Doctoral thesis submitted to
the Faculty of Behavioural and Cultural Studies
Heidelberg University
in partial fulfillment of the requirements of the degree of
Doctor of Philosophy (Dr. phil.)
in Psychology

Title of the publication-based thesis

The Relative Importance of Motivation in the School Context

presented by
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year of submission
2019

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Advisor: Prof. Dr. Birgit Spinath

Acknowledgements

On my way to complete this dissertation, numerous people have motivated and supported me in different ways. I am grateful to all of them!

First of all, I would sincerely like to thank my supervisor Prof. Dr. Birgit Spinath. After having completed my Bachelor and Master thesis under her supervision, she ultimately was the person that inspired me to do research in the framework of this dissertation project. I am incredibly thankful for her interest in my work, her valuable advice, and reliable feedback. Even in difficult times, she managed to offer sound advice and essentially motivated me to carry on with my research. Moreover, I thank her very much for providing me the opportunity to be part of additional projects and publications. Not only did she enable me to teach undergraduate and graduate courses in psychology, but she also encouraged me to participate at national and international conferences where I could present my research. She definitely fostered my academic as well as my personal development and I am very happy and grateful that she became my supervisor.

I would also like to thank my co-author of Study 1, Dr. Nicolas Becker, for our pleasant and fruitful collaboration. Working together fostered my abilities in applying structural equation models on a meta-analytic level and paved the way to successfully publishing Study 1.

Another researcher I would like to thank is Prof. Dr. Ricarda Steinmayr, who co-authored Study 3. Her time and reliable answers to my questions concerning the revision of the third manuscript were very supportive. Collaborating with her also fostered my scientific skills.

I would sincerely like to thank Prof. Dr. Silke Hertel. I am very thankful for her being the second supervisor of this dissertation. Both the time and effort that she invested in reading and evaluating this dissertation are very rewarding.

I would also like to extend my gratitude to the Research Data Centre (FDZ) at the Institute for Educational Quality Improvement (IQB) for providing me with the PISA-I-Plus dataset. It would have been impossible to conduct Study 2 of this dissertation without this dataset. Moreover, I would like to thank Dr. Verena Freiberger for providing the MEGA (motivation development in elementary school) dataset. Analyzing this dataset enabled me to realize Study 3 of this dissertation.

I am sincerely thankful for the financial support that I received from Landesgraduiertenförderung Baden-Württemberg by providing me with a fellowship for individual doctoral training. This helped me to better focus on my research for this dissertation project.

My special thanks goes to Nikolay Sergeev for proofreading important parts of this dissertation.

I would like to thank my colleagues and friends from the Department of Psychology and the Institute for Education Studies for our interesting and constructive discussions. I always enjoyed the pleasant atmosphere and excellent working conditions. All these colleagues shared their knowledge and experience with me for which I am very thankful. Cheers for being such amazing companions!

Not to forget, I would also like to thank my former student research assistant Rahel Milla for coding the primary studies for the meta-analysis of Study 1 which was very supportive.

A special shout of thanks goes out to my parents Kornelia and Hans-Willi Kriegbaum. Their continuous support and care enabled me to pursue my scientific career and achieve all goals so far. They are the ones that are always there for me listening to my questions and thoughts. Thank you very much for your support, confidence, and endless love!

With all my heart, I would eventually like to thank my partner Tom Reschke for always believing in me as well as his professional and emotional support. He has given me the positive energy to complete this dissertation. I am incredibly thankful for having him by my side and for his love!

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List of Papers Included in This Publication-Based Dissertation

1st Paper (Study 1)

Kriegbaum, K., Becker, N., & Spinath, B. (2018). The relative importance of intelligence and motivation as predictors of school achievement: A meta-analysis. *Educational Research Review, 25,* 120–148. doi: 10.1016/j.edurev.2018.10.001

2nd Paper (Study 2)

Kriegbaum, K., & Spinath, B. (2016). Explaining Social Disparities in Mathematical Achievement: The Role of Motivation. *European Journal of Personality, 30*, 45–63. doi: 10.1002/per.2042

3rd Paper (Study 3)

Kriegbaum, K., Steinmayr, R., & Spinath, B. (2019). Longitudinal reciprocal effects between teachers' judgments of students' aptitude, students' motivation, and grades in math. *Contemporary Educational Psychology*. Advance online publication. doi: 10.1016/j.cedpsych.2019.101807

Summary

A high degree of motivation is an important prerequisite for learning and school achievement (Spinath, 2010). The purpose of this dissertation was to expand the knowledge about the importance of motivation in the context of school, both relative to other well-established predictors and as a potential mediating and explaining factor. The goal was to examine different aspects of the predictive power of motivation for school achievement and teachers' judgment of students' aptitude. In particular, this dissertation aimed at examining the interplay between motivation and other student characteristics, such as intelligence and socio-economic status (SES), when predicting school achievement.

