Discussion

Similar to Study 1, intraclass correlation coefficients (.01−.08) indicated a low amount of variance attributable to the class level (see Table 4). Thus, again only between 1% and 8% of the variance in Big Five personality traits could be attributed to differences between classrooms and the remaining amount of variance is due to interindividual differences between students within the same classroom. Table 5 presents manifest correlations between the Big Five personality traits at both measurement points and all covariates. Across all three modeling approaches, our models with and without covariates fit the data well (see Table S7 in the OSM). Again, we apply the same reporting strategy as described for Study 1.

Table 4

Study 2 - Intraclass Correlation Coefficients (ICCs) and Cluster Variances for Personality Scales

	ICC	var_{within}	$var_{between}$
Openness T1	0.08	0.80	0.07
Conscientiousness T1	0.01	1.09	0.02
Extraversion T1	0.02	0.98	0.02
Agreeableness T1	0.05	0.73	0.04
Neuroticism T1	0.01	1.05	0.01

Note. T1 = first measurement at the start of 10th grade; var_{within} = variance within classes; $var_{between}$ = variance between classes.

Regarding the rank-order stability of the Big Five traits at the individual level, results were similar across all modeling approaches revealing relatively high stability (*b*s: 0.74−0.89, *p*s < .001). Again, the stability estimates were robust for the addition of covariates (see Tables S8 and S9 for detailed results). Thus, results indicated that the Big Five traits were highly stable at the individual level across the school year in 10th grade.

Regarding the composition effects, estimates obtained from the different modeling approaches are presented in Table 6. Across all three modeling approaches and across models without and with covariates, no significant compositions effects emerged contradicting our hypotheses. The class level average of the Big Five traits did not predict differences in individual personality change across one school year. Regarding the covariates, girls again reported higher levels of neuroticism (bs = 0.22−0.27, *p*s < .001). Furthermore, classes at academic track schools reported lower levels of neuroticism (bs = −0.15 to −0.14, *p*s ≤ .008). Again, we ran exploratory multigroup models following the double-latent modeling approach. No significant composition effects emerged across school tracks (see Table S10 for detailed parameter estimates).

Taken together and similar to Study 1, the results of Study 2 do not support the relevance of personality peer composition effects for individual personality development across 10th grade. This is contrary to our hypothesis regarding the relevance of class-level openness and conscientiousness and to initial results in university learning contexts supporting the relevance of peer personality (Shan & Zölitz, 2023). Still, the results again point towards a relative stability of the Big Five traits across the 10th grade and little systematic personality differences between classrooms.

Table 5

Study 2 – Full Sample Descriptives (Means, Standard Deviations, Number of Observations, and Correlations of Big Five Traits, Socio-Demographic Characteristics and Covariates)

Variable	*M*	*SD*	*N*	1	2	3	4	5	6	7	8	9	10	11	12	13	14
1. Openness T1	4.64	0.93	788														
2. Openness T2	4.58	0.97	258	**.74**													
3. Conscientiousness T1	4.42	1.00	788	**.21**	.15												
4. Conscientiousness T2	4.30	0.94	258	.11	**.20**	**.81**											
5. Extraversion T1	4.48	1.03	788	**.35**	**.27**	**.25**	.13										
6. Extraversion T2	4.46	0.98	258	**.28**	**.30**	**.23**	**.21**	**.79**									
7. Agreeableness T1	4.78	0.87	788	**.18**	.10	**.35**	**.27**	.08	−.01								
8. Agreeableness T2	4.74	0.91	258	.11	**.18**	**.25**	**.34**	.04	.06	**.79**							
9. Neuroticism T1	4.17	1.05	788	−.04	.03	**−.34**	**−.26**	**−.24**	−.14	**−.20**	−.13						
10. Neuroticism T2	4.05	1.02	258	.04	−.01	**−.22**	**−.32**	**−.20**	**−.20**	−.06	−.14	**.77**					
11. Female	0.50	0.50	788	**.16**	**.23**	**.11**	.07	.04	.11	**.20**	**.25**	**.38**	**.40**				
12. Fluid Reasoning T1	5.71	2.74	778	.05	−.02	**−.10**	−.04	.00	−.00	.04	.09	−.01	−.12	.01			
13. School Track	0.56	0.50	788	.07	−.00	**−.11**	−.02	.09	.13	**.11**	**.17**	.06	−.08	.08	**.50**		
14. Parental Education	1.44	0.56	423	.12	−.08	−.05	−.01	.06	−.04	−.04	.01	.08	.06	.01	**.23**	**.28**	
15. Immigrant Background	0.47	0.50	788	.01	.04	**.11**	.10	.04	−.03	−.03	.01	−.06	−.10	−.07	**−.16**	**−.15**	−.05

Note. Significant correlations ($p < .01$) are in bold. Sample sizes vary across correlations from 153 to 788. School track is dummy coded with 1 = academic track. Parental Education is highest educational degree of both parents differentiated according to the CASMIN scale (Brauns et al., 2003) ranging from 0 to 2. Immigrant background is dummy coded with 1 = immigrant background.

Table 6

Study 2 − Composition Effect Estimates Across Modelling Approaches

	Doubly Latent			Manifest Latent			Bayesian		
	Estimate	*p*	99% CI	Estimate	*p*	99% CI	Estimate	*p*	99% CI
				Openness					
Uncontrolled	−0.46	.076	[−1.12, 0.21]	−0.24	.270	[−0.80, 0.32]	−0.35	.144	[−1.31, 0.59]
Controlled	−0.47	.122	[−1.26, 0.31]	−0.26	.264	[−0.84, 0.33]	−0.33	.188	[−1.43, 0.74]
				Conscientiousness					
Uncontrolled	−0.06	.708	[−0.47, 0.35]	−0.07	.757	[−0.65, 0.51]	−0.09	.390	[−1.04, 0.82]
Controlled	0.13	.557	[−0.46, 0.72]	0.15	.707	[−0.89, 1.19]	−0.08	.439	[−6.53, 2.17]
				Extraversion					
Uncontrolled	−0.76	.042	[−1.71, 0.20]	−0.62	.133	[−1.68, 0.44]	−0.31	.247	[−1.59, 1.00]
Controlled	−1.04	.014	[−2.13, 0.05]	−0.93	.175	[−2.69, 0.84]	−0.48	.292	[−7.05, 5.40]
				Agreeableness					
Uncontrolled	0.16	.653	[−0.74, 1.06]	0.30	.373	[−0.58, 1.19]	0.12	.341	[−0.72, 1.08]
Controlled	0.17	.633	[−0.74, 1.08]	0.33	.373	[−0.62, 1.28]	0.07	.441	[−2.44, 2.11]
				Neuroticism					
Uncontrolled	−0.20	.751	[−1.78, 1.39]	0.07	.865	[−0.93, 1.06]	−0.21	.320	[−1.58, 1.18]
Controlled	−0.14	.837	[−1.87, 1.60]	0.22	.569	[−0.79, 1.24]	−0.14	.409	[−4.08, 2.14]

Note. Bold estimates are significant at $p < .01$. Uncontrolled = No covariates included. Controlled = Models include sex, HISEI, and fluid reasoning as individual, and school track as class level covariates.
Doubly Latent = Maximum likelihood estimation of doubly-latent contextual models.
Manifest Latent = Maximum likelihood estimation of manifest-latent contextual models.
Bayesian = Bayesian estimation of doubly-latent contextual models.

General Discussion

Based on two large German samples spanning two distinct time frames, we investigated the relevance of class-level personality for individual personality development. The results revealed three main findings: First, from 7th to 9th grade and from the beginning to the end of 10th grade, individual-level personality showed high stability. Second, class-level openness and conscientiousness were not robustly linked to individual personality development, and the only found effects were opposite to our hypotheses. Specifically, students in classes with higher average levels of openness experienced a decrease in openness to experience but only in one of our samples. Third, our analyses of the remaining Big Five traits revealed no additional composition effects. In the following, we will draw theoretical implications from these findings and discuss the methodological challenges of investigating personality composition effects.

Classrooms as Reference Groups for Personality Development

Given that schools and classrooms are key developmental contexts in adolescence and are strongly characterized by peer interactions (Eccles & Roeser, 2011), we investigated the relevance of class-average peer personality for individual personality development. Previous educational research has established the relevance of peer characteristics within educational settings for learning outcomes and socioemotional characteristics (Belfi et al., 2012; Fang et al., 2018; Van Ewijk & Sleegers, 2010). Theoretically, these peer composition effects may arise from different psychological processes including social comparison and socialization processes (Dreeben & Barr, 1988; Thrupp et al., 2002). First findings based on adult samples indicated both the relevance of social comparison for personality self-reports (Lenhausen, Bleidorn, et al., 2023; Lenhausen, Hopwood, et al., 2023) and socialization processes for individual personality development within educational peer groups (Shan & Zölitz, 2023) thereby implying that the rationale of composition effects in schools and classrooms might reasonably apply to individual personality development.

Given the similarity of the learning contexts, we wanted to test whether the socialization effects reported by Shan and Zölitz (2023) could be transferred to adolescents within the context of school classrooms. More specifically, we hypothesized that higher classroom levels of openness and conscientiousness should be associated with more pronounced individual gains in these traits across time. However, our results did not support this hypothesis. In contrast, there were no robust indications of classroom composition effects on individual Big Five development. Moreover, the composition effect of openness to experiences was even in the opposite direction in one sample. Thus, individual students did not benefit from higher classroom levels of openness but they contributed to a more negative developmental trend.

Theoretical and Methodological Reasons for Unexpected Result Pattern

What are potential reasons for the unexpected result patterns? There are theoretical and methodological explanations for the absence of the hypothesized effects in our study. First, theoretically the absence of robust personality composition effects in our sample might indicate the irrelevance of peers in the classroom for individual personality development. While our results indeed do not rule out the absence of classroom peer effects, we believe the absence contradicts previous research giving both theoretical and empirical support for the relevance of peers for personality self-reports (Lenhausen, Bleidorn, et al., 2023; Lenhausen, Hopwood, et al., 2023) and personality development in adolescence (e.g., Israel et al., 2023). However, given the absence of clear composition effects in both of our classroom samples, it might be possible that the different psychological processes, expected to be involved in composition effects (Dreeben & Barr, 1988; Thrupp et al., 2002), might have counteracted each other at the classroom level. That is, there is support for the relevance of social comparison for personality self-perceptions (Credé et al., 2010; Lenhausen, Bleidorn, et al., 2023; Lenhausen, Hopwood, et al., 2023) as well as a first study supporting peer socialization effects for trait development (Shan & Zölitz, 2023). While peer comparison processes imply a negative correlation, peer socialization processes imply a positive association between the expression of a characteristic at the group versus the individual level. Therefore, the joint appearance of both processes might explain the absence of robust findings in our study.

Second, the unexpectedly negative composition effect regarding openness might indicate the importance of social comparison processes within classrooms at least to some degree. As openness is known to be positively related to cognitive ability (Anglim et al., 2022), composition effects on openness self-perceptions might be more similar to those on ability self-perceptions (e.g. academic self-concepts) which are known to illustrate social comparison rather than socialization effects (Fang et al., 2018). That is, students seem to contrast their level of open-minded behavior with that of their classmates and use their classroom as a feedback and reference group for their self-reports (Credé et al., 2010; Lenhausen, Bleidorn, et al., 2023; Lenhausen, Hopwood, et al., 2023). However, the negative composition effect regarding openness should be interpreted cautiously, as it did not emerge robustly across samples and modeling strategies.

Third, research on other self-related constructs also indicates that the formation of self-related beliefs involves not only social comparison processes but also self-related comparisons. For example, the formation of academic self-concepts involves comparing one’s abilities to their classmates’ abilities as well as their own previous abilities (e.g., Trautwein & Möller, 2016; Wolff et al., 2018). While we did not specifically address self-related comparisons within our study, it could be that given the increasing self-reflection abilities in adolescence, self-related comparisons are more relevant to the development of Big Five personality traits in this period.

Fourth, it is important to note that academic self-concepts conceptually differ from the Big Five personality in terms of their specificity. In contrast to the Big Five traits reflecting broad behavioral tendencies across domains and contexts, academic self-concepts refer to self-perceptions of academic abilities that are specific to educational contexts and/or even academic domains. Furthermore, research designs investigating classroom effects on academic self-concepts often involve more objective class-level predictors (e.g., standardized ability tests). These measures are less affected by possible class-specific frame-of-reference effects given that they are distinct from the respective self-perception. Accordingly, future research on class composition effects on individual personality development could benefit from using more context-specific or objective measures of classmates' typical behavioral tendencies.

Fifth, another potential reason for the absence of the expected results are the low ICCs of our personality data. That is, the average levels of Big Five personality traits differed only to a very limited amount across classrooms. Rather most variance in Big Five traits was attributable to individual differences within classes. While this was not unexpected and this kind of variance distribution is comparable to those of other psychological constructs within educational contexts (Martin et al., 2011), it poses a conceptual and methodological challenge. On the one hand, the small differences in average levels of personality traits between classes could actually reflect potential reference group effects, even referred to as "biases" in self-reports within classes (Lira et al., 2022). That is, students' personality self-reports potentially reflect their perceived level of the Big Five traits relative to their class, rather than relative to all students their age. However, we were not able to directly test such effects in our study due to the research design. On the other hand, the low ICCs impose a methodological challenge as they reduce the possibility of finding potential effects of class-level personality within our correlational study design. That is, the power of the statistical models is partly a function of the ICC of the construct under investigation (for further information on power see also *Limitations and Future Research* section*)*

Finally, the high rank-order stabilities of personality are a second methodological issue that further complicate the statistical detection of composition effects. Although the stability estimates were somewhat higher and more consistent across modeling strategies in Study 2 as compared to Study 1, all Big Five traits were highly stable from 7th to 9th grade (Study 1) and across 10th grade (Study 2). Study differences are most likely due to design differences, with Study 1 spanning a longer time interval and using a shorter personality measure. Longer time intervals typically result in lower stability estimates as they potentially allow for more changes to occur as more time passes. The short personality scale is less representative of the broadness of the traits. Thereby it is more sensitive to minor changes in response behavior or the specific behaviors captured by the two items per trait. The higher relative weight of each item could contribute to the lower stability of the traits, especially in manifest models that do not control for measurement error (Brandt et al., 2023). In addition, the difference in the robustness of the stability estimates potentially illustrates an age effect between middle and later adolescence. That is, previous research has shown that the Big Five traits become increasingly stable across adolescence (Borghuis et al., 2017). Therefore, the older average age of the students in Study 2 might have contributed to the higher stability of the Big Five traits.

Characteristics of the Research Design and Composition Effects

What are potential differences in research design that contribute to differential composition effects? We would like to discuss four differences between the research designs used by Shan and Zölitz (2023) and in our study that are potentially relevant to the investigation of composition effects: group size, group function, time of group initiation, and the broader contextual setting. First, our study differed from the study of Shan and Zölitz (2023) regarding the group size. Whereas they based their study on small learning groups of only four students, our investigation focused on classes comprising up to 31 students. One might argue that not all classmates are equally important for an individual’s personality development. It could be that the class average of certain traits does not sufficiently reflect the trait levels of the peers most relevant to one individual (e.g., friends, seatmates). Therefore, potential socialization processes at more specific peer levels might have been masked at the class level due to the large group size and should be specifically targeted in future research.

Second, the impact of the peer group on an individual's perception of specific traits might vary not only with group size but also with group function. The learning groups studied by Shan and Zölitz (2023) served a rather specific academic function potentially resulting in more pronounced composition effects indicating socialization processes regarding the academically relevant traits of openness and conscientiousness (Mammadov, 2022). To illustrate, it seems reasonable that an individual adapts the typical academic behavior of their learning group peers as they regularly share their learning experiences and thus their typical learning behavior. By contrast, our study involved classroom peers who not only share academic experiences but experience various (social) interactions across the day with different classroom peers that do not exclusively serve an academic function. In line with such arguments, the average class level of openness and conscientiousness in a classroom might be less explanatory for an individual's development in these traits compared to the average group levels in small, focused learning groups at university. To illustrate, students might rather infer something about their academic behavior based on specific others that they share academic interactions with. Within the school context, such specific others might be close friends who students select as study partners or classmates with whom they work together at a given task rather than all classmates.

Third, the study of Shan and Zölitz (2023) assessed initial personality directly at the beginning of the group interaction, that is, their first measurement directly preceded the group initiation phase. On the contrary, in our two samples, the groups were existing classrooms that neither changed nor were randomly assigned at the beginning of the studies. This difference in study settings might explain the absence of most and the opposite direction of some of the hypothesized composition effects. On the one hand, positive socialization processes might be most pronounced in the specific period following group initiation. In this sensitive period at the beginning, individuals might be more susceptible to group information due to their desire to become part of the group (Deci & Ryan, 2002). On the other hand, different peer processes might occur at differing time points after the initiation of a group. Within already existing peer groups such as classrooms, it could be possible that social comparison processes might be more prevalent than socialization. This could result in the negative association of class-average openness with individual development of this trait in our sample. That is, students rather downgrade their intellectual curiosity due to the many more open behaviors of classmates. Unfortunately, our research design did not allow us to disentangle the different processes involved in peer composition effects. Thus, future research should adopt methodological approaches enabling a more differentiated picture of composition effects on personality development.

Fourth, our exploratory analyses indicated that the broader contextual setting, that is, the school track potentially plays a role in (classroom) composition effects. Specifically, in Study 1 the negative composition effect of openness was only present at academic track schools but not at nonacademic track schools. This finding suggests that characteristics of the general school context further differentiate classroom composition effects on personality development. Potential reasons for more pronounced effects at academic track schools might be differences in the composition, organization, and expectations across school tracks in the German school system (Brandt et al., 2020). Tracking practices in Germany are mostly based on ability. Given the associations between openness and cognitive abilities (Anglim et al., 2022), social comparison effects on openness might be specifically pronounced in academic environments with higher cognitive ability levels. As for organizational reasons, in academic track schools students mostly share their lessons with the same classmates, whereas in nonacademic track schools, they often practice course-by-course tracking (Becker et al., 2017). This course-by-course tracking softens the definition of classrooms, potentially making it harder to find clear composition effects. As for values and expectations, there is first evidence indicating that personality performance associations differ between school tracks (Brandt et al., 2020). These differences most likely reflect distinct representations of learning environments that result in different demands and opportunities for trait expression and, thus, in possibilities for perceiving the traits of classroom peers. Thus, it might be possible that different school tracks involve distinct peer processes affecting personality development.

