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Motivational Aspects of Development in School Achievement – The Case of Specific Learning Situations and Mathematical Development

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Abstract

Cognitive, social, emotional, and motivational aspects of development play their part in the assessment, prediction, and design of interventions with regard to school achievement, although intelligence, one major cognitive precondition, is generally ascribed the strongest relationship. However, current literature has revealed that motivational aspects such as self-efficacy, self-concept, and flow experiences contribute uniquely and substantially to school achievement across developmental stages, making the need for an integrative view evident. Findings based on skill development and self-enhancing perspectives of motivational aspects suggest that potential virtuous cycles become relevant at different levels of specificity, for instance, regarding separable learning situations or skill domains during the secondary school years. Thus, the overarching goal of this thesis was to determine how motivational aspects contribute to school achievement irrespective of cognitive preconditions in the context of (a) specific learning situations and (b) mathematical development. In three studies, predictive patterns were empirically investigated, using longitudinal data from secondary school students and by taking intelligence measures as well as skill tests, teacher assessments of achievement, and self-assessed motivational aspects into account. Results indicate that (a) flow experiences are linked to school achievement in specific learning situations, (b) self-efficacy mediates effects of prior achievement on later mathematical modeling, and (c) the effects of motivational aspects on mathematical development transfer to overall skill development. Taken together, potentiating effects of motivational aspects on school achievement irrespective of cognitive preconditions can be deduced, indicating a strong starting point to enter a potential virtuous cycle, which practitioners, that is, teachers, diagnosticians, and counselors, should be especially aware of.

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Introduction

In school psychology, as in developmental psychology, researchers and practitioners take a holistic view of children when assessing, consulting, or intervening. Therefore, it is crucial for research to investigate multiple predictors and outcomes in the realm of school achievement. School achievement—an umbrella term—usually refers to educational outcomes measured through examinations and assessments (Ward et al., 1996).

In developmental research, it is common to distinguish between cognitive, social, emotional, and motivational aspects of development, which are often studied separately (e.g., Ayoub & Fischer, 2006). Given that these different aspects of development are usually studied discretely, and considering that school achievement refers to various educational outcomes, a comprehensive view is needed to reach a sophisticated understanding of children's development in general as well as school achievement in particular.

To draw a comprehensive picture of school achievement, current findings on the interrelations among different aspects have to be elaborated. When looking at *cognitive* aspects and school achievement, intelligence is considered the strongest predictor of educational outcomes (Gottfredson, 2002; Roth et al., 2015). However, in recent years, the influence of *social* aspects has also been studied, resulting in findings on student–teacher relationships being related to achievement too (e.g., Hamre & Pianta, 2001). Meta-analytic results showed that positive as well as negative aspects of relationships were linked to achievement and that this connection was to some extent mediated by student engagement, meaning that student–teacher relationships influenced how much students were willing to participate in the classroom and enjoyed learning, resulting in higher or lower achievement, accordingly (Roorda et al., 2017). With regard to *emotional* aspects, in the field of positive psychology, subjective well-being, among other variables, was found to be associated with school achievement: High-achieving students reported higher well-being than low-achieving learners (Bücker et al., 2018). However,

longitudinal research on potential bidirectional relations between well-being and achievement hints at subjective well-being being more an outcome of achievement than a promoting factor (Yang et al., 2019). Similar to the comprehensive approach that Roorda et al. (2017) followed by exploring the influence of both social and motivational aspects on school achievement, Kriegbaum et al. (2018) looked simultaneously at the relative importance of intelligence and *motivational* aspects in predicting school achievement, confirming the former as the strongest cognitive predictor. Yet, different motivational constructs (i.e., self-concept, self-efficacy, intrinsic and extrinsic motivation, achievement goals, interest) were found to contribute substantially and uniquely to the variance in school achievement in this meta-analysis.

Furthermore, motivational aspects have emerged as promising starting points for supporting school achievement on both a theoretical and practical level. The high stability of intelligence (e.g., Yu et al., 2018) makes it difficult to build interventions targeting cognitive skills, and often there is no significant effect of interventions on overall intelligence (te Nijenhuis et al., 2007). In contrast, motivational aspects were found to be influenced by prior achievement and seemed to in turn enhance future achievement; reciprocal effects emerged, for instance, for self-efficacy and achievement in mathematics and reading (Schöber et al., 2018). In line with the self-enhancement perspective in Bandura's (1977) social-cognitive learning theory, especially *self-efficacy* is thought to enhance learning independently of students' skill level and cognitive preconditions (Zimmerman et al., 1992), potentially entering a virtuous cycle of motivational aspects and skill development. Further, the skill development model (Calsyn & Kenny, 1977) argues that students' *self-concept* evolves as a result of perceiving their own achievement. Burns et al. (2020) confirmed these established theoretical propositions, finding reciprocal relationships for both self-efficacy and self-concept with school achievement.

Related to self-enhancement and skill development, positive psychology focuses on the experience of *flow*, that is, the mental state in which learning is facilitated and intrinsically

motivated (Nakamura & Csikszentmihalyi, 2009). In theory, because flow experiences are intrinsically rewarding, students are thought to replicate the state of flow, resulting in a mechanism that fosters growth (Massimini & Delle Fave, 2000). Although a few studies have supported this claim (e.g., Shernoff et al., 2014), of which some even ascribe a mediating role to flow for the relation of self-efficacy to school achievement (Adil et al., 2020), empirical research on flow experience and school achievement remains scarce.

To sum up, besides social and emotional aspects of development, motivational aspects, that is, self-efficacy, self-concept, and flow, have been associated in recent research with school achievement, potentially irrespective of cognitive preconditions (e.g., Kriegbaum et al., 2018). In practical as well as theoretical work, they have thus been considered promising facilitators of learning even when intelligence remains unchanged (cf., Yu et al., 2018). The need for research on the role of motivation in addition to intelligence with regard to school achievement is evident.

In the following section, I provide further theoretical background on school achievement with a focus on specific learning situations and mathematical development—where motivational aspects have been shown to be especially relevant. This background provides the framework for the three studies of this thesis and the basis of the hypotheses that were empirically investigated within them.

Theoretical background

Motivational aspects of development contribute uniquely to the variance in school achievement and sometimes more strongly than intelligence (Kriegbaum et al., 2018; Richardson et al., 2012). When investigating school achievement, researchers often rely on the overall measure of grade point average (GPA; e.g., Robbins et al., 2004). Richardson et al. (2012) reviewed a large body of empirical studies looking for psychological correlates of GPA in university students. They found the largest correlation of $r = .59$ for self-efficacy, which was

even higher than correlations obtained for prior GPA in high school (r = .40) or intelligence (r = .20). Recognizing high correlations among domain tests in the Program for International Student Assessment (PISA; Organisation for Economic Co-operation and Development [OECD], 2013), J. Lee and Stankov (2018) used students' mathematics score as a proxy for their overall school achievement. Relying on large-scale international databases, they showed that a group of self-belief variables, such as self-efficacy in the PISA and confidence in the Trends in International Mathematics and Science Study (TIMSS; Mullis et al., 2009), best predicted school achievement, replicating findings from a mega-analysis from Hattie (2009), which revealed Cohen's d = 0.48 for engagement and d = 0.43 for self-concept. Taken together, meta-analytic results confirm that motivational aspects play a major role in the prediction of school achievement, while mathematical development is argued as a representative case. Moreover, self-efficacy and self-concept, among several motivational aspects, were found to be prominent predictors.

Although high correlations of achievement in different school subjects (so-called intersubject correlations) have been repeatedly reported in large-scale database (e.g., PISA results [OECD, 2019]), theoretical assumptions have been made about subject-specific characteristics of motivational aspects. Bandura's (1977, 1997) definition of self-efficacy as individuals' belief in their capability to impact future events and attain given goals is admittedly broad but entails characteristics of specificity (i.e., subject-specific goals). The skill development model of self-concept (Calsyn & Kenny, 1977), as well as a multidimensional perspective on self-concept (meaning that self-concept can differ by school subject; Marsh & O'Mara, 2008), assumes that self-concept can to some extent be bound to a specific domain. This is reflected in the common practice of using subject-specific scales in addition to global assessments of self-concept and self-efficacy (cf., Self Description Questionnaire [SDQ]; Marsh, 1990), without which the effect of interventions, for instance, could be underestimated (Bracken, 1996). In the expectancy–value theory of achievement motivation, ability beliefs are

defined even more specifically as the perception of one's competence at a given activity (Wigfield & Eccles, 2000). Flow is by definition bound to specific activities such as chess playing, climbing, or dancing (Csikszentmihalyi, 2000). However, it remains unexplored whether flow is subject specific in school, expands to learning in general, or is specific to different situations, for instance, individual tasks versus group work. Given the high correlations found for motivational aspects and school achievement, which are sometimes greater than correlations with prior achievement measures and cognitive preconditions (Richardson et al., 2012), and considering the reciprocal influence of skill development and motivation (Schöber et al., 2018), the influence of motivational aspects could tend to become more subject specific as children progress through school. It is thus important to investigate the effects of motivational aspects on two levels: school achievement in general and specific cases such as mathematical development or specific learning situations in particular.

In mathematical development, again, when it comes to the investigation of early predictors, cognitive aspects have received the most attention in longitudinal studies (e.g., Siegler et al., 2012). Number sense (Jordan et al., 2007), counting skills (Aunola et al., 2004), calculation (Andersson, 2007), and quantitative knowledge (Chu et al., 2016) have been established as important predictors of children's mathematical development, apart from domain-general abilities such as intelligence (Kriegbaum et al., 2015), working memory (Swanson, 2011), and executive functioning (Best et al., 2011). However, motivational aspects have likewise been thought to contribute to mathematical development (Schiefele & Csikszentmihalyi, 1995). Current literature indicates that cognitive (i.e., intelligence) and motivational aspects jointly but uniquely contribute not only to school achievement in general but to mathematical development in particular (Kriegbaum et al., 2015; Murayama et al., 2013). Notably, motivational aspects such as self-concept, self-efficacy, and intrinsic motivation were assessed using subject-specific items in these studies, resulting in better prediction compared to global operationalization. Moreover, self-efficacy and self-concept were revealed to account

for mathematical development when prior performance was accounted for, underlining the unique importance of these motivational aspects (Y. Lee & Seo, 2021; Van der Beek et al., 2017). Recent findings indicate that the association is moderated by the value students give to mathematics and the emotions they experience during mathematical activities (Hanin & Van Nieuwenhoven, 2016), which, on theoretical reflection, would be in line with assumptions on flow experiences.

A sophisticated investigation of the relationship between motivational aspects and school achievement must include consideration of specific developmental stages. Early predictors of mathematical development are often studied from preschool to lower primary school because basic mathematical skills emerge at this stage of development (Krajewski & Schneider, 2009; LeFevre et al., 2010). Research on mathematical literacy, that is, the application of acquired mathematical knowledge to everyday problems, often takes place in the transition from primary to secondary school because this is where mathematical development can be investigated comprehensively as an integrative skill set of different competencies (Baumert et al., 2012; Geary, 2011; Korpipää et al., 2017) and under conditions where many students lack important skills (Phonapichat et al., 2014). It can be assumed that at this stage, motivational aspects become closely associated with mathematical development, which becomes more distinct. However, current literature on motivational aspects of mathematical development has focused mainly on the high school and college level (J. Lee & Shute, 2010; Richardson et al., 2012), indicating that at this stage, motivational aspects contribute distinctly and subject specifically to mathematical development. Studies on motivational aspects across secondary school likewise have shown significant associations with school achievement (Kriegbaum et al., 2018; J. Lee & Stankov, 2018) but characteristics specific to this stage of mathematical development remain unclear. Following the control-value theory of achievement emotions (Pekrun & Perry, 2014), Hanin and Van Nieuwenhoven (2016) found that the relationship between motivation and mathematical development in secondary school was linked to emotions and the value

students attached to mathematics, supplying a theoretical argument for why motivational aspects could be especially relevant at this age. In sum, early predictors of mathematical development have so far been studied mostly in preschool to lower primary school, while motivational aspects have been found to influence mathematical development at the high school and college level. The years spent in secondary school could therefore be particularly fertile ground for investigating motivational aspects of mathematical development following a subject-specific approach.

In conclusion, research on school achievement has revealed that irrespective of cognitive preconditions, motivational aspects of development contribute uniquely and substantially to skill development (Kriegbaum et al., 2018; J. Lee & Stankov, 2018; Richardson et al., 2012). Self-efficacy, self-concept, and flow have been theoretically conceptualized as well as empirically investigated to account for individual differences in achievement on different levels of specificity regarding school domains (e.g., GPA vs. mathematical development), learning activities (e.g., global vs. specific situations), and school years (e.g., overall vs. secondary school). To deepen the understanding of the role of motivational aspects in school achievement, it is crucial to look at these different levels of specificity to challenge other prominent influences, for instance, intelligence. The overarching goal of this thesis was to investigate how motivational aspects influence school achievement irrespective of cognitive preconditions and in specific learning situations as well as in the context of mathematical development. Driving this investigation were three hypotheses, which I introduce next.

Hypotheses

The expectancy–value theory of achievement motivation (Wigfield & Eccles, 2000) suggests that motivation especially arises when one's competence is perceived as high in a given activity. According to the control-value theory of achievement emotions (Pekrun & Perry, 2014), motivation is further potentiated when students assign value to the school content they

are working on. In line with flow theory (Csikszentmihalyi, 2000), motivation is therefore linked to achievement when the fit between a student's characteristics and task demands is high. Thus, motivational aspects can be regarded as multipliers of achievement irrespective of cognitive preconditions, the influence of which has already been empirically investigated (Kriegbaum et al., 2018; J. Lee & Stankov, 2018). However, few researchers have focused on specific learning situations. This leads to my first hypothesis:

1. Flow experiences link to school achievement in secondary school students in learning situations that fit the students' characteristics.

Current literature highlights that self-efficacy and self-concept codevelop with school achievement in a reciprocal way (Burns et al., 2020; Schöber et al., 2018). Taking skill development (Calsyn & Kenny, 1977) and self-enhancement (Bandura, 1997) into account leads to the awareness that a virtuous as well as a vicious cycle can occur with prior achievement and learning experience. However, findings indicate that such cycles are subject specific such that the effects of self-concept and self-efficacy might be underestimated when assessed in a global way (Bracken, 1996) and should thus be differentiated for different school subjects (Y. Lee & Seo, 2021; Van der Beek et al., 2017). For mathematical achievement, studies so far have assigned motivational aspects a crucial role (Kriegbaum et al., 2015; Murayama et al., 2013), hinting that a subject-specific perspective is especially important for mathematics—a subject that causes major struggles for many students (e.g., Phonapichat et al., 2014). These considerations together informed my second hypothesis:

2. Self-efficacy and self-concept predict mathematical achievement when assessed subject specifically and when taking prior achievement as well as cognitive preconditions into account.

Although students' interests and the value they assign to school domains tend to become more specific during secondary school (Hanin & Van Nieuwenhoven, 2016; Richardson et al., 2012), transfer effects among different domains might be assumed with regard to self-

enhancement effects of motivational aspects. On the one hand, flow experiences are not necessarily bound to specific school domains but could also be linked to characteristics of different activities (e.g., individual work, group work) and facilitate learning as a whole (Nakamura & Csikszentmihalyi, 2009). On the other hand, research indicates that mathematical skills—a comprehensive skill set (cf., Baumert et al., 2012; Korpipää et al., 2017)—show high intersubject correlation (J. Lee & Stankov, 2018) and students thus might profit in terms of their overall school achievement in the long run. This leads to my third hypothesis, specific to the secondary school years:

3. Students profit from the effects of motivational aspects on mathematical development in their overall school achievement across the secondary school years.

Empirical support

These three hypotheses form the basis of a general investigation of the role of motivational aspects of development in school achievement with special attention to specific learning situations and mathematical development across the secondary school years. In my first study, I investigated how flow links to school achievement in individual work, group work, and traditional teacher-centered learning. In a second study, I took the self-enhancement perspective to investigate if self-concept and self-efficacy predicted mathematic achievement when assessed subject specifically. In a third study, I investigated whether the effects of these motivational aspects on mathematical development transfer to other school domains specifically in the secondary school years, to complement the picture of the effects of motivational aspects irrespective of cognitive preconditions, which in all three studies were to some extent accounted for.

Motivational aspects of school achievement in specific learning situations

Under the framework of flow theory (Nakamura & Csikszentmihalyi, 2009), as part of a first study on character strengths (Peterson & Seligman, 2004), the relationship of flow

experience and school achievement was examined in three different learning situations: individual work, group work, and teacher-centered learning. A sample of N = 255 students (53.7% girls) from 18 different classrooms that were representative of secondary school in terms of school years (Grades 7 to 9) as well as school tracks (basic and advanced requirements) self-rated their flow experience in the three learning situations (Rheinberg et al., 2003). School achievement was assessed from students' self-ratings as well as from teacher ratings specific to these three situations. Three months prior, students' psychometric intelligence as a control variable and their character strengths were assessed. Results regarding Hypothesis 1 were twofold: Students' flow experiences correlated with achievement measures across learning situations and turned out to be to some extent situation specific, especially for individual tasks. Moreover, students experienced flow in different learning situations depending on their levels of various character strengths (e.g., perseverance for flow in individual tasks, or teamwork for flow in group work), meaning that student characteristics that on a theoretical basis fit the respective learning situation linked to this motivational aspect. Together, the two findings confirmed Hypothesis 1, that flow experiences are related to school achievement irrespective of cognitive preconditions combined with character strengths (i.e., student characteristics) that fit given learning situations.

Self-efficacy predicts and mediates mathematical achievement

Following the self-enhancement perspective on self-efficacy (Bandura, 1997) and building on findings on reciprocal development of achievement and motivation (Burns et al., 2020), predictive effects of self-efficacy and self-concept were examined in mathematical development as part of a second study. At the first measurement occasion conducted for an interventional study on mathematical modeling (i.e., applying acquired mathematical knowledge in realistic situations), N = 279 representative secondary school students self-assessed their mathematical self-efficacy (cf., OECD, 2019) and self-concept (SDQ; Marsh,

1990) in a subject-specific way and completed a mathematical modeling test. Correlation analyses suggested that both self-efficacy and self-concept were associated with mathematical modeling but only self-efficacy showed a predictive effect when the school-classroom-related nested structure and an intelligence measure were taken into account. A mediation analysis with school grades received from the official school report prior to assessments further revealed that self-efficacy fully mediated the effect of students' grade in mathematics on mathematical modeling. To sum up, these results partly confirmed Hypothesis 2, that self-efficacy predicts mathematical achievement when assessed subject specifically and when taking prior achievement and cognitive preconditions into account.

Transfer effects of motivational aspects on skill development

Theoretical and empirical arguments suggest that students might see gains in overall school achievement as a result of the effects of motivational aspects on mathematical development. Shared comprehensive skill sets were found especially when skill development in mathematics was conceptualized as literacy (Baumert et al., 2012; Korpipää et al., 2017). Although such sets are mainly thought to consist of cognitive skills, motivational aspects might add to the picture (Kriegbaum et al., 2018). In a third study, transfer effects of mathematical literacy on later achievement were examined in an integrative approach that considered multiple predictors, such as mathematical self-concept, calculation skills, and reasoning. A large longitudinal sample of N = 4,001 students from the National Education Panel Study (NEPS; Blossfeld et al., 2011) who were followed from Grades 5 to 9 was analyzed. Structural equation modeling analyses revealed a unique and substantial contribution of self-concept in Grade 5 to later mathematical literacy in Grade 9 irrespective of cognitive preconditions and prior achievement in different domains. Moreover, a transfer effect was revealed for mathematical literacy in Grade 5 on other school domains 3 or 4 years later irrespective of prior achievement in these respective domains. Taken together, these results confirmed Hypothesis 3, highlighting

the motivational basis of skill development and implying that students profit from the effects of motivational aspects on mathematical development in other school domains.

Discussion

The overall goal of the three studies was to determine how motivational aspects of development contribute to school achievement irrespective of cognitive preconditions across the secondary school years in specific learning situations (individual work, group work, teacher-centered learning) and in the context of mathematical development. In the first study, the experience of flow was linked to different achievement measures with regard to specific learning situations (i.e., individual work, group work, and teacher-centered learning), which is in line with the flow theory expectation that such experiences facilitate learning (Nakamura & Csikszentmihalyi, 2009). Moreover, different student characteristics (i.e., character strengths) predicted flow as well as achievement in the three settings examined. Notably, motivational aspects were associated with outcome variables irrespective of students' cognitive preconditions. However, with these correlational findings causal relationships are theoretically deduced from skill development models and self-enhancement perspectives (Bandura, 1997; Calsyn & Kenny, 1977).