Study 1 is a meta-analysis that systematically examined the relative importance of both motivation and intelligence for school achievement. This meta-analysis summarized 74 primary studies (N = 80,145) that reported correlations between motivation, intelligence, and school achievement. First, significant positive average correlations between motivation and school achievement (r = .27), between intelligence and school achievement (r = .44), and between intelligence and motivation (r = .17) were found. Moderator analyses showed no differences in these correlations depended on the achievement measures used such as school grades or standardized test achievement. The association between motivation and school achievement was higher for expectancies as a motivational construct compared to values. The correlation between intelligence and school achievement was higher for general intelligence than for nonverbal intelligence. No moderator effects were found for grade level, school type, gender, or continent. Second, a meta-analytic path model showed that both intelligence and motivation were important predictors of school achievement and explained 24% of its overall variance. Of this 24%, intelligence alone accounted for 66%, whereas motivation alone accounted for 16%.

Motivation and intelligence together accounted for 16%. Even though intelligence was a stronger predictor of school achievement, motivation incrementally predicted school achievement over intelligence. Therefore, both intelligence and motivation are student characteristics that should be considered when predicting school achievement.

Study 2 focused on the underlying effects of the relationship between parents' SES and students' school achievement. Students' motivation and intelligence were examined as mediators of this relationship. Longitudinal data from the Programme for International Student Assessment (PISA) were analyzed (two measurement occasions). The sample consisted of N = 6,020 German students (M_{Age} = 15.5 years, SD = .55) who were in 9th grade at the time of the first (2003) and in 10th grade at the time of the second measurement occasion (2004). Students completed a questionnaire on their SES, math-specific self-concept, self-efficacy, and interest in math. Moreover, students' intelligence and mathematical competence were assessed. The results showed a small to moderate significant positive correlation between parents' SES and students' test achievement in math. Motivation partially mediated the relationship between parents' SES and students' achievement. This mediating effect remained significant after including students' intelligence and prior test achievement as additional mediators. These findings are important to understand the underlying mechanisms of the association between SES and school achievement. They are also relevant for discussing topics such as educational equality.

Study 3 investigated potential reciprocal effects between students' motivation, their school achievement in form of grades, and teachers' judgments of students' aptitude. It was hypothesized that teachers' judgments of students' aptitude are predicted by students' motivation and their school grades. Also, it was expected that

teachers' judgments of students' aptitude determine students' grades and motivation. A sample of *N* = 519 students in elementary school gave self-reports on their math-specific motivation in form of academic self-concepts and intrinsic task values in math. Teachers (*N* = 27) evaluated students' aptitude in math and gave information about students' grades in math. Measurements were performed four times from the end of 3rd grade until the end of 4th grade. Cross-lagged panel models showed that teachers' prior judgments of students' aptitude had significant positive effects on students' grades in math but not on their motivation. Students' prior math grades and their academic self-concepts significantly predicted teachers' subsequent judgments of students' aptitude. These findings are very important for understanding which factors play a role in teachers' judgments of students' aptitude. Important practical implications will be discussed later.

To summarize, the findings of all studies showed that motivation plays an important role in the school context, both relative to other well-established predictors and as a potential mediating and explaining factor. In Study 1, motivation predicted school achievement over and beyond intelligence. In Study 2, motivation mediated the relationship between parents' SES and students' school achievement. In Study 3, motivation in form of students' academic self-concepts longitudinally predicted teachers' judgments of students' aptitude. The findings of this dissertation have a number of implications for theory and future research but can also give practical advice for school contexts.

Keywords: motivation, school achievement, intelligence, socio-economic status, teachers' judgments, expectancies, values, academic self-concept, structural equation modeling, meta-analysis

1 Introduction

Why is it that some students outperform others in class? How come that some students get better aptitude judgments from their teachers than others? Is there an explanation why students with less privileged family backgrounds show lower academic competencies? One thought that would come to mind is that maybe intelligence differentiates good students from poorer achieving students. Typically, one would expect that students with higher intelligence would earn better grades and score higher on standardized achievement tests. Another idea could point to motivation being the driving force behind the achievement differences in school. In this context, one would expect that highly motivated students would get better grades and achievement test results.

While there is an emerging field of research that looks at the interplay of intelligence and motivation in school, less attention has been given to the relative importance of motivation. For example, there may be a scenario where one of two equally intelligent students shows higher motivation in a certain subject and therefore receives better grades. However, can a student’s motivation possibly be powerful enough to predict school achievement over and beyond intelligence? Also, there may be a scenario where two students come from opposing socio-economic backgrounds and the student of a higher socio-economic status (SES) performs better than the other. Is there a chance for motivation to explain this achievement difference in a way that higher SES is related to higher motivation which in turn affects achievement? Furthermore, there may be a scenario where only one of two students is highly motivated in a subject and is therefore judged as more talented by the teacher. Again, can motivation predict school achievement as well as teachers’ judgments of students’ aptitudes?

Motivation is defined as the mental power that influences direction, perseverance, and intensity of one's behavior (Rheinberg, 2006; Schunk, Pintrich, & Meece, 2008). Therefore, motivation is an important construct to determine and explain a person's behavior. In educational context, a high degree of motivation over