Limitations and Future Research

While our study was based on two independent large-scale samples and we applied three state-of-the-art methodological approaches to investigate the role of class-average personality for individual personality development, the following limitations should be considered when interpreting the results and developing future studies. First, while our power simulations suggest that our samples were appropriately sized to detect a range of effect sizes, it is important to note that the power to detect small class-level effects, particularly in Study 2, was considerably lower. Given the low ICCs, the NEPS sample provided sufficient power to detect small to medium (b = .20) class-level effects, while the SEED sample did so only for medium (b = .50) class-level effects. This discrepancy in power might partly explain why the significant effect of class-level openness, identified in Study 1, did not replicate in Study 2. However, we also need to point out that our power simulations were based on manifest modeling approaches. Existing literature suggests that latent variable modeling—which accounts for measurement error and captures underlying constructs more effectively—may offer higher statistical power than the manifest approaches we applied (Wolf et al., 2013). Therefore, the results of our simulations represent the lower bounds of the actual power achieved, and we consider our analyses to be sufficiently powered overall.

Second, the correlational design of our study does not allow for causal interpretations. Despite using a longitudinal design and including relevant covariates, we cannot rule out that the associations between initial class level and changes in individual traits were mediated or masked by other (unobserved) variables or driven by selection effects. For example, there might be additional variables shared by classes affecting the individual personality development such as teaching characteristics, performance feedback, or school policy differences. At the same time, studies in naturally existing groups are typically characterized by such correlational designs as any form of randomization, particularly in educational contexts, is often impractical.

Third, while we based our analyses on two samples with different measurement intervals, there might not have been enough variation in personality changes across these intervals. Future research should consider various time points and measurement intervals to gain a more comprehensive view of potential peer composition effects on personality development. To illustrate, it might be insightful to study classroom composition effects right after the transition to secondary school, given the new formation of classes at this time point. Such natural changes in class composition might be best suited to address the relevance of peer composition utilizing a quasi-experimental design. Furthermore, it appears to be important to assess personality not just across this sensitive period, but also at several time points after such a transition, because the timing of classroom composition effects is not yet well understood.

Fourth, the measurement of personality has two important limitations: On the one hand, we used self-report measures in both studies. As we were interested in the relevance of peer personality for the development of an individual's self-perception, self-reports are an informative outcome measure. However, additional personality measures such as other reports or behavioral data might help to deepen the understanding of class-level personality and disentangle the processes involved in peer composition effects, as they potentially allow for a differentiation between changes in observable behavior and self-related cognitions. On the other hand, the shortness of the personality scale in our Study 1 imposed certain challenges in estimating our models. That is, although this is a widely used and established Big Five scale, particularly its brevity might reduce the potential to find school-specific associations with personality change (Johannsen et al., in press).

Conclusion

Taken together, our study provided the first empirical test of peer composition effects on individual personality development. Across two large adolescent samples, evidence for the effects of the average classroom personality on a student's personality development was weak or even absent. In the light of highly stable traits across relatively short time intervals, a singular significant effect of class-level personality on openness was found that might hint at the relevance of composition effects for trait development. Future research should explore potential processes involved in peer composition effects on personality development by systematically varying peer group size, function, and different states of peer group formation.

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4. Exploring the Roots: The Role of Perceived Teaching Behavior and Student Personality in Adolescents' Academic Self-Concept Development

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Abstract

Students' academic self-concepts are important for various educational outcomes; however, they significantly decline from childhood to adolescence. This study examines how perceived teaching behavior and student personality predict the development of academic self-concepts as students transition to German upper secondary school. Using conditional latent growth models with 1,131 German 10th graders (M_{age} = 14.98 years, 50% female, 45% with immigrant background), we predicted levels and changes in student-reported academic self-concepts (verbal and math) by perceived teaching behaviors (classroom management, cognitive activation, and emotional support), student Big Five personality traits (openness, conscientiousness, extraversion, agreeableness, neuroticism), and their respective interactions. The four key insights are: First, verbal and math self-concepts declined across 10th grade. Second, higher perceived emotional support, classroom management, conscientiousness, and agreeableness, and lower neuroticism, related to higher initial self-concept levels. Third, apart from a more pronounced decrease in the verbal self-concept associated with higher perceived emotional support and agreeableness, there were no robust associations with the development of academic self-concepts. Finally, we found significant interactions as the effects of perceived teaching behavior varied across students' openness, agreeableness, and neuroticism. Our results highlight the relevance of perceived teaching behavior and student personality for academic self-concepts and show their mutual dependencies.

[Word Count: 200 words]

Keywords: adolescence, academic self-concept development, teaching behavior, personality, Big Five

Exploring the Roots: The Role of Teaching Behavior and Student Personality in Adolescent's Academic Self-Concept Development

Domain-specific academic self-concepts—defined as individual beliefs about academic abilities in a given domain (Marsh & Craven, 1996)—serve as building blocks for the academic development of adolescents. They predict various aspects of academic success: better performance in school (Möller et al., 2020) and university (Von Keyserlingk et al., 2020) and students' academic choices such as high school course and university major selection (Jansen et al., 2021; Musu-Gillette et al., 2015). At the same time, empirical research illustrates that academic self-concepts decrease considerably across childhood and adolescence (e.g., Nagy et al., 2010; Postigo et al., 2022; Wigfield et al., 2015). Such declines in adolescent confidence in academic abilities could undermine these positive academic developments. Thus, a better understanding of the factors contributing to the development of academic self-concepts in adolescence is needed.

Stage-environment fit theory (e.g., Eccles & Roeser, 2009) proposes that the alignment between characteristics of the learning environment and of the student is essential for a positive academic development. In accordance with this transactional perspective, we selected one key characteristic of the learning context and of the individual, respectively, while also considering their interplay in the prediction of academic self-concept development. Contextually, student perceptions of important socializers such as the beliefs, attitudes, and behaviors of teachers shape academic experiences within the immediate classroom context (Eccles & Roeser, 2009; c.f., Kunter et al., 2013; Lazarides & Ittel, 2012) and, thus, should contribute to the development of academic self-concepts. Individually, interindividual differences in general tendencies to think, feel, and act, i.e., the students' personality (Roberts, 2009) can be described based on the Big Five personality traits (McCrae & Costa, 2008). In line with theoretical considerations (Eccles & Roeser, 2009; Eccles & Wigfield, 2020), student Big Five personality traits should contribute directly to academic self-concept development as well as indirectly by molding the link between perceived teaching behaviors and academic self-concept development.

Cross-sectional research has established differential associations of academic self-concepts with key aspects of perceived teaching behavior (e.g., Lazarides & Ittel, 2012) and students' Big Five personality traits (Johannsen et al., 2024; Marsh et al., 2006). Longitudinal settings, however, are necessary to examine the factors also predicting changes in academic self-concepts across adolescence. Our study seeks to fill this gap by testing the specific and combined contributions of perceived teaching behavior and student personality to academic self-concept development in a longitudinal setting. Specifically, we examine this joint predictive power within a crucial period: the transition to upper secondary school. We use a sample of German 10th graders (N = 1,131) and estimate conditional latent growth models (LGMs) to predict the level and change in academic self-concepts (verbal/German and math) by three teaching behaviors (classroom management, cognitive activation, and emotional support), student Big Five personality traits (openness, conscientiousness, extraversion, agreeableness, neuroticism), and their respective interactions.

Theoretically Derived Factors Predicting Academic Self-Concept Development

According to expectancy-value theory (EVT; Eccles & Wigfield, 2020; Wigfield & Eccles, 2000), the academic self-concept, defined as individual beliefs about academic abilities, plays a crucial role in academic success. That is, students with a more positive academic self-concept have higher expectations of success in academic challenges and, consequently, more often engage in such challenges and show better performance. The present study focuses on domain-specific academic self-concepts. They are hierarchically arranged beneath a general self-concept and relate to domain-specific academic performance (Arens et al., 2011; Möller et al., 2009, 2020). These relations are stronger with corresponding and slightly negative with non-corresponding performance measures. Previous research on adolescent developmental trajectories of (domain-specific) academic self-concepts showed four central findings: First, the differentiation between verbal and mathematical self-concepts becomes more pronounced (Wan et al., 2021). Second, the stability patterns of academic self-concepts are comparable to those of other self-related constructs like interests or personality (Rieger et al., 2017).Third, sample average mean-level changes illustrate that academic self-concepts decline from childhood throughout adolescence (Nagy et al., 2010; Postigo et al., 2022; Wigfield et al., 2015). This decline may partly be based on an increasing sense of realism, particularly in late childhood and early adolescence (cf. Wigfield et al., 2015), this might not be true anymore in middle or late adolescence, where reasons for such declines may be more diverse. Fourth, adolescents differ considerably in their change trajectories (e.g., Archambault et al., 2010; Nagy et al., 2010; Postigo et al., 2022), pointing toward the importance of understanding these individual differences.

Stage-environment-fit theory and EVT provide comprehensive frameworks for deriving potential predictors of the development of academic self-concepts (Eccles & Roeser, 2009; Eccles & Wigfield, 2020). EVT states that performance experiences are key predictors for later academic self-concepts. Empirical studies support a reciprocal association between academic self-concepts and performance (Lauermann et al., 2020; Möller et al., 2020). However, with increasing age, we suggest a more diverse set of predictors is needed to account for interindividual differences in students' change trajectories. From a theoretical perspective (Eccles & Roeser, 2009; Eccles & Wigfield, 2020), academic developments result from transactions between the context and the individual student. Accordingly, we examined whether student-perceived teaching behavior and student personality predict academic self-concept development. Educational transitions and the connected contextual changes might be specifically challenging for a positive development as they potentially endanger the fit between the context and individual students (Eccles & Roeser, 2009). Hence, we looked into academic self-concept development across 10th grade and the transition to upper secondary school.

The Role of Perceived Teaching Behaviors

EVT specifies that student perceptions of primary socializers' beliefs, attitudes, and behaviors are crucial to academic self-concept formation (Eccles & Wigfield, 2020; Wigfield & Eccles, 2000). Within classrooms, teachers function as primary socializers and thus contribute to the academic self-concept development of adolescents (Pianta & Hamre, 2009). Educational research has identified various teaching behaviors that contribute to fulfilling students' needs and, thereby, shape a positive learning experience (Hamre & Pianta, 2010). The COACTIV model of instructional quality (e.g., Kunter & Voss, 2013) subsumes various teaching behaviors within three key dimensions of teaching behavior: emotional support, classroom management, and cognitive activation. Emotional support refers to the emotional and motivational support teachers provide their students and is expressed through respectfulness and being approachable. Effective classroom management refers to the optimal use of available time and thereby reflects an effective handling of classroom disturbances. Cognitive activation describes properties of the given tasks and their potential to contribute to goal-oriented cognitive activities in learners.

All three dimensions of teaching behavior are empirically related to differences in (domain-specific) academic self-concepts (Jensen et al., 2019; Lazarides & Ittel, 2012; Skaalvik & Skaalvik, 2013; W. Wagner et al., 2016). More specifically, previous cross-sectional studies found a positive association of overall instructional quality with the mathself-concept (e.g., Lazarides & Ittel, 2012), of emotional support with the general (Skaalvik & Skaalvik, 2013) and the verbal self-concept (Jensen et al., 2019), as well as of classroom management with the mathematical self-concept (W. Wagner et al., 2016). Besides cross-sectional associations, only one study controlled for initial levels of the general academic self-concept when testing the effects of teaching behaviors on later academic self-concept (W. Wagner et al., 2016). Results indicate that longitudinal associations follow the same direction, but are comparatively small.

Therefore, we investigate longitudinal predictions of the three teaching behaviors on levels and changes of verbal and mathematical self-concepts at the transition to upper secondary school.

The Role of a Student's Big Five Personality Traits

In accordance with stage-environment fit theory (Eccles & Roeser, 2009), an additional source of academic self-concept development may be individual characteristics, such as personality. Student personality may contribute directly and indirectly to adolescents' perception and evaluation of their abilities and talents. The most established conceptualization of personality are the Big Five personality traits (John, 2021; McCrae & Costa, 2008). The Big Five personality traits are *openness*, which involves being open-minded, intellectually curious, and creative; *conscientiousness*, characterized by being organized, productive, and responsible; *extraversion*, which reflects sociability, assertiveness, and energy; *agreeableness*, indicating a prosocial and communal orientation; and *neuroticism*, which involves a tendency toward negative emotionality and emotional instability.

We propose that the Big Five traits directly shape the development of academic self-concept in three ways: First, some Big Five traits might directly contribute to success in performance-related experiences. Especially openness and conscientiousness are valid predictors of favorable skills in educational settings (Bidjerano & Dai, 2007; Poropat, 2009; Ziegler et al., 2012) and academic performance (Mammadov, 2022). According to first studies, the differential associations of openness and conscientiousness with performance (Brandt et al., 2020; Israel et al., 2019; Meyer et al., 2019) seem to translate to the associations with academic self-concepts. Openness positively relate to verbal self-concept but slightly negatively to math self-concept, while conscientiousness positively relates to both (Johannsen et al., 2024; Marsh et al., 2006). As first longitudinal studies indicate a developmental interrelatedness of both traits with more general self-perceptions (Brandt et al., 2021), we expect the longitudinal interrelatedness to translate to adolescents' development of domain-specific academic self-concepts.

Second, students' level of neuroticism might contribute to the subjective evaluation of performance-related experiences. As neuroticism reflects negative emotionality and emotional instability, it might shape affective reactions to performance-related experiences. Cross-sectional studies support a negative association of neuroticism with academic self-concepts. Longitudinal studies focusing on (non-academic) self-perceptions like self-esteem (Bien et al., 2024; Wagner et al., 2013) showed that higher levels of neuroticism were associated with lower levels and less positive development in self-esteem. Correspondingly, we expect higher levels of neuroticism to relate to lower levels of and a more pronounced decline in academic self-concepts over time.

Third, given the relevance of agreeableness and extraversion in social situations and relationships (J. Wagner et al., 2014; Wieczorek et al., 2022), these personality traits might also contribute to experiences of evaluative feedback and, thus, to academic self-concepts and their development. However, cross-sectional associations of agreeableness and extraversion with academic self-concepts are small and somewhat inconsistent (Johannsen et al., 2024; Jonkmann et al., 2012). The current study extends these findings by exploring their role in academic self-concept development.

Students' Big Five Personality Traits Moderating Relevance of Perceived Teaching Behavior

Personality theories (McCrae & Costa, 2008) propose that interindividual differences in Big Five personality traits manifest in differences in how people perceive the world, which subsequently affects more specific characteristics such as academic self-concepts. stage-environment fit theory (Eccles & Roeser, 2009) provides a transactional perspective on school and states that contextual characteristics shaped by teachers must align with the individual needs and characteristics of students to promote a positive academic development. Accordingly, we argue that adolescents' perceptions of their teachers' behaviors vary with their personality traits. Specifically, the same teaching behaviors can be interpreted differently depending on an individual's personality, thereby shaping the development of their academic self-concept. Hence, we propose that the extent to which students experience positive developmental trajectories in their math self-concept is associated with the teaching behaviors they observe in math classes, their Big Five personality traits, which serve as overarching tendencies to think, feel, and behave, and the interplay between these two factors. The interplay could be synergistic or compensatory. In a synergistic interaction, a student who views his teacher as highly structured might experience more pronounced increases in their math self-concept if they are highly conscientious. In a compensatory interaction, perceiving a teacher as well-structured might compensate for a lack of conscientiousness, helping to boost the academic self-concept despite lower levels of this trait. Due to the lack of previous research, we refrain from making specific predictions about the type of interactions that may exist and instead conduct an exploratory investigation of potential interactions.

The Present Study

This study extends previous research on the development of academic self-concepts by examining the joint predictive power of perceived teaching behaviors and student personality across 10th grade and the transition to upper secondary school. Specifically, we investigated if student-perceived emotional support, classroom management, and cognitive activation in German and math classes interact with students' Big Five personality traits in predicting levels and changes in students' verbal and mathematical self-concepts. We controlled our analyses for gender, previous grades, fluid reasoning abilities, and school track.

The present study had four aims: First, we examined changes in domain-specific self-concepts. We hypothesized a decline in individual verbal (H1a) and math self-concepts (H1b) across 10th grade. Second, testing predictive effects of perceived teaching behaviors on self-concept development, we expected higher levels of perceived emotional support from German teachers to relate to a more positive development of verbal self-concepts beyond initial levels (H2a). We explored associations of classroom management and cognitive activation. Moreover, we hypothesized higher levels of perceived emotional support, classroom management, and cognitive activation from math teachers to predict a more positive development of students' math self-concepts beyond initial levels (H2b). Third, we tested if Big Five personality traits predict the development of academic self-concepts. We expected higher levels of openness and conscientiousness, along with lower levels of neuroticism to predict a more positive development of verbal self-concepts (H3a), independent of initial levels. We hypothesized higher conscientiousness and lower neuroticism to predict a more positive development of math self-concepts beyond initial levels (H3b). We explored the associations with the remaining traits. Fourth, we explored the potential interplay between teaching behaviors and students' Big Five personality traits on domain-specific academic self-concept development. We addressed these research questions using conditional LGMs in a longitudinal sample of $N = 1{,}131$ German students transitioning from grade 10 to 11—a particularly important period for the academic development of adolescents.

Method

Subsequently, we describe the sample, procedures, and measures of the SEED project (J. Wagner et al., 2024) and the analyses used in this study. This study used data from the longitudinal SEED project that tracked 10th-grade students over one year, encompassing their transition to 11th grade (junior year of upper secondary school). A codebook describing all the methods and measures used in this project can be found at the OSF (https://osf.io/xyf8c/). The project received official approval from the Local School Authority in September 2022 and the Local Ethics Committee in October 2022 under identification code 2022_45. Before preregistration, some studies used data from the SEED project (Bien et al., 2025; Johannsen et al., 2025). However, these studies focused on different variable sets, leaving us unaware of patterns relating to academic self-concept development and the role of student personality and teaching behavior therein.

Participants

The SEED project explores adolescents' socio-emotional development, focusing on students' perceptions of their learning environment. It included three measurement points: T1 and T2 during 10th grade and T3 after transitioning to 11th grade. The project employed a drop-in design, allowing students to join at T2 or T3. A total of N = 1,131 students from 12 schools and 54 classes participated. Sample sizes varied substantially across measurement points with n_{T1} = 788, n_{T2} = 411, and n_{T3} = 413. For details on participant drop-out see the study flowchart (Figure S1) in the online supplementary material (OSM). Across the whole sample, 610 (53,93%) participants attended an academic-track school. Furthermore, 478 (44.92 %; 67 missing) reported having an immigrant background, and 566 (50.36%) were female. On average, participants were 15.49 (SD = 0.67) years old at T1.

Selectivity analyses comparing students that participated at only one measurement point (68.52%) with participants that participated in at least two measurement points (31.68%) revealed the following systematic differences: First, students participating more than once were more likely to be female (t(1,122) = 3.44, p = .001, d = .22) and to attend an academic track school (t(1,129) = 6.94, p < .001, d = .44), and less likely to report an immigrant background (t(1,062) = -4.57, p < .001, d = .30)[25]. Regarding the variables of interest, students who participated more than once reported higher levels of verbal self-concept (t(1,129) = 2.49, p = .013, d = .16) and agreeableness (t(786) = 2.33, p = .020, d = .17), as well as lower levels of emotional support by their German teacher (t(786) = -2.09, p = .037, d = .15) at their first participation. There were no substantial differences in the math self-concept, in any of the remaining Big Five traits, or the two additional teacher variables (see Table S1 in the OSM).