Empirical support for associations of motivational aspects (i.e., self-efficacy) with achievement was strengthened in the second study, which investigated how prior achievement relates to mathematical modeling. Self-efficacy was revealed as a mediator in the relationship of prior school grades to later assessed mathematical modeling ability, again, irrespective of students' cognitive preconditions. This further confirmed the suggestion that the effects of motivational aspects on educational outcomes are more than a simple reflection of prior achievement (Caprara et al., 2008; Pajares & Schunk, 2001).

The third study indicated that a potentiating effect of motivational aspects (i.e., self-concept) on mathematical development in turn might be useful for school achievement as a

whole, since transfer effects were found from mathematical literacy to later achievement in other school domains. As J. Lee and Stankov (2018) argued for noncognitive predictors of mathematical achievement, results from the third study hinted that motivational aspects play a crucial role in school achievement in the long run, across disciplines, and to some extent independently of cognitive preconditions.

Strengths, limitations, and calls for future research

In this thesis I pursued an overarching idea of motivational aspects of development influencing school achievement irrespective of cognitive preconditions, which are believed to be stable and therefore less malleable (te Nijenhuis et al., 2007; Yu et al., 2018). As a methodological strength, all three studies had in common that cognitive preconditions were assessed first and then statistically controlled for in the analyses. Moreover, results were based on longitudinal data so that I could investigate predictive effects and draw conclusions on potential effects, highlighting a virtuous cycle that would be most useful for practical applications. As theoretical assumptions on motivational aspects suggest and empirical literature has shown, it is crucial to differentiate between levels of specificity (Hanin & Van Nieuwenhoven, 2016; Marsh, 1990; Richardson et al., 2012). The second and third study followed this approach with regard to specific school domains, scrutinizing the case of mathematical development. While many studies on overall and mathematical achievement have focused on primary school or the college years (Krajewski & Schneider, 2009; J. Lee & Shute, 2010; Richardson et al., 2012; Siegler et al., 2012), the present studies spotlighted the secondary school years, assuming that at this stage motivational aspects become crucial when interests and values become more distinct (Hanin & Van Nieuwenhoven, 2016) and content, for instance, in mathematical development, becomes more difficult to learn (Phonapichat et al., 2014). With regard to self-beliefs, in the second and third study, the assessment of self-efficacy and self-concept was subject specific, asking students to indicate their beliefs about mathematics in

particular. However, self-beliefs were not directly related to the tasks assessed as outcome variables (i.e., mathematical modeling in the second study and mathematical literacy in the NEPS [Blossfeld et al., 2011]), which might have led to stronger connections with corresponding measures.

In terms of limitations, although the three studies all target some level of specificity, direct measures of students' interests or value (cf., Pekrun et al., 2014) regarding the respective learning context were not included. To directly explore assumptions about secondary school being a critical stage for motivational aspects to influence school achievement, studies targeting the interplay of subject-specific interests as well as overall school motivation would be promising. Also limiting conclusions on motivational aspects showing potentiating effects on achievement irrespective of cognitive preconditions is that findings were based on longitudinal rather than interventional study designs, stressing the need for theoretical arguments on causal effects that empirically were hinted at by uncovering predictive patterns. Given that intelligence is stable (Yu et al., 2018), interventional confirmation of motivational aspects being modifiable is further needed (cf., Czocher et al., 2019). While cognitive preconditions were included as control variables in the analyses, future research might provide insight into the interplay of cognitive and motivational aspects. Empirical reflections on cognitive processes, for instance, in mathematical problem solving (e.g., Taub et al., 2008) are complemented by findings on cognitive as well as motivational aspects obtained with an integrative approach (Kriegbaum et al., 2018). However, with respect to a holistic view of child development, an integrative approach that considers motivational and cognitive as well as emotional and social aspects would be the ideal way forward for future studies.

Practical implications

Despite some questions remaining to be investigated in future research, implications can be drawn from this thesis for assessing, consulting, and intervening in the context of child

development in school. First, having been shown to contribute uniquely and substantially to school achievement, motivational aspects hold one important opportunity: They provide a starting point for entering a potentially virtuous cycle of different aspects of learning and achieving (cf., Zimmerman et al., 1992). Compared to cognitive preconditions such as intelligence, which turns out to be less malleable (te Nijenhuis et al., 2007), motivational aspects have been shown in numerous studies to be improvable in school children, for instance, regarding mathematical problem solving (Hoffman & Spatariu, 2008; Prabawanto, 2018; Schukajlow et al., 2019). The present results—flow experiences going along with achievement, self-efficacy mediating effects of prior achievement on mathematical modeling, and potential effects transferring to overall school achievement—fit into the current literature in that together, they confirm that via motivational aspects learning can be improved. Moreover, the potential growth cycle ascribed to flow (Massimini & Delle Fave, 2000) indicates that such experiences potentiate relationships of motivational aspects and school achievement, which is in line with research on a mediating role of flow (Adil et al., 2020). Therefore, teachers and caregivers are encouraged to deliberately foster motivation from an early age. Further, this advice should be maintained even when cognitive preconditions look less promising, since independent effects of motivational aspects were uncovered.

In school psychology, we often rely on cognitive aspects in predicting achievement and building interventions (Benson et al., 2019). Aside from this posing a danger of getting a one-sided rather than holistic view of development, motivational aspects provide a differentiated, specific impression regarding the prediction of outcome variables. Furthermore, motivational aspects have the advantage that they can be assessed economically and reliably (e.g., self-concept: Marsh, 1990; self-efficacy: OECD, 2019; flow experiences: Rheinberg et al., 2003). With the three studies combined, effects from these self-assessed motivational aspects in secondary school students were found on outcome variables using multi-informant operationalization, such as teacher-rated achievement (first study), mathematical modeling tests

(second study), and competence assessment in different school domains (third study). In my view, digesting these results, schools need to foster students' motivation by offering encouraging, resource-based, and supportive learning situations for the benefit of child development. Taken together, the present results should encourage diagnosticians as well as counselors to promote the awareness of motivational aspects such as flow experiences, self-concept, and self-efficacy in assessing as well as intervening.

Conclusion

With the findings of three studies and conclusions drawn, this thesis contributes to practice in school as well as educational psychology investigating motivational aspects in school achievement, specific learning situations, and the case of mathematical development. The consideration of motivational aspects and their interplay with cognitive preconditions adds to existing research on flow experiences, self-efficacy, and self-concept playing their part in potentiating learning and competence development across different stages of school when children are provided with specific challenges or otherwise given opportunities. Given that there may be a virtuous cycle of motivational aspects and school achievement, this thesis represents a strong starting point for future research and may guide educational decision makers and practitioners as they work to promote positive development.

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Appendix A: Study 1

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Character Strengths Are Related to Students' Achievement, Flow Experiences, and Enjoyment in Teacher-Centered Learning, Individual, and Group Work Beyond Cognitive Ability

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While character strengths have been found to predict educational outcomes beyond broad personality traits and cognitive ability, little is known about their differential contribution to success and positive learning experiences in different school settings. In this study, we use trait activation theory to investigate the relationships of students' character strengths with achievement, flow experiences, and enjoyment in different learning situations (i.e., teacher-centered learning, individual tasks, and group work). In studying these relationships, we controlled for psychometric intelligence. Secondary school students (N = 255; 46.3% male; mean age = 14.5 years) completed a self-report measure of character strengths, the VIA-Youth (Park and Peterson, 2006b). Cognitive ability was assessed using a standardized intelligence test (PSB-R; Horn et al., 2003) at baseline. Three months later, students completed the Flow Short Scale (Rheinberg et al., 2003) adapted to the three learning situations and indicated their typical enjoyment of these situations. Both the students and their teachers (N = 18; 50% male; mean age = 44.8 years) provided ratings on school achievement in each of the three learning situations. Results indicate that, as expected, (a) certain character strengths (love of learning and perseverance) show consistent relationships with achievement and positive learning experiences (flow and enjoyment) above and beyond cognitive ability across all learning situations, whereas (b) other character strengths show differential trait-outcome relationships (e.g., the character strength of teamwork was predictive of achievement and positive learning experiences in group work). Taken together, these results suggest that different character strengths play a role in different school situations and that their contribution to explaining variance in educational outcomes is incremental to the contribution of cognitive ability.

Keywords: character strengths, socio-emotional skills, positive education, optimal experience, trait activation theory

INTRODUCTION

As early as 1940, non-cognitive variables were discussed as important predictors of educational outcomes that could add to the predictive value of cognitive ability (Harris, 1940). Many decades later, there is substantial evidence that personality traits explain variance in educational outcomes (Poropat, 2009) and also do so incrementally above the influence of cognitive ability (e.g., Lechner et al., 2017). However, much is still unknown about which aspects of students' learning experiences and performance are influenced by individual differences in cognitive and non-cognitive (i.e., personality) traits and the most useful level of analysis (i.e., broader vs. narrower traits; see O'Connor and Paunonen, 2007).

In the present study, we use the concept of character strengths (Peterson and Seligman, 2004) to investigate the role of a comprehensive set of (narrower) positively valued personality traits. While previous studies found character strengths to go along with overall school achievement (e.g., Wagner and Ruch, 2015), when controlling for broader personality traits and cognitive ability (Wagner and Ruch, 2020), school does not represent a uniform situation but rather a range of different settings, in which achievement and positive learning experiences might be facilitated by different personality traits. Therefore, we aimed at studying whether character strengths explain variance in achievement across different learning situations – namely teacher-centered learning, individual tasks, and group work – above and beyond cognitive ability. Given the relevance of positive learning experiences both for overall well-being (e.g., Stiglbauer et al., 2013) and for future achievement (e.g., Engeser and Rheinberg, 2008), we also include variables related to well-being by studying the relationships of character strengths to the experience of flow and enjoyment in the different learning situations.

Character Strengths

Building on the theoretical framework of the Values in Action (VIA) classification (Peterson and Seligman, 2004), character is defined as a set of positive characteristics shown in feelings, thoughts, and actions. The VIA classification suggests a hierarchical structure of character where 24 character strengths are organized under six broad virtues: (1) wisdom and knowledge (encompassing the character strengths of creativity, curiosity, judgment, love of learning, and perspective), (2) courage (i.e., bravery, perseverance, honesty, and zest), (3) humanity (i.e., love, kindness, social intelligence), (4) justice (i.e., teamwork, fairness, and leadership), (5) temperance (i.e., forgiveness, humility, prudence, and self-regulation), and (6) transcendence (i.e., appreciation of beauty and excellence, gratitude, hope, humor, and spirituality). In that sense, character strengths are the "psychological processes or mechanisms that define the virtues" (Peterson and Seligman, 2004, p. 13). By definition, character strengths are ubiquitous, positively morally valued, fulfilling, trait-like, distinct, and measurable individual differences that contribute to optimal development across the lifespan (Peterson and Seligman, 2004). Importantly, character strengths are defined as malleable, which makes them ideal targets for interventions (for an overview in the educational context, see Lavy, 2019).

Character strengths also seem to be measurable and relevant in young people. Previous research has established that character strengths are already present in young children (Park and Peterson, 2006a) and can be reliably and validly measured using self-reports from the age of 10 years (e.g., Park and Peterson, 2006b; Ruch et al., 2014). A number of studies using those instruments established robust associations between character strengths and well-being among adolescents across different cultures (e.g., van Eeden et al., 2008; Gillham et al., 2011; Toner et al., 2012; Ruch et al., 2014).

Character Strengths and Educational Outcomes

How do character strengths relate to educational outcomes? Evidence suggests that the character strengths of love of learning and perseverance are particularly conducive to a range of educational outcomes (e.g., Weber and Ruch, 2012; Shoshani and Slone, 2013; Wagner and Ruch, 2015, 2020; Weber et al., 2016). However, previous studies suggest that, depending on the outcomes assessed (e.g., school achievement, school satisfaction, or positive relationships at school), different character strengths are additionally of relevance. For instance, the character strengths of zest and social intelligence are relevant in explaining variance in positive affect at school, whereas the character strengths of teamwork, hope, self-regulation, and love are most strongly associated with low negative affect at school (Weber et al., 2016). Specifically, the strengths found to be associated with achievement and with positive experiences at school overlap strongly, but some strengths (such as prudence) tend to show stronger relationships with achievement and other strengths (such as zest) tend to show stronger relationships with positive experiences at school. Recently, it was also demonstrated that a number of character strengths still predicted a range of educational outcomes when cognitive ability and personality traits of the five-factor model were controlled for (Wagner and Ruch, 2020).

Differential Relationships Between Personality or Character and Educational Outcomes

Studies on the relationships between character strengths and achievement almost exclusively rely on overall school achievement, or GPA. However, a first hint for differential relationships is represented by the finding that character strengths are generally more strongly related to grades in core academic subjects than to grades in non-academic subjects (e.g., physical education, and arts; Wagner and Ruch, 2015). Academic achievement is not a unidimensional construct and therefore, using overall school achievement or only using school grades as criterion might not allow for uncovering relationships with specific components of achievement (see O'Connor and Paunonen, 2007; Poropat, 2009). This idea is supported by findings that demonstrate differential trait-outcome relationships of the personality dimensions of the five-factor model for

different school subjects or different assessments of educational achievement (e.g., Spengler et al., 2013; Zhang and Ziegler, 2016; Brandt et al., 2020). This underlines the need for a more fine-grained examination of the associations between personality traits and educational outcomes. Using broader and more varied criterion measures of academic performance than GPA to study their relationships with personality traits (e.g., Kappe and van der Flier, 2010) has generally yielded two conclusions: First, certain traits (mainly conscientiousness) are consistently positively related with academic performance irrespective of the chosen measure. Second, for a number of personality traits (such as extraversion or neuroticism), the existence and size of relationships with academic achievement depend on how achievement is measured (i.e., GPA, thesis, performance in a group project, etc.).

In interpreting such findings and in hypothesizing relationships between character strengths and educational outcomes, we relied on the theoretical framework of trait activation theory (Tett and Guterman, 2000; Tett and Burnett, 2003). The theory's central premise is that situations differ in their relevance to any given trait, which is a well-accepted idea (see, e.g., Allport, 1937). A second premise of the theory assumes that trait expression is a rewarding experience – that is, individuals enjoy situations that allow the expression of their traits (Tett and Burnett, 2003). Trait expression (i.e., showing trait-related behavior) in a given situation is enabled by a set of situational cues, which can also be construed as opportunities or expectations. While much work on trait activation theory refers to predicting work-related outcomes, these ideas can also be applied to predicting educational outcomes (see Brandt et al., 2020). Brandt et al. (2020) argue that, for instance, different ability-grouped school tracks represent different learning contexts with distinguishable characteristics. These characteristics include different instructional styles as well as behavioral norms and expectations. Based on the notions of trait activation theory, these serve as situational cues that activate different sets of traits, which in turn causes differences in trait-performance associations between academically oriented and vocationally oriented school tracks. Specifically, Brandt et al. (2020) found, in a large sample of German students in grade nine, that conscientiousness had a stronger positive association with school performance in academic than in vocational school tracks. This finding supports the hypothesis that conscientiousness is activated to a stronger degree in a setting with higher academic demands.

The Role of Learning Situations as Trait-Relevant Learning Contexts

Trait activation theory (Tett and Guterman, 2000; Tett and Burnett, 2003) assumes that traits are activated in response to cues within the situation. In the educational context, these cues can be located within (a) the task a student performs, (b) the social environment a student is in, or (c) the wider organizational context (Brandt et al., 2020). Differential trait-performance relationships have been observed across different types of performance assessments, such as grades or performance in standardized tests (which might mostly represent a variation within the task), grades in various subjects (again mostly a variation within the tasks), and different ability-grouped school tracks (a variation at the organizational level). Up to now, little attention has been paid to the second aspect, the students' social environment. Yet, different learning situations that teachers use in organizing their school lessons (see Rubin and Hebert, 1998; Rimm-Kaufman et al., 2005; Meyer, 2013) may be an important cause of variability. Diverse learning situations (e.g., teacher-centered learning, individual tasks, or group work) are likely to impose differential expectations and norms for students' behavior, thus activating traits differentially, which results in differential trait-performance associations.

Learning situations can be described as either teacher-centered learning or student-centered learning (e.g., Rubin and Hebert, 1998; Rimm-Kaufman et al., 2005), with the latter including both individual tasks and group work. *Teacher-centered learning* is characterized by the leading role of the teacher in presenting the lessons' contents, either in a lecture-type presentation or through a moderated conversation in class. When working on *individual tasks,* students are independently working on assignments. *Group work* is characterized by students working together on assignments in (small) groups (see Meyer, 2013). A varying social environment characterizes these different learning situations: Teacher-centered learning typically involves mainly interactions with the teacher, with the entire classroom present. Individual work features minimal interactions with others and a single focus on the task given. In contrast, group work is characterized by a lot of interactions with peers and a need for cooperation.

Aims of the Present Study and Hypotheses

The present study aims at investigating whether students' character strengths predict both achievement and positive learning experiences (flow experiences and enjoyment) in different learning situations (i.e., teacher-centered learning, individual tasks, and group work) over and above cognitive ability. Drawing on trait activation theory, we assume that character strengths (as trait-like individual characteristics) are expressed in response to trait-relevant situational cues, thus giving rise to behaviors that impact performance and the level of achievement in this situation, and that their expression leads to positive learning experiences. As a consequence, we expect different character strengths to be related to positive learning experiences and achievement in different situations.

We derived a set of hypotheses regarding specific character strengths and achievement and positive learning experiences in different learning situations based on several sources: (a) theoretical assumptions on character strengths (Peterson and Seligman, 2004) and characteristics of the three learning situations studied (see Meyer, 2013), (b) trait activation theory (Tett and Guterman, 2000; Tett and Burnett, 2003), (c) previous findings on the relationships between character strengths and school achievement (e.g., Weber and Ruch, 2012, 2015; Weber et al., 2016) and differential personality-outcome associations

(e.g., Kappe and van der Flier, 2010), and (d) teachers' definitions of achievement in the three learning situations. To obtain these definitions, we asked participating teachers (N = 18) to provide their own definitions of achievement (i.e., what it means to be successful and to show a good performance in each of the learning situations) using an open-ended format at the first measurement occasion (i.e., 3 months before the outcomes variables were assessed). The answers were content-coded and the most common behavioral criteria for achievement that were mentioned are summarized in **Figure 1**.

We hypothesized that some character strengths (in particular, love of learning and perseverance) should be conducive to academic achievement and positive learning experiences across a wide range of settings, whereas other strengths should specifically contribute to achievement and positive learning experiences in certain settings as they are specifically activated by cues present in these contexts. Specifically, we expected that love of learning and perseverance would be conducive to achievement *across all learning situations*. This was also supported by the fact that teachers mentioned behaviors that are expressive of the character strengths of love of learning (e.g., "showing interest in the topic") and perseverance (e.g., "working on the task persistently" and "working toward a goal") as relevant for achievement across all learning situations (see **Figure 1**).

Achievement in *teacher-centered learning* was hypothesized to be additionally related to specific character strengths since it requires active participation in class (zest), the ability to focus one's attention (self-regulation), and self-confidence (hope). As working on *individual tasks* requires working in a self-regulated manner, we also expected achievement in individual tasks to be related to the strength of self-regulation. Successfully working on a task in a group also requires integrating different opinions or types of information (strengths of judgment and perspective) and working well with other students (strengths of love, kindness, social intelligence, teamwork, fairness, and leadership), which is why we assumed that these strengths would be associated with better performance in *group work*. We expected those strengths that should go along with better performance to also relate to positive learning experiences (flow and enjoyment) in the respective situation. With regard to flow experiences, we additionally expected that creativity, curiosity, judgment, love of learning, perseverance, zest, self-regulation, and hope would be conducive to experiencing flow in all of the learning situations,

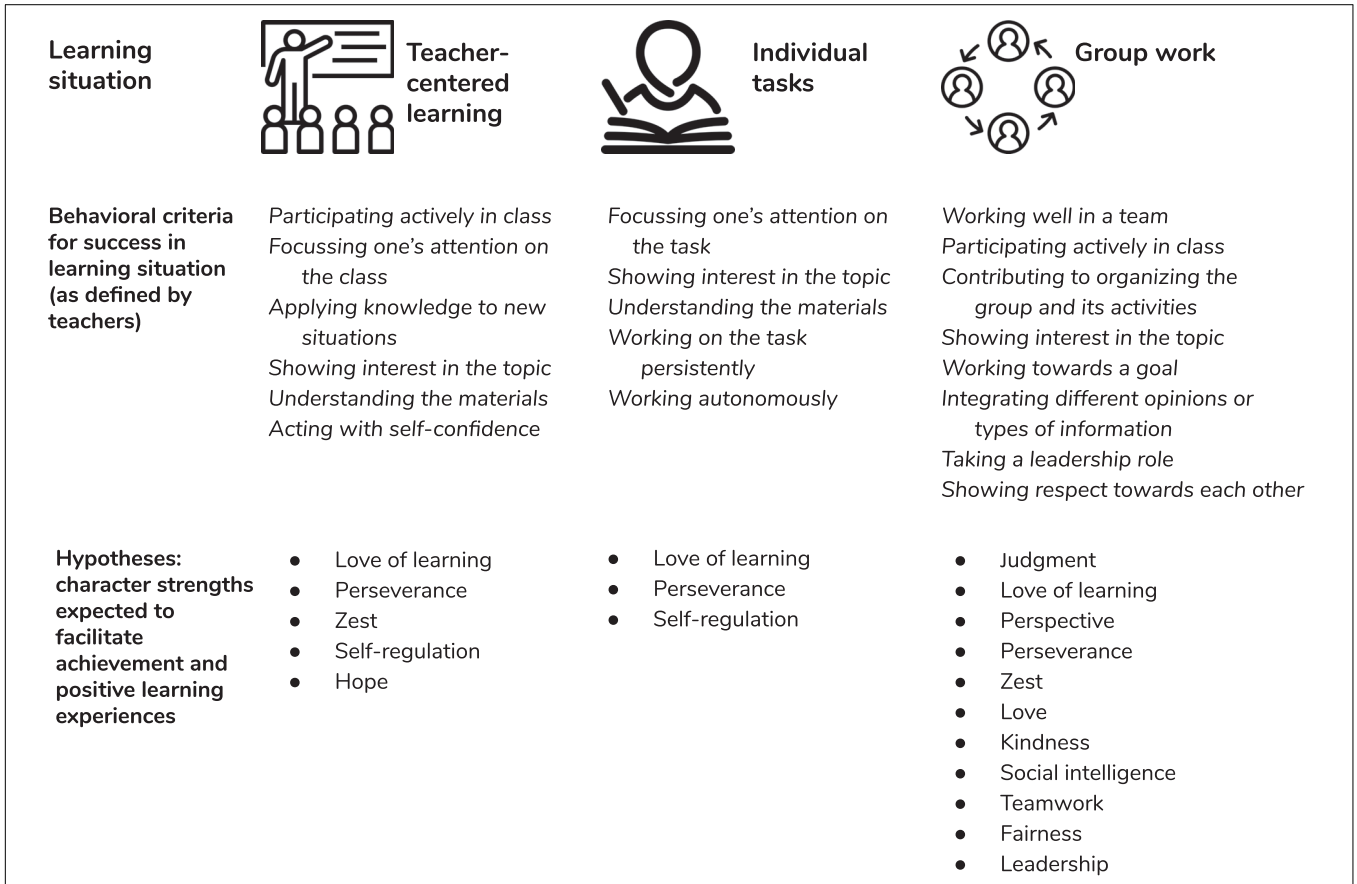

FIGURE 1 | Teachers' definitions of behaviors related to success in learning situations and hypothesized relationships of character strengths with achievement and positive learning experiences. Teachers' answers were content-coded and are listed when they were mentioned at least three times (i.e., by at least 16.7% of the teachers).

in line with earlier findings (Wagner and Ruch, 2020). **Figure 1** gives an overview of the hypothesized relationships.

MATERIALS AND METHODS

Participants

We calculated the required sample size using G*Power 3.1 (Faul et al., 2009) based on a power of at least 0.80 to detect an effect of $r = 0.20$ (based on previous studies' results; e.g., Wagner and Ruch, 2015) using an α-level of 0.01 and one-tailed tests. This resulted in a required sample size of at least $N = 247$.

Altogether, we collected data of 301 participants in 19 classrooms. Data of 48 participants were excluded from the analyses because they had missing data in several relevant instruments ($n = 18$, mostly because they did not participate in both data collections), did not complete the intelligence test ($n = 14$, i.e., one classroom), showed response patterns indicative of careless responding ($n = 8$, determined by examining repeated answers, the consistency of recoded and non-recoded items, and response times), or had too little knowledge of German ($n = 6$). Thus, the analyzed sample consisted of $N = 255$ students (46.3% boys and 53.7% girls) from 18 different classrooms. At the time of the first data collection, participants had a mean age of 14.49 years ($SD = 1.07$; ranging from 12.42 to 18.75 years). Most (83.2%) were between 13 and 15 years old. In Switzerland, secondary schools can be categorized into two tracks: Around one-quarter of participants attended schools with basic requirements (i.e., with a vocational orientation) and 76.5% of participants attended schools with augmented requirements (i.e., with an academic orientation), which approximately represents the distribution of schools in the respective communities.

The sample of teachers consisted of $N = 18$ teachers (8 female and 10 male) with a mean age of 43.67 years ($SD = 12.16$, ranging from 24 to 60 years). They had been working as teachers for on average of 19.17 years ($SD = 12.46$). In the Swiss secondary school system, students in one classroom typically attend most classes together as a group. The teachers participating in the present study were their homeroom teachers in most cases (i.e., in 94.4%) and typically taught several school subjects to the same class (on average 10.78 hours per week, with $SD = 4.08$). All teachers had also been teaching the respective students for at least 6 months ($M = 15.44$ months, $SD = 9.79$). Thus, it can be assumed that they were sufficiently familiar with the students to rate their achievement in different learning situations.

Instruments

To assess students' character strengths, we used the *Values in Action Inventory of Strengths for Youth* (VIA-Youth; Park and Peterson, 2006b) adapted to German by Ruch et al. (2014), which is based on the VIA classification (Peterson and Seligman, 2004) and consists of 198 items with a 5-point answer format (from 5 = *very much like me* to 1 = *not like me at all*). A sample item is "I don't boast about what I achieve" (character strength of humility). The VIA-Youth has demonstrated its reliability and validity in a number of studies (e.g., Park and Peterson, 2006b; Ruch et al., 2014). In this study, the internal consistency coefficients of the 24 scales yielded a median of α = 0.77 (ranging from 0.67 to 0.88, see **Table 1**). As not all VIA-Youth scales can be assumed to be fully unidimensional, these coefficients might be biased and need to be interpreted with caution. However, previous research (Ruch et al., 2014) testing other forms of reliability, namely test-retest correlations across 4 months (median $r_{tt} = 0.72$), provides further evidence for the reliability of the measure.

To assess school achievement across the different learning situations, we used both *teacher- and self-reports*. For each learning situation, teachers were asked to rate each student on two items (e.g., for individual tasks "The student is successful in individual tasks." and "The student performs well in individual tasks.") using a 7-point scale (ranging from 1 = *completely disagree* to 7 = *completely agree*). Each learning situations was explained in a short description (provided in **Supplementary Material**). For example, individual tasks were introduced by the following description: "At school, there are situations, in which the teacher gives the students a task to complete. In some of these situations, students are asked to work on these tasks individually. We refer to these situations as 'individual tasks.'" Since the two items correlated highly [$r(253) = 0.86$ for teacher-centered learning, $r(253) = 0.93$ for individual tasks, and $r(253) = 0.93$ for working in groups, all $p < 0.001$], we used the means across the respective two items in our analyses. Similarly, students were

TABLE 1 | Descriptive statistics, internal consistencies, and correlations with age, gender, and school track for VIA-Youth scales.

	M	*SD*	*Min*	*Max*	α	r_{age}	r_{gender}	r_{track}
Creativity	3.60	0.62	1.50	5.00	0.77	−0.13*	−0.10	0.02
Curiosity	3.54	0.58	2.00	5.00	0.76	−0.06	−0.10	0.09
Judgment	3.52	0.54	2.25	5.00	0.73	−0.02	0.04	−0.01
Love of learning	3.44	0.59	1.63	4.88	0.75	−0.08	0.21*	0.02
Perspective	3.68	0.49	2.38	4.88	0.70	−0.03	0.17*	0.12
Bravery	3.73	0.58	2.38	5.00	0.79	−0.03	0.10	0.00
Perseverance	3.49	0.60	1.56	5.00	0.79	−0.10	0.23*	−0.16*
Honesty	3.78	0.57	1.25	5.00	0.82	−0.01	0.27*	−0.04
Zest	3.52	0.56	1.88	5.00	0.73	−0.18*	0.04	−0.03
Love	4.04	0.63	1.89	5.00	0.81	−0.03	0.21*	−0.06
Kindness	4.08	0.55	2.11	5.00	0.82	−0.10	0.41*	−0.02
Social intelligence	3.78	0.48	2.25	5.00	0.67	0.02	0.19*	0.09
Teamwork	3.99	0.49	2.13	5.00	0.72	0.01	0.23*	0.07
Fairness	3.58	0.55	1.89	4.89	0.72	0.03	0.32*	0.08
Leadership	3.34	0.67	1.25	5.00	0.85	0.01	0.01	0.01
Forgiveness	3.78	0.62	1.29	5.00	0.77	0.04	0.03	0.15
Humility	3.69	0.57	1.67	5.00	0.73	−0.02	0.25*	0.09
Prudence	3.34	0.58	1.63	4.63	0.73	0.04	0.15*	0.03
Self-regulation	3.49	0.59	1.56	5.00	0.75	0.06	0.16*	0.00
Beauty	3.51	0.69	1.63	5.00	0.79	0.01	0.37*	0.14*
Gratitude	4.18	0.53	2.00	5.00	0.79	−0.03	0.17*	−0.08
Hope	3.80	0.59	1.75	5.00	0.80	0.02	−0.03	0.02
Humor	3.96	0.60	1.67	5.00	0.79	−0.01	−0.10	0.10
Spirituality	3.51	0.99	1.00	5.00	0.88	−0.17*	0.12	−0.21*

*N = 255. Beauty = Appreciation of beauty and excellence. Age: 12.42–18.75 years. Gender: 0 = male, 1 = female. Track: 0 = school with vocational orientation, 1 = school with academic orientation. *p < 0.05 (two-tailed).*

also provided with descriptions of the learning situations (see **Supplementary Material**) and asked to rate their achievement in each learning situation (e.g., for individual tasks "I am successful in individual tasks." and "I perform well in individual tasks.") using a 7-point scale (ranging from 1 = *completely disagree* to 7 = *completely agree*). Again, the two respective items correlated highly [$r(253) = 0.75$ for teacher-centered learning, $r(253) = 0.87$ for individual tasks, and $r(253) = 0.78$ for working in groups, all $p < 0.001$], so we also used the means in the analyses.

To assess habitual flow experiences across the different learning situations, we used an adaptation of the Flow Short Scale (FSS; Rheinberg et al., 2003). The FSS consists of 10 items (answered on a 7-point scale) covering different components of flow experiences and was designed to assess flow in specific situations. We adapted the scale to assess habitual experiences by presenting it with an instruction to think of the different learning situations (referring to the same description as for the achievement rating). The three versions of the scale (and a version assessing experiences in school in general, which is not relevant for the present study) were presented in a randomized order to avoid systematic order effects. In the present study, these three scales reached internal consistencies of $\alpha = 0.82$ (teacher-centered learning), $\alpha = 0.89$ (individual tasks), and $\alpha = 0.86$ (group work).

To assess the enjoyment of learning situations, we used three items, one for each situation (e.g., for individual tasks "I enjoy individual tasks."). Students rated to what extent they agreed with each statement on a 7-point scale (ranging from 1 = *completely disagree* to 7 = *completely agree*).

To assess psychometric intelligence, we used the *Prüfsystem für Schul-und Bildungsberatung für 6. bis 13. Klassen, Revidierte Fassung* (Testing System for Scholastic and Educational Counseling, Grades 6–13 –revised version; PSB-R 6–13; Horn et al., 2003). The PSB-R 6–13 was designed for use in educational settings and encompasses the assessment of reasoning and verbal intelligence (including school-specific knowledge) as well as concentration. It consists of nine subtests (three for the assessment of verbal intelligence, four for the assessment of reasoning, and two for the assessment of concentration). The PSB-R 6–13 has previously demonstrated strong convergent validity with other measures of cognitive ability as well as criterion validity in the prediction of outcomes such as school grades (Horn et al., 2003). In the present study, we used the total score, which is based on all nine subtests and offers a comprehensive measure of cognitive ability that was found of particular relevance to predicting school achievement. For the analyses, we used age-standardized scores ($M = 100$; $SD = 10$) of this total score.

Procedure

The study's procedures were approved by the institutional ethical board at the Faculty of Philosophy at the University of Zurich. All participants gave their written consent and participated voluntarily. Students under the age of 14 years were provided written permission to participate by a parent or legal guardian. As an incentive, participating students were offered individualized feedback on their character strengths.

Data presented here were collected as part of a larger project and the sample presented here overlaps (by 70.6%) with Wagner and Ruch (2020). Wagner and Ruch (2020) studied the incremental validity of character strengths in predicting educational outcomes beyond intelligence and the personality traits of the five-factor model. Two of the predictors overlap between both studies, but none of the outcomes. Specifically, Wagner and Ruch (2020) focused on educational outcomes in general, whereas the present study investigates differential trait-outcome associations across different learning situations. Questionnaire data were collected on school computer or tablets, whereas the intelligence test was administered in paper/pencil-format. The VIA-Youth and the intelligence test (PSB-R 6–13) were completed at a baseline assessment, and the data on outcome variables (achievement ratings by teachers and students, FSS, and enjoyment ratings) were collected about 3 months later ($M = 95.49$ days, $SD = 3.87$, range: 84–102). Both data collections also contained other measures not relevant to the present study.

Data Analysis

To account for the nested structure of the data, we first computed ICC(1) coefficients to evaluate the amount of variance in our outcome variables on the classroom level. For some of the outcomes, the ICC(1) coefficients were significant; that is, the levels of students in the same classroom were not independent of each other. Those outcomes were teacher-rated achievement in teacher-centered learning, ICC(1) = 0.10, $F(17, 237) = 2.644$, $p < 0.001$; teacher-rated achievement in group work, ICC(1) = 0.11, $F(17, 237) = 2.687$, $p < 0.001$; self-rated achievement in teacher-centered learning, ICC(1) = 0.05, $F(17, 237) = 1.757$, $p = 0.035$; flow in individual tasks, ICC(1) = 0.08, $F(17, 237) = 2.331$, $p = 0.003$; and enjoyment of group work, ICC(1) = 0.08, $F(17, 237) = 2.150$, $p = 0.006$. Based on this non-independence, we decided to run multilevel analyses to address the study's research questions.

We ran random-intercept models using the lme4 package (Bates et al., 2015) in R (R Core Team, 2013), that is, the respective intercepts could vary between the classrooms. Adding a random slope to the models did not yield an increase in explained variance; hence, we report the results of the random-intercept models. The models used restricted maximum likelihood (REML) estimation. We used lmerTest (Kuznetsova et al., 2017) to compute *p*-values. In the main analyses, we applied an alpha level of $\alpha = 0.01$ to account for the effects of multiple testing. Given the associations of various study variables with age, gender, and ability-based school track (vocational or academic orientation; see **Tables 1**, **2**), we decided to include these variables as covariates in the analyses testing the hypotheses.

RESULTS

Descriptive Statistics

Descriptive statistics for character strengths and correlations with age, gender, and school track (vocational or academic orientation) are shown in **Table 1**.

TABLE 2 | Descriptive statistics, correlations with age, gender, and school track, and intercorrelations for intelligence and dependent variables.

	Descriptives					Intercorrelations											
	M	*SD*	r_{age}	r_{gender}	r_{track}	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)
(1) Intelligence	100.51	8.73	0.05	−0.05	0.56	0.17	0.18	0.28	0.17	0.06	0.13	0.12	0.22	0.04	−0.09	0.12	0.02
(2) Teacher-rated achievement: teacher-centered	5.02	1.22	−0.06	0.02	0.02		0.43	0.35	0.29	0.26	0.21	0.21	0.27	0.16	0.14	0.13	0.07
(3) Teacher-rated achievement: individual tasks	5.19	1.24	−0.16	0.24	−0.04			0.51	0.16	0.33	0.14	0.20	0.27	0.11	0.07	0.29	−0.02
(4) Teacher-rated achievement: group work	4.94	1.36	−0.11	0.34	0.11				0.17	0.13	0.22	0.16	0.17	0.15	0.02	0.18	0.09
(5) Self-rated achievement: teacher-centered	4.96	1.20	−0.12	0.00	−0.06					0.40	0.40	0.60	0.45	0.34	0.54	0.12	0.15
(6) Self-rated achievement: individual tasks	5.50	1.08	−0.04	0.09	0.06						0.32	0.40	0.64	0.24	0.13	0.56	0.03
(7) Self-rated achievement: group work	5.38	1.07	−0.04	0.13	−0.10							0.34	0.29	0.49	0.23	0.03	0.60
(8) Flow: teacher-centered	4.38	0.91	−0.14	0.01	0.03								0.65	0.57	0.42	0.17	0.17
(9) Flow: individual tasks	4.70	1.05	−0.16	0.00	0.16									0.50	0.21	0.39	−0.01
(10) Flow: group work	4.64	0.98	−0.15	0.05	0.05										0.24	0.12	0.42
(11) Enjoyment: teacher-centered	4.58	1.64	−0.08	−0.02	−0.08											0.03	0.17
(12) Enjoyment: individual tasks	4.81	1.59	−0.05	0.17	0.11												−0.27
(13) Enjoyment: group work	5.84	1.34	−0.05	0.00	−0.04												

N = 255. Intelligence: Age-standardized scores (M = 100, SD = 10). Flow, achievement, and enjoyment: Range 1–7. Age: 12.42–18.75 years. Gender: 0 = male, 1 = female. Track: 0 = school with vocational orientation, 1 = school with academic orientation. Correlations r ≥ 0.13 are significant at p < 0.05.

As displayed in **Table 1**, some small- and medium-sized correlations with demographic variables emerged. Descriptive statistics of intelligence and the dependent variables (school achievement, flow experience, and enjoyment in three learning situations), as well as the respective intercorrelations are displayed in **Table 2**.

Intelligence was positively related to achievement in all three situations (with the exception of self-rated achievement in individual tasks) and to flow experience in individual tasks, but unrelated to the remaining outcome variables. Both achievement and flow ratings showed high intercorrelations between the three situations, but also seemed separable. Enjoyment ratings seemed to overlap less between the situations, with the enjoyment of individual tasks being negatively related to the enjoyment of group work. The results also show generally small to medium-sized positive correlations between achievement and flow as well as between achievement and enjoyment and medium to large correlations between flow and enjoyment. With the exception of achievement in and enjoyment of group work, the outcomes regarding one type of situation were always positively related.

Multilevel Analyses

The main analyses refer to the relationships between character strengths and outcomes (teacher- and self-rated achievement, flow, and enjoyment) while controlling for age, gender, school track, and intelligence. The results of the analyses regarding achievement are displayed in **Table 3**, the results without a control for intelligence are displayed in **Supplementary Table S1**.

As shown in **Table 3**, in line with our expectations, and across both self- and teacher-ratings love of learning, perseverance, zest, and hope were positively related to achievement in teacher-centered learning, and love of learning was also positively related to achievement in individual tasks. However, we did not find the expected association between self-regulation and achievement in teacher-centered learning and the associations of perseverance and self-regulation with achievement in individual tasks were only found in self-ratings of achievement. With regards to achievement in group work, the hypothesized positive relations with perspective and teamwork were found across both ratings. In contrast, no significant relationships for love and kindness were observed and the character strengths of judgment, love of learning, zest, social intelligence, fairness, and leadership were only associated with self-rated achievement in group work. Additionally, we found several strengths to positively relate to teacher-rated achievement in teacher-centered learning (i.e., bravery, honesty, fairness, teamwork, and gratitude) and in group work (i.e., prudence), as well as a larger number of strengths to positively relate to self-rated achievement.