To determine power, we conducted a simulation in Mplus (Muthén & Muthén, 2002) for detecting effects in three measurement point second-order LGMs with two predictors and implementing longitudinal missing value patterns (30% at T1, 50% at T2, and 50% at T3). We used variance estimates from previous research on adolescent academic self-concept development (Nagy et al., 2010). Based on the given total sample size N = 1,131, we simulated the power to detect predictive effects of varying effect sizes (small: b = .10, very small: b = .05) on the slope factor. Findings indicated that the existing sample size provides sufficient power (100%) to detect small effects (b ≥ .10) and marginally satisfactory power (70%) to detect very

[25] Importantly, the differences regarding academic track attendance and immigrant background resulted partly from systematic missings due to school principals not wanting to participate in the longitudinal part of the study and, thus, were not revisited after the first measurement.

small effects (b ≥ .05) considering two predictors. Importantly, given the complex assumptions for SEM approaches, the simulation results are expected to illustrate the lower boundaries of power (Wolf et al., 2013).

Procedures

We recruited schools and students at the start of the 2022/23 school year, targeting 10th-grade students. We presented the study and its goals to 10th-grade students in the classroom. Participation was voluntary, requiring informed consent from students, with additional parental notification for those under age 16. Due to school authority regulations, we were not allowed to incentivize participation. Most students completed the T1 questionnaire (including the fluid reasoning test) in November or December 2022[26], the T2 questionnaire in May and June 2023, and the T3 questionnaire in September and October 2023. Student self-reports were collected digitally using the m-Path app (www.m-path.io) on the students' smartphones during in-class data collection sessions. Detailed data collection procedures are available on the project page at the OSF (https://osf.io/n96uc/).

Measures

For a detailed overview of the materials used within the SEED project, see the codebook on the OSF project page (https://osf.io/xyf8c/). Subsequently, we only describe the variables relevant to the present study. In the case of reverse-coded items, we recoded items so that higher values indicate a higher level of the respective construct. Whenever we aggregated items, we computed a mean per participant.

Domain-Specific Academic Self-Concepts

At all three measurement points, verbal and mathematical academic self-concepts were each assessed with three parallel worded items per subject (e.g., "I learn quickly in German/math classes") adapted from the German version of the SDQ I (Arens et al., 2013). All items were rated on a 7-point scale ranging from 1 (*does not apply at all*) to 7 (*fully applies*). Across all measurement points, reliabilities as indicated by McDonald's ω were high (Verbal Self-Concept: ωs between .90 and .92; Math Self-Concept: ωs between .95 and .96).

Teaching Behaviors

We assessed teachers' *emotional support* using student reports with four parallel worded items (e.g., "Our German/math teacher provides additional support when we need help")

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[26] A subsample of n = 267 was recruited after the start of the primary data collection and participated at T1 in February 2023. The remaining time points were equivalent for all participants. To account for the varying time intervals, we re-estimated the latent growth curve models with the slope loadings on the first and third latent academic self-concept factor fixed to 0 and 1, respectively, while estimating the loading of the second measurement freely. Results of this robustness check remained comparable to the original models (see Table S2 in the OSM). Hence, all consecutive models were based on the preregistered models.

adapted from Aldrup and colleagues (2018) per subject. Likewise, students reported on teachers’ *classroom management* in German and math classes based on four parallel worded items (e.g., “In German/math class, instruction is barely disturbed”) adapted from Aldrup and colleagues (2018) per subject. The perceived level of *cognitive activation* in German and math classes was again rated by students and measured based on three items (e.g., “Our German/math teacher gives us assignments in which we need time to think in order to find solutions”) adapted from the NEPS study (Blossfeld & Rossbach, 2019). All items measuring teaching behaviors were rated on a 7-point scale ranging from 1 (*does not apply at all*) to 7 (*fully applies*). We included student perceptions of teaching behaviors reported at T1 in our analyses. All scales were sufficiently reliable as indicated by McDonald’s ωs (Emotional Support$_{\text{German/math}}$: ωs = .90/.87; Classroom Management$_{\text{German/math}}$: ωs = .89/.87; Cognitive Activation$_{\text{German/math}}$: ωs = .76/.75).

Big Five Personality Traits

Big Five personality was assessed using the well-established and reliable German BFI-2 (Danner et al., 2016). The BFI-2 measures the Big Five traits with 12 items (four items per facet) each (e.g., openness: “I am inventive, find clever ways to do things”; conscientiousness: “I keep things neat and tidy”). All items were self-rated on a 7-point scale ranging from 1 (*does not apply at all*) to 7 (*fully applies*). Across all traits, McDonald’s ω reliability estimates were sufficient (Openness: ω = .77; Conscientiousness: ω = .84; Extraversion: ω = .85; Agreeableness: ω = .79; and Neuroticism: ω = .84).

Control Variables

We ensured the robustness of our results by including a range of control variables: First, we included self-reported *gender* as a dummy-coded variable (0 = male, 1 = female). Second, we used *fluid reasoning* assessed with 12 items retrieved from the international cognitive ability resource (Condon & Revelle, 2014) presented as a paper-pencil assessment at T1. We used the sum score of these items as a manifest indicator. Third, we included self-reported *previous academic performance* (end-of-year grades from 9th grade) in the respective subject. Grades were recoded for the main analyses so that higher values indicated better academic performance (range: 1-6). Fourth, we included s*chool track* (0 = non-academic; 1 = academic) as a dummy coded variable. We considered all control variables from T1 and included them as manifest variables.

Analytical Strategy

Data were analyzed in Mplus Version 8 (Muthén & Muthén, 2021) using the MplusAutomation package (Hallquist & Wiley, 2018) in RStudio (RStudio Team, 2015). This study's hypotheses and analyses have been pre-registered (see https://osf.io/n96uc/).

Our analytical strategy comprised three analytical steps, described in more detail below. Across all analytical steps, we based our model fit evaluation on well-established criteria: In addition to the χ^2 test statistic, which is known to be overly sensitive with increasing sample sizes, we inspected the comparative fit index (CFI), the root-mean square error of approximation (RMSEA), and the standardized root mean square residual (SRMR). We considered the model fit acceptable and excellent, respectively, if the CFI was above .90 or .95, the RMSEA was below .08 or .05, and the SRMR was below .10 or .05 (Hu & Bentler, 1999; Schermelleh-Engel et al., 2003). We dealt with longitudinal attrition by applying the robust Full Information Maximum Likelihood estimator. Furthermore, to account for the hierarchical data structure (students clustered in classes), we used the type = COMPLEX option in *M*plus to adjust the standard errors in all models. We report exact *p*-values and 95% confidence intervals to provide the reader with complete information. To account for multiple testing, we computed adjusted *p*-values based on the false discovery rate (FDR; Benjamini & Hochberg, 1995).

As a preanalytical step, we first tested for measurement invariance of verbal and mathematical self-concept across time (T1-T3) using the *lavaan* package in R (Rosseel, 2012). We based measurement models of the verbal and mathematical self-concept on three academic self-concept items per subject and ensured identification using the effect-coding approach (Little et al., 2006). We specified increasingly restrictive measurement models: initially testing for configural invariance, followed by metric invariance (equal factor loadings), then strong invariance (equal factor loadings and item intercepts), and finally strict invariance (equal factor loadings, item intercepts, and residual variances). In addition to the overall fit, we evaluated established change criteria, where a change in CFI greater than .010 and a change in RMSEA greater than .015 indicated a statistically significant model fit deterioration (Chen, 2007). The results in Table 1 demonstrate an excellent fit for the measurement models of verbal and math self-concept across time. Moreover, there was no substantial model fit distortion upon applying equality constraints across time. Therefore, we used strictly invariant measurement models in all subsequent analyses. Additionally, we tested for homogeneity of error variances associated with the first-order factors, confirming that these variances were homogeneous. Consequently, we included an equality constraint for the variance of the latent academic self-concept factors across time in all further analyses.

Table 1

Measurement Invariance of Academic Self-Concepts across Measurement Points

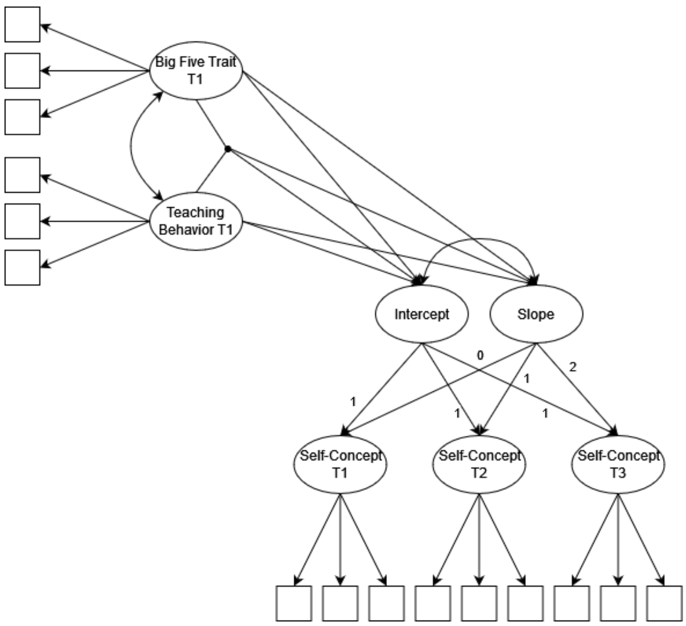
Model	χ^2	*df*	*p*	CFI	ΔCFI	RMSEA	ΔRMSEA	SRMR	ΔSRMR
	Verbal Self-Concept								
Configural	16.16	15	.076	.998		.022		.026	
Metric	19.15	19	.110	.998	.000	.019	−.003	.028	.002
Scalar	27.44	23	.042	.996	−.001	.022	.003	.030	.002
Strict	46.50	29	< .001	.988	−.008	.035	.013	.033	.004
Factor Variances	49.63	31	< .001	.988	.000	.034	−.001	.048	.015
	Math Self-Concept								
Configural	15.47	15	.061	.998		.023		.015	
Metric	19.25	19	.107	.999	.000	.019	−.004	.016	.001
Scalar	23.48	23	.109	.998	.000	.018	−.001	.016	.001
Strict	26.57	29	.039	.997	−.001	.021	.003	.016	.000
Factor Variances	30.45	31	.027	.997	.000	.022	.001	.037	.021

Note. *N* = 1,131. Models allowed for correlated residuals of same-worded items across time. CFI = comparative fit index; RMSEA = root-mean square error of approximation; SRMR = standardized root-mean square residual.

Second, we analyzed interindividual differences in intraindividual changes in academic self-concepts (RQ1) utilizing second-order LGMs (Sayer & Cumsille, 2001). Second-order LGMs discriminate between structural relations and measurement error by controlling the latter at the level of indicators (Bollen & Curran, 2005). Based on the invariant measurement models, we estimated two latent factors of academic self-concept development: the latent intercept and the latent slope factor. By fixing all of its loadings onto the time-specific latent factor to unity, the intercept factor represents the mean level of academic self-concept at T1. The intercept variance illustrates interindividual differences in academic self-concept levels at T1. We fixed latent slope loadings onto the time-specific latent academic self-concept factor at T1, T2, and T3 to 0, 1, and 2, respectively (cf. Figure 1). Thus, the latent slope reflects the amount of linear individual change that occurred between T1 and T3. The variance component of the slope factor represents interindividual differences in change trajectories across time. We allowed for correlated item residuals across time to account for the effects of the specific indicators and thereby avoid potentially biased results (Bollen & Curran, 2005; Marsh & Craven, 1996). Third, we estimated three sets of conditional second-order LGMs to address the predictive research questions. Considering predictors as latent time-invariant variables, we separately included each perceived teaching behavior (RQ2) and student Big Five trait (RQ3). We based the latent teaching behavior variables on the three/or four items as manifest indicators. Regarding the Big Five personality traits, we followed a content-based parceling approach (e.g., Matsunaga, 2008). Thus, we used the facet means as the three manifest indicators per trait. We applied the effect-coding method (Little et al., 2006) to identify the measurement models of all latent time-invariant predictor variables. Finally, we estimated moderated second-order LGMs by including each combination of one perceived teaching behavior and one student Big Five trait and their respective latent interaction (RQ4) as latent time-invariant predictors (see Figure 1). We included the latent interactions using the XWITH command in M*plus*.

Figure 1

Moderated Second-Order LGMs



Note. Circles and ellipses represent latent and squares represent observed variables. Due to parsimony error variances are not depicted. T = time.

Table 2

Descriptive Statistics and Correlations

Variable	*M*	*SD*	*N*	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18	19	20	21
1. Verbal Self-Concept T1	4.80	1.47	788																					
2. Verbal Self Concept T2	4.81	1.50	411	**.70**																				
3. Verbal Self-Concept T3	4.78	1.42	413	**.61**	**.67**																			
4. Math Self Concept T1	4.24	1.96	788	−.00	−.03	−.09																		
5. Math Self-Concept T2	4.14	2.01	411	−.06	.02	**−.18**	**.79**																	
6. Math Self Concept T3	3.95	1.90	413	−.11	−.05	**−.15**	**.73**	**.80**																
7. Teacher Support German	4.52	1.54	788	**.22**	**.17**	−.01	−.01	−.09	.02															
8. Classroom Management German	4.05	1.49	788	**.13**	.06	−.05	.05	**−.16**	.04	**.33**														
9. Cognitive Activation German	4.44	1.30	788	**.12**	.11	−.08	.03	−.02	.03	**.48**	**.36**													
10. Teacher Support Math	4.50	1.61	788	.01	.06	−.02	**.29**	**.29**	**.23**	**.13**	.02	**.15**												
11. Classroom Management Math	3.88	1.47	788	.06	.02	.01	**.15**	.10	.12	**.08**	**.29**	**.09**	**.28**											
12. Cognitive Activation Math	4.76	1.26	788	**.11**	.07	−.03	**.09**	.03	.13	**.24**	**.15**	**.30**	**.37**	**.30**										
13. Openness	4.64	0.93	788	**.25**	**.32**	**.26**	.03	.03	.02	.07	.02	**.14**	.05	.01	**.07**									
14. Conscientiousness	4.42	1.00	788	**.24**	**.20**	.07	**.15**	**.17**	**.16**	.06	**.13**	**.08**	**.14**	**.13**	**.11**	**.21**								
15. Extraversion	4.48	1.03	788	**.26**	**.20**	**.32**	.06	.01	−.07	.03	.06	.07	−.01	.02	.04	**.35**	**.25**							
16. Agreeableness	4.78	0.87	788	**.13**	.10	−.14	.05	−.03	.08	**.16**	**.16**	**.17**	.04	**.10**	**.12**	**.18**	**.35**	**.08**						
17. Neuroticism	4.17	1.05	788	**−.09**	−.06	−.09	**−.31**	**−.28**	**−.38**	−.02	**−.11**	.00	**−.14**	**−.15**	.01	−.04	**−.34**	**−.24**	**−.20**					
18. Gender	0.50	0.50	1,124	**.12**	**.20**	**.16**	**−.24**	**−.19**	**−.22**	.01	−.04	−.00	**−.09**	**−.08**	−.02	**−.16**	**.11**	.04	**.20**	**.38**				
19. Fluid Reasoning	5.70	2.73	790	.05	.08	.09	**.27**	**.21**	.07	**−.13**	**−.08**	**−.09**	.05	−.04	−.03	.05	**−.10**	.00	.04	−.01	.00			
20. Grade German	4.29	1.02	741	**.48**	**.50**	**.39**	**.11**	.03	.02	**.13**	.05	.04	.02	−.00	.05	**.22**	**.17**	**.19**	**.07**	−.01	**.19**	**.22**		
21. Grade Math	4.13	1.22	749	.06	**.20**	.08	**.64**	**.56**	**.61**	−.03	−.00	.01	**.23**	.05	.06	**.12**	**.15**	.07	.03	**−.14**	.01	**.47**	**.34**	
22. School Track	0.54	0.50	1,131	.00	.06	**.25**	.01	−.04	−.02	**−.15**	−.02	**−.11**	−.06	−.03	−.02	**.07**	**−.11**	**.09**	**.11**	.06	.04	.17	**.19**	**.51**

Note. *N* = 1.131. Gender is dummy coded with 1 = female. School track is dummy coded with 1 = academic track.
Statistically significant correlations (p < .05) are in bold with varying sample sizes due to missing values.

Results

In Table 2, we provide an overview of descriptive statistics and correlations. Subsequently, we present the results corresponding to our preregistered hypotheses and the exploratory analyses.

Differential Declines of Academic Self-Concepts Across Time

Results on the change in verbal and math self-concept (RQ1), are presented in Table 3. To test the robustness of our results, we present uncontrolled and controlled models, which include gender, fluid reasoning abilities, previous grades, and school track as manifest time-invariant covariates. All models fit to data excellently, with all CFIs ≥ 0.988, RMSEAs ≤ 0.024, and SRMRs ≤ 0.063 (cf. Table S3 and Table S4 in the OSM for detailed model fit information).

The latent intercepts representing the average academic self-concepts at the beginning of 10th grade were both above the scale's midpoint indicating average positive evaluations of the verbal and math competencies. Looking at the uncontrolled LGMs, contrary to our hypothesis H1a, the results illustrated no mean-level changes in the verbal self-concept, but consistent with our hypothesis H1b, a substantial decline in math self-concept across 10th grade. The significant intercept variances for both self-concepts indicate that some students initially felt more confident than others regarding their abilities. While the slope variances were not substantial for both self-concepts, they were reliably estimated, and the 95% plausible value ranges (PVR; Raudenbush & Bryk, 2010) illustrated that individual slope estimates ranged between –0.22 and 0.13 for the verbal and between –0.34 and –0.02 for the math self-concept. Accordingly, participants varied regarding the experienced declines across time (see also Figure S3 in the OSM for an illustration). The latent intercept and slope were unrelated, as indicated by their insignificant covariances for both self-concepts.

In the second step, we included all control variables (see Table 3). Regarding the verbal self-concept, most parameters remained unchanged in the controlled model, but one important change occurred: the slope now reached significance, aligning with our expectation of H1a. Furthermore, looking at control variable effects, higher grades in German classes in 9th grade were linked to higher, while attending an academic track school was linked to lower initial levels of the verbal self-concept. Regarding the slope, higher grades related to an enhanced decline while attending an academic track was associated with a less steep decline or even stability of the verbal self-concept across the time of the study. Regarding the math self-concept, all estimated parameters remained robust when the control variables were included. Regarding control variable effects on the math self-concept, female and academic track students showed lower initial levels. Students with higher fluid reasoning abilities and grades in math reported higher initial levels of the math self-concept. Additionally, higher fluid reasoning abilities and better math grades at T1 were related to a more substantial decline in the math self-concept.