Considering flow experiences, we found that, as expected, the strengths of creativity, judgment, love of learning, perseverance, zest, self-regulation, and hope were positively related to flow across the different learning situations beyond intelligence (see **Table 4** and **Supplementary Table S2** for results without control for intelligence). Curiosity did not show the expected positive relationships with flow experiences. Perspective, love, social intelligence, teamwork, fairness, and leadership (but not kindness) were also additionally related with flow in group work.

TABLE 3 | Fixed effects (standardized) of intelligence and character strengths predicting self- and teacher-rated school achievement in three learning situations (controlling for influences of age, gender, school track, and for character strengths also for intelligence).

	Teacher-rated achievement			Self-rated achievement		
	Teacher-centered learning	Individual tasks	Group work	Teacher-centered learning	Individual tasks	Group work
Intelligence	0.23*	0.30*	0.35*	0.20*	0.08	0.17
Character strengths						
Creativity	−0.07	−0.06	0.04	0.21*	0.21*	0.21*
Curiosity	0.10	0.13	0.11	0.18*	0.19*	0.09
Judgment	0.07	0.04	0.11	0.20*	0.26*	0.15*
Love of learning	0.19*	0.16*	0.13	0.35*	0.42*	0.16*
Perspective	0.13	0.02	0.15*	0.25*	0.24*	0.24*
Bravery	0.18*	0.00	0.10	0.20*	0.19*	0.07
Perseverance	0.22*	0.12	0.14	0.32*	0.34*	0.21*
Honesty	0.16*	0.05	0.05	0.11	0.24*	0.19
Zest	0.26*	0.03	0.13	0.37*	0.25*	0.16*
Love	0.13	−0.02	0.09	0.28*	0.14	0.09
Kindness	0.12	0.02	0.13	0.12	0.12	0.14
Social intelligence	0.10	−0.01	0.10	0.19*	0.24*	0.19*
Teamwork	0.20*	0.03	0.17*	0.12	0.26*	0.41*
Fairness	0.16*	0.14	0.13	0.06	0.25*	0.19*
Leadership	0.13	−0.09	0.06	0.25*	0.11	0.25*
Forgiveness	0.12	0.10	0.06	0.07	0.17*	0.20*
Humility	0.03	0.04	0.03	−0.11	0.15*	0.12
Prudence	0.07	0.11	0.15*	0.10	0.22*	0.09
Self-regulation	0.14	0.08	0.04	0.11	0.34*	0.18*
Beauty	−0.04	−0.05	0.10	0.20*	0.13	0.11
Gratitude	0.19*	0.04	0.11	0.23*	0.20*	0.17
Hope	0.20*	0.07	0.10	0.34*	0.25*	0.15
Humor	0.01	−0.12	0.06	0.07	0.00	−0.03
Spirituality	0.04	0.02	0.05	0.09	0.13	0.05

*N = 255. Beauty = Appreciation of beauty and excellence. *p < 0.01 (one-tailed).*

In line with our expectations, love of learning, perseverance, zest, and hope were associated with enjoying teacher-centered learning, whereas no relationships were found with self-regulation (see **Table 4**). Love of learning and self-regulation (but not perseverance) were predictors of enjoying individual tasks, and only the character strength of teamwork predicted enjoying group work. In addition, enjoying teacher-centered learning was also positively related to curiosity, judgment, and perspective and enjoying individual tasks was also positively related to creativity, curiosity, judgment, fairness, and appreciation of beauty and excellence.

DISCUSSION

The present study followed the principles of trait activation theory in testing the extent to which character strengths show differential trait-outcome relationships across different learning situations that are assumed to activate different sets of character strengths. In doing so, it demonstrated differential relationships of positively valued traits with both achievement and positive learning experiences (flow and enjoyment) across different learning situations beyond cognitive ability. The results are summarized in **Figure 2**, which gives an overview on the hypotheses supported and not supported by the observed results.

With regard to achievement in different learning situations, we found support for both the idea that certain strengths (such as love of learning and perseverance) are conducive to school achievement in general and the idea that other strengths are activated and contribute to achievement only in specific learning situations.

For instance, the character strength of zest was found to be of particular relevance for achievement and positive learning experiences in *teacher-centered learning*. In this learning situation, students seem to be mostly required to keep up a level of focus and activity, which is favored by approaching the situation with zest. Previous research has demonstrated that extraversion tends to show no (or even negative) relationships with overall academic achievement, at least in secondary and tertiary education (Poropat, 2009). Nonetheless, studies using specific performance criteria, such as oral participation in class (Furnham and Medhurst, 1995), report a positive relationship of extraversion with these achievement criteria, arguably because extraverted behaviors help interact with teachers. The character strength of zest might capture some of the most relevant aspects of extraversion's facet "activity" that contribute to an advantage in interacting with teachers in teacher-centered learning. Additionally, the character strength of hope was positively related to all four outcome measures regarding teacher-centered learning, in line with expectations. Hope has been

TABLE 4 | Fixed effects (standardized) of intelligence and character strengths predicting flow and enjoyment in three learning situations (controlling for influences of age, gender, school track, and for character strengths also for intelligence).

	Flow			Enjoyment		
	Teacher-centered learning	Individual tasks	Group work	Teacher-centered learning	Individual tasks	Group work
Intelligence	0.13	0.16	0.00	−0.07	0.07	0.06
Character strengths						
Creativity	0.23*	0.24*	0.21*	0.16	0.19*	0.08
Curiosity	0.13	0.14	0.11	0.17*	0.20*	−0.04
Judgment	0.28*	0.31*	0.21*	0.16*	0.23*	0.02
Love of learning	0.34*	0.40*	0.18*	0.26*	0.35*	−0.09
Perspective	0.21*	0.29*	0.21*	0.25*	0.08	0.10
Bravery	0.12	0.20*	0.05	0.11	0.03	−0.03
Perseverance	0.35*	0.41*	0.22*	0.23*	0.11	−0.02
Honesty	0.16*	0.24*	0.14	0.09	0.05	0.09
Zest	0.32*	0.26*	0.20*	0.18*	0.10	0.04
Love	0.22*	0.20*	0.17*	0.14	−0.03	0.14
Kindness	0.15	0.08	0.12	0.03	−0.01	0.10
Social intelligence	0.25*	0.26*	0.22*	0.14	0.08	0.09
Teamwork	0.16*	0.16*	0.25*	0.04	0.04	0.31*
Fairness	0.15	0.28*	0.17*	0.05	0.20*	0.02
Leadership	0.14	0.16*	0.20*	0.14	−0.01	0.12
Forgiveness	0.10	0.15*	0.13	0.07	0.06	0.11
Humility	0.01	0.13	0.07	−0.13	0.13	0.09
Prudence	0.26*	0.28*	0.23*	0.14	0.14	0.03
Self-regulation	0.20*	0.28*	0.18*	0.01	0.19*	0.04
Beauty	0.16*	0.17*	0.17*	0.13	0.20*	0.02
Gratitude	0.14	0.16*	0.11	0.08	0.10	0.14
Hope	0.30*	0.34*	0.16*	0.20*	0.14	0.00
Humor	−0.04	−0.02	0.00	0.04	−0.06	0.03
Spirituality	0.06	0.11	0.01	0.10	0.04	0.01

*N = 255. Beauty = Appreciation of beauty and excellence. *p < 0.01 (one-tailed).*

shown to be predictive of academic achievement in a variety of educational settings (e.g., Day et al., 2010; Gallagher et al., 2017) and the present results suggest that these relationships found with overall GPA may in part be driven by teacher-centered learning situations, in which hope seems to be particularly activated.

Achievement in *individual tasks* seems to be least explained by character strengths, which might be because it relates least to overt behavior and is thus more difficult to be rated from the teacher's perspective. Nonetheless, we also found some evidence for the expected relevance of self-regulation, though only with regard to self-reported measures. However, no relationships were found for self-regulation with achievement in *teacher-centered learning*. As self-regulation is a relatively common individual difference variable studied in relation to academic achievement (for an overview, see, e.g., Duckworth and Carlson, 2013), the notion of differential trait-outcome relationships for different learning situations might also be relevant for this research.

In line with our expectations, the character strengths of perspective and teamwork were positively related to both teacher- and self-rated achievement in *group work*. Previous research (Kappe and van der Flier, 2010) investigating the personality dimensions of the five-factor model was not able to find the expected relationships between agreeableness and performance in a learning situation involving a group project. Thus, the narrower traits of character strengths, and traits such as teamwork in particular, might be better suited than the broader and "neutral" dimension of agreeableness to describe individual differences relevant to doing well in a task completed in a group. However, the character strengths of love and kindness were unrelated to both teacher- and self-rated achievement in group work. Both strengths have been found to be of particular relevance for positive peer relationships in the classroom (Wagner, 2019; Wagner and Ruch, 2020), but it seems that this advantage does not necessarily extend into improved performance in situations that require cooperation with peers.

The present study also showed that specific traits can offer a deeper understanding of relationships with outcomes than broader traits. For example, Kappe and van der Flier (2010) found openness to experience to relate to lower performance ratings in group settings and argued that bringing a lot of different perspectives into the discussion can distract from completing a group task in a timely manner. However, the strength of judgment covers exactly this specific aspect (i.e., considering different perspectives), whereas openness to experience is a much broader and non-valued trait that includes many different aspects, which might also be relevant to how openness to

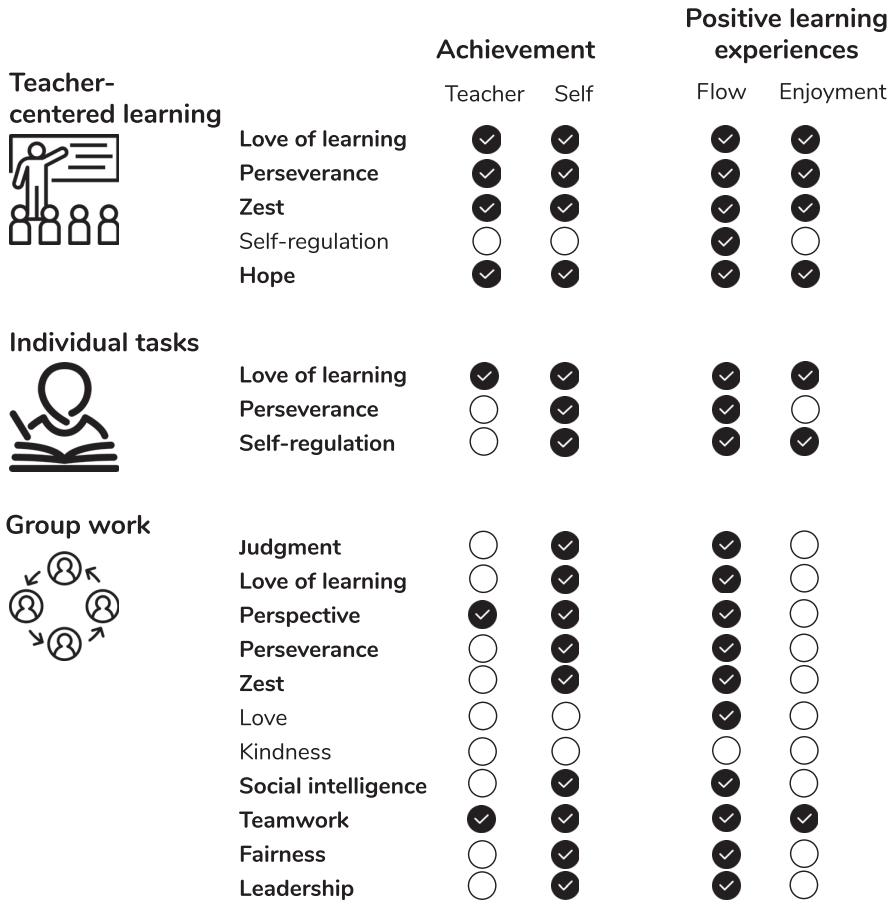

FIGURE 2 | Overview of results in relation to hypotheses. Boldface = positive relationships with at least one indicator of achievement and one indicator of positive learning experiences in the respective learning situation.

experience contributes to performing in a group task. Our results suggest that the narrower strength of judgment is conducive to self-rated achievement and to flow experiences in group settings, at least in the context of secondary school. Thus, specific traits allow for a more nuanced examination of the relationships between personality traits and educational outcomes.

When we assess the full picture of relationships with achievement against previous studies on the role of character strengths for overall school achievement (e.g., Wagner and Ruch, 2015), we find that the strengths of love of learning and perseverance show the strongest and most consistent relationships with achievement across various learning situations beyond the influence of cognitive ability. Wagner and Ruch (2015) found that, in addition to love of learning and perseverance, overall school achievement was positively correlated with zest, prudence, gratitude, hope, and perspective across two samples. In the present study, zest, hope, and perspective show at least some evidence of differential trait-outcome relationships, with zest and hope, in particular, being mostly related to performance in teacher-centered learning. There were no hypotheses for gratitude and prudence; however, gratitude was linked with both teacher- and self-rated achievement, but not with positive learning experiences, in teacher-centered learning, and prudence demonstrated a positive relationship with teacher-rated achievement in group tasks. Thus, the present results offer some support that these character strengths are predictive of academic achievement even when controlling for the influence of cognitive ability.

With regard to flow experiences in the different learning situations, we also found support for our expectations. At the same time, while some character strengths showed differential patterns of relationships (such as love of learning, which was associated more strongly with flow in individual than in group tasks, or self-regulation, which showed the strongest association with flow in individual tasks), many others showed similar associations across the different learning situations. This might suggest that certain traits are generally linked to a proneness to experience flow in the school setting, irrespective of the learning situation. A number of strengths might generally predispose students to enter a flow state in the educational setting (such as creativity, judgment, and love of learning). In contrast, other strengths can be assumed to be conducive to entering a flow state (such as zest or hope) or staying in a flow state in the face of distractions (such as perseverance or self-regulation; see

Wagner et al., 2020; Wagner and Ruch, 2020). Future research would benefit from a more fine-grained analysis of situations in which flow occurs at school to allow uncovering differential associations with personality traits.

Finally, when considering enjoyment of the three learning situations, the relationships varied a lot between the different learning situations; that is, results were much more in line with the notion of different character strengths predisposing individuals to enjoy learning in different contexts. These findings are again in line with the arguments of trait activation theory, which also assumes that the display of traits leads to satisfaction. Specifically, if a contextual cue activates a trait and the trait is displayed, the individual will in turn be likely to enjoy this situation.

In our analyses, we controlled for intelligence with the aim to study the incremental contribution of character strengths in predicting educational outcomes beyond cognitive ability. In theory, character strengths and intelligence do not overlap, and also the observed overlap in the present study was small. It should be considered, though, that we used a comprehensive measure of cognitive ability that includes both fluid and crystallized aspects of intelligence. Character strengths demonstrated incremental validity even above this broadly defined assessment of intelligence, suggesting that they represent useful constructs to study relationships between narrower traits and achievement as well as positive experiences at school (see O'Connor and Paunonen, 2007). The size of the relationships for intelligence and the relevant character strengths with the main outcome (teacher-rated achievement) was overall comparable. In the case of teacher-rated achievement in teacher-centered learning, when intelligence was considered together with love of learning, perseverance, zest, teamwork, or hope, the relationship proved to be numerically smaller yet very similar-sized. For the other two learning situations, the relationships of achievement with intelligence were somewhat stronger than the associations of the relevant strengths with achievement, albeit also of comparable size. These analyses include three different methods (intelligence test, self-reported character strengths, and teacher-rated achievement) and intelligence was measured more reliably than character strengths. As a consequence, the findings represent a strong argument for the relevance of positively valued traits, such as character strengths, in predicting achievement in the educational context. With regard to self-rated achievement, flow, and enjoyment in the three learning situations, character strengths clearly outperform intelligence in their predictive power.

Our findings contribute to the understanding of specific contextual factors that determine how personality traits relate to educational outcomes. Learning situations that vary with regards to demands, type, and amount of social interaction should be further considered as contextual factors in understanding these complex relationships. Future research should also study whether strengths-related behavior varies as expected between the different learning situations. The three learning situations we studied only represent one of many aspects in which achievement and positive learning experiences can vary; other characteristics, such as the subject content as well as relationships with classmates and teachers involved, might be of equal importance. Nonetheless, performing well in different types of social interactions might also be relevant in later life, such as in university education or at the workplace. Thus, the present findings might also have implications for how character strengths relate to different aspects of performance in adulthood (see Harzer and Ruch, 2014). Furthermore, when considering the possibility of interventions to foster certain personality traits or character strengths, information on the role of specific contexts, such as learning situations, should be considered. Another practical recommendation following the current findings could extend to designing schools and planning specific lessons. Based on the present results, offering a variation or a choice of learning situations would allow different strengths to be activated and as a consequence, more students (with diverse strengths) to be able to perform well and enjoy learning.

Strengths and Limitations

The present study has several strengths. For instance, it uses different data sources (self-reports, standardized tests, teacher ratings) and different time points (3 months apart) to reduce or eliminate the influence of common method bias. However, the present results also need to be interpreted in light of several limitations. First, the learning situations selected in the present study certainly do not cover all situations that are potentially relevant to learning in a classroom, and the descriptions provided were rather general. Thus, students and teachers might have differed in their understanding of the types of situations described. Second, teachers might not be the best informants about achievement in group work; hence, future studies might also consider peer ratings. Third, the assessment of all outcomes relied on ratings of habitual behavior (teacher- and self-rated school achievement) or habitual experiences (self-reported flow experience and enjoyment). In future studies, it would be desirable to assess these outcomes through either observation or experience-sampling methods. Fourth, even though participants were diverse to some extent (attending different school tracks in several communities in German-speaking Switzerland), the present results might not extend to other cultural contexts. Finally, an important limitation is that it is impossible to draw conclusions regarding directionality or causality based on the present results.

CONCLUSION

The present study looked at the role of students' character strengths in predicting educational outcomes beyond the influence of cognitive ability. Specifically, we asked the question: Which students perform well and have positive experiences in different situations at school, irrespective of their intelligence? We focused on three learning situations and the results demonstrated that the associations differed between those situations. Our results support the notion that character strengths represent a useful framework for a nuanced examination of the complex relationships between personality traits and educational

outcomes. Overall, quite a large number of character strengths are relevant when predicting different educational outcomes and the strengths' narrow definitions allow for depicting differential relationships.

DATA AVAILABILITY STATEMENT

The datasets generated for this study are available on request to the corresponding author.

ETHICS STATEMENT

The studies involving human participants were reviewed and approved by the University of Zurich, Zurich, Switzerland; Ethikkommission (für psychologische und verwandte Forschung). All participants gave their written consent and participated voluntarily. Students under the age of 14 years were provided written permission to participate by a parent or legal guardian.

AUTHOR CONTRIBUTIONS

LW and WR contributed to the conception and design of the study. MH and HW collected the data and wrote sections of the manuscript. LW performed the statistical analysis and wrote the first draft of the manuscript. All authors contributed to the article and approved the submitted version.

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SUPPLEMENTARY MATERIAL

The Supplementary Material for this article can be found online at: https://www.frontiersin.org/articles/10.3389/fpsyg.2020.01324/full#supplementary-material

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Conflict of Interest: WR is a senior scientist at the VIA Institute on Character, which holds the copyright of the VIA-Youth.

The remaining authors declare that the research was conducted in the absence of any commercial or financial relationships that could be construed as a potential conflict of interest.

Appendix B: Study 2

How do self-efficacy and self-concept impact mathematical achievement? The case of mathematical modelling

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Abstract

Background. According to the self-enhancement perspective, self-efficacy and self-concept are shaped by prior achievement and have a crucial impact on future development. Their role in improving performance on challenging tasks, such as mathematical modelling (i.e., solving realistic problems mathematically), has barely been studied.

Aims. We investigated patterns of self-efficacy and self-concept and their predictive effects on mathematical modelling while taking into account school grades as measure of prior achievement and reasoning to reveal cognitive and motivational effects on achievement.

Sample. $N = 279$ secondary students in Grade 8 or 9 from 16 classes and 6 schools participated in the study.

Method. The multi-informant design consisted of teachers' reports of school grades, students' reports of self-efficacy and self-concept (questionnaire based), and assessment of students' reasoning and mathematical modelling.

Results. Using random-intercept models, we found that the predictive effect of self-efficacy on mathematical modelling withstood taking the school-classroom-related nested structure into account, whereas self-concept lost its predictive value. Further, self-efficacy fully mediated the effect of school grades on mathematical modelling.

Conclusions. In line with the self-enhancement perspective on self-efficacy, our findings highlight the strength of motivational effects on mathematical modelling. When we take the nested structure into account, our results indicate an impact of school grades via self-efficacy on mathematical modelling independent of students' cognitive level or classroom. Given the diverse challenges such complex tasks present, important pedagogical and didactical recommendations, such as targeting the enhancement of students' self-efficacy by teachers and educational decision makers, can be drawn.

Keywords: self-efficacy; self-concept; mathematical modelling; mathematical achievement; school grades

How do self-efficacy and self-concept impact mathematical achievement? The case of mathematical modelling

Introduction

Self-efficacy—believing in one's capability to create an impact on current and future events and possessing the means to attain given goals (Bandura, 1977, 1997)—is crucial for students to realize their capabilities. Hence, self-efficacy has been investigated as an important predictor of achievement (Bandura, 1997; Chemers et al., 2001; Kriegbaum et al., 2015; Zimmerman et al., 1992). Building on these findings, researchers have studied the enhancement of self-efficacy to improve students' performance in general (Bandura, 1997; Multon et al., 1991; Zimmerman et al., 1992) and mathematical achievement in particular (Prabawanto, 2018; Schunk, 1983; Schunk & Cox, 1986). The relationship between self-efficacy and achievement appears especially relevant for mathematics, a cognitively and emotionally challenging subject for students (Hackett & Betz, 1989). Self-efficacy has been found to be an important motivational predictor of performance in mathematical problem solving (Pajares & Miller, 1995). When predicting school achievement, cognitive predictors—with intelligence considered the strongest among them—have also been investigated (Gottfredson, 2002; Roth et al., 2015). These studies indicate that to investigate the relationship between self-efficacy and mathematical problem solving, intelligence needs to be taken into account.

In the academic motivation literature, self-concept and self-efficacy appear to be highly related constructs, and researchers oftentimes struggle to differentiate them (cf., Bong & Skaalvik, 2003). We differentiate between prospective and evaluative self-efficacy—one's belief about how capable one is of doing something—and retrospective and descriptive self-concept—one's belief about how good one is at doing something (Marsh et al., 2019; Pajares & Schunk, 2001). There are a few studies concerning the relationship to mathematical

achievement of both self-belief variables, self-efficacy and self-concept (e.g., Marsh et al., 2019). Empirically disentangling the effects of self-concept and self-efficacy seems crucial when investigating effects on mathematical achievement while looking at influences of intelligence and prior achievement.

When students face a task in mathematics where they cannot rely on previous mastery experiences, which Bandura (1997) described as the most influential source of self-efficacy and which could be the case in mathematical modelling (Blum & Borromeo Ferri, 2009), they have to draw on external feedback. This idea is supported by the effect found for previous school grades and self-efficacy on later achievement (Caprara et al., 2008). Studies revealed that self-efficacy contributed to later achievement when prior performance was taken into account (Bandura, 1997; Gore, 2006; Lee & Seo, 2020). Similar links to mathematics achievement were also found for self-concept (e.g., Van der Beek et al., 2017). In summary, previous research indicates that prior achievement and students' self-beliefs are strongly connected. Although research remains rather inconclusive on the role of self-efficacy and self-concept in learning mathematics, current literature highlights the relevance of mathematical modelling for students' application of mathematics in everyday life (for an overview see Greefrath & Vorhölter, 2016). We, therefore, investigated the motivational effects of self-efficacy and self-concept and their role in the relationship between prior achievement (i.e., school grades) and mathematical modelling while controlling for influences of intelligence.

Theoretical background

Mathematical modelling

Related to the conceptual category of problem solving, mathematical modelling is classified as a primary and secondary school standard for mathematical practice and as one of eight principles of mathematical practice (Common Core State Standards Initiative [CCSSI], 2010; also see Blum & Niss, 1991). CCSSI described mathematical modelling as “the process

of choosing and using appropriate mathematics and statistics to analyze empirical situations, to understand them better, and to improve decisions" (CCSSI, 2010, p. 72). Research on teaching and learning mathematical modelling often draws on established conceptualizations of the modelling process as a multi-step cycle. Figure 1—as an example of one possible illustration (Blum & Borromeo Ferri, 2009; Blum & Leiss, 2007)—demonstrates that mathematical modelling is by definition linked to different mathematical and non-mathematical competencies such as calculating, applying problem-solving strategies, and reading and communicating (cf., Niss, 2003). According to Leiss and Tropper (2014), solving realistic problems with mathematical means, that is, mathematical modelling, constitutes a crucial topic in the didactics of mathematics.

Insert Fig. 1 about here

Predictors of mathematical modelling

Even more than geometry or calculus, mathematical modelling is considered especially difficult for students (Blum & Borromeo Ferri, 2009). These difficulties can vary depending on the phase of the modelling process (e.g., Stillman et al., 2010). When learning mathematical modelling, students are encouraged to use metacognitive strategies such as reflecting on their activities to approach certain difficulties (Stillman, 2011), supporting the assumption that self-efficacy plays a crucial role. Current literature reveals several predictors aside from self-beliefs in general and self-efficacy in particular. In addition to predictors that account for differences in achievement such as intelligence (Gottfredson, 2002; Roth et al., 2015), reasoning skills (Baumert et al., 2007), and reading comprehension (Borromeo Ferri, 2006; Leiss et al., 2010; Phonapichat et al., 2014), some predictors seem to be specifically relevant to mathematical modelling. Prior mathematical skills such as counting (Aunola et al., 2004) and calculation (Andersson, 2007) as well as results of mathematics tests (Leiss et al., 2010; Marsh et al., 2018) and self-beliefs (Pajares & Miller, 1994; Schukajlow et al., 2019) have likewise been found to be linked to mathematical modelling. The combination of its important position in educational

standards and the fact that many students struggle with mathematical modelling stresses the need to look more deeply at predictors of mathematical modelling in efforts to help students improve their mathematical modelling. Looking at the effects of self-beliefs, namely, self-efficacy and self-concept, can provide such insights.

Relationship of self-efficacy and self-concept to mathematical modelling

Social-cognitive learning theory, which takes a self-enhancement perspective (Bandura, 1977), postulates that self-efficacy has a positive effect on students' ability to make use of their competencies and, therefore, predicts their achievement. Using path analysis, Pajares and Miller (1994) found a predictive effect of mathematical self-efficacy on mathematical problem solving. Together with a study from Pajares and Graham (1999) medium to strong positive coefficients resulted for the relationship between self-efficacy and mathematical achievement. Recent research found that students' beliefs in their capability to solve mathematical modelling tasks was low compared to other mathematical challenges such as ‘dressed-up’ word problems and intra-mathematical problems (Krawitz & Schukajlow, 2017). Czocher et al. (2019) showed in an interventional study that mathematical self-efficacy could be improved with a mathematical modelling competition. Moreover, an investigation of interventions with specific modelling techniques targeting enhancement of self-efficacy in relation to perceived competence found that especially students who created multiple solution gained from higher self-efficacy (Schukajlow et al., 2019). Taken together, the evidence highlights that mathematical self-efficacy is a crucial predictor of mathematical modelling.

We believe it necessary to empirically disentangle the effects of self-concept and self-efficacy when investigating how self-beliefs influence mathematical modelling. Meißner et al. (2016) revealed that students' self-concept affected mathematical problem solving differently depending on the measurement when comparing achievement tests with school grades. Marsh et al. (2018) found that mathematical self-concept was predictive of test scores and school grades. Moreover, self-concept measures seemed to have higher predictive value than self-

efficacy measures for later school grades and test scores in mathematics (Marsh et al., 2019). In contrast, Bong and Clark (1999) found that evidence for their predictive utility was more consistent for self-efficacy than self-concept though the direction remains unclear. More recently, consistent support was found for a reciprocal relationship to skill development for both self-concept and self-efficacy (Burns et al., 2020), indicating a dependence regarding the operationalization of self-belief constructs.

Relationship of school grades to mathematical modelling

Not surprisingly, prior mathematical skills account for much of students' mathematical modelling competency or, stated conversely, the lack of such skills for students' difficulties (Andersson, 2007; Aunola et al., 2004; Leiss et al., 2010). Although many studies have explored the difficulties in fostering students' mathematical modelling when teaching mathematics, little is known about the influence of prior achievement. Considering the strong effect social comparison has on students' achievement (cf., the big-fish-little-pond effect, Marsh & Seaton, 2015), it can be assumed that prior achievement plays a crucial role in how students achieve in mathematical modelling tasks. For the prediction of general mathematical competency, a study using data from the Program for International Student Assessment (PISA; Organisation for Economic Co-operation and Development [OECD], 2019) revealed prior competence as the most important longitudinal predictor of mathematical achievement (Kriegbaum et al., 2015). The authors further found that intelligence was the best cross-sectional predictor and self-efficacy the strongest motivational predictor. Given these findings, one might argue that part of the connection between prior achievement and mathematical modelling can be explained by the effect that school grades, as a strong source of achievement feedback, have on students' self-concept and self-efficacy.

Meißner et al. (2016) found different predictive effects of self-concept measures on problem-solving abilities as an outcome when compared to school grades as an outcome although the two outcome variables were intercorrelated. Whereas for mathematical problem

solving, cognitive abilities combined with self-concept were of predictive value, for school grades the impact of self-concept on its own was stronger. Examining a large longitudinal study over 6 years at the start of secondary school, Marsh et al. (2018) found reciprocal predictive effects of mathematical self-concept, mathematical test scores, and school grades. Reciprocal effects between school grades and self-concept measures, which in these studies partly overlap our definition of self-efficacy, were consistently found for school achievement in general (e.g., Marsh & O'Mara, 2008) and mathematical achievement in particular (Julie, 2020; Niepel et al., 2014). In most studies, school grades were treated as outcome variables for mathematical problem solving (e.g., Wüstenberg et al., 2016) but so far they have not been investigated as predictors. However, regarding the assumed reciprocal effects of prior achievement, self-concept, self-efficacy, and mathematical modelling, school grades should also be considered predictors of mathematical modelling when arguing that they constitute an important source of students' self-beliefs.

Self-efficacy mediating the relationship of school grades to mathematical modelling

Taking Bandura's (1977) self-enhancement perspective, self-beliefs can be perceived as mediators in the relationship between school grades and mathematical modelling. Research on achievement development in general showed that especially self-efficacy acts as a mediator between achievement and predictors such as positive emotions (Oriol-Granado et al., 2017), classroom environment (Tosto et al., 2016), test accommodations (Einav et al., 2018), cognitive activation strategies (Li et al., 2020), or, as described above, mathematical test scores and school grades (Marsh et al., 2019). While various studies have hinted that self-efficacy serves as an important mediator in the effects of predictors of school achievement and at the same time is treated as a crucial covariate of mathematical modelling, little is known about how self-efficacy acts as mediator in the relationship between school grades, mathematical achievement, and especially mathematical modelling. Further, how the effects of the two self-belief variables on mathematical modelling differ remains unclear.

Aims of the present study and hypotheses

Research on issues related to mathematical modelling, such as mathematical problem solving, indicates that prior achievement, in many studies operationalized as school grades, is of predictive value to mathematical modelling (Julie, 2020; Marsh et al., 2018; Niepel et al., 2014). However, because self-concept and self-efficacy are widely perceived as being influenced by the feedback students receive on their performance (Burns et al., 2020; Marsh et al., 2019; Meißner et al., 2016) and because school grades constitute an important feedback source for students (Bandura, 1977), we presumed that self-concept and self-efficacy play a crucial role in the assumed predictive effect of school grades on mathematical modelling (see Hypothesis 1a and b). We therefore investigated how school grades, mathematical self-concept, and mathematical self-efficacy predict mathematical modelling.

While research so far hinted that mathematical self-concept tends to be a better predictor of outcomes such as later school grades and test scores than self-efficacy (Marsh et al., 2019), we assumed that the reverse is true for a more immediate achievement measure, which is the case for mathematical modelling (cf., Bong & Clark, 1999), which would be in line with Kriegbaum et al. (2015), who found self-efficacy to be the strongest motivational predictor of mathematical competence on the PISA (OECD, 2019). Following this argument, we presumed that students especially need to believe in their capability in a prospective, evaluative sense, that is, believe in their self-efficacy (rather than the retrospective, descriptive evaluation, i.e., relying on their self-concept), when confronted with modelling tasks that are especially challenging for them and structurally new to them. This idea is supported by Kriegbaum et al. (2015), who argued that self-efficacy items (compared to self-concept items) are more closely aligned with achievement tasks and explained their finding with the level of specificity of self-efficacy. Moreover, and in addition to the prospective, evaluative sense of self-efficacy, the task-specificity of self-efficacy implies a criterion-based comparison rather than a social one (Bong & Skaalvik, 2003), which, again, accounts for the assumption of a stronger connection

of mathematical modelling with self-efficacy than with self-concept. Taken together, these studies inspired us to investigate how self-concept and self-efficacy predict mathematical modelling (see Hypothesis 1a and b). We assumed self-efficacy would be more strongly connected to our outcome for theoretical and measurement-related reasons (see Hypothesis 2).

Concerning school grades, we assumed that prior achievement in terms of feedback given by teachers, namely, grades when investigated on its own would do little to explain students' performance in mathematical modelling tasks when controlling for reasoning skills and accounting for effects of the reference group, namely, the respective class. In contrast, we assumed that self-efficacy would act as a mediator in the effect of school grades on mathematical modelling (see Hypothesis 3). This, again, we assumed would be the case only for mathematical self-efficacy because of its specificity, alignment, and prospective orientation, which mathematical self-concept lacks.

We postulated the following hypotheses:

Hypothesis 1a. Mathematical self-efficacy predicts mathematical modelling.

Hypothesis 1b. Mathematical self-concept predicts mathematical modelling.

Hypothesis 2. When investigated together, mathematical self-efficacy will more strongly predict mathematical modelling than mathematical self-concept.

Hypothesis 3. Mathematical self-efficacy mediates the effect of school grades on mathematical modelling.

To better investigate our assumption on the role of mathematical self-efficacy in contrast to mathematical self-concept, we also looked at potential mediating effects of the latter. Given the strong connection of intelligence and achievement (Gottfredson, 2002; Roth et al., 2015), we targeted predictive and mediating effects above influences of students' cognitive level and, therefore, included students' reasoning skills as a control variable in the analyses. Because school grades play a decisive role in determining students' future, they become highly important in the transition from secondary school to higher education or work life (e.g., Ogg et al., 2009).

It is at this stage of students' life when the predictive value of school grades should be examined thoroughly. We, therefore, investigated our hypotheses in the secondary school years.

Method

Sample

For our analyses, 279 students (53.9% girls, missing information for gender = 8) from 16 classes in six schools in [Country; blinded for review] were assessed as part of a larger research project in spring 2020. Written consent that highlighted the voluntariness of participation was obtained from all participants. Students had a mean age of 15.1 years (SD = 0.68; ranging from 13.3 to 16.8 years, missing information for age = 7) and were attending their eight (n = 123) or ninth (n = 156) school year (see United Nations Educational, Scientific and Cultural Organization Institute for Statistics, 2013). Most federal states in [Country; blinded for review] differentiate between two secondary school levels: one follows a basic vocational orientation (basic requirements), and the other follows an advanced vocational and academic orientation (advanced requirements). Sixty-seven students (24.0%) were allocated to basic requirements and 212 students (76.0%) followed advanced requirements, which is fairly representative of the distribution in [Country; blinded for review].

Measures

To answer our research questions, information was collected from different sources: direct test assessment of students' mathematical modelling and reasoning skills, self-assessment of students' self-efficacy and self-concept in a questionnaire, as well as students' school grades from their official school certificate reported by their teachers. Teachers were instructed to conduct test assessments, to administer the questionnaire, and to send back all material to be analysed by the project. Participation altogether took two school lessons' time in the students' regular timetable.

To assess students' mathematical modelling, two tests with five tasks each were put together, resulting in parallel versions with items being similar regarding mathematical content and solution path. Modelling tasks were adopted from a pool originally established for the DISUM project (e.g., Schukajlow et al., 2015). Students' answers were rated as correct or incorrect and a sum score was calculated. Cronbach's alphas for the two test versions were .34 and .48, respectively.

To assess students' reasoning skills, four subtests of the Testing System for Scholastic and Educational Counseling, Grades 6 to 13—Revised (German language version: PSB-R 6-13; Horn et al., 2003) were used. The PSB-R 6-13 is a standardized intelligence assessment consisting of numerical, visuo-spatial, and verbal subtests and was designed for educational settings. In the present study, we used the reasoning subscale containing four subtests: numerical, literal, and figural series as well as conception of spaces, yielding a Cronbach's alpha of .66.

To assess students' mathematical self-efficacy, a scale consisting of four items from the PISA (OECD, 2019) was used, which followed our definition in an evaluative and prospective sense of how capable one is of something (see the Introduction). A mean score was calculated from answers on a 5-point Likert scale; a sample item is "In mathematics, I am certain of being able to understand the most difficult topics." Cronbach's alpha for this scale was .90.

To assess students' mathematical self-concept, an adaption of the Academic Self Description Questionnaire (ASDQ; Marsh, 1990) was used, which followed our definition in a descriptive and retrospective sense of how good one is at something (see the Introduction). Students were given a 4-point Likert scale to answer six items on their self-concept in mathematics (e.g., "I am good at mathematics"), for which a mean score was calculated. Cronbach's alpha was .93.

Teachers reported students' half-year school grades in mathematics and language (German) from their official school certificate as a measure of their prior achievement. Grades

in German range from 1 to 6, in most cases effectively ranging from 3 (insufficient) to 6 (very good), and are given in half-grade intervals.

Data analysis

All analyses were conducted using R (R Development Core Team, 2008). To treat missing values that were mainly due to students being absent on the respective measurement occasion, we imputed these values using the Multivariate Imputation by Chained Equations package (mice; van Buuren & Groothuis-Oudshoorn, 2011). For preliminary analyses on the hypotheses, bivariate correlations were calculated. To account for the nested structure of the data, especially regarding effects of the reference group, that is, the classroom, in relation to school grades, we then ran random-intercept models using the lme4 package (Bates et al., 2015); that is, the respective intercepts could vary between classrooms. To compute p values for random-intercept models we used the package lmerTest (Kuznetsova et al., 2017). We ran mediation analyses on these models with the mediation package (Tingley et al., 2014).

Results

Descriptive statistics

Descriptive statistics for all variables analysed and correlations with gender as well as among all variables are shown in Table 1. No significant correlations were found with students' age. Correlations with gender were found for grade in German (girls had better grades), mathematical self-efficacy, and mathematical self-concept (both lower for girls). Moreover, significant correlations were found among most variables of interest. Reasoning correlated positively with all other variables. Grade in German correlated with mathematical modelling ($r = .17$, $p < .01$), which was expected because of the need for language and reading comprehension skills. We, therefore, included gender, reasoning, and grade in German as control variables for the following analyses. No significant correlations were found for grade

in German with self-concept or self-efficacy, presumably because these were assessed in a subject-specific way.

Insert Table 1 about here

Multilevel analyses

In Table 2, a random-intercept model is displayed that was calculated to take the nested structure of the data, that is, classroom and school level, into account. When classroom levels were controlled and variables of interest examined simultaneously, a significant predictive effect was found for mathematical self-efficacy but not for mathematical self-concept on mathematical modelling. This finding confirmed only Hypothesis 1a and not Hypothesis 1b, meaning that only self-efficacy predicted mathematical modelling while self-concept did not. Further, Hypothesis 2 was confirmed: mathematical self-efficacy more strongly predicted mathematical modelling than mathematical self-concept. The relationship of reasoning with mathematical modelling lost its significance when the nested structure was considered. We did not include grades in this model because these relations were examined in the following analyses on Hypothesis 3.