Our results show that 10th graders' verbal and math self-concepts tend to decline as they progress to 11th grade. This developmental trend was related to students' previous performance in the respective subject. Moreover, the development of the verbal self-concept differed across school tracks, while the development of the math self-concept differed across students' reasoning abilities. Given the significant associations of the control variables with both intercept and slope of verbal and math self-concept, we included these variables in all subsequent models reported in this manuscript. We point out important differences between the controlled and uncontrolled analyses, and for full transparency provide the complete results of the uncontrolled models in Tables S5 to S9 in the online supplementary material.

Table 3

Estimates of Unconditional LGMs of Academic Self-Concept Development

	Verbal Self-Concept						Math Self-Concept					
	Intercept			Slope			Intercept			Slope		
	Estimate	*p*	95% CI	Estimate	*p*	95% CI	Estimate	*p*	95% CI	Estimate	*p*	95% CI
Uncontrolled Models												
Mean	**4.79**	< .001	[4.65, 4.93]	−0.04	.430	[−0.12, 0.05]	**4.27**	< .001	[4.11, 4.43]	**−0.18**	.001	[−0.29, −0.07]
Variance	**1.61**	< .001	[1.32, 1.91]	0.09	.269	[−0.07, 0.24]	**2.98**	< .001	[2.62, 3.34]	0.08	.259	[−0.06, 0.22]
Covariance	−0.12	.109	[−0.28, 0.03]				−0.10	.262	[−0.28, 0.08]			
Controlled Models												
Mean	**4.92**	< .001	[4.70, 5.13]	**−0.32**	< .001	[−0.46, −0.19]	**5.09**	< .001	[4.86, 5.32]	**−0.25**	.001	[−0.40, −0.10]
Variance	**1.05**	< .001	[0.81, 1.29]	0.06	.473	[−0.10, 0.21]	**1.16**	< .001	[0.82, 1.50]	0.04	.647	[−0.12, 0.19]
Covariance	−0.07	.344	[−0.23, 0.08]				0.11	.250	[−0.08, 0.31]			
Control variables												
Gender	0.09	.406	[−0.12, 0.29]	0.08	.167	[−0.03, 0.19]	**−0.93**	< .001	[−1.16, −0.70]	0.13	.129	[−0.04, 0.29]
Fluid Reasoning	−0.03	.553	[−0.14, 0.07]	−0.02	.583	[−0.10, 0.06]	**0.28**	< .001	[0.16, 0.39]	**−0.11**	.030	[−0.21, −0.01]
Grade	**0.75**	< .001	[0.63, 0.87]	**−0.09**[a]	.043[a]	[−0.17, −0.00]	**1.19**	< .001	[1.09, 1.30]	**−0.10**[a]	.038[a]	[−0.19, −0.01]
School Track	**−0.25**[a]	.035[a]	[−0.48, −0.02]	**0.39**	< .001	[0.23, 0.55]	**−0.64**	< .001	[−0.90, −0.37]	0.03	.773	[−0.18, 0.25]

Note. N = 1.131. Gender is dummy coded with 1 = female. Fluid reasoning scores and grades were z-standardized. School track is dummy coded with 1 = academic track.

Significant estimates ($p < .05$) are in bold.

a: Estimates were not significant anymore after *p*-value adjustment (Benjamini & Hochberg, 1995).

Perceived Teaching Behaviors Predicting Academic Self-Concept Level and Slope

The six conditional LGMs predicting the development of verbal and math self-concept by each of the three perceived teaching behavior fit the data well with CFIs ≥ 0.990, RMSEAs ≤ .022, and SRMRs ≤ .054 (see Table S3 and Table S4 in the OSM for detailed fit estimates). Table 4 summarizes all parameter estimates (see Table S5 in the OSM for results regarding the control variables). Importantly, conditional models illustrate the stability of the estimated level and slope parameters for both academic self-concepts.

Looking at the verbal self-concept, all perceived teaching behaviors were associated with higher initial levels: Students perceiving more emotional support, classroom management, and cognitive activation in their German classes were initially more confident about their verbal abilities. Contrary to the attenuation hypothesis H2a, students experiencing more emotional support reported a more pronounced decline of the verbal self-concept during the study than those experiencing less emotional support. Neither classroom management nor cognitive activation related significantly to the slope of verbal self-concept. Two of the four associations with the control variables from the previous modeling step emerged consistently across models: Students with better German grades reported higher initial levels (*b*s = 0.70 – 0.74, *p*s < .001), and students attending an academic track school reported a less pronounced decline (*b*s = 0.32 – 0.39, *p*s < .001) of the verbal self-concept (see Table S5 in the OSM for detailed results).[27]

[27] Regarding the effects of teaching behavior, the uncontrolled models yielded comparable results except for one additional significant association of cognitive activation with the slope of the verbal self-concept ($b = -0.19$, $p = .041$). Accordingly, the associations of perceived teaching behaviors with the verbal self-concept (development) were widely independent of the inclusion of the control variables.

Table 4

Estimates of Conditional LGMs Predicting Academic Self-Concept Development by Teaching Behavior

	Verbal Self-Concept						Math Self-Concept					
	Intercept			Slope			Intercept			Slope		
	Estimate	*p*	95% CI	Estimate	*p*	95% CI	Estimate	*p*	95% CI	Estimate	*p*	95% CI
						Emotional Support						
Mean	**4.87**	< .001	[4.63, 5.11]	**−0.29**	< .001	[−0.44, −0.13]	**5.03**	< .001	[4.83, 5.23]	**−0.24**	.003	[−0.39, −0.08]
Variance	**1.00**	< .001	[0.78, 1.22]	0.04	.611	[−0.10, 0.18]	**1.10**	< .001	[0.78, 1.43]	0.03	.668	[−0.12, 0.18]
Covariance	−0.04	.573	[−0.19, 0.11]				0.13	.189	[−0.06, 0.32]			
Emotional Support	**0.28**	< .001	[0.13, 0.44]	**−0.17**[a]	.024	[−0.33, −0.02]	**0.32**	.001	[0.13, 0.51]	−0.09	.210	[−0.22, 0.05]
						Classroom Management						
Mean	**4.91**	< .001	[4.69, 5.14]	**−0.32**	< .001	[−0.46, −0.18]	**5.07**	< .001	[4.86, 5.29]	**−0.27**	< .001	[−0.42, −0.12]
Variance	**1.02**	< .001	[0.79, 1.25]	0.05	.508	[−0.10, 0.20]	**1.12**	< .001	[0.79, 1.45]	0.01	.853	[−0.14, 0.17]
Covariance	−0.06	.411	[−0.22, 0.09]				0.13	.182	[−0.06, 0.31]			
Classroom Management	**0.21**	.005	[0.06, 0.36]	−0.07	.194	[−0.19, 0.04]	**0.23**	.011	[0.05, 0.41]	0.08	.365	[−0.10, 0.27]
						Cognitive Activation						
Mean	**4.90**	< .001	[4.67, 5.12]	**−0.31**	< .001	[−0.45, −0.17]	**5.09**	< .001	[4.87, 5.31]	**−0.25**	.001	[−0.40, −0.10]
Variance	**1.03**	< .001	[0.80, 1.26]	0.05	.523	[−0.10, 0.19]	**1.16**	< .001	[0.82, 1.49]	0.04	.629	[−0.11, 0.18]
Covariance	−0.06	.425	[−0.21, 0.09]				0.11	.239	[−0.08, 0.30]			
Cognitive Activation	**0.21**[a]	.039	[0.01, 0.40]	−0.14	.106	[−0.30, 0.03]	0.10	.420	[−0.14, 0.35]	−0.01	.886	[−0.18, 0.16]

Note. N = 1.131. All models are controlled for gender (1 = female), fluid reasoning (z-standardized), previous grades (z-standardized), and school track (1 = academic).

Significant estimates (p < .05) are in bold.

a: Significance was not robust for p-value adjustment according to Benjamini and Hochberg (1995).

Looking at the math self-concept, higher perceived emotional support and classroom management were associated with higher intercepts, whereas no intercept effect occurred for cognitive activation. Contrary to our hypothesis H2b, all three perceived teaching behaviors were unrelated to the slope of the math self-concept. Regarding the relevance of the control variables, all intercept associations remained stable (see Table S5 in the OSM for detailed results): Female students (*b*s = –0.93 to –0.88, *p*s < .001) and those attending an academic track school (*b*s = –0.64 to –0.58, *p*s < .001) had lower initial levels, whereas students with higher fluid reasoning abilities (*b*s = 0.27 – 0.29, *p*s < .001) and better math grades (*b*s = 1.13 – 1.18, *p*s < .001) exhibited higher initial levels of the math self-concept. Regarding the slope associations, only higher fluid reasoning was still associated with a more pronounced decline in the math self-concept (*b*s = –0.11, *p*s < .001). Notably, the main intercept effects of emotional support and classroom management only reached significance in the models that included the control variables.

Student Personality Predicting Academic Self-Concept Level and Slope

All conditional LGMs including student Big Five personality traits as predictors of the development of verbal and math self-concept fit the data well with CFIs ≥ 0.983, RMSEAs ≤ .030, and SRMRs ≤ .072 (see Tables S3 and S4 in the OSM for detailed model fit information). Table 5 presents the results from our models including control variables (see Table S6 in the OSM for the uncontrolled results and for estimates regarding the control variables). As in the models before, the estimated level and slope parameters for both academic self-concepts remained unchanged.

Regarding the verbal self-concept, all Big Five personality traits were associated with initial levels. Students reporting higher levels of openness, conscientiousness, extraversion, and agreeableness reported higher levels. In comparison, students with higher levels of neuroticism reported lower levels of verbal self-concept at the beginning of the 10th grade. Notably, students with higher initial levels of agreeableness experienced a more pronounced decline in their verbal self-concept over time. However, none of the hypothesized associations between openness, conscientiousness, and neuroticism with the verbal self-concept slope (H3a) were confirmed.

The control variables exhibited the same significant patterns as those in the models including the teaching behaviors reported above. Additionally, the regression weights of school track in three out of the five models indicated that students who attended an academic track school reported lower initial levels of verbal self-concept (*b*s = –0.31 to –0.28, *p*s = .026; see Table S6 in the OSM for detailed associations with control variables)[28].

Regarding the math self-concept, three of the Big Five traits were associated with interindividual differences in the initial levels: Students with higher levels of conscientiousness and agreeableness were more confident, while students with higher levels of neuroticism were less confident in their mathematical abilities at the first measurement. Contrary to hypothesis H3b**,** no significant associations emerged between personality traits and the slope. Students' personality traits did not predict the development of mathematical self-concept. The associations with control variables were consistent with those in previous modeling steps.[29]

[28] The overall result pattern of the controlled models was comparable to the results of the uncontrolled models with two exceptions: The effect of neuroticism on the intercept was not significant (b = –0.19, p = 0.77), while the effect of conscientiousness on the slope was significant (b = –0.13, p = .033).
[29] Results of the uncontrolled models were widely comparable with one exception: Agreeableness was unrelated to the initial level (b = 0.15, p = .319).

Table 5

Estimates of Conditional LGMs Predicting Academic Self-Concept Development by Student Personality

	Verbal Self-Concept						Math Self-Concept					
	Intercept			Slope			Intercept			Slope		
	Estimate	*p*	95% CI	Estimate	*p*	95% CI	Estimate	*p*	95% CI	Estimate	*p*	95% CI
Openness												
Mean	**4.96**	< .001	[4.74, 5.17]	**−0.33**	< .001	[−0.47, −0.19]	**5.10**	< .001	[4.87, 5.33]	**−0.25**	.002	[−0.41, −0.09]
Variance	**0.97**	< .001	[0.73, 1.21]	0.05	.484	[−0.10, 0.21]	**1.16**	< .001	[0.83, 1.50]	0.04	.639	[−0.12, 0.19]
Covariance	−0.06	.424	[−0.22, 0.09]				0.11	.259	[−0.08, 0.30]			
Openness	**0.49**	< .001	[0.29, 0.68]	−0.06	.530	[−0.24, 0.13]	0.05	.708	[−0.20, 0.30]	0.04	.729	[−0.19, 0.27]
Conscientiousness												
Mean	**4.89**	< .001	[4.68, 5.10]	**−0.32**	< .001	[−0.46, −0.18]	**5.06**	< .001	[4.84, 5.28]	**−0.25**	.001	[−0.41, −0.10]
Variance	**0.99**	< .001	[0.76, 1.22]	0.05	.497	[−0.10, 0.20]	**1.08**	< .001	[0.76, 1.41]	0.04	.601	[−0.11, 0.19]
Covariance	−0.06	.429	[−0.22, 0.09]				0.10	.290	[−0.09, 0.29]			
Conscientiousness	**0.35**	< .001	[0.17, 0.54]	−0.07	.215	[−0.19, 0.04]	**0.42**	< .001	[0.24, 0.61]	0.02	.740	[−0.11, 0.16]
Extraversion												
Mean	**4.95**	< .001	[4.74, 5.15]	**−0.32**	< .001	[−0.46, −0.18]	**5.11**	< .001	[4.88, 5.34]	**−0.26**	.001	[−0.41, −0.11]
Variance	**0.97**	< .001	[0.74, 1.21]	0.05	.510	[−0.10, 0.20]	**1.16**	< .001	[0.82, 1.49]	0.03	.668	[−0.12, 0.19]
Covariance	−0.07	.393	[−0.22, 0.09]				0.12	.243	[−0.08, 0.31]			
Extraversion	**0.38**	< .001	[0.21, 0.54]	−0.01	.781	[−0.11, 0.09]	0.11	.176	[−0.05, 0.27]	−0.07	.382	[−0.22, 0.08]
Agreeableness												
Mean	**5.01**	< .001	[4.76, 5.25]	**−0.39**	< .001	[−0.54, −0.24]	**5.17**	< .001	[4.93, 5.41]	**−0.25**	.001	[−0.40, −0.10]
Variance	**1.02**	< .001	[0.79, 1.24]	0.03	.658	[−0.12, 0.18]	**1.13**	< .001	[0.80, 1.46]	0.03	.672	[−0.12, 0.18]
Covariance	−0.05	.488	[−0.20, 0.09]				0.12	.243	[−0.08, 0.31]			
Agreeableness	**0.32**	.008	[0.09, 0.56]	**−0.26**	< .001	[−0.41, −0.12]	**0.30**	.014	[0.06, 0.53]	0.01	.913	[−0.15, 0.16]
Neuroticism												
Mean	**4.82**	< .001	[4.61, 5.03]	**−0.36**	< .001	[−0.50, −0.21]	**4.92**	< .001	[4.71, 5.13]	**−0.29**	.001	[−0.46, −0.11]
Variance	**1.02**	< .001	[0.78, 1.26]	0.05	.534	[−0.10, 0.20]	**1.07**	< .001	[0.74, 1.41]	0.03	.671	[−0.11, 0.18]
Covariance	−0.08	.316	[−0.23, 0.07]				0.10	.336	[−0.10, 0.29]			
Neuroticism	**−0.26**	.004	[−0.44, −0.09]	−0.08	.200	[−0.20, 0.04]	**−0.46**	< .001	[−0.64, −0.28]	−0.09	.277	[−0.26, 0.07]

Note. N = 1.131. Models controlled for gender, fluid intelligence score, grades, and school track.
Significant estimates (p < .05) are in bold.

Student Personality Moderating Associations Between Perceived Teaching Behavior and Academic Self-Concept Level and Slope

Testing research question 4, we extended the previous models including two predictors and their latent interaction, respectively. Thus, each model included one teaching behavior, one Big Five personality trait, their respective interaction, and our control variables (see Table S7, S8, and S9 in the OSM for uncontrolled results and Table S10 for model fit information). We were interested in the robustness of the previous main effects of teaching behaviors and personality traits and also in potential interaction effects. Thus, the result presentation will focus on these two aspects, but we present full results in Table S7, Table S8, and Table S9 in the OSM.

Regarding the verbal self-concept, the first set of models concentrates on perceived emotional support and its interplay with students' Big Five traits (see Table 6). The models on the left side of the table illustrate a consistent and, thus, robust positive intercept and negative slope effect of emotional support across all Big Five traits. Likewise, the main effects of all personality traits remained stable. One unpredicted additional slope effect emerged in the combined model: Higher levels of conscientiousness were related to a more pronounced decrease in the verbal self-concept. Beyond these main effects, there was one significant compensatory interaction effect of perceived emotional support and openness on verbal self-concept levels: Students receiving high emotional support from their German teacher was linked to even more positive self-concept levels for less open students than for more open students.

Table 7 presents the results of the second set of models, including classroom management as a perceived teaching behavior. The models illustrate a consistent positive intercept effect of classroom management. Furthermore, the main effects of all personality traits on the intercept and agreeableness on the slope remained stable. Beyond these main effects, no significant interaction between classroom management and students' Big Five personality traits emerged.

Lastly, Table 8 summarizes the results of models including perceived cognitive activation as a predictor of the verbal self-concept. The main effect of cognitive activation on initial levels was less robust and only remained statistically significant if considered together with students' neuroticism. In contrast, the experience of more or less cognitively activating German lessons was unrelated to initial verbal self-concept levels, beyond the main effects of students' openness, conscientiousness, extraversion, and agreeableness. The main effects of students' Big Five personality traits remained stable. One unpredicted slope effect emerged:

Higher conscientiousness related to a more pronounced decrease in the verbal self-concept. Beyond these main effects, one significant interaction effect between cognitive activation and neuroticism emerged on the slope of verbal self-concept development. As illustrated in Figure 3a, for students reporting high levels of neuroticism, attending cognitively activating German lessons was associated with a more pronounced decline in their verbal self-concept. This result suggests that perceiving German classes as cognitively challenging might be particularly harmful to the verbal self-concept development of more anxious and emotionally unstable students. In contrast, for students with lower levels of neuroticism, the decline of the verbal self-concept was unaffected by the level of cognitive activation.[30]

Concerning the math self-concept, the models including student-perceived teachers' emotional support and Big Five traits are summarized on the right side of Table 6. In line with the simple models, the main effects of emotional support and the three personality traits conscientiousness, agreeableness, and neuroticism remained stable. While there were, again, no significant associations with the slope, one significant interaction effect on the intercept emerged. Illustrating a compensatory interaction, students with higher agreeableness benefitted less from perceiving a math teacher as particularly emotionally supportive than less agreeable students, who benefitted substantially from such support.

We present estimates of the models including classroom management on the right side of Table 7. Results indicate the robustness of the positive intercept effect of classroom management and the three main effects of Big Five traits. Furthermore, no significant associations with the slope or interaction effects on either the level or the slope emerged.