Insert Table 2 about here

To test for Hypothesis 3, we ran random-intercept models, again to account for values nested in classrooms, to investigate mediating effects of mathematical self-efficacy and self-concept on the relationship between mathematics grade and mathematical modelling. The mediation analysis is displayed in Figure 2. We included gender, reasoning, and grade in German as control variables in these analyses. We first tested for the predictive effect of mathematics grade on mathematical modelling ($r = .14$, $p < .05$), which appeared to be significant. We then tested the predictive effects of mathematics grade on mathematical self-efficacy ($r = .45$, $p < .001$) and on mathematical self-concept ($r = .67$, $p < .001$). Finally, we ran a model with mathematics grade predicting mathematical modelling and both mediators, that is, mathematical self-efficacy and self-concept, which revealed a significant predictive effect

of mathematical self-efficacy on mathematical modelling ($r = .16$, $p < .05$). No significant predictive effect was found for mathematical self-concept ($r = .04$) while the effect of mathematics grade on mathematical modelling lost its significance ($r = .06$). In summary, a mediation effect of mathematical self-efficacy could be assumed.

Insert Fig. 2 about here

Using bootstrapping procedures with 1,000 samples, we tested the significance of the indirect effect of mathematics grade through mathematical self-efficacy on mathematical modelling. The bootstrapped indirect effect was .07 ($p < .05$), confirming Hypothesis 3: The effect of mathematics grade on mathematical modelling was fully mediated via mathematical self-efficacy. With the corresponding analysis, no mediation effect was found for mathematical self-concept.

Discussion

The aim of this study was to investigate mathematical self-efficacy and mathematical self-concept as motivational predictors of mathematical modelling and, moreover, as mediators for effects of school grades on mathematical modelling. In an extension of previous research on self-beliefs and mathematical modelling, we assumed that mathematical self-efficacy plays a crucial role in effects that prior achievement measured by school grades is shown to have on mathematical modelling. We found that students' mathematics grade influenced both self-efficacy and self-concept to a high degree, indicating that self-beliefs are shaped through the feedback learners receive. Further, we intended to shed light on the distinction between mathematical self-concept and self-efficacy, both constituting students' self-beliefs at the secondary school level.

While significant bivariate correlations hinted at predictive effects of self-efficacy and self-concept on mathematical modelling, our results revealed that only self-efficacy was predictive of mathematical modelling when taking the nested structure of the data into account.

Following social learning theory (Bandura, 1997), we claim that this finding is due to a potential self-enhancement effect of self-efficacy on a more immediate measure such as mathematical modelling. Students need to believe, prospectively, in their potential to achieve something (i.e., their self-efficacy) rather than relying on whether they, retrospectively, think they are good at something (i.e., their self-concept). This is in line with recent findings on motivational predictors of achievement showing that self-efficacy acts as a strong predictor aside from the influence of cognitive skills such as intelligence (Kriegbaum et al., 2015). Note that our results revealed self-efficacy as a predictor of mathematical modelling and as a mediator in the relationship between mathematics grade and mathematical modelling above students' school grades in German. This is especially important considering that students' language skills were previously found to be linked to mathematical modelling (e.g., Author et al., 2020) through their role in reading comprehension (Leiss et al., 2010; Vilenius-Tuohimaa et al., 2008) or understanding context (Borromeo Ferri, 2006; Phonapichat et al., 2014). Regarding reasoning, the influence on mathematical modelling was diminished when taking the nested structure into account. By looking only at descriptive statistics, a positive relationship can be assumed. We argue that some variance in reasoning was lost when students were assigned to different school levels. Further, we found that the relationship of mathematics grade, a form of previous achievement feedback, and mathematical modelling also seemed to be dependent on the respective classroom. When the nested structure was taken into account, a connection between grades and mathematical modelling became less clear, whereas mathematical self-efficacy served as a mediator and shed light on this relation.

Finally, full mediation was found for mathematical self-efficacy for the effect of school grades on mathematical modelling. This is in line with arguments in previous studies that self-efficacy independently contributes to academic achievement and is more than a simple reflection of prior performance (Bandura, 1997; Caprara et al., 2008; Pajares & Schunk, 2001). We argue that students rely on prior achievement feedback given by teachers in different

domains—in our study mathematics and German—in building their self-efficacy, which affects their mathematical modelling performance. Keeping in mind that at the same time grades were found to be highly class dependent (cf., Fang et al., 2018), serious implications can be concluded.

Practical implications

Our results reveal a predictive effect of mathematical self-efficacy on mathematical modelling, extending previous research on predictors of mathematical development. In this regard and following the self-enhancement perspective (Bandura, 1977), improving self-efficacy constitutes an opportunity to help students foster their mathematical modelling independent of their skill level. We advise teachers, firstly, to scrutinize the self-beliefs of their protégés in order to be especially aware of students with low self-efficacy and then, secondly, to integrate supportive, benevolent elements into their teaching to help enhance students' motivation when new tasks such as mathematical modelling are introduced; our findings suggest that students' performance might profit in return. Keeping in mind the lack of causal evidence our results contain, a reverse impact might occur when students show progress in self-efficacy by receiving positive feedback on mathematical modelling. We therefore, thirdly, advise teachers to make sure that mathematical modelling tasks are taught in a way that allows for individual levels and that students understand how these tasks can be solved. Taking different steps of the modelling cycle into consideration (Blum & Borromeo Ferri, 2009) and supporting learning by applying a solution plan (Schukajlow et al., 2015) are promising approaches in this regard.

Considering the mediating role of self-efficacy in the effect of school grades on mathematical modelling, we examined grades as a feedback source. In line with previous research (Fang et al., 2018; Wößmann & West, 2006), we found in our study that grades were highly dependent on the respective classroom. With regard to the big-fish-little-pond effect (Marsh & Seaton, 2015) and the effects grades are supposed to have on mathematical self-

efficacy (Marsh et al., 2018), one could argue that grades have a negative effect on some students' self-beliefs. Assuming that there is some causality in the effects of school grades on later achievement mediated by self-efficacy, students receiving low grades might get into a downward spiral that is more likely a consequence of low grades rather than of their level in mathematical development. We therefore, fourthly and again, encourage teachers to provide feedback in a way that positively affects students' self-beliefs. In sum, basing feedback on individual progress rather than social comparison might be in order.

Limitations of the current study and directions for future research

Although our study design includes some longitudinality by assessing students' grades from the previous semester and later assessing students' self-assessment and testing their mathematical modelling, our results mainly rely on cross-sectional data. Therefore, the validity of causal effects is theoretically assumed. Concerning intellectual preconditions, note that we relied solely on reasoning, whereas verbal dimensions might also contribute to mathematical modelling especially because of the requirements of reading comprehension. Predictive effects of school grades and mathematical self-efficacy are strengthened by controlling for reasoning and self-concept measures. Nevertheless, future studies should aim to follow longitudinal designs that take a look at long-term (potential co-)development of self-efficacy, self-concept, and mathematical achievement. Moreover, interventional studies are needed to challenge the practical implications of improving students' self-efficacy beliefs in order to turn the downward spiral into a virtuous circle.

Looking at our measures, some limitations lie in the mathematical modelling tasks and the corresponding rating we used. While we used 10 items established for the DISUM project (e.g., Schukajlow et al., 2015), more mathematical modelling tasks are needed to investigate broader aspects of different phases of mathematical modelling to shed light on specific challenges students struggle with on such tasks. Regarding scales on self-beliefs, we used established measures from PISA (OECD, 2019) and the ASDQ (Marsh, 1990) focusing on

subject-specific assessment. We encourage future researchers to investigate discrete forms of self-beliefs in different domains or more general conceptualizations when investigating such complex tasks as mathematical modelling, where various skills and challenges play a decisive role. Considering today's variety of possibilities for evaluating students' academic achievement, following a multi-informant design as we did with test assessment, questionnaire information, and teacher reports holds promising chances to broaden the understanding of the effects of school grades, self-beliefs, and academic achievement.

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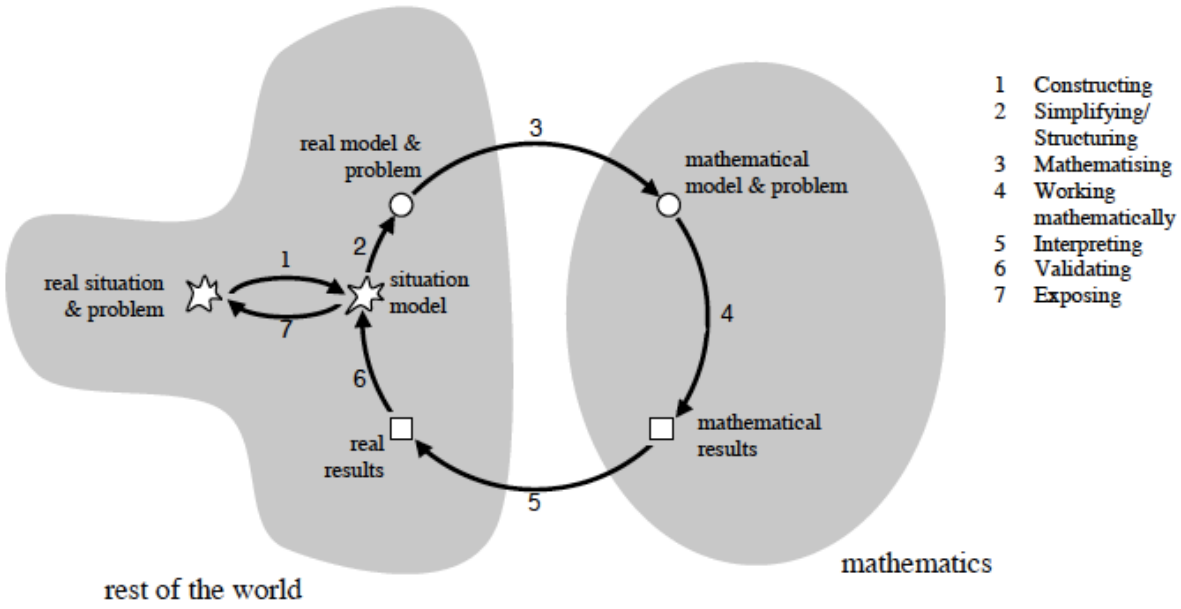

Fig. 1. Modelling cycle (according to Blum & Leiss, 2007).

Table 1. Minima, maxima, means, standard deviations, and correlations with gender for reasoning, grades in German and mathematics, mathematical self-efficacy, mathematical self-concept, and mathematical modelling; manifest correlations among all variables

Variable	*n*	Min	Max	*M*	*SD*	r_{gender}	Reasoning	German grade	Mathematics grade	Mathematical self-efficacy	Mathematical self-concept
Reasoning	255	21.00	79.00	49.41	8.92	.10					
German grade	274	3.00	6.00	4.73	0.49	.34***	.24***				
Mathematics grade	274	3.00	6.00	4.66	0.60	-.02	.33***	.36***			
Mathematical self-efficacy	260	1.00	5.00	3.16	0.97	-.20***	.24***	.04	.45***		
Mathematical self-concept	261	1.00	4.00	2.68	0.84	-.22***	.27***	.05	.64***	.75***	
Mathematical modelling	260	0.00	4.00	1.62	1.16	.00	.27***	.17**	.24***	.24***	.24***

Note. $N = 279$. Descriptive statistics with complete data on the respective scales; correlations with gender as well as among variables of interest with imputed data. Gender coding: 1 = male, 2 = female.

$^{*}p < .05$. $^{**}p < .01$. $^{***}p < .001$.

Table 2. Fixed effects of mathematical self-efficacy and mathematical self-concept predicting mathematical modelling, controlling for reasoning and gender

Variable	Standardized coefficients Beta (β)
(Intercept)	.03
Gender	-.01
Reasoning	.08
Mathematical self-concept	.07
Mathematical self-efficacy	.17*

Note. $N = 279$.

*$p < .05$.

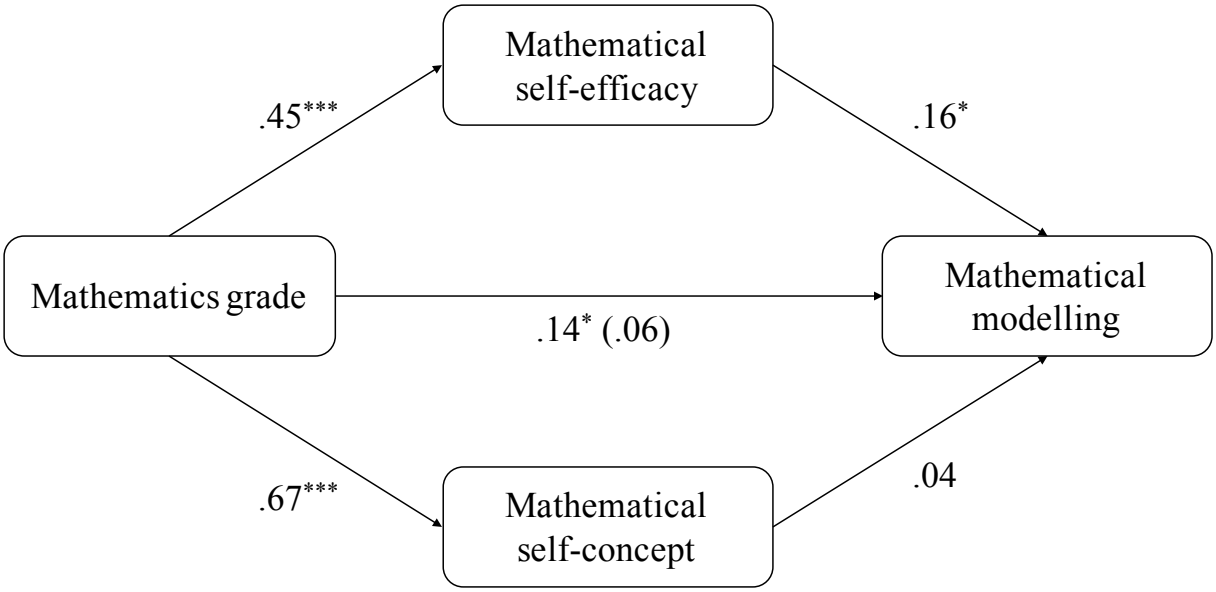

Fig. 2. Mediation analyses for mathematical self-efficacy and mathematical self-concept mediating the effect of mathematics grade on mathematical modelling with fixed effects (z-standardized), controlling for gender, reasoning, and grade in German.

Appendix C: Study 3

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Transfer effects of mathematical literacy: an integrative longitudinal study

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Abstract
Mathematical literacy (ML) is considered central to the application of mathematical knowledge in everyday life and thus is found in many comparative international educational standards. However, there exists barely any evidence about predictors and outcomes of ML having a lasting effect on achievement in nonmathematical domains. We drew on a large longitudinal sample of $N = 4001$ secondary school students in Grades 5 to 9 and tested for effects of ML on later academic achievement. We took prior achievement in different domains (information and communication technology literacy, scientific literacy, reading comprehension, and listening comprehension), socioeconomic status, and gender into account and investigated predictive effects of math grade, mathematical self-concept, reasoning, and prior achievement on ML. Using structural equation models, we found support for the importance of integrating multiple predictors and revealed a transfer effect of ML on achievement in different school domains. The findings highlight the importance of ML for school curricula and lasting educational decisions.

Keywords Mathematical literacy · Academic achievement · Mathematical self-concept · Secondary school · Transfer effects

This paper uses data from the National Educational Panel Study (NEPS): Starting Cohort Grade 5, doi:https://doi.org/10.5157/NEPS:SC3:7.0.1. From 2008 to 2013, NEPS data were collected as part of the Framework Program for the Promotion of Empirical Educational Research funded by the German Federal Ministry of Education and Research (Bundesministerium für Bildung und Forschung, BMBF). Since 2014, NEPS has been carried out by the Leibniz Institute for Educational Trajectories (Leibniz-Institut für Bildungsverläufe e.V., LIfBi) at the University of Bamberg in cooperation with a nationwide network.

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Introduction

Learning mathematics is oftentimes assumed to be learning for everyday life. We share this assumption and frame it in educational standards. According to the Program for International Student Assessment (PISA; Organisation for Economic Co-operation and Development (OECD) 2019), *Mathematical literacy* (ML) is defined as "an individual's capacity to formulate, employ, and interpret mathematics in a variety of contexts." The importance of ML as an element in the definition of educational standards has been made apparent in, for example, the USA and Germany (National Council of Teachers of Mathematics 2003; Standing Conference of the Ministers of Education and Cultural Affairs of the Federal Republic of Germany 2004). ML is crucial for students' understanding of mathematics in today's life contexts (Baumert et al. 2007).

International educational studies such as PISA and the Trends in International Mathematics and Science Study (TIMSS) aim to assess students' ML by having them solve everyday problems with mathematical means (Mullis et al. 2009; OECD 2003). Researchers have investigated the development of ML by using large-scale longitudinal studies, for instance, in Germany, PISA studies (PISA Plus 2012–2013: OECD 2013; PISA-I-Plus: Prenzel 2006), and by conducting national studies, for instance the COACTIV[1] research program (Kunter et al. 2013), the Study of Initial Achievement Levels and Academic Growth in Secondary Schools in the City of Hamburg (e.g., Caro and Lehmann 2009), and the longitudinal Element study (Lehmann and Nikolova 2007).

This large body of research investigating predictors and outcomes of ML has generated partly contradictory results. Among others, prior achievement, migration, and social background (Kiemer et al. 2017), socioeconomic status (Caro and Lehmann 2009), self-efficacy, self-concept, interest, and learning goals (Kriegbaum et al. 2015) were identified as relevant *predictors* of ML. For the relationship between ML and achievement in other domains, such as reading, studies using longitudinal data found covariation effects in Grades 1 to 7 (Korpipää et al. 2017) and predictive effects of third-grade reading comprehension on ML throughout early primary school when controlling for prior achievement (Grimm 2008).

Hence, ML is also thought to *determine* later academic achievement in many ways (cf., Duncan et al. 2007; Gut et al. 2012; Siegler et al. 2012). In the context of solving realistic problems, studies on mathematical word problems, mathematical modeling competence, and mathematical problem-solving in general showed that predictors such as calculation skills, mathematical self-concept, reading comprehension, and cognitive skills are relevant for ML development and the relationship to later achievement (Blum and Borromeo Ferri 2009; Brown and Stillman 2017; Leiss et al. 2010; Leutner et al. 2012; Phonapichat et al. 2014). Studies on mathematical modeling, which is typically considered a cognitive process consisting of different phases of solving a real-world problem by means of mathematics, showed that reading comprehension, cognitive skills, and self-concept are important predictors of problem-solving success (Jensen 2007; Leiss et al. 2010; Maass 2006).

However, as argued in a recent study on teaching practice in ML (Kuger et al. 2017), the influence of single predictors is often overestimated, especially in cross-sectional analyses. Therefore, longitudinal studies that take various predictors comprehensively into account are necessary. Furthermore, the empirical support that does exist for predictors and outcomes of

[1] COACTIV is the abbreviation for the Professional Competence of Teachers, Cognitively Activating Instruction, and Development of Students' Mathematical Literacy project.

ML is mostly restricted to early primary school (e.g., Grimm 2008; Korpipää et al. 2017) or tertiary education (e.g., Hwang and Riccomini 2016; Pape and Wang 2003; Sokolowski 2015). Only a few studies are related to secondary school (Caro and Lehmann 2009; Kriegbaum et al. 2015). Hence, we argue that longitudinal studies across secondary school are needed to examine the influence of ML on later academic achievement while at the same time taking its crucial predictors into account.

Theoretical background of ML

The relationship between ML, reading, and achievement in other domains

We understand *academic achievement* as achievement in different school domains, for instance, mathematics, language, and science. Achievement in most studies is either operationalized as grade point average (GPA) or assessed with achievement tests in the respective domain, sometimes by using multiple-domain tests such as the Wide Range Achievement Test (Wilkinson 1993), the California Achievement Test, or the Stanford Achievement Test (e.g., Sirin 2005). In line with studies on the development of problem-solving competence, we argue that fostering ML results in higher achievement in other domains later on (Leutner et al. 2012). Later academic achievement is assumed to be linked with success in mathematical tasks, because a strong relationship has been found with mathematical performance in general (Duncan et al. 2007).