Results of the models including perceived cognitive activation are depicted on the right-hand side of Table 8. While the main effect of cognitive activation and the three main effects of personality were robust across all models, results indicated an interplay between cognitive activation and students' neuroticism levels, predicting both the intercept and the slope of the math self-concept. Interestingly, the effects pointed in the opposite direction of those of the verbal self-concept. As illustrated in Figure 3b, perceiving classes to be high in cognitive activation (the black lines) was related to a more pronounced decline in math self-concept for students with lower levels of neuroticism (the black triangles) but to a less pronounced decline

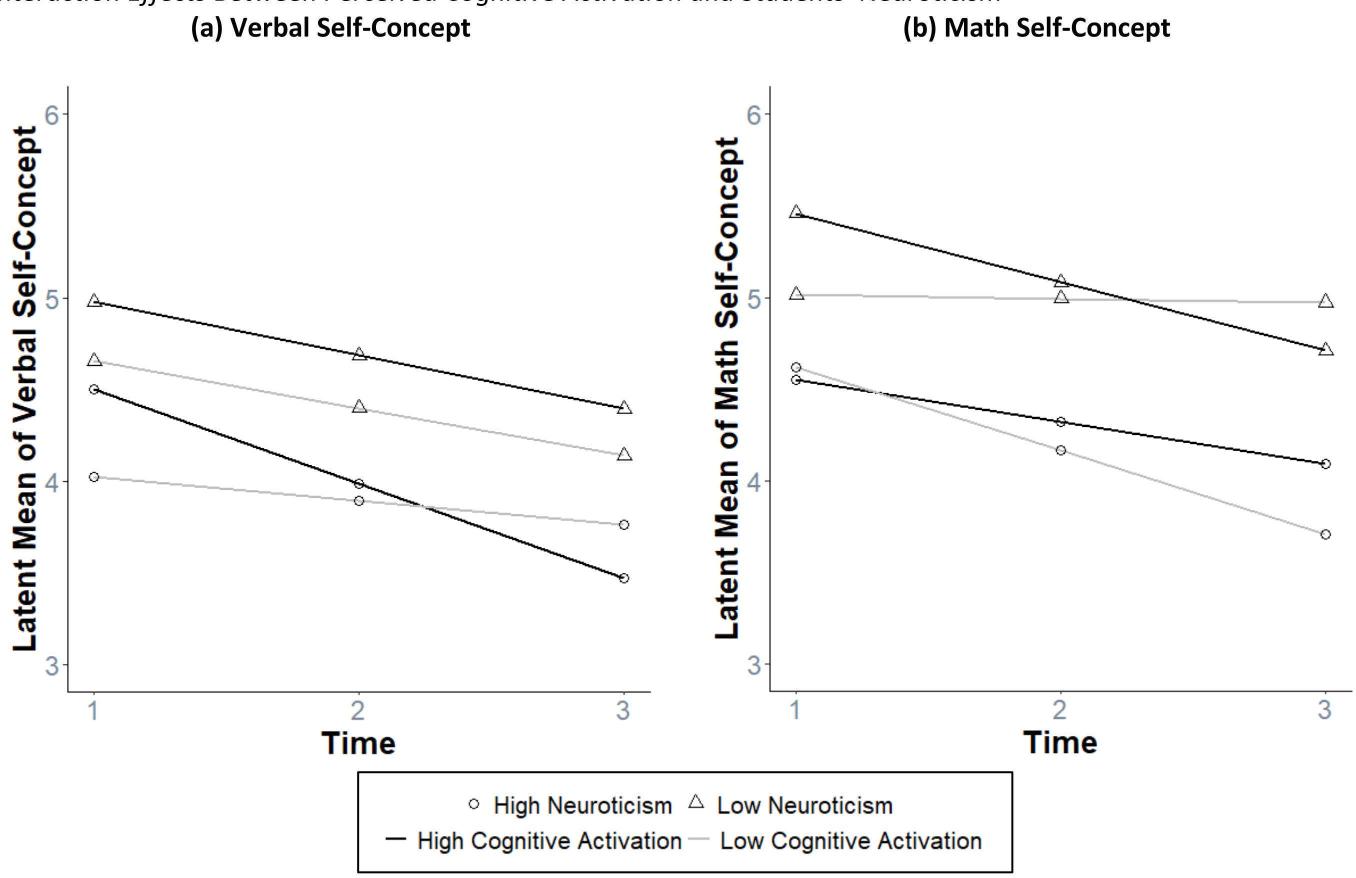
[30] Across all three model sets, only two robust effects of the control variables emerged (see Tables S7 to S9 in the OSM for more detailed results). Deviating from previous models, gender was significantly associated with differences in initial levels of the verbal self-concept (*b*s: 0.25 – 0.62, *p*s < .024). In line with previous modeling steps, attending an academic track school was associated with a less pronounced decline in the verbal self-concept (*b*s: 0.30 – 0.43, *p*s < .001). Some additional effects reached significance within the uncontrolled models presented in Table S6 to S8 in the OSM. Given that the controlled models provide stricter and more conservative tests of our hypotheses, we refrain from interpreting these additional effects.

for those students with higher levels of neuroticism (the black circles). On the other hand, perceiving classes to be low in cognitive activation (the gray lines) was related to a less pronounced decline in math self-concept for students with lower levels of neuroticism (the gray triangles) but to a more pronounced decline for those students with higher levels of neuroticism (the gray circles). Despite this interaction, in all considerations, students with lower levels of neuroticism reported a more positive math self-concept across all measurement points as compared to students with high levels of neuroticism.[31]

In summary, our results support the incremental predictive value of both perceived teaching behavior and student personality for initial verbal and math self. Moreover, there is initial evidence for an interplay of perceived emotional support with students' level of openness and agreeableness and perceived cognitive activation with students' level of neuroticism.

Figure 3

Interaction Effects Between Perceived Cognitive Activation and Students' Neuroticism



Note. High = +1SD of the respective predictor. Low = −1 SD of the respective predictor.

[31] Across all integrative models, the previously established main effects of the control variables on initial levels remained robust. In contrast, their effects on changes did not (see Tables S6 to S8 in the OSM for more detailed results). Without considering the control variables, the reported effects of perceived teaching behavior, student personality, and their interplay were robustly present, except that the interaction effect between emotional support and agreeableness was insignificant ($b = –0.20$, $p = .156$).

Table 6

Estimates of Moderated Conditional LGMs Predict Academic Self-Concept Development by Teacher Support and Student Personality

Predictor	Verbal Self-Concept						Math Self-Concept					
	Intercept			Slope			Intercept			Slope		
	Estimate	*p*	95% CI	Estimate	*p*	95% CI	Estimate	*p*	95% CI	Estimate	*p*	95% CI
	Openness											
Mean	**4.75**	< .001	[4.50, 4.99]	**−0.29**	.001	[−0.45, −0.12]	**5.04**	< .001	[4.83, 5.24]	**−0.24**	.004	[−0.40, −0.08]
Variance	**1.21**	< .001	[0.94, 1.48]	0.02	.802	[−0.13, 0.17]	**1.11**	< .001	[0.78, 1.43]	0.03	.720	[−0.13, 0.18]
Covariance	−0.03	.666	[-0.19, 0.12]				0.12	.196	[−0.06, 0.32]			
TS	**0.38**	< .001	[0.21, 0.54]	**−0.17**[a]	.022	[−0.32, −0.03]	**0.32**	.001	[0.13, 0.50]	−0.10	.159	[−0.23, 0.04]
O	**0.79**	< .001	[0.57, 1.01]	−0.14	.122	[−0.32, 0.04]	0.02	.858	[−0.23, 0.28]	0.02	.863	[−0.22, 0.26]
TS×O	**−0.29**[a]	.047	[-0.58, -0.00]	0.19	.056	[−0.00, 0.38]	0.02	.901	[−0.29, 0.33]	0.14	.171	[−0.06, 0.35]
	Conscientiousness											
Mean	**4.65**	< .001	[4.41, 4.88]	**−0.27**	.001	[−0.43, −0.12]	**5.02**	< .001	[4.81, 5.22]	**−0.24**	.003	[−0.40, −0.08]
Variance	**1.28**	< .001	[1.03, 1.53]	0.03	.660	[−0.11, 0.18]	**1.05**	< .001	[0.73, 1.36]	0.04	.633	[−0.11, 0.19]
Covariance	−0.06	.486	[-0.21, 0.10]				0.11	.236	[−0.07, 0.30]			
TS	**0.41**	< .001	[0.24, 0.59]	**−0.18**[a]	.035	[−0.34, −0.01]	**0.27**	.003	[0.09, 0.44]	−0.10	.132	[−0.22, 0.03]
C	**0.55**	< .001	[0.35, 0.75]	**−0.13**[a]	.042	[−0.26, −0.00]	**0.37**	< .001	[0.20, 0.55]	0.04	.545	[−0.10, 0.18]
TS×C	−0.20	.087	[-0.43, 0.03]	0.02	.839	[−0.14, 0.18]	0.01	.920	[−0.20, 0.22]	0.03	.684	[−0.12, 0.18]
	Extraversion											
Mean	**4.72**	< .001	[4.49, 4.95]	**−0.28**	< .001	[−0.43, −0.12]	**5.05**	< .001	[4.84, 5.25]	**−0.25**	.001	[−0.40, −0.10]
Variance	**1.27**	< .001	[1.02, 1.52]	0.04	.616	[−0.11, 0.18]	**1.09**	< .001	[0.77, 1.42]	0.03	.714	[−0.13, 0.18]
Covariance	−0.08	.304	[-0.23, 0.07]				0.13	.177	[−0.06, 0.32]			
TS	**0.42**	< .001	[0.26, 0.57]	**−0.18**[a]	.021	[−0.34, −0.03]	**0.32**	.001	[0.14, 0.51]	−0.09	.206	[−0.22, 0.05]
E	**0.55**	< .001	[0.37, 0.72]	−0.03	.630	[−0.14, 0.08]	0.12	.151	[−0.04, 0.28]	−0.07	.369	[−0.22, 0.08]
TS×E	−0.05	.652	[-0.26, 0.17]	−0.06	.309	[−0.18, 0.06]	−0.08	.460	[−0.28, 0.13]	0.03	.741	[−0.15, 0.21]
	Agreeableness											
Mean	**4.73**	< .001	[4.47, 5.00]	**−0.34**	< .001	[−0.50, −0.17]	**5.11**	< .001	[4.90, 5.32]	**−0.23**	.006	[−0.40, −0.07]
Variance	**1.42**	< .001	[1.16, 1.68]	0.02	.771	[−0.12, 0.16]	**1.06**	< .001	[0.75, 1.37]	0.03	.720	[−0.12, 0.18]
Covariance	−0.07	.345	[-0.21, 0.07]				0.14	.167	[−0.06, 0.33]			
TS	**0.39**	< .001	[0.21, 0.56]	**−0.16**[a]	.034	[−0.31, −0.01]	**0.31**	< .001	[0.14, 0.48]	−0.09	.198	[−0.23, 0.05]
A	**0.27**[a]	.046	[0.00, 0.54]	**−0.21**	.002	[−0.34, −0.08]	**0.26**	.015	[0.05, 0.47]	0.02	.788	[−0.14, 0.19]
TS×A	−0.00	.991	[-0.28, 0.27]	0.07	.381	[−0.09, 0.24]	**−0.24**[a]	.041	[−0.47, −0.01]	0.11	.325	[−0.11, 0.32]
	Neuroticism											
Mean	**4.50**	< .001	[4.26, 4.74]	**−0.28**	.001	[−0.45, −0.12]	**4.88**	< .001	[4.68, 5.08]	**−0.27**	.004	[−0.45, −0.09]
Variance	**1.36**	< .001	[1.11, 1.61]	0.03	.666	[−0.11, 0.17]	**1.03**	< .001	[0.70, 1.35]	0.03	.692	[−0.12, 0.17]
Covariance	−0.08	.293	[-0.23, 0.07]				0.11	.266	[−0.08, 0.30]			
TS	**0.45**	< .001	[0.27, 0.62]	**−0.18**[a]	.028	[−0.34, −0.02]	**0.29**	.001	[0.11, 0.46]	−0.10	.194	[−0.25, 0.05]
N	**−0.39**	< .001	[-0.59, -0.18]	−0.03	.643	[−0.14, 0.09]	**−0.43**	< .001	[−0.60, −0.26]	−0.10	.229	[−0.26, 0.06]
TS×N	0.20	.105	[-0.04, 0.44]	−0.10	.216	[−0.25, 0.06]	0.02	.874	[−0.20, 0.23]	0.01	.873	[−0.15, 0.18]

Note. N = 1.131. Models controlled for gender (1 = female), fluid reasoning (z-standardized), previous grades (z-standardized), and school track (1 = academic). Significant estimates ($p < .05$) are in bold. a: Significance was not robust for p-value adjustment according to Benjamini & Hochberg (1995).

Table 7

Estimates of Moderated Conditional LGMs Predicting Academic Self-Concept Development by Classroom Management and Student Personality

Predictor	Verbal Self-Concept						Math Self-Concept					
	Intercept			Slope			Intercept			Slope		
	Estimate	*p*	95% CI	Estimate	*p*	95% CI	Estimate	*p*	95% CI	Estimate	*p*	95% CI
	Openness											
Mean	**4.79**	< .001	[4.55, 5.04]	**−0.31**	< .001	[−0.46, −0.17]	**5.08**	< .001	[4.86, 5.30]	**−0.26**	.001	[−0.42, −0.11]
Variance	**1.30**	< .001	[1.02, 1.58]	0.06	.462	[−0.09, 0.20]	**1.12**	< .001	[0.79, 1.45]	0.01	.843	[−0.14, 0.17]
Covariance	−0.11	.186	[−0.27, 0.05]				0.12	.189	[−0.06, 0.31]			
CM	**0.28**	.005	[0.08, 0.47]	−0.07	.247	[−0.19, 0.05]	**0.23**[a]	.012	[0.05, 0.41]	0.08	.366	[−0.10, 0.26]
O	**0.80**	< .001	[0.57, 1.03]	−0.11	.217	[−0.28, 0.06]	0.05	.677	[−0.20, 0.30]	0.03	.793	[−0.22, 0.28]
CM×O	−0.08	.713	[−0.49, 0.33]	−0.10	.393	[−0.32, 0.12]	−0.02	.855	[−0.29, 0.24]	−0.00	.996	[−0.32, 0.32]
	Conscientiousness											
Mean	**4.68**	< .001	[4.46, 4.90]	**−0.28**	< .001	[−0.42, −0.14]	**5.04**	< .001	[4.82, 5.26]	**−0.27**	.001	[−0.42, −0.11]
Variance	**1.39**	< .001	[1.12, 1.66]	0.05	.524	[−0.10, 0.20]	**1.05**	< .001	[0.73, 1.37]	0.02	.796	[−0.13, 0.17]
Covariance	−0.11	.153	[−0.27, 0.04]				0.12	.204	[−0.06, 0.29]			
CM	**0.20**	.017	[0.04, 0.37]	−0.07	.209	[−0.18, 0.04]	**0.18**[a]	.040	[0.01, 0.35]	0.08	.371	[−0.10, 0.27]
C	**0.54**	< .001	[0.34, 0.74]	−0.10	.072	[−0.22, 0.01]	**0.39**	< .001	[0.21, 0.58]	0.00	.955	[−0.14, 0.15]
CM×C	0.08	.523	[−0.18, 0.35]	−0.18	.064	[−0.36, 0.01]	0.09	.347	[−0.10, 0.29]	0.03	.691	[−0.11, 0.17]
	Extraversion											
Mean	**4.74**	< .001	[4.52, 4.96]	**−0.29**	< .001	[−0.43, −0.15]	**5.08**	< .001	[4.86, 5.30]	**−0.28**	< .001	[−0.43, −0.13]
Variance	**1.33**	< .001	[1.08, 1.57]	0.05	.527	[−0.10, 0.19]	**1.11**	< .001	[0.78, 1.43]	0.01	.925	[−0.15, 0.17]
Covariance	−0.10	.171	[−0.25, 0.04]				0.13	.160	[−0.05, 0.31]			
CM	**0.21**[a]	.021	[0.03, 0.39]	−0.09	.105	[−0.20, 0.02]	**0.23**[a]	.013	[0.05, 0.40]	0.10	.348	[−0.11, 0.30]
E	**0.55**	< .001	[0.37, 0.72]	−0.04	.520	[−0.15, 0.07]	0.11	.165	[−0.04, 0.27]	−0.07	.403	[−0.23, 0.09]
CM×E	0.28	.091	[−0.04, 0.60]	−0.09	.193	[−0.22, 0.04]	0.11	.339	[−0.12, 0.34]	0.06	.617	[−0.16, 0.28]
	Agreeableness											
Mean	**4.79**	< .001	[4.55, 5.04]	**−0.37**	< .001	[−0.52, −0.22]	**5.15**	< .001	[4.92, 5.38]	**−0.27**	< .001	[−0.42, −0.12]
Variance	**1.48**	< .001	[1.21, 1.76]	0.04	.623	[−0.11, 0.18]	**1.09**	< .001	[0.76, 1.41]	0.01	.876	[−0.14, 0.16]
Covariance	−0.11	.153	[−0.25, 0.04]				0.13	.175	[−0.06, 0.31]			
CM	**0.22**	.014	[0.04, 0.39]	−0.06	.245	[−0.17, 0.04]	**0.20**[a]	.027	[0.02, 0.38]	0.09	.347	[−0.10, 0.27]
A	**0.32**[a]	.025	[0.04, 0.60]	**−0.24**	.001	[−0.39, −0.10]	**0.26**	.029	[0.03, 0.50]	0.00	.967	[−0.15, 0.16]
CM×A	−0.05	.726	[−0.35, 0.24]	−0.01	.891	[−0.20, 0.17]	−0.09	.496	[−0.36, 0.17]	0.03	.672	[−0.12, 0.18]
	Neuroticism											
Mean	**4.57**	< .001	[4.35, 4.80]	**−0.32**	< .001	[−0.47, −0.17]	**4.90**	< .001	[4.69, 5.11]	**−0.30**	.001	[−0.47, −0.13]
Variance	**1.47**	< .001	[1.19, 1.74]	0.05	.528	[−0.10, 0.19]	**1.03**	< .001	[0.70, 1.36]	0.01	.905	[−0.13, 0.15]
Covariance	−0.13	.097	[−0.28, 0.02]				0.11	.231	[−0.07, 0.29]			
CM	**0.24**	.008	[0.06, 0.42]	−0.09	.112	[−0.20, 0.02]	**0.18**[a]	.032	[0.01, 0.35]	0.08	.410	[−0.11, 0.26]
N	**−0.34**	.002	[−0.55, −0.13]	−0.05	.484	[−0.17, 0.08]	**−0.42**	< .001	[−0.60, −0.25]	−0.10	.282	[−0.27, 0.08]
CM×N	0.00	.969	[−0.27, 0.28]	−0.05	.472	[−0.20, 0.09]	−0.18	.084	[−0.38, 0.02]	0.05	.461	[−0.08, 0.18]

Note. *N* = 1.131. Models controlled for gender (1 = female), fluid reasoning (z-standardized), previous grades (z-standardized), and school track (1 = academic). Significant estimates (p < .05) are in bold. a: Significance was not robust for p-value adjustment according to Benjamini & Hochberg (1995).