Recent research on the covariation of ML and *reading achievement* indicated that gains in ML-related skills such as problem-solving and reasoning as well as cognitive abilities in general lead to better achievement in other domains (Baumert et al. 2012). The authors suggested the cumulative advantage effect (DiPrete and Eirich 2006) as a possible explanation. Additionally, a transfer effect can be assumed; ML involves skills that are shared with other processes, such as reasoning and general cognitive abilities, so gains in ML will support students' progress in other achievement domains. A study comparing adults with PISA students showed that the average ML in adults was on the level of a secondary school student (Ehmke et al. 2005). These authors also showed that ML in adults was linked to an individual's vocational degree. However, research on mathematical modeling mainly focused on distinct phases of the problem-solving process (Baumert et al. 2007; Blomhoj and Jensen 2003; Blum et al. 2004; Jensen 2007; Leiss and Tropper 2014). Intervention studies have shown that teaching students to construct a situational model of a problem given in text or pictorial form improves their ability to solve mathematical problems (English and Watters 2005; Hwang and Riccomini 2016; Kaiser et al. 2015; Schukajlow et al. 2015). This seems to be especially relevant for students with difficulties in learning mathematics (Phonapichat et al. 2014).

With respect to *achievement in other domains*, a meta-analysis on applying mathematical modeling to support students' mathematical knowledge acquisition at the high school and college level found positive effects of mathematical-modeling techniques on achievement in different content domains (Sokolowski 2015). Hoffman and Spatariu (2008) examined influences on problem-solving efficiency and found middle to high cross-sectional correlations between GPA and performance on a math achievement test as well as between GPA and problem-solving efficiency. When predictors such as reading competence and self-concept were considered using path analysis, lower coefficients were found (Schommer-Aikins et al. 2005). Jordan et al. (2002) showed longitudinally that over 2 years, growth in reading

competence was diminished for children with difficulties in mathematical problem-solving. This, again, accounts for the assumption that ML affects achievement in other domains. Moreover, Korpipää et al. (2017) found that reading and arithmetic in Grades 1 to 7 covaried substantially over time.

In summary, reported covariations of ML and achievement in other domains (Jordan et al. 2002; Korpipää et al. 2017; Sokolowski 2015) as well as a relationship between ML and gains in general cognitive abilities (Baumert et al. 2012) hint at common elements in ML and skills relevant to various school domains. This leads to assuming transfer effects of ML on academic achievement. Current research on the relationship between ML and academic achievement is barely conclusive because important predictors remain unconsidered. The necessity for research that takes an integrative view of ML that considers comprehensive predictors and outcomes using longitudinal data is evident.

The role of predictors of ML

A longitudinal study from Chu et al. (2016) on the development of ML that followed children's gains in reading and mathematics achievement while also assessing preliteracy knowledge, intelligence, executive functions, and parental educational background identified all variables assessed as being predictive for children's ML from preschool to kindergarten. The authors concluded that a combination of domain-general and domain-specific abilities plays an important role in ML development. Using a large sample ($N = 6020$) of 15-year-old German PISA students, Kriegbaum et al. (2015) showed that besides task-specific self-efficacy, intelligence and prior achievement predicted ML 1 year later.

Current research indicates that multiple predictors play a role in the development of ML. These empirically investigated predictors of ML can also be derived from theories on mathematical modeling that view the cognitive process of solving realistic problems as consisting of several distinct but interdependent phases (Leiss and Tropper 2014). Depending on a given task, certain challenges (e.g., reading correctly, extracting the mathematical information, understanding the context) are essential to solving the problem (Kaiser et al. 2015). Predictors of success in mathematical tasks can be deduced from studying these challenges.

As problems are mainly given in text form, *reading comprehension* was found to be crucial to understanding the problem and its context (Borromeo Ferri 2006). Qualitative studies showed that many students have difficulties comprehending key words (Phonapichat et al. 2014). A middle to high correlation was reported between mathematical reading comprehension and modeling competence (Leiss et al. 2010). Lee et al. (2004) showed that the strength of this relationship is comparable with that of the influence of cognitive skills on solving mathematical word problems. Reading comprehension for a given problem, additionally, seems independent of technical reading skills such as reading speed and accuracy (Vilenius-Tuohimaa et al. 2008).

To correctly solve the mathematics extracted from a problem, basic *calculation skills* are needed. Leiss et al. (2010) found a positive correlation between students' results in a general mathematics test used as a measure of non-subject-specific mathematics skills and modeling competence. Counting skills were found to be a valid predictor of later problem-solving skills (Aunola et al. 2004). Using multiple regression analysis, Andersson (2007) showed that calculation had an influence on solving word problems that was larger than that of reading comprehension.

Mathematical *self-concept* is also considered crucial for problem-solving achievement (Pajares and Miller 1994). Additionally, academic self-concept was demonstrated to play a role in achievement in many school domains (e.g., Marsh et al. 2005). Examining reciprocal effects of mathematical self-concept and achievement, Marsh et al. (2005) found significant path coefficients favoring the effect of self-concept on later achievement. This finding seems to be domain specific (Schöber et al. 2018). *Self-efficacy* was found to be linked with efficient problem-solving (Hoffman and Spatariu 2008). *Belief* in one's own capability to solve mathematical problems was also found to be linked with problem-solving performance (Schommer-Aikins et al. 2005). Also gender differences seem to play a role in this relationship: Studies found that boys, especially when stereotypes were evident, outperformed girls when they had higher scores on a self-concept measure (Ehrtmann and Wolter 2018; Preckel et al. 2008).

Besides math-related predictors such as basic calculation skills and mathematical self-concept, domain-general abilities, that is, *cognitive processes*, are found to be associated with ML. Baumert et al. (2007) argued that *reasoning* skills and mathematical modeling cannot be investigated independently. There exists research on the relationship of subskills of ML and cognitive skills such as *working memory* and *fluid intelligence* (Lee et al. 2004; Swanson 2011; Swanson et al. 2008) as well as *executive functioning* and *intelligence* (Arán Filippetti and Richaud 2016; Best et al. 2011). Fuchs et al. (2006) conducted path analyses and found significant path coefficients for language comprehension and nonverbal problem-solving skills on solving arithmetic word problems. Taken together, prior calculation skills, mathematical self-concept, reading comprehension, and cognitive skills are theoretically derived as well as empirically studied predictors of ML.

Socioeconomic status and gender

In studies on ML and academic achievement, among several control variables, two in particular seem to play a prominent role: socioeconomic status (SES) and gender (e.g., Grimm 2008). Children of higher *SES* tend to receive better grades (Lekholm and Cliffordson 2008) and perform better on academic achievement measures (Sirin 2005). Kiemer et al. (2017) found in PISA data that migration status and SES were interconnected because much of the difference in achievement was due to financial resources when prior achievement was controlled for. Over the secondary school years, the achievement gap associated with SES seems to narrow (Caro and Lehmann 2009).

Gender differences have been found in some studies, presumably depending on the operationalization of outcome variables. For instance, Robinson and Lubienski (2011) found that teachers rated female students higher on mathematics and reading, while cognitive assessments suggest males have an advantage in mathematics. We can conclude that it is important to consider gender and SES when investigating the effects of ML on academic achievement.

Objectives of the current study

The current state of research lacks empirical evidence for the relationship between ML and achievement in domains outside mathematical development. However, this is very relevant because educational standards as well as international studies have focused on promoting ML

as a means of enabling students to use their mathematical knowledge in their everyday lives (Hwang and Riccomini 2016; Kaiser et al. 2015; Schukajlow et al. 2015). Moreover, studies so far have not paid enough attention to the comprehensive influence of ML on academic achievement in different school domains. Theories on ML indicate that a gain in ML leads to domain-general problem-solving abilities from which students' overall *academic achievement* could profit in the sense of transfer effects from learning mathematics on other school domains (Baumert et al. 2012; Chu et al. 2016; Korpipää et al. 2017). Assuming common skill sets for reasoning, reading comprehension, and problem-solving, transfer effects from ML to achievement in other school domains are expected.

Several *predictors* have been empirically documented as having an effect on or being related to ML (Chu et al. 2016; Kriegbaum et al. 2015; Leiss et al. 2010; Marsh et al. 2005). Although calculation skills (Andersson 2007; Aunola et al. 2004), mathematical self-concept (Hoffman and Spatariu 2008; Marsh et al. 2005), reading comprehension (Lee et al. 2004; Leiss et al. 2010), other prior achievement (Kriegbaum et al. 2015), and reasoning (Fuchs et al. 2006) were separately found to be empirically related to ML, research so far has lacked an integrative view of these predictors using longitudinal data to account for effects on both ML and academic achievement in general.

Applying mathematical knowledge in the sense of ML becomes crucial for *further mathematical development* above the primary-school level, particularly throughout secondary school (United Nations Educational, Scientific and Cultural Organization Institute for Statistics 2013), yet several studies examining mathematical development have focused on primary school (e.g., Duncan et al. 2007; Geary 2011; Korpipää et al. 2017). Furthermore, studies on SES indicate that development in secondary school is a determinant for later achievement because cumulative advantages (Baumert et al. 2012) and the gap between low and high SES (Caro and Lehmann 2009) play an important role at this stage. Thus, it becomes apparent that studies on ML investigating the secondary school years, which constitute an important phase in ML development, are needed.

Hypotheses and research questions

Our study extends previous research by taking an integrative view of ML that considers multiple predictors to explore the effects of ML on later academic achievement, using longitudinal data from a large sample in Grades 5 to 9. Our goal was to investigate how ML predicts academic achievement (information and communication technology (ICT) literacy, scientific literacy, reading comprehension, and listening comprehension) in different school domains throughout secondary school while controlling for prior achievement. We assumed that ML would still have an effect on later academic achievement in different domains when prior achievement in the respective domain is controlled for—in the sense of a transfer effect of ML on achievement in other domains.

We investigated whether existing results regarding predictors of ML can be replicated when a comprehensive set of predictors is studied simultaneously. On the basis of previous findings, we assumed that calculation skills, mathematical self-concept, reasoning, and prior achievement in ML as well as in other domains are linked to later ML. We presumed that these predictors would show effects on ML throughout secondary school when effects of prior achievement are controlled for. Therefore, our research questions and hypotheses are as follows:

1. How does ML predict academic achievement in different school domains (i.e., ICT literacy, scientific literacy, reading comprehension, and listening comprehension) throughout the secondary school years?

   Hypothesis 1. ML predicts achievement in different school domains later on even when prior achievement in the respective domain is controlled for.

2. How do calculation skills, mathematical self-concept, reading comprehension, and reasoning affect ML when studied comprehensively?

   Hypothesis 2. Calculation skills, mathematical self-concept, reading comprehension, and reasoning predict ML later on when the respective other predictors are controlled for.

As minor questions, we investigated whether hypotheses 1 and 2 are still valid when potential effects of the control variables SES and gender are taken into account.

In sum, it is notable that recent research focused mainly on either preschool and the early school years or high school and college. We examined the postulated relationships from Grades 5 to 9, hence across secondary school.

Method

Sample

We examined our research questions using data from the National Educational Panel Study (NEPS), a longitudinal study conducted in Germany designed for research on educational trajectories (Blossfeld et al. 2011). We used data provided as scientific-use files for registered users of NEPS, which began investigating fifth-grade students in 2010, at two measurement points (Grades 5 or 6, and 9). NEPS provided separate files for competence measures, cohort information, and both student and parent questionnaires, which were prepared for scientific use following professional guidelines and by publishing reports about validity, scaling, and reliability. The original panel cohort consisted of 6112 students, of whom 5778 participated in the first wave in Grade 5. Four years later, 5452 students from the original sample were targeted, of whom 4001 participated in Grade 9 (cf., Zinn et al. 2018). The sample is suited for answering our research questions because this cohort follows students through the course of secondary school (Fabian et al. 2019).

Analyses for testing the postulated hypotheses were conducted with domain-specific competence data (ML, reading, and reasoning) and questionnaire information (math grade, mathematical self-concept, and gender) in Grade 5, domain-specific competence data in Grade 6 (ICT literacy, scientific literacy, and listening comprehension), and the corresponding domain-specific competence data in Grade 9. Information about SES was obtained from parent questionnaires.

The final sample consisted of 4001 students ($N = 1963$ female (49.4%), missing values in gender: $N = 26$). Students in Germany in most federal states follow one of three school tracks (*Hauptschule*, *Realschule*, or *Gymnasium*, typically considered general, intermediate, and advanced secondary school, respectively) after the end of Grade 4. In our sample, 51.9% ($N = 1701$) were allocated to *Gymnasium*, 30.0% ($N = 917$) to *Realschule*, and 7.6% ($N = 249$) to *Hauptschule*, thus being fairly representative regarding German school tracks. Relying on the German federal school system,

students attending some schools were not yet divided into school tracks ($N = 238$), and for some students, the declared school track was unclear ($N = 722$) or missing ($N = 174$). Regarding SES, 13.8% ($N = 418$) of students were categorized as having low, 62.9% ($N = 1771$) intermediate, and 23.3% ($N = 668$) high SES (missing: $N = 1144$).

Measures

ML

A mathematical competence assessment was administered consisting of 24 items in Grade 5 and 34 items in Grade 9. The theoretical framework for the mathematics test construction was based on the PISA as well as national educational standards and was designed to measure ML on the basis of mathematical problems from students' life contexts (Neumann et al. 2013). Students were asked to solve mathematical problems and answer mostly multiple-choice questions. As in the PISA, items could be assigned to one of four content areas: quantity, change and relationship, shape and space, and data and chance. Six different cognitive components were distributed over these items with modeling as one of these six components. A sample item titled "The Fence" goes as follows: "Mr. Brown owns a rectangular piece of land that he wants to fence. After calculating, he buys 40 meters of fence. The piece of land has a width of 8 meters. How long is the piece of land?" This item involving modeling belongs to the content area space and shape (Schnittjer and Duchhardt 2015).

Weighted maximum likelihood estimates (WLEs), which are estimates of a student's most likely competence (Pohl and Carstensen 2013), were computed to indicate domain-specific competence. Scaling relies on item response theory (IRT; Pohl and Carstensen 2012). For the following analyses, WLEs of ML were used from Grades 5 to 9, for which sufficient reliabilities (.78 and .81, respectively) have been reported (Duchhardt and Gerdes 2012; Van den Ham et al. 2018). WLEs, theoretically, are standardized scores with $M = 0.00$ and $SD = 1.00$, but the values can differ from zero or one, respectively, due to sample selection procedures. Analyses on panel attrition in the NEPS showed that students in this sample with good or medium ML have a stronger tendency to drop out (Zinn et al. 2018). This could mean that students with lower ML are overrepresented in our sample.

Math grade

Students reported their final math grade from the previous year, which, therefore, referred to Grade 4. Students in Grade 4 were not yet divided into school tracks, which enhances the comparability and validity of our measure. Germany uses a grading system of 1 to 6, with 1 indicating the best grade possible. In German-speaking countries, basic calculation skills, for instance, unit operations, are learned in primary school during Grades 1 to 4. For this reason, we argue that math grade at this age represents students' ability in the basic calculation skills needed to solve ML problems, which is why we used it as a measure of mathematical performance in terms of students' calculation skills.

Mathematical self-concept

Mathematical self-concept was conceptualized as domain specific and was geared to the PISA (Wohlkinger et al. 2011). Domain-specific self-concept is widely seen as a subdimension of students' overall academic self-concept and can be investigated in a subject-specific way

(Wohlkinger et al. 2016). It was measured using three items (i.e., "I get good grades in mathematics," "Mathematics is one of my best subjects," and "I have always been good at mathematics") with answers ranging from 1 (*does not apply at all*) to 4 (*applies completely*) on a 4-point Likert scale. A mean score was calculated from these items. Mathematical self-concept was assessed in Grade 5; Cronbach's alpha for this scale was .87.

ICT literacy

ICT literacy was conceptualized as computer literacy from a functional perspective and relies on everyday problems in modern-day societies (Weinert et al. 2011). Students were presented corresponding problems and asked to accomplish computer-based tasks mostly with screenshots of applications. Moreover, students were asked to answer 30 (Grade 6) or 36 (Grade 9) multiple-choice items. The test was designed to measure students' ability to access, create, manage, and evaluate software applications. ICT literacy was used from Grades 6 to 9, for which sufficient reliabilities (.69 and .81, respectively) were reported (Senkbeil and Ihme 2017; Senkbeil et al. 2014).

Scientific literacy

Scientific literacy was conceptualized as the ability to apply scientific knowledge of personal, social, and global importance in the contexts of environment, technology, and health (Hahn et al. 2013). The test was designed to measure knowledge about matter, systems, development, and interactions in scientific inquiry and reasoning. WLEs were calculated and used from 27 (Grade 6) to 28 (Grade 9) items. Good reliabilities of .77 (Grade 6) and .83 (Grade 9) were reported (Funke et al. 2016; Hahn et al. 2013).

Reading comprehension

Reading comprehension was conceptualized as functional understanding of texts (Gehrer et al. 2013). Students were asked to answer multiple-choice questions about texts meant to represent everyday reading such as information, commentaries, argumentations, instructions, or advertisements. Requirements were categorized into finding information, drawing conclusions, and reflecting texts. Reading comprehension (WLEs) was used from Grades 5 to 9, for which sufficient reliabilities (.77 and .79, respectively) were reported (Pohl et al. 2012; Scharl et al. 2017).

Listening comprehension

Listening comprehension in the NEPS was assessed differently over time. In Grade 6, receptive vocabulary was assessed using an adapted version of the Peabody Picture Vocabulary Test (PPVT; Roßbach et al. 2005). In the PPVT with 77 items in total, students choose one of four pictures based on a given word. Sum scores were calculated for listening comprehension in Grade 6. Cronbach's alpha for this scale was .88.

In Grade 9, listening comprehension was conceptualized as the ability to extract information from spoken texts and to draw conclusions that are implied in these texts (Hecker et al. 2015). In line with the literacy perspective, texts were based on realistic contexts. Students heard two texts (a conversation and a narration) and were asked to answer two sets of eight complex multiple-choice items. Listening comprehension (WLE) was used from Grade 9, for which sufficient reliability (.76) was reported (Rohm et al. 2017).

Reasoning

To measure basic cognitive skills, two tests were constructed for the NEPS: a picture symbol test assessing perceptual speed, and a matrices test assessing reasoning (Haberkorn and Pohl 2013). It has been argued that these two indicators are suitable for assessing fluid intelligence because they are theoretically central and have been empirically found to be crucial for successful development (Brunner et al. 2014). For our study, students' results from the matrices test in Grades 5 and 9 were used to investigate reasoning. Reasoning was assessed using three sets of four items, with Cronbach's alpha = .66 in both grades. Sum scores were calculated, which resulted in a maximum of 12.

SES

In the parent questionnaire at Grade 5, a parent reported his or her highest educational attainment. Responses were rated based on the Comparative Analysis of Social Mobility in Industrial Nations Scale (Brauns et al. 2003). The scale was recoded into three categories: low (no degree or degree with basic work-related training), intermediate (advanced work-related training or postsecondary school), and high (university level or higher), as has been suggested for studies using NEPS data (cf., Zinn et al. 2018).

Modeling issues and missing data

We estimated a structural equation model with regression analyses for assumed paths using the lavaan package in R (R Development Core Team 2008). Fit indices (root mean square error of approximation (RMSEA), confirmatory fit index (CFI), Tucker–Lewis index (TLI)) were used to examine model fit. We applied cutoff values of .06 for RMSEA and .95 for CFI and TLI, which according to Hu and Bentler (1999) indicate a good fit between a hypothesized model and the observed data.

Measurement invariance for ML, ICT literacy, scientific literacy, reading comprehension, and listening comprehension (all by means of WLE) was ensured with an elaborated conceptualization in the NEPS based on models of IRT as well as an anchor-item design (cf., Pohl et al. 2015). It was strengthened by testing for unidimensionality and demonstrating the absence of differential item functioning (e.g., Fischer et al. 2016). Reasoning was measured using the same items on both occasions.

Missing data in single competence tests were already treated when calculating WLEs (cf., Pohl and Carstensen 2013). For missing data in one of the other instruments as well as for participants missing whole competence test assessments, we used a full information maximum likelihood (FIML) approach because statistical power is maintained and FIML typically produces less biased results than listwise deletion (Enders 2010).