Table 8

Estimates of Moderated Conditional LGMs Predicting Academic Self-Concept Development by Cognitive Activation and Student Personality

Predictor	Verbal Self-Concept						Math Self-Concept					
	Intercept			Slope			Intercept			Slope		
	Estimate	*p*	95% CI	Estimate	*p*	95% CI	Estimate	*p*	95% CI	Estimate	*p*	95% CI
Openness												
Mean	**4.78**	< .001	[4.54, 5.03]	**−0.30**	< .001	[−0.45, −0.14]	**5.09**	< .001	[4.86, 5.32]	**−0.24**	.003	[−0.40, −0.09]
Variance	**1.35**	< .001	[1.08, 1.62]	0.06	.465	[−0.09, 0.20]	**1.16**	< .001	[0.83, 1.49]	0.04	.620	[−0.11, 0.19]
Covariance	−0.11	.189	[−0.27, 0.05]				0.11	.247	[−0.08, 0.30]			
CA	0.13	.252	[−0.10, 0.36]	−0.12	.193	[−0.30, 0.06]	0.10	.442	[−0.15, 0.34]	−0.02	.845	[−0.19, 0.16]
O	**0.75**	< .001	[0.49, 1.01]	−0.08	.455	[−0.31, 0.14]	0.03	.826	[−0.21, 0.27]	0.05	.711	[−0.21, 0.30]
CA×O	−0.01	.962	[−0.52, 0.49]	−0.09	.591	[−0.40, 0.23]	0.11	.686	[−0.43, 0.66]	−0.03	.877	[−0.43, 0.37]
Conscientiousness												
Mean	**4.66**	< .001	[4.44, 4.89]	**−0.27**	< .001	[−0.42, −0.13]	**5.04**	< .001	[4.82, 5.26]	**−0.24**	.002	[−0.40, −0.09]
Variance	**1.40**	< .001	[1.14, 1.67]	0.05	.469	[−0.09, 0.20]	**1.06**	< .001	[0.74, 1.39]	0.04	.569	[−0.10, 0.19]
Covariance	−0.12	.169	[−0.28, 0.05]				0.11	.253	[−0.08, 0.29]			
CA	0.22	.054	[−0.00, 0.44]	−0.11	.213	[−0.29, 0.06]	0.06	.631	[−0.18, 0.29]	−0.02	.805	[−0.21, 0.16]
C	**0.55**	< .001	[0.35, 0.75]	**−0.14**[a]	.037	[−0.27, −0.01]	**0.42**	< .001	[0.23, 0.61]	0.02	.734	[−0.12, 0.17]
CA×C	0.08	.674	[−0.29, 0.45]	−0.21	.116	[−0.48, 0.05]	0.31	.054	[−0.00, 0.63]	−0.10	.255	[−0.26, 0.07]
Extraversion												
Mean	**4.75**	< .001	[4.53, 4.97]	**−0.28**	< .001	[−0.43, −0.14]	**5.10**	< .001	[4.88, 5.33]	**−0.27**	< .001	[−0.42, −0.12]
Variance	**1.38**	< .001	[1.13, 1.63]	0.05	.462	[−0.09, 0.20]	**1.16**	< .001	[0.83, 1.49]	0.04	.637	[−0.11, 0.19]
Covariance	−0.11	.122	[−0.26, 0.03]				0.11	.247	[−0.08, 0.30]			
CA	0.21	.051	[−0.00, 0.43]	−0.15	.090	[−0.32, 0.02]	0.09	.454	[−0.15, 0.34]	−0.02	.835	[−0.20, 0.16]
E	**0.54**	< .001	[0.37, 0.72]	−0.05	.401	[−0.16, 0.07]	0.11	.187	[−0.05, 0.27]	−0.06	.418	[−0.21, 0.09]
CA×E	0.06	.760	[−0.35, 0.48]	−0.16	.064	[−0.34, 0.01]	0.08	.636	[−0.26, 0.43]	−0.13	.312	[−0.39, 0.12]
Agreeableness												
Mean	**4.78**	< .001	[4.53, 5.03]	**−0.36**	< .001	[−0.51, −0.21]	**5.16**	< .001	[4.92, 5.41]	**−0.26**	.001	[−0.42, −0.11]
Variance	**1.49**	< .001	[1.22, 1.76]	0.03	.659	[−0.11, 0.17]	**1.13**	< .001	[0.81, 1.46]	0.04	.606	[−0.11, 0.18]
Covariance	−0.10	.178	[−0.24, 0.04]				0.11	.252	[−0.08, 0.29]			
CA	0.19	.079	[−0.02, 0.41]	−0.11	.163	[−0.27, 0.05]	0.06	.649	[−0.19, 0.30]	−0.01	.941	[−0.18, 0.17]
A	**0.35**[a]	.010	[0.09, 0.62]	**−0.21**[a]	.026	[−0.39, −0.03]	**0.29**[a]	.012	[0.06, 0.52]	−0.01	.923	[−0.18, 0.17]
CAXA	0.05	.788	[−0.30, 0.39]	0.08	.509	[−0.17, 0.33]	0.04	.836	[−0.32, 0.39]	0.18	.398	[−0.24, 0.61]
Neuroticism												
Mean	**4.54**	< .001	[4.31, 4.76]	**−0.30**	< .001	[−0.45, −0.15]	**4.91**	< .001	[4.71, 5.11]	**−0.27**	.002	[−0.44, −0.10]
Variance	**1.46**	< .001	[1.19, 1.72]	0.03	.646	[−0.10, 0.17]	**1.05**	< .001	[0.72, 1.38]	0.01	.917	[−0.14, 0.16]
Covariance	−0.11	.144	[−0.25, 0.04]				0.11	.243	[−0.07, 0.29]			
CA	**0.28**[a]	.012	[0.06, 0.50]	−0.15	.075	[−0.31, 0.01]	0.13	.298	[−0.12, 0.38]	−0.04	.626	[−0.23, 0.14]
N	**−0.39**	< .001	[−0.60, −0.17]	−0.03	.600	[−0.16, 0.09]	**−0.46**	< .001	[−0.64, −0.27]	−0.10	.279	[−0.28, 0.08]
CA×N	0.08	.638	[−0.24, 0.40]	**−0.17**[a]	.025	[−0.32, −0.02]	**−0.26**[a]	.036	[−0.50, −0.02]	**0.29**	.002	[0.11, 0.47]

Note. *N* = 1.131. Models controlled for gender (1 = female), fluid reasoning (z-standardized), previous grades (z-standardized), and school track (1 = academic). Significant estimates (p < .05) are in bold. a: Significance was not robust for p-value adjustment according to Benjamini & Hochberg (1995).

Discussion

How is students' academic self-concept development linked to their perception of teaching behaviors and personality traits? Do personality traits moderate the link between perceived teaching behaviors and academic self-concept development? Given the relevance of academic self-concepts for academic outcomes (e.g., Jansen et al., 2021; Möller et al., 2020; Musu-Gillette et al., 2015; Von Keyserlingk et al., 2020) and the previously reported decline across late childhood and adolescence (cf., Wigfield et al., 2015), our study addressed these research questions focusing on developmental trends in a large longitudinal study across the transition to German upper secondary school. Four result patterns stand out: First, verbal and math self-concepts declined across this transition. Second, higher perceived emotional support, classroom management, conscientiousness and agreeableness, and lower neuroticism related to higher initial self-concept levels. Third, aside from more pronounced declines in the verbal self-concept in light of higher perceived emotional support and agreeableness, robust associations with the development of academic self-concepts were sparse. Finally, supporting a moderation, the effects of perceived emotional support and cognitive activation varied across students' openness, agreeableness, and neuroticism. In the following, we discuss implications of these findings in light of previous literature.

Predicting Verbal and Math Self-Concept (Development)

In line with previous work (e.g., Nagy et al., 2010; Postigo et al., 2022; Wigfield et al., 2015), students' verbal and math self-concept substantially decline across our study. At younger ages, the decline in academic self-concepts probably reflects an increasing sense of reality in the self-perception of students' abilities (Wigfield et al., 2015), which might be considered a good development. Contrary, the persistence of this negative trend in adolescence and its magnitude across a single year, can be considered concerning for at least two reasons: First, academic self-concepts are particularly relevant in the transition to adulthood because of their predictive power concerning academic performance (Möller et al., 2020; Von Keyserlingk et al., 2019). Second, academic self-concepts affect the choice of educational pathways and, thereby, are linked to career opportunities (Von Keyserlingk et al., 2020). Moreover, our results emphasize that established predictors such as previous grades and the attended school track (Eccles & Wigfield, 2020; Fang et al., 2018; Möller et al., 2020) only accounted for a small portion of the decline in academic self-concepts, highlighting the need to consider additional factors. Building on theoretical assumptions of the EVT (Eccles & Wigfield, 2020; Wigfield & Eccles, 2000), we examined the contribution of students' perceptions of teaching behavior and their Big Five personality to academic self-concept development.

Associations of Perceived Teaching Behavior and Student Personality with Initial Self-Concept Levels

Although our primary interest was a better understanding of the academic self-concept development, our study also replicates and extends findings on academic self-concept levels. First, we substantiate that perceptions of teaching behaviors (Jensen et al., 2019; Lazarides & Ittel, 2012; Skaalvik & Skaalvik, 2013; W. Wagner et al., 2016) and their Big Five personality traits (Johannsen et al., 2024; Marsh et al., 2006) are closely linked to academic self-concepts. That is, the way students perceive their academic abilities cross-sectionally related to both the behavior of German and math teachers and the students' general behavioral tendencies.

Second, our results indicate subject-specific associations of perceived cognitive activation and students' openness and extraversion. That is, associations emerged only with verbal but not math self-concept levels. These differential patterns align with previous cross-sectional studies linking students' academic self-concept and Big Five personality (Johannsen et al., 2024; Marsh et al., 2006). They probably reflect the less-specific requirements of language classes that are often characterized by more diverse tasks, which also require and reward oral participation. Thus, there might be more possibilities to express a student's personality (Brandt et al., 2020; Meyer et al., 2023), and this might be particularly beneficial for more open-minded and extraverted students. Along these lines, they may experience more positive feedback and establish higher levels of verbal self-concept.

Third, we expand on research focusing on only one teaching behavior by considering three key aspects (Jensen et al., 2019; Lazarides & Ittel, 2012). Notably, the results show that students' perceptions of emotional support and classroom management were consistently related to initial academic self-concepts, but perceptions of perceived cognitive activation were not. Specifically, the positive associations of cognitive activation with initial levels of the verbal self-concept were not robust concerning the conjoint consideration of student personality. That is, including a student's personality and the moderation effect showed that the main effects of higher cognitive activation supporting higher self-concepts cannot be generalized, but appear to be dependent on students' personality traits. We will discuss these moderating effects in more detail under a later headline (see *Coloring the Perception of Teaching Behaviors: The Role of Big Five Personality*).

Lack of Associations with Academic Self-Concept Development

Somewhat surprising were the limited predictive effects of perceived teaching behaviors and student personality traits regarding the verbal and math self-concept development. Furthermore, some of the effects were contrary to our expectations. We want to highlight two aspects that might explain these unexpected results. First, despite the null findings, we do not rule out more predictive effects at other time points or across different time frames. Theoretical notions and empirical results support the relevance of perceived teaching behaviors and students' personality traits for academic self-concept levels and development (Brandt et al., 2021; Eccles & Roeser, 2009; Eccles & Wigfield, 2020). However, our study focused on a short and specific time frame within students' educational pathways: one year including the transition to upper secondary school. The limited extent of change within such a short time frame might limit the probability of finding predictive effects. Nevertheless, our findings do not rule out that predictive effects exist over other or longer time periods. When it comes to age differences, one might argue that effects could be more pronounced in lower grade levels because associations of academic self-concept with previous performance become stronger over time (Denissen et al., 2007; Möller et al., 2020), while associations between personality and performance become less pronounced in higher grade levels (Brandt et al., 2020; Israel et al., 2022; Poropat, 2009). Thus, future research needs to consider varying time frames and time points throughout students' educational paths to test this assumption.

Second, our study targeted the transition to upper secondary school as it is a relevant period for academic self-concept development (cf. Eccles & Roeser, 2009). Within our study, two measurement points took place in the 10th grade, and the third measurement point captured the transition to upper secondary school in Germany. This transition involves substantial contextual changes in academic and social domains (Becker et al., 2017; W. Wagner et al., 2011). Looking at the academic side, the transition is associated with the increasing relevance of academic performance for future life outcomes and increased academic demands. These academic changes might be important drivers of academic self-concept development in their own right and, thus, contributed to the absence of longitudinal effects in our study. Looking at the social side, the transition involves changes in peer and teacher relationships. These social changes potentially contributed to two unexpected findings in our study: Students who perceived higher emotional support and reported higher levels of agreeableness experienced more pronounced declines in their verbal self-concept. On the one hand, this finding may indicate that teachers provide more (emotional) support to students who exhibit a consistent decline in their verbal self-concept. Consequently, teachers might recognize this negative trend and seek to address it. On the other hand, high perceived emotional support and high agreeableness may indicate that these students strive for positive teacher and peer relationships. Positive teacher and peer relations generally contribute to positive school experiences and should, therefore, have a positive effect on academic self-concepts (e.g., Aldrup et al., 2018;

Israel et al., 2022; Kunter et al., 2013). At the same time, research indicates that higher levels of agreeableness are particularly effective in close and stable relationships (J. Wagner et al., 2014). The transition to upper secondary school involves a certain level of instability in peer and teacher relationships that may undermine their positive effects. Consequently, the transition might be particularly challenging for those with a pronounced need for positive peer and teacher relationships.

Our results indicated that perceived teaching behaviors and students' Big Five personality traits could not per se protect against the decline in academic self-concepts across the important educational transition to upper secondary school. Future research could further broaden the perspective by, first, considering teacher behaviors and personality traits across other educational periods and, second, adding more nuanced information on social relationships.

Coloring the Perception of Teaching Behaviors: The Role of Big Five Personality

To what degree do Big Five personality traits tint students' perceptions of teaching behaviors and their effect on academic self-concepts? We could detect dependencies between perceived teaching behavior and individual student personality by conjointly considering their associations with academic self-concepts. Our results indicate the robustness of most of the main effects of perceived teaching behaviors and personality traits. Additionally, some interesting interaction effects emerged.

The robustness of cross-sectional main effects was especially evident for perceived classroom management and students' level of conscientiousness. Despite theoretical notions indicating that students' perceptions of primary socializers partly depend on students' individual characteristics (Eccles & Wigfield, 2020; Wigfield & Eccles, 2000), the cross-sectional effects of perceived classroom management and students' conscientiousness seem to be additive rather than interactive. Across German and math classes, students benefitted from the structure provided by their teachers (i.e. high classroom management) and from the structured being rooted in their general behavioral tendencies (i.e. higher conscientiousness). In line with previous findings, well-structured classrooms support students in their development of self-regulatory skills and thereby lead to more positive learning experiences (e.g., Hamre et al., 2013; Hamre & Pianta, 2010), and students with high organizing skills and self-control are well equipped to meet the academic demands (Bidjerano & Dai, 2007; Trautwein et al., 2015).

Significant interaction effects emerged for two of the three teaching characteristics, supporting the expected moderating effect of student personality: First, students with lower levels of openness and agreeableness benefitted more profoundly from experiencing emotional support from their teachers. Thus, perceptions of higher levels of emotional support by their teachers compensate for the challenges faced by students with lower levels of these traits, such as being less curious and intellectual and having more conflictual relationships with teachers and peers. Despite these positive effects on initial academic self-concept levels at the beginning of the 10th grade, these compensatory effects did not generalize to developmental trends and, thus, did not protect against the decline of verbal and math self-concept. Importantly, only openness moderated the association of perceived emotional support with verbal self-concept, while agreeableness moderated the association with math self-concept. This finding further corroborates essential differences between subject domains. The subject-specific associations are in line with main-effect findings from our study, showing the specific relevance of openness regarding the verbal self-concept as well as with initial findings from Talić and colleagues (2024), proposing an interplay between teacher support and student’ agreeableness on lesson-specific math self-perceptions.

Second, students who tend to be less emotionally stable and more anxious show less favorable developments of their verbal self-concept, but more favorable developments of their math self-concept in classrooms they perceive as being particularly cognitively challenging. Thus, we have opposite interaction effects for the two considered academic self-concepts. Neuroticism is a relevant trait with regard to self-evaluations and coping with challenging demands (Bien et al., 2024; J. Wagner et al., 2013). Similar to the two opposite interaction effects, however, previous findings in adolescent and school contexts also emphasize that higher levels of neuroticism can have both beneficial and detrimental effects. Some studies find no or even positive relations between neuroticism and school performance (Israel et al., 2019; Johannsen et al., 2024), as more neurotic students potentially prepare themselves better for exams. On the other hand, in many studies, higher levels of neuroticism are associated with a myriad of adverse outcomes (Wieczorek et al., submitted manuscript). Our findings emphasize the need to further disentangle the functionality of neuroticism within adolescence, generally, and educational contexts, specifically.

Additionally, the subject-specific differences raise the question of whether the meaning and function of cognitive activation differ across subject domains. Cognitive activation refers to the properties of tasks and their potential to engage students in goal-oriented cognitive activities. Items assessing cognitive activation refer to the time, thought, and explanation needed to fulfill the given tasks. Tasks requiring more time, thought, and explanation may, however, be perceived and interpreted differently across subjects. To illustrate, in German or other language classes, students may interpret assignments requiring more time, thought, and explanation as creative freedom. In contrast, in math classes, assignments are more clearly structured into right and wrong. Thus, students may perceive tasks requiring more time, thought, and explanation as more challenging. Our results now suggest that for students with higher levels of neuroticism, the creative freedom in German classes might complicate the adaptation to the higher academic demands in upper secondary school. In contrast, when it comes to math classes, students with higher levels of neuroticism might adapt their learning behavior to the more challenging tasks, which might also prepare them more effectively for this transition.

Our results provide first evidence of an interplay between perceived teaching behavior and student personality. While the positive effects of effective classroom management remained robust even when conjointly considered with student personality, the effects of perceived emotional support and cognitive activation vary with students' Big Five personality traits. Interestingly, moderation effects even differ across subject domains of the academic self-concept. Future research should further investigate the interplay of known contextual and individual characteristics in predicting academic self-concept levels and change.

Limitations and Future Directions

Despite the strengths of using a longitudinal design with a large and diverse sample, self-report scales, objective test scores for cognitive variables, and latent variable approaches to control for potential measurement errors, we need to consider a number of limitations. First, our sample was characterized by a considerable amount of longitudinal dropout. More specifically, participants who dropped out differed from those providing longitudinal data regarding gender, school track[32], and immigrant background, and they reported lower levels of verbal self-concept, emotional support by their German teachers, and agreeableness. While the selectivity effects were small in size regarding our variables of interest, the differences in our control variables were partly medium in size. Although we included the control variables in all reported models and accounted for missing data using a FIML approach, which produces robust and widely unbiased results in latent modeling with missing data (Enders & Bandalos, 2001), selective attrition might limit the generalizability of our findings.

Second, although our data is based on a large demographically diverse sample, our results are based on data from one federal state and might not generalize to other educational systems. That is, school systems across the federal states in Germany differ regarding teacher

[32] Importantly, the differences regarding academic track attendance and immigrant background resulted partly from to school principals not wanting to participate in the longitudinal part of the study and, thus, were not revisited after the first measurement. Moreover, this study took place in a federal state in which students at all tracks can move on to 11th grade.

training and professional incentives provided to teachers (see Becker et al., 2017, for an overview). Consequently, teaching behaviors and students’ perceptions of these behaviors might systematically vary, and our results might not generalize across federal states or countries. Future research should test whether the relevance of perceived teaching behaviors, student personality traits, and their interplay varies across educational environments.

Third, we used students’ self-reports to assess most of our constructs. Self-evaluations are one key method to capture students' individual perceptions of academic self-concepts and personality. Furthermore, students’ perceptions of teaching behavior may be considered particularly informative for their own academic self-concept development (cf. Talić et al., 2024), as compared to teacher perceptions of their own behaviors or objective measures of the same behavior. That is, the idiosyncratic perception of a student might be particularly important for their own development. Such perceptions are known to differ substantially between students as well as from other perceptions (Aldrup et al., 2018; Putnick et al., 2020), but may better reflect the differential relevance of teaching behaviors. Nevertheless, as EVT also proposes additional effects of teachers' behaviors, it would be most informative to extend the students' perception by including teacher perceptions or even observations of teaching behavior to capture the educational context more comprehensively. Moreover, personality other reports provided by teachers, peers, or parents could add a different perspective to the relevance of behavioral aspects of personality and add further depth to our understanding of academic self-concept development.

Conclusion

In conclusion, this study enhances our understanding of the predictors of academic self-concept levels and change during the critical transitional period to upper secondary school. Our findings illustrate a general decline in verbal and math self-concepts from the 10th into the 11th grade. While the theoretically identified predictors of teachers' emotional support and classroom management, as well as students' Big Five personality traits accounted for individual differences in self-concept levels, there was minimal evidence to suggest that these factors predicted the decline in academic self-concept. Our results offer preliminary evidence of that students' personalities color their perception of teaching behaviors. Future research should investigate these associations and potential dynamics over extended periods and across various educational contexts. This will help assess our findings' robustness and enhance our understanding of how contextual and individual characteristics co-shape the development of academic self-concepts. Such insights are essential for tailoring educational approaches that better support increasingly diverse classrooms and foster a more positive development of academic self-concepts during this critical developmental period**.**

Open Science Statement

All hypotheses of this study have been preregistered (https://osf.io/qser2). We report how we determined our sample size, all data exclusions (if any), all manipulations, and all measures in the study, and the study follows JARS (Applebaum, et al., 2018). We describe the demographic composition of our sample. We provide information regarding all procedures and measures used in this study by referring to openly accessible material. We disclose if the data have been used in other papers and, if yes, where. All data and analysis code needed to reproduce the results https://osf.io/n96uc/. We provide a rationale for including covariates and tested models with and without the covariates. We report basic descriptive statistics, effect sizes, exact p-values, and 95% confidence intervals.

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5. General Discussion

Based on the importance of academic success in adolescence for future life paths, within this dissertation I addressed three overarching research objectives: First, I investigated in what way students' personality traits and academic self-concepts as two crucial self-perceptions relate to each other and academic performance in adolescence. Second, I examined how individual self-perceptions differentiate social inequalities in academic performance associated with individual sociodemographic characteristics. Third, I looked into how self-perceptions and their development vary with classroom peers and teachers' behavior. Study 1 focused on the first research objective and shed light on cross-sectional associations of student personality and their academic self-concepts with each other and with academic performance levels and changes. Additionally, it addressed the second research objective by testing student personality and academic self-concepts qualify the predictive effect individual sociodemographic characteristics as distal contextual conditions. Study 2 addressed the third research objective and investigated the role of classroom peers in individual personality development. Study 3 looked into the first and third research objective by investigating the role of student personality in academic self-concept development, while considering three central teaching behaviors as contextual predictors.

Collectively, the three studies provide important insights regarding the interrelatedness, relevance in social inequalities, and development of student personality and academic self-concept within the school context. In the following sections, I first, summarize the key findings of the empirical studies and afterwards derive theoretical, methodological, and practical implications. Concluding this chapter, I critically address the limitations encountered in the studies and provide an outlook for future research.

5.1 Central Findings

Within the following section, I will present the key findings referring to the three overarching research objectives of this dissertation. First, I focus on findings regarding the integration of students' Big Five personality traits and domain-specific academic self-concepts as two crucial self-perceptions predicting academic performance. Second, I elaborate on the how these individual self-perceptions qualify social inequalities and summarize the findings on how peer and teachers as contextual conditions contribute to these individual self-perceptions and their development in adolescence.

This is Me Trying: Integrating Student Personality and Academic Self-Concepts

Addressing the first overarching research objective, Studies 1 and 3 took an integrative look at students' personality traits and academic self-concepts as two crucial self-perceptions predicting academic performance in adolescence. As there are different theoretical and empirical approaches to integrate domain-general dispositions and context-specific characteristic adaptations, the two studies integrated student personality and academic self-concepts in three ways: 1) they addressed their cross-sectional interrelatedness within a nomological net (Study 1 and 3); 2) they tested their conjoint predictivity in terms of incremental and interactive effects (Study 1); 3) they tapped into their sequential ordering (Study 3).

Regarding the *nomological net*, the results of Study 1 and 3 support the cross-sectional interrelatedness of student personality traits and academic self-concepts. Thereby, they replicate initial results (Marsh et al., 2006; Spengler et al., 2016) by demonstrating strong and widely consistent cross-sectional associations across three independent samples. Moreover, the results refine our understanding of the cross-sectional interrelatedness by illustrating important domain-specific differences. That is, across the two samples of Study 1 and the original sample of Study 3, the verbal self-concept consistently related to lower levels of neuroticism and higher levels of all remaining Big Five traits, while the math self-concept was only consistently associated with higher levels of conscientiousness and lower levels of neuroticism. Hence, the association between student personality and the math self-concept seem less pronounced or more dependent on sample characteristics and personality measures, or additional unobserved confounders.

Specifically addressing the *conjoint predictivity* of student personality and academic self-concepts, Study 1 replicated previous results on the incremental cross-sectional predictivity of conscientiousness and openness beyond the verbal self-concept (Marsh et al., 2006; Spengler et al., 2016). Findings regarding math performance and the remaining traits, however, were less consistent. Moreover, academic self-concepts also predicted changes in performance, whereas for personality, the longitudinal results differed from the cross-sectional findings. Such inconsistencies underline the complexity of personality-performance associations also evident in previous research (Brandt, Lechner, et al., 2020; Tetzner et al., 2020). Importantly, Study 1 moved beyond existing research by also testing interactive effects in predicting academic performance. While the specific interactions were not completely consistent across samples, two important result patterns stand out: First, there were more interactive effects regarding the prediction of grades than test scores. These results refine earlier assumptions, indicating that teachers' evaluations of academic performance across extended periods, which permit greater expression of personality, are more strongly associated with student personality than evaluations based on one-time testing situations (Borghans et al., 2016; Lechner et al., 2017;

Spengler et al., 2013). Second, a pattern of synergistic interactive effects emerged. All significant interaction effects illustrated that those students with high domain-specific academic self-concepts benefited even more from academically favorable personality traits compared to those with lower academic self-concepts.

Regarding their *sequential ordering*, Study 3 tested whether students' personality predicted the development of academic self-concepts. While there was no evidence regarding the expected longitudinal predictivity of openness and conscientiousness, the exploratory analyses revealed that students with higher initial levels of agreeableness showed more pronounced decreases in the verbal self-concept across time. Nevertheless, the size of this effect was rather small and, therefore, replication is needed to confirm its robustness.

Altogether, the results of Studies 1 and 3 make an important contribution to integrating student personality and academic self-concepts. That is, they corroborate their cross-sectional interrelatedness and partly replicate the incremental validity of students' openness and conscientiousness. Moreover, the findings provide first evidence regarding an interactive interplay. The results, however, do not paint a clear picture regarding the sequential ordering of student personality and academic self-concepts. Importantly, the emerging inconsistencies emphasize the complexity of learning experiences and highlight the importance of potential systematic differences between academic domains, across different measures and contextual conditions. Taking a transactional perspective, this dissertation specifically addressed how contextual conditions potentially contribute to these differences.

So High School: Contextual Conditions Differentiating Academic Performance and Individual Development

In line with the second and third overarching research objectives, all three studies followed a context-sensitive approach and looked into transactions between individual characteristics and contextual conditions. At the distal contextual level, Study 1 examined the role of student personality and academic self-concept in social inequalities linked to their sociodemographic characteristics. At the most immediate contextual level—the classroom—Study 2 explored the relevance of peer composition for individual personality development, and Study 3 investigated how teaching behaviors contribute to adolescents' academic self-concepts and their development.

Addressing *social inequalities*, Study 1 looked into the interplay of individual self-perceptions with students' sociodemographic characteristics in predicting academic performance. The results contribute to a more holistic understanding of social inequalities in the academic context in two ways: First, and in line with previous findings (OECD, 2019; Sirin, 2005; Voyer & Voyer, 2014), the results underline the effects of student gender, immigrant background, and parental socioeconomic status onto academic performance, that were also evident beyond students' personality and academic self-concepts. Importantly, the main effects were less pronounced for grades, indicating that grading practices may partially mitigate social inequalities (cf. Doyle et al., 2023). Second, by testing the proposed interplay between students' self-perceptions and sociodemographic characteristics (cf. Brandt & Wagner, 2024), the results of Study 1 illustrate the complexity of social inequalities and their contribution to academic performance. Overall, the pattern of interaction effects indicates a synergistic interplay between students' sociodemographic characteristics and their self-perceptions. These results contradict previous findings indicating that students' personality and academic self-concept compensate for social inequalities in international samples (Ayoub et al., 2018; Damian et al., 2015; Ross & Mirowsky, 2006; Shanahan et al., 2014) but rather support that they reinforce social inequalities within the German school system (Lechner et al., 2021). Interestingly, interactions with student personality were more evident in relation to grades, while academic self-concepts were more strongly associated with differences in social inequalities based on test scores.

Testing for classroom *peer composition* effects on individual personality development in adolescence, Study 2 investigated whether the class-level of student personality traits related to individual developments therein. Despite theoretical notions highlighting the relevance of peers for individual personality development (e.g., Back et al., 2011) and the relevance of class composition regarding academic self-concepts (Möller et al., 2020; Wolff et al., 2021), the results did not indicate any peer composition effects. While first evidence from a university sample indicated that there might be composition effects on personality development in academic contexts (Shan & Zölitz, 2022), this dissertation failed to replicate these findings—in line with another recent study (Krämer et al., 2025). That is, in light of the high stability of student personality, no substantial peer composition effects on individual personality development emerged.

Considering *teaching behaviors* as conditions within the immediate classroom context, Study 3 provided insights into the role of teacher's emotional support, classroom management, and cognitive activation for individual academic self-concept development. Given the marked decline in adolescents' verbal and math self-concepts during the transition to upper secondary school, the findings replicate positive cross-sectional links between perceived emotional support and classroom management and students' verbal and math self-concepts (Jensen et al., 2019; Lazarides & Ittel, 2012; Skaalvik & Skaalvik, 2013; W. Wagner et al., 2016), although longitudinal evidence was scarce. Importantly, the effects of perceived emotional support and cognitive activation varied across students' openness, agreeableness, and neuroticism. Thereby, the findings illustrated a transactional interplay between students' individual personality and their perception of teaching behaviors as contextual conditions.

Altogether, the empirical findings of this dissertation underscore the importance of adopting an integrative, context-sensitive perspective on individual performance predictors, their role in social inequalities, and their development in adolescence. Furthermore, the results from the three studies point to the need for further theoretical refinement—both in integrating different levels of self-perceptions and in examining their development through a transactional lens.

5.2 Theoretical Implications

This dissertation supports and refines theoretical considerations regarding the integration of student personality and academic self-concepts, their role in social inequalities and their contextualized development in school. As an overarching theoretical implication, the results support taking an interdisciplinary and transactional perspective on learning and development in school. They do so by 1) illustrating complex and partly domain-specific interactive associations between individual self-perceptions and contextual conditions and 2) underlining the advantages of taking an interdisciplinary perspective on student-environment transactions. In the following, I will elaborate on these two theoretical implications in more detail.

The Interactive and Domain-Specific Contribution of Self-Perceptions to Academic Performance

Beyond supporting the cross-sectional nomological net between student personality and academic self-concept, this dissertation illustrates their conjoint predictivity and indicates an interactive interplay, with notable differences across personality measures and academic domains. These findings reinforce the idea of hierarchically ordered levels of the self (Graziano et al., 1997; Kandler et al., 2014; McAdams, 1995; McAdams & Olson, 2010; McCrae, 2009) by replicating that domain-general personality traits and context-specific academic self-concepts are interrelated (Marsh et al., 2006; Spengler et al., 2016). Moreover, domain-general traits demonstrated incremental validity beyond the stronger relations of academic self-concepts, emphasizing that self-perceptions at different levels of the self are relevant within academic contexts. Importantly, the findings related to the first overarching research aim contribute to our understanding of interactive predictive effects and underscore the importance of accounting for both specific personality facets and academic domains.

Extending previous findings with initial indications of an interactive interplay between student personality and academic self-concepts, this dissertation provides an inductive impulse for further theory development. Previous theoretical elaborations have assumed general dispositions (i.e. specific personality traits) to interact with different characteristic adaptations in academic contexts (Trautwein et al., 2019; Ziegler et al., 2012). This dissertation applied this assumption to Big Five personality traits and domain-specific academic self-concepts. While the results only provide first evidence and especially single interaction effects should be interpreted cautiously, the overall interactive patterns indicating synergistic effects can inform further deductive theory development. Importantly, the overall synergistic interactive pattern deviates from theoretical assumptions regarding the compensatory pattern of conscientiousness and interests (Trautwein et al., 2019), but rather aligns with the synergistic pattern proposed regarding openness and interests (Ziegler et al., 2018). Consequently, the latter could guide further theoretical developments regarding the interactive interplay of student personality and academic self-concepts. In line with expectancy-value theory (Eccles & Wigfield, 2020), students' academic self-concepts shape their expectations of success regarding academic tasks and, thereby, similarly to interests potentially regulate in which domains students express their academically favorable personality traits such as openness and conscientiousness. In line with the idea of trait expression being relevant to the interactive interplay between personality and academic self-concepts, interactive patterns were more pronounced regarding grades. This result pattern fits the proposition that teachers' evaluations of academic performance across longer time periods allow for more personality expression compared to one-time testing settings (e.g., Borghans et al., 2016; Lechner et al., 2017). Accordingly, future research may expand upon this dissertation's indication of an interactive interplay by considering the role of personality expression across longer time frames therein.

Importantly, this dissertation also points towards the need for theoretical refinements by considering the subcomponents of personality traits (cf. Stewart et al., 2022) and the academic self-concept (Arens et al., 2021). Regarding personality traits, inconsistencies in the associations—particularly with respect to openness—suggest that different personality facets may relate differently to academic self-concepts and academic outcomes. This assumption is supported by first studies addressing the differential predictivity of personality facets regarding academic performance (Bergold & Steinmayr, 2018; Brandt et al., 2025). Regarding the academic self-concept, this dissertation differentiated between domain-specific verbal and math self-concepts. The findings underscore the importance of accounting for this domain-specificity also in relation to personality (Meyer et al., 2023) and when integrating both self-perceptions.

Overall, associations of student personality with their academic self-concept and performance were stronger and more consistent in the verbal domain. This finding replicates previous indications of domain-specific personality-performance relations (Brandt, Lechner, et al., 2020; Israel et al., 2019) and potentially reflect the diverse requirements of different school subjects. Consequently, future research needs to deduce facet- and domain-specific theoretical assumptions that match the current empirical indications.

Taking an Interdisciplinary Perspective on Complex Student-Environment Transactions in School

Taking a transactional perspective, this dissertation considered contextual conditions at different levels of the school environment (Eccles et al., 1993; Eccles & Roeser, 2009). Importantly, this dissertation benefitted from enriching sociological perspectives on social inequalities by considering the role of individual self-perceptions from personality and motivational psychology therein. Similarly, combining perspectives from personality, motivational, and educational psychology reflected the complexity of transactions between individual self-perceptions and peers and teachers as contextual conditions. Subsequently, I will further substantiate the need for an interdisciplinary perspective to adequately reflect the complexity of student–environment transactions in school.

Regarding social inequalities in education, this dissertation enriched the sociological perspectives on social inequalities (Boudon, 1974; Bourdieu, 1990) by integrating important self-perceptions from personality (McCrae, 2009) and educational psychology (Marsh & Craven, 1996). Thereby, these results indicate a crucial role of individual self-perceptions in shaping social inequalities. More specifically, the results of Study 1 indicate an interactive pattern between individual self-perceptions and sociodemographic background characteristics that potentially also varies across educational systems. In line with the hierarchical structure of the school environment postulated by stage-environment fit theory (Eccles et al., 1993; Eccles & Roeser, 2009), this dissertation considered sociodemographic characteristics as distal contextual conditions. Importantly, it refines our understanding of social inequalities by looking into interactive effects between two crucial self-perceptions and these sociodemographic characteristics (Boudon, 1974; Bourdieu, 1990; Brandt & Wagner, 2024). Despite some researchers reasoning that individual self-perceptions might compensate for sociodemographic disadvantages (Ayoub et al., 2018; Damian et al., 2015; Lechner et al., 2021; Ross & Mirowsky, 2006; Shanahan et al., 2014), findings point towards a mostly synergistic interactive pattern across the two German samples in Study 1. While there is considerable variation in the way individual self-perceptions differentiate social inequalities across international samples (cf.

meta-analysis by Ayoub et al., 2018), the synergistic pattern replicates previous findings within the German educational system (Becker et al., 2021; Lechner et al., 2021). Accordingly, this dissertation indicates that the role of individual self-perceptions in social inequalities might systematically vary across educational systems. This assumption should be addressed by further integrating theoretical perspectives from different disciplines that investigate social inequalities and findings obtained within different educational systems.

The fruitfulness of taking an interdisciplinary perspective is further supported by the indication that classroom peers differentially affect individual self-perceptions. Building on theoretical reasoning (Back et al., 2011; Credé et al., 2010; J. R. Harris, 1995) and previous empirical studies (Deventer et al., 2019; Neyer et al., 2014; Wieczorek et al., 2025) highlighting the relevance of peers for individual personality development, this study extended the concept of classroom composition effects—well established in the context of academic self-concepts (Fang et al., 2018) —to the domain of personality. Accordingly, the underlying processes might be more complex when it comes to general dispositions such as personality. Researchers from different disciplines have argued for the relevance of comparison processes, normative socialization processes, and interpersonal processes (Back et al., 2011; Credé et al., 2010; Lenhausen, Hopwood, et al., 2023; Lira et al., 2022; Shan & Zölitz, 2022) when it comes to peer effects on personality. These diverse processes may account for the absence of effects at the overall classroom level. Nevertheless, it remains important to examine personality configurations within classrooms in future research, as this line of inquiry is theoretically well justified and may hold important practical implications. In order to gain a better understanding, future research should look into more specific peer groups within academic contexts (i.e. social network approaches; Knoke & Yang, 2008; Snijders et al., 2010; Veenstra et al., 2013), and specifically target the underlying social interaction processes (Bleckmann et al., 2023). In doing so, researchers might benefit from incorporating alternative theoretical and methodological approaches to group composition effects present in other disciplines (e.g., Bleckmann et al., 2025; Kristof-Brown et al., 2005; Prewett et al., 2009).