Results

Descriptive statistics

Table 1 shows manifest correlations, minima, maxima, means, and standard deviations for all variables. Bivariate correlations were found between variables of interest, of which most

Table 1 Manifest correlations of mathematical literacy, math grade, mathematical self-concept, information and communication technology (ICT) literacy, scientific literacy, reading comprehension, listening comprehension, reasoning, socioeconomic status (SES), and gender; minima, maxima, means, and standard deviations of all variables

Variable	Mathematical literacy	Math grade	Mathematical self-concept	ICT literacy	Scientific literacy	Reading comprehension	Listening comprehension	Reasoning
Assessed in grade	5	4	5	6	6	5	6	5
Math grade	.52***							
Mathematical self-concept	.28***	.47***						
ICT literacy	.60***	.36***	.15***					
Scientific literacy	.66***	.38***	.15***	.64***				
Reading comprehension	.64***	.56***	.09***	.59***	.66***			
Listening comprehension	.53***	.29***	.08***	.54***	.64***	.55***		
Reasoning	.55***	.39***	.20***	.42***	.46***	.45***	.38***	
Mathematical literacy	.71***	.46***	.29***	.55***	.65***	.57***	.50***	.49***
ICT literacy	.62***	.35***	.18***	.62***	.64***	.58***	.51***	.45***
Scientific literacy	.62***	.36***	.18***	.57***	.69***	.59***	.61***	.45***
Reading comprehension	.54***	.32***	.05**	.55***	.62***	.61***	.52***	.39***
Listening comprehension	.51***	.31***	.07***	.48***	.58***	.53***	.51***	.41***
Reasoning	.51***	.33***	.17***	.38***	.43***	.40***	.35***	.50***
SES	.33***	.22***	.02	.26***	.32***	.29***	.32***	.21***
Gender	− .13***	− .10***	− .25***	− .04**	− .09***	.07***	− .13***	− .04**
Min	−4.37	1.00	1.00	−2.44	−3.43	−3.42	14.00	0.00
Max	4.03	6.00	4.00	3.99	7.92	4.07	76.00	12.00
M	0.13	2.23	2.97	0.05	0.10	0.12	52.79	7.09
SD	1.16	0.90	0.83	0.76	1.18	1.24	10.08	2.57

Table 1 (continued)

Variable	Mathematical literacy	ICT literacy	Scientific literacy	Reading comprehension	Listening comprehension	Reasoning	SES
Assessed in grade	9	9	9	9	9	9	–
Math grade							
Mathematical self-concept							
ICT literacy							
Scientific literacy							
Reading comprehension							
Listening comprehension							
Reasoning							
Mathematical literacy							
ICT literacy	.68***						
Scientific literacy	.70***	.70***					
Reading comprehension	.60***	.64***	.65***				
Listening comprehension	.55***	.56***	.61***	.63***			
Reasoning	.53***	.48***	.45***	.44***	.45***		
SES	.33***	.28***	.33***	.29***	.31***	.21***	
Gender	− .12***	− .02	− .07***	.09***	.12***	.02	− .02
Min	−4.15	−2.20	−3.39	−3.26	−5.13	0.00	1.00
Max	5.26	4.48	3.64	4.84	6.91	12.00	3.00
M	0.05	0.80	0.02	0.04	0.07	9.35	2.09
SD	1.20	0.89	0.92	1.11	1.55	2.21	0.61

Math grade: inverted so that higher values mean better performance. Gender coding: 1 = male, 2 = female. SES coding: 1 = low, 2 = intermediate, 3 = high. $N = 4001$.

$^{*}p < .05$, $^{**}p < .01$, $^{***}p < .001$

appeared to be highly significant. All predictor and outcome variables correlated positively with each other, showing that ML was associated with academic achievement in different school domains 4 years later. Moreover, the correlations among predictors support our assumption that calculation skills, mathematical self-concept, reading comprehension, and reasoning need to be studied together. With respect to control variables, gender differences were found for all variables except SES, ICT literacy, and reasoning in Grade 9. Male students scored higher on all variables except listening comprehension in Grade 9 and reading comprehension in Grades 5 and 9, on which female students scored higher. This finding indicates that gender is an important control variable for our analyses. For all variables of interest apart from mathematical self-concept, significant correlations with SES were found, with higher SES students scoring higher on all measures.

Structural equation model

As our descriptive statistics indicate, ML was associated with later academic achievement in different school domains (research question 1). Furthermore, predictors of ML were correlated with each other, implying that they should be studied together (research question 2). To explore our hypotheses about controlling for prior achievement in the respective domain when looking for predictive effects of ML on achievement in different domains (hypothesis 1) and studying predictors comprehensively (hypothesis 2), we calculated a structural equation model. The estimated model is presented in Fig. 1. Since, as expected, we did not find math grade and mathematical self-concept to significantly add to later achievement in school domains other than

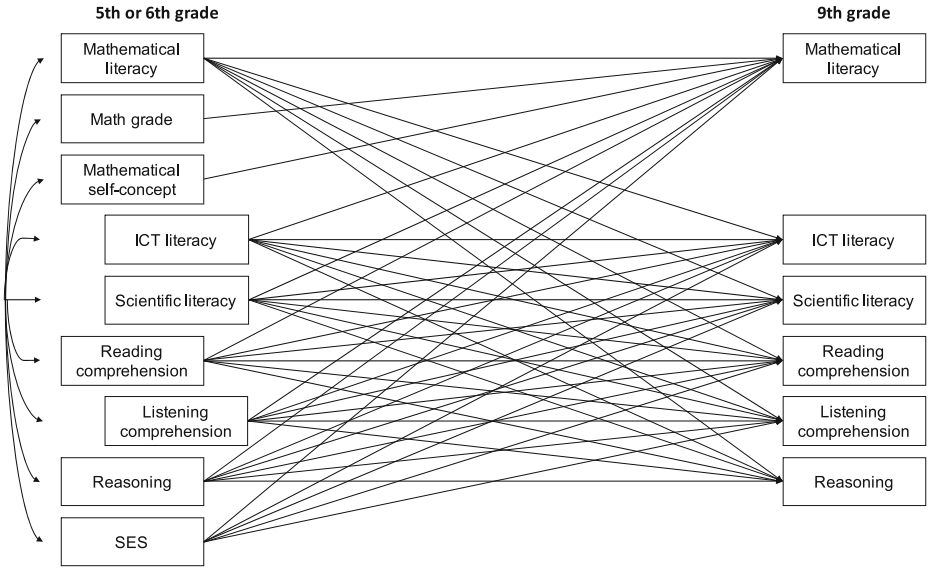

Fig. 1 Estimated model without coefficients. Root mean square error of approximation = .035, comparative fit index = .998, Tucker–Lewis index = .982. ICT = information and communication technology; SES = socioeconomic status. On the left, ICT literacy, scientific literacy, and listening comprehension from Grade 6 (indented), math grade from Grade 4, others from Grade 5. Paths for the effect of math grade and mathematical self-concept on later achievement in school domains other than mathematical literacy were not included because no significant effects were found

ML when controlling for prior achievement, we did not include corresponding paths in the model. We found significant covariances for all exogenous variables (values are not depicted in Fig. 1 for better readability). For better readability of the figure, the corresponding path coefficients for our regression analyses are presented in Table 2. Given skewness ranging from − 1.12 (reasoning) to 0.63 (math grade) and kurtosis ranging from − 0.69 (mathematical self-concept) to 1.21 (reasoning), normal distribution of the data was assumed (cf., Kaplan 2009). The model produced a good fit of the data (cf., Hu and Bentler 1999), with RMSEA = .035, CFI = .998, and TLI = .982.

As we wanted to investigate only the effects of ML on later academic achievement while controlling for prior achievement in the respective domain (research question 1), we did not need to predict mathematical self-concept in Grade 9. While math grade was used as a predictor in terms of students' basic calculation skills in Grade 5, we did not include students' math grade as an outcome variable in Grade 9. Moreover, SES was assessed in Grade 5 and was used as a control variable, which is why we did not include SES in Grade 9 in the model. To account for the nested structure of the data, we tested for models with values centered around schoolhouse as well as classroom means but found no changes in the significances of path coefficients.

As we found bivariate correlations with *gender* for several variables, we estimated a multigroup model to test for gender differences. No significant gender differences were found for loadings or path coefficients when testing for differences in model fit indices among different models. Regarding our minor hypothesis on gender effects, we conclude that analyses with respect to our other hypotheses are valid since we did not find any gender differences. We also tested for different models with paths regarding influences of *SES* on later reasoning but did not find a significant effect.

Research question 1: impact of ML on academic achievement

Our model revealed significant path coefficients from ML in Grade 5 to achievement in four school domains and reasoning in Grade 9 while considering prior achievement in the respective domain. First, on *ICT literacy* in Grade 9 ($R^2 = .54$ for all predictors), a significant effect ($\beta = .19$) of ML was found. Second, a significant path coefficient ($\beta = .17$) was found from ML in Grade 5 to *scientific literacy* in Grade 9 ($R^2 = .57$). Third, for *reading comprehension* in Grade 9 ($R^2 = .49$), a significant path coefficient ($\beta = .06$) was found from ML in Grade 5. Fourth, a significant path coefficient of $\beta = .09$ was found from ML in Grade 5 to *listening comprehension* in Grade 9 ($R^2 = .42$). Fifth, regarding *reasoning* in Grade 9 ($R^2 = .33$), a significant path coefficient ($\beta = .23$) was found from ML in Grade 5. Prior achievement in other domains showed no significant effects on reasoning in Grade 9, apart from scientific literacy, for which there was also a significant path coefficient ($\beta = .10$). Though we did not make assumptions on the effects of ML on reasoning, ML was found to impact reasoning 4 years later, while prior achievements in other domains except scientific literacy did not have a significant effect on later reasoning. Moreover, significant paths were found for *SES* to later academic achievement in different school domains except for ICT literacy, confirming the importance of SES as a control variable. Our results confirm hypothesis 1, showing that ML predicted achievement in different school domains 4 years later when prior achievement in the respective domain was taken into account. This provides evidence for the presumed transfer effect of ML on achievement in other school domains over time.

Table 2 Standardized path coefficients (β) of the structural equation model in Fig. 1

Predictor/outcome		Mathematical literacy (9)	ICT literacy (9)	Scientific literacy (9)	Reading comprehension (9)	Listening comprehension (9)	Reasoning (9)
Mathematical literacy	(5)	$.35^{***}$	$.19^{***}$	$.17^{***}$	$.06^{**}$	$.09^{***}$	$.23^{***}$
Math grade	(4)	$.06^{***}$	–	–	–	–	–
Mathematical self-concept	(5)	$.08^{***}$	–	–	–	–	–
ICT literacy	(6)	$.07^{***}$	$.25^{***}$	$.09^{***}$	$.12^{***}$	$.06^{**}$	.04
Scientific literacy	(6)	$.23^{***}$	$.21^{***}$	$.29^{***}$	$.23^{***}$	$.21^{***}$	$.10^{***}$
Reading comprehension	(5)	$.06^{***}$	$.11^{***}$	$.08^{***}$	$.27^{***}$	$.16^{***}$	.04
Listening comprehension	(6)	$.03^{*}$	$.04^{*}$	$.19^{***}$	$.09^{***}$	$.14^{***}$	.01
Reasoning	(5)	$.09^{***}$	$.08^{***}$	$.07^{***}$	$.05^{**}$	$.10^{***}$	$.29^{***}$
SES		$.07^{***}$	.02	$.05^{**}$	$.05^{**}$	$.09^{***}$	–
R^2		.60	.54	.57	.49	.42	.33

The numerals in parentheses refer to the grade in which the respective variable was assessed. No coefficients for the effect of math grade and mathematical self-concept on later achievement in school domains other than mathematical literacy were included because corresponding paths were not assumed

ICT = information and communication technology; SES = socioeconomic status; R^2 = proportion of variance explained. $N = 4001$

$^{*}p < .05$, $^{**}p < .01$, $^{***}p < .001$

Research question 2: predictors of ML

Significant paths were found for all assumed predictors on ML in Grade 9, namely math grade, mathematical self-concept, prior achievement in different domains (i.e., ICT literacy, scientific literacy, reading, and listening comprehension), reasoning, and SES with the autoregressive path showing the highest effect ($\beta = .35$). The regression analysis explained 60% of the variance in ML in Grade 9. This finding confirms hypothesis 2, supporting the assumption that predictors found in previous studies still have an effect on ML throughout the secondary school years even if predictive effects among them and prior achievement in ML and other domains are accounted for. This supports taking an integrative view of predictor variables when investigating ML.

Discussion

The main goal of this study was to examine transfer effects of ML on later academic achievement in different school domains (i.e., ICT literacy, scientific literacy, reading comprehension, and listening comprehension) while taking known predictors into account and considering prior achievement in the respective domain, SES, and gender. In an extension to previous research, we focused on ML across the secondary school years using representative longitudinal data from the NEPS (Blossfeld et al. 2011).

Consistent with our hypotheses, we found effects of ML on *later academic achievement* in different domains. These results confirm our hypotheses regarding the influence of ML on achievement in different school domains in terms of a transfer effect. In line with previous findings from Baumert et al. (2012), Chu et al. (2016), and Korpipää et al. (2017), we suggest that the transfer effect of ML is due to the promotion of domain-general abilities such as problem-solving and a deeper understanding of texts, realistic contexts, and students' everyday life through competence development linked with students' ML. We even found a significant effect of ML in Grade 5 on reasoning in Grade 9—while controlling for prior reasoning—which strengthens this explanation.

In line with current research on *predictors* of ML, our study confirmed the role of calculation skills, mathematical self-concept, reading comprehension, and reasoning as predictive factors of ML (Andersson 2007; Baumert et al. 2007; Borromeo Ferri 2006; Chu et al. 2016; Kriegbaum et al. 2015; Pajares and Miller 1994). We assumed these predictors, found in separate studies to have an effect on ML, to predict later ML when examined at the same time and while controlling for prior achievement. Our results support an integrative view of different phases of the process of solving mathematical problems, as has been suggested in various theoretical articles and qualitative studies (e.g., Kaiser et al. 2015; Leiss and Tropper 2014). Concerning cognitive models of ML, which typically view the process of solving mathematical problems as consisting of different phases, our results reveal that mathematical self-concept still has an effect on ML when prior achievement is controlled for. This is in line with findings from Marsh et al. (2005) and self-enhancement models of self-concept (Bandura 1997), which suggest there is an underlying motivational basis to the effects of mathematical self-concept on ML. Students profit from high self-concept because it enhances their motivation, which is especially useful when attempting the complex tasks involved in ML. We found that reasoning also showed an effect on later ML, which is in accordance with

previous arguments on the role of cognitive skills in ML (Baumert et al. 2007) and underlines the role of general cognitive abilities, in the sense of shared skill sets of ML and achievement in other domains.

In contrast to what previous research showed (e.g., Robinson and Lubienski 2011), we found no gender differences in paths from comprehensive predictors to ML or from ML, prior achievement, and reasoning to achievement in different school domains. We presume that this may be due to our operationalization of outcome variables as competence measures (in contrast to GPA) and the fact that taking other explanatory variables such as math grade or self-concept into account may diminish gender effects.

Regarding SES, we found significant paths to ML and achievement in different school domains 4 years later, which is in line with previous research on achievement measures (Sirin 2005). Though an SES-related achievement gap appears to narrow through the course of secondary school (Caro and Lehmann 2009), students with higher SES still score higher on different achievement measures in Grade 9.

Limitations and directions for future research

We examined the influence of ML on later academic achievement longitudinally throughout secondary school with a national representative sample. While this is an important time span previously neglected in studies on ML, a longer time span reaching into students' vocational years would shed light on further academic as well as nonacademic outcomes.

Because we used data from the large-scale NEPS assessments, limitations lie in the restriction to scales used in the study. Mathematical self-concept, for instance, while having the strength of being domain specific (Schöber et al. 2018), consisted of only three items. Broader and more differentiating concepts such as self-efficacy, attitudes, or motivational variables would be interesting to take into account to cover self-concept. Especially the role of self-efficacy in ML would appear to warrant further attention (Krawitz and Schukajlow 2017; Schukajlow et al. 2012). With respect to cognitive skills, which have been argued and empirically found to play an important role in mathematical problem-solving, the domain of verbal intelligence should be examined as well, because reading and listening comprehension were found to influence ML.

Disregarded by our research approach were other phases in the cognitive process of ML, such as metacognitive skills (Maass 2006), working memory (Swanson 2011), and personality (Phonapichat et al. 2014), all argued to have an influence on solving mathematical problems. Concerning individual differences in competence development, differences regarding migration background are a broadly discussed topic in the current literature. With controlling for SES, we have partly addressed this issue because SES is considered to be linked to migration background (e.g., Lenkeit et al. 2015). Future studies should address the influence of migration background directly to broaden the integrative view of predictive factors of ML, as differences in mathematical development were found to be entangled with reading competence (e.g., Lehner et al. 2017).

From a methodological perspective, though our results are longitudinal, they are restricted in that they are not interventional. Besides this, the possibility of there being other paths that were not analyzed restricts the validity of causal effects. The argument for causal transfer effects of ML on achievement in different school domains relies on theoretical assumptions (i.e., shared skill sets being fostered by gains in ML) and is methodologically strengthened by controlling for prior achievement in the respective domains as well as taking ML 4 years previous into account. Nevertheless, we only tested for predictive patterns, resulting in the

need for experimental manipulations (e.g., instructional approaches to teaching ML) to get more evidence of causal transfer effects. Moreover, with respect to other scholars, Leiss et al. (2010) argued that addressing how teachers themselves are taught to foster their students' ML is essential. Lehner et al. (2017) postulated encouraging, motivating lessons, classroom management, and schooling structure to be central for mathematical competence development. Applying a solution plan when solving mathematical problems could foster ML as well as mathematical self-efficacy (Schukajlow et al. 2015). Also, class sizes seem to play a role, though findings are still inconclusive (Ehrenberg et al. 2001; Hattie 2009; Schukajlow and Blum 2011). To enlarge the integrative view, interventional studies are needed to further investigate ML and its role in achievement and life success.

Conclusion and practical implications

We found consistent support for the importance of ML for general academic achievement. ML was found to be linked with achievement in math-related domains (ICT literacy, scientific literacy) as well as domains not directly related to mathematics (listening and reading comprehension). We argue that this not only underlines the effect of ML on understanding mathematics in today's life contexts (Baumert et al. 2007) but also indicates the existence of a transfer effect of applying this understanding for better life competence in domains other than mathematics. In our view, this means that students profit—in terms of their future academic achievement—when educators and policy makers invest in students' ML. Our results suggest that the success of such investment is comparable with that obtained by the investment in fostering other competences such as reading comprehension. The universality of our model regarding gender differences reinforces the idea of not differentiating between boys and girls concerning the support they get in learning mathematics and reading.

The consistent support we found in line with previous studies regarding the influence of predictive factors on ML could encourage teachers and parents to foster students' mathematical self-concept as well as their ML from early on. This also supports the current directions in international educational standards to implement the literacy perspective in the domain of mathematics in the conceptualizations of school curricula (National Council of Teachers of Mathematics 2003; Standing Conference of the Ministers of Education and Cultural Affairs of the Federal Republic of Germany 2004). Given our findings and following the ML concept of PISA 2021 (OECD 2019), teachers should, when designing their mathematics lessons and motivating their students, keep in mind the applicability for current and post-school participation in a culture. The theoretical insights and evidence of our study indicate that making ML part of a daily routine elicits mathematical development and trains skills that advance students in other school domains. We assume that this different perspective on ML leads to a deeper, broadened understanding of the significance of mathematics in students' everyday lives. Keeping in mind the relationships of reasoning and self-concept as well as the links between SES and ML, we strongly suggest integrating encouraging, vivid, and resource-based teaching methods that foster students' mathematical self-concept when guiding students to tackle the challenging elements of ML problems. Applying a solution plan (Schukajlow et al. 2015) might prove to be useful in this regard. Following these recommendations, we are convinced that ML is key to motivating a diverse range of students. Finally, the impact we found of SES on later achievement in different school domains when controlling for prior achievement highlights the need for educational equity.

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Compliance with ethical standards

Conflict of interest The authors declare that they have no conflict of interest.

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Current themes of research

Holenstein's research focuses on (1) mathematical literacy and mathematical self-efficacy in school-age children and (2) on the development of academic self-concept. *Bruckmaier's* research focuses on (1) didactic competencies of teachers and (2) on mathematical modeling. *Grob's* research focuses on (1) intelligence and developmental diagnostics across childhood, adolescence, and adulthood, and (2) on early interventions to improve the life-course and academic achievement of regularly developing and disadvantaged children.

Most relevant publications in the field of Psychology of Education

Bünger, A., Urfer-Maurer, N., & Grob, A. (accepted). Multimethod assessment of attention, executive functions, and motor skills in children with and without ADHD: children's performance and parents' perceptions. *Journal of Attention Disorders.* doi.org/10.1177/1087054718824985

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