The integrative and interdisciplinary perspective of this dissertation also illustrates the complexity of student–environment transactions in relation to teachers as contextual conditions. Specifically, the results of Study 3 show that teachers' behaviors, that have been thoroughly studied in educational contribute differently to students' self-perceptions, that have been the focus in personality and motivational psychology. Beyond grades as a formalized performance feedback that inform students' academic self-concepts (Möller et al., 2020), results indicated that the three dimensions of teaching behavior proposed by the educational COACTIV framework (Kunter & Voss, 2013) are suitable to address the impact of student-environment fit on students individual self-perceptions. Importantly, the results of Study 3 illustrate an interactive interplay with student personality. Accordingly, teachers' behaviors might differentially affect how students perceive their academic abilities depending on their general dispositions. Thereby, this dissertation underlines the need of considering theoretical perspectives on personality within educational theories.

Altogether, the current dissertation offers important insights into the complexity of teaching and learning in educational contexts and their impact on individual development. This complexity emerged in interactive, domain-specific associations between different individual self-perceptions. Moreover, integrating theoretical perspectives and empirical findings from multiple disciplines enriched our understanding of individual self-perceptions and their role in education, thereby underscoring the need for future research to maintain this interdisciplinary perspective.

5.3 Methodological Implications

The results of this dissertation point towards important methodological implications and challenges in investigating individual development within the school environment. In the following, I will highlight three central methodological implications. These relate to the assessment of interrelated individual self-perceptions and social inequalities in education, as well as to the statistical modeling of student–environment transactions.

First, the results on integrating individual self-perceptions and their theoretical implications underline the need to incorporate differentiated measures within fine-grained longitudinal research designs. In Studies 1 and 3, using differentiated measures of self-perceptions proved essential for integrating general dispositions and characteristic adaptations, as their associations varied across personality measures and academic domains. Accordingly, future research should emphasize using appropriate scales capturing facet- and domain-specific differences in student personality and academic self-concepts (e.g., Arens et al., 2011; Soto & John, 2017). At the same time, the cross-sectional interactive interplay at the trait level may reflect complex underlying dynamics (Kuper et al., 2021; Rauthmann, 2021) that should be addressed in future research designs. Such designs should apply measures at higher temporal resolutions and, hence, allow for the differentiation of interindividual and intraindividual variations in the interrelated development of self-perceptions (DeYoung, 2015; Jayawickreme et al., 2019; Tett et al., 2021; Wrzus & Mehl, 2015). Applying assessment strategies with higher temporal resolutions, however, requires the use of alternative measures that are suited to reflect temporal states in individual self-perceptions (Horstmann & Ziegler, 2020). At the same time, using differentiated measures at a higher temporal resolution is also more challenging because participants can only answer a limited number of self-report questions when asked frequently. To address this challenge, future research can make use of innovative research strategies including planned missingness designs (Little & Rhemtulla, 2013).

Second, this dissertation highlights the importance of including diverse samples, especially when investigating social inequalities. The inclusion of the socio-demographically diverse samples of the EIKA (Entwicklung und Implementierung eines neuen Konzeptes zur Eingliederung Jugendlicher in die Berufs- und Arbeitswelt in Schulen mit erhöhtem Förderbedarf, 2005) and the SEED study (J. Wagner et al., 2024) allowed for a sufficient investigation of such inequalities. Both samples included participants from diverse sociodemographic backgrounds and were comparatively less selective than the convenience samples typically used in psychological research (Nielsen et al., 2017; Sherman, 2024). The use of such diverse samples proved important, as results of Study 1 illustrate that the role of individual self-perceptions in academic performance and in social inequalities potentially varies with the sociodemographic sample composition. The use of diverse samples, however, comes with certain challenges. That is, data collection within diverse samples often requires more effort. Moreover, sample diversity might limit the reliability of parameter estimates by introducing more variance into statistical models (Jager et al., 2025). Additionally, characteristics at different levels of the school environment (Eccles et al., 1993; Eccles & Roeser, 2009) might vary with the overall sociodemographic composition of the sample and, thus, heterogenous sample composition might also introduce confounding variables (Sherman, 2024). Accordingly, future research should be mindful of the impact of sample composition on the effects of interest. To allow for future meta-analytic integration of findings, researchers should thoroughly assess and transparently document their sample composition and associated contextual characteristics (Simons et al., 2017). Such meta-analytic integrations are necessary to sufficiently address the generalizability of current findings and, thereby, identify sample and population characteristics that contribute to systematic variations in effects.

Third, the investigation of contextual effects on individual development in this dissertation highlights the challenges of testing interaction effects and the extent to which results depend on the chosen modeling strategies. While interaction effects are relevant indicators of student-environment transactions, addressing interactive effects has been rather challenging in personality psychology (Mueller et al., 2019; Mund & Neyer, 2014). The statistical power of testing for interactive effects can be limited due to the unreliability of the product term and restrictions in the range of predictors. Accordingly, this dissertation applied latent estimation approaches, used rather large and diverse samples, and included power simulations for all three studies. Nevertheless, there was only limited evidence for small interactive effects. The considerably smaller size of interaction effects, as shown in previous research on personality traits, has been proposed to reflect the complexity of human behavior (Chaplin, 1991). Accordingly, even small significant interaction effects are relevant for understanding student-environment transactions and the results of this dissertation can be considered as initial evidence for the interplay between student personality and academic self-concepts, as well as student personality and teaching behaviors. Still, future research should replicate these findings to ensure their validity. Beyond linear interactive effects, it is also possible that the non-linearity of some relationships may have masked more pronounced interactive effects in this dissertation. For example, both well-structured students (i.e., high conscientiousness) and unorganized students (i.e., low conscientiousness) might benefit more from the structure provided by their teacher (i.e., high classroom management). Applying polynomial regressions with response surface analysis (e.g., Humberg et al., 2019; Shanock et al., 2010) in future research might allow to detect such non-linearity. Besides the challenge of testing interaction effects, this dissertation points towards the importance of addressing the dependability of results on statistical modeling strategies. Within Study 2, I tested for composition effects (Hattie, 2002) on individual personality development. Using multiple modeling strategies (Marsh et al., 2009) revealed no evidence for such effects, except for one significant finding obtained with a single approach. Relying on only that modeling strategy could have led to an overconfident interpretation of this isolated result. Therefore, the results indicate that conceptual replications across different statistical approaches are a necessary step towards ensuring the robustness and replicability of findings in future research (Plucker & Makel, 2021).

Altogether, the integrated and context-sensitive investigation of self-perceptions requires differentiated measures of individual self-perceptions and contextual conditions, diverse and extensive sampling strategies, and advanced statistical models. Accordingly, future research faces the challenge of incorporating these methodological approaches into suitable research designs.

5.4 Practical Implications

The results of this dissertation have several implications for educational policies and teachers. In the following, I will address three of these implications by focusing on 1) the need for educational policies to address the fostering of beneficial individual self-perceptions, 2) teachers as potential intervention target for addressing social inequalities, and 3) the importance of teachers considering individual differences.

First, as students' self-perceptions are important predictors of academic performance, they should be regarded as key targets for educational policies and interventions. More specifically, the results of Study 1 show that both general personality dispositions and context-specific academic self-concepts predict academic achievement beyond students' cognitive abilities. Importantly, this dissertation highlights that personality matters beyond context-specific predictors such as academic self-concepts. This means that educational success is shaped not only by subject-specific and content-related abilities perceptions but also by self-perceptions of overarching behavioral tendencies. Extending upon previous findings, this dissertation also indicates an overall synergistic interplay of personality and academic self-concepts. Accordingly, both kinds of individual self-perceptions represent important resources in relation to academic success, which should be specifically promoted through education (Haehner et al., 2024; Hörsch et al., 2025; cf. OECD, 2015). As the findings of Study 1 and 3 once again corroborate the importance of conscientiousness in academic contexts (Mammadov, 2022; Meyer et al., 2023; Trautwein et al., 2019), conscientious behavior such as organizing and self-regulation skills should be specifically promoted by incorporating strategies to develop such skills within educational policies (Santos et al., 2022). Beyond the established importance of conscientiousness, results of Study 1 and 3 add indications of the relevance of neuroticism. That is, students' levels of neuroticism contributed to their academic self-concepts and academic performance, and also differentiated the effects of other performance predictors as well as the effects of teaching behavior on academic self-concepts. Previous results likewise indicate a crucial role of neuroticism in the affective evaluation and subsequent integration of experiences into one's more general self-perceptions (Bien et al., 2024; Hong et al., 2013; J. Wagner et al., 2013). Along these lines, educational policies should aim to promote students' affective regulation strategies to help prevent negative biases in the (academic) self-perceptions of more neurotic students (Pedrini et al., 2022)

Second, this dissertation illustrates the contribution of teachers to social inequalities and, hence, identifies teachers as key agents in addressing such inequalities. The findings of Study 1 clearly support the persistence of social inequalities, despite them being discussed for decades (Boudon, 1974; Bourdieu, 1990). Importantly, this dissertation also adds to our understanding of social inequalities and illustrates an overall synergistic interactive pattern between students' self-perceptions and their sociodemographic background characteristics within the German educational system. That is, results of Study 1 corroborated previously evident differences between grades and standardized test performance (Brandt, Lechner, et al., 2020; Meyer et al., 2023). As grades awarded by teachers in particular show stronger correlations with individual self-perceptions and especially student personality, teachers should be aware that their assessment is not only based on objective academic performance. Moreover, interactive patterns concerning the role of student personality in social inequalities were more pronounced for grades than for standardized test scores, suggesting that teachers may incorporate their perceptions of students' general behaviors into grading differently depending on the students' sociodemographic background. Accordingly, teachers' evaluations of their students' general behavior potentially contribute to or even reinforce social inequalities (Calarco et al., 2022). Thereby, this dissertations indicates that teachers and their attitudes and perceptions are an important intervention target for addressing social inequalities (Turetsky et al., 2021). In the past, interventions aimed at reducing inequalities have focused primarily on students (Yeager & Walton, 2011). Researchers have, however, argued that intervening at multiple levels of the school environment might be more effective (Destin, 2020) and first studies indicate the effectiveness of teacher interventions (e.g., Gregory et al., 2016; Muntoni & Retelsdorf, 2018; Okonofua et al., 2016). Such interventions can entail changing teachers' attitudes and beliefs or implementing strategies like reducing bias through awareness, using blind grading, and promoting inclusive instructional practices (cf. Turetsky et al., 2021 for an overview).

Third, teachers need to be aware of their differential impact on students' individual self-perceptions and, accordingly, should apply individualized teaching strategies. Results of Study 3 indicated that beyond grading, overall teaching behaviors contribute to students' academic self-concepts. This is especially true regarding the structure teachers provide (i.e. classroom management) as it robustly contributes to the way students perceive themselves. Importantly, the results of Study 3 show that teaching behavior differentially impacts students' academic self-perceptions, as evidenced by interactive effects between their personality and teaching behaviors. Consequently, different students might differentially benefit from the relation to their teacher (i.e. emotional support) and the cognitive challenge (i.e. cognitive activation) they experience. Such individual preferences should be addressed through teaching practices that account for interindividual differences in students' behavioral tendencies (Bernard et al., 2019; Lindner et al., 2019).

To sum up, this dissertation highlights the importance of supporting students in developing academically beneficial behavioral skill sets, involving teachers as key agents in social inequality interventions, and offering individualized learning opportunities to foster positive academic experiences.

5.5 Limitations and Outlook for Future Research

Despite its important theoretical, methodological, and practical implications, this dissertation does not capture the full breadth and complexity of individual self-perceptions as performance predictors and their development in school. Hence, the following four conceptual and methodological limitations need to be considered when interpreting the results. Additionally, I highlight potential avenues for future research.

First, all three studies followed a correlational study design and, thus, do not allow for any conclusions about the direction and causal foundations of the reported associations. Taking a first step towards a better understanding of the associations between individual students and contextual predictors of academic performance, this dissertation applied mostly longitudinal designs and tested theoretically derived hypotheses. Nevertheless, it leaves open questions about the directionality in the established associations between student personality and academic self-concepts in academic contexts. To simultaneously address opposing theoretical elaborations (McCrae, 2009; Specht et al., 2014), future research can benefit from applying complex modeling techniques such as cross-lagged panel models to further explore the reciprocity of established cross-sectional and longitudinal associations (e.g., Hounkpatin et al., 2018; Lüdtke et al., 2023). These modeling techniques require large datasets, which are even more difficult to obtain given the equally important need for fine-grained measures of relevant variables to examine differential associations across domains or facets. To integrate these partly contradictory requirements, researchers should consider collaborative strategies allowing larger data collections. Moreover, researchers can use diverse design strategies such as planned missingness to still enable a differentiated assessment of multiple variables (Little & Rhemtulla, 2013; Silvia et al., 2014), and further support open science practices to enable replications across and the integration of multiple samples (e.g., Leising et al., 2022). To move even closer to identifying causal relationships, it is also necessary to employ experimental research designs. Initial studies show possibilities in the area of virtual reality scenarios (Hasenbein et al., 2024). However, in order to maintain ecological validity, quasi-experimental studies are a good middle ground (e.g., Fleischmann et al., 2021). The educational context offers various opportunities for such research. For instance, transitions within the education system can be used to investigate the relevance of class compositions and changes in teacher allocation are well-suited for investigating the impact of teaching behavior on students. However, coordinating the timing of assessments with these transitions can be challenging.

Second, the investigations relied primarily on student self-report measures. Given the focus on student self-perceptions, self-report questionnaires were the most appropriate choice for assessing personality and academic self-concept, as they best capture students' subjective perspectives (Soto et al., 2008). Nevertheless, incorporating additional data sources (e.g., other reports, behavioral data) could help provide a more holistic picture in future research. Applying multi-method approaches that include such sources would allow for differentiation between objective and subjective perspectives on both the individual and the context. In particular, discrepancies between self- and other reports or between self-reports and objectively measured behavior may be especially informative for identifying the unique subjective components of self-perceptions, and should therefore be considered when examining the processes involved in their formation.

Third, while this dissertation used data from three diverse and large-scale samples, the generalizability of the results is limited to some extent. In line with considerations of the stage-environment fit theory (Eccles et al., 1993; Eccles & Roeser, 2009), schools as development contexts are always embedded within more general contextual levels, therefore, questions of generalizability need to be considered both at the level of society and the educational system. Regarding the level of society, all three samples used within this dissertation included exclusively German students attending German schools. Consequently, it is unclear which results might generalize to international student populations. Regarding the level of educational systems, there are differences in the respective school systems between all federal states of Germany (cf. Becker et al., 2017). Within Study 1 and 2, I accounted for potential differences across educational systems. That is, I based the respective analyses of Study 1 and 2 on both a representative sample drawn from all federal states of Germany and a more specific sample that was collected within one specific federal state. The results point towards some important differences between more general and more specific student populations. Consequently, future research should aim at replicating the found associations across different educational systems both within Germany, but also across different countries. Again, collaborative strategies might aid such replication attempts and can contribute to an adequate reflection of different contextual levels and their impact on student-context transactions.

Lastly, this dissertation examined associations between individual self-perceptions and contextual factors at the trait level, revealing complex and interactive relationships among student personality, academic self-concept, sociodemographic background, and the school environment. However, it did not specifically explore the mechanisms underlying these interactions. Theoretical perspectives emphasize the importance of studying temporal dynamics that may influence trait development (for an overview cf. Kuper et al., 2021). Accordingly, future research should incorporate such dynamics to better understand how individual development of student personality and academic self-concepts unfolds within educational contexts. For instance, research shows that academic self-perceptions can fluctuate between lessons or days (Blume & Schmiedek, 2024; Niepel et al., 2021; Parrisius et al., 2021) and accumulating directional variation may be an important precursor of change at the trait level of student personality and academic self-concepts (Wrzus & Roberts, 2017). The empirical insights from this dissertation provide a valuable foundation. Future studies should further refine theoretical models of how self-perceptions relate to social inequalities and develop over time, considering both trait and state levels of analysis.

5.6 Conclusion

In conclusion, this dissertation adopted an integrative and context-sensitive approach to study individual self-perceptions, their contribution to academic performance and social inequalities, and their development in school. The findings illustrate, first, the interrelatedness of student personality and academic self-concepts in terms of their nomological net and interactive prediction of academic performance. Second, they point towards a reinforcing role of self-perceptions in social inequalities in educations. Third, they illustrate student-environment transactions in form of an interactive interplay between student personality and teaching behavior in predicting academic self-concepts. These new findings enrich our understanding of the role of interconnected self-perceptions in education and identify teachers as a potential target group for interventions that address social inequalities and support positive individual development of students. Future research might further advance this understanding by implementing advanced research designs across various educational systems that tap into the causality of associations, incorporate multi-method measures, and disentangle inter- and intraindividual variations in developmental trajectories.

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Declarations

Attached declarations:

- Erklärung gemäß § 5 (4d) der Promotionsordnung des Instituts für Psychologie der Universität Hamburg vom 20.08.2003

- Eidesstattliche Erklärung nach § 9 (1c und 1d) der Promotionsordnung des Instituts für Psychologie der Universität Hamburg vom 20.08.2003

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Erklärung gemäß ***(bitte Zutreffendes ankreuzen)***

☐ **§ 4 (1c) der Promotionsordnung des Instituts für Bewegungswissenschaft der Universität Hamburg vom 18.08.2010**

☒ **§ 5 (4d) der Promotionsordnung des Instituts für Psychologie der Universität Hamburg vom 20.08.2003**

Hiermit erkläre ich,

Mieke Johannsen (Vorname, Nachname),

dass ich mich an einer anderen Universität oder Fakultät noch keiner Doktorprüfung unterzogen oder mich um Zulassung zu einer Doktorprüfung bemüht habe.

HH, 06.08.2025
Ort, Datum

M Johannsen
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Eidesstattliche Erklärung nach ***(bitte Zutreffendes ankreuzen)***

☐ **§ 7 (4) der Promotionsordnung des Instituts für Bewegungswissenschaft der Universität Hamburg vom 18.08.2010**

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Hiermit erkläre ich an Eides statt,

1. dass die von mir vorgelegte Dissertation nicht Gegenstand eines anderen Prüfungsverfahrens gewesen oder in einem solchen Verfahren als ungenügend beurteilt worden ist.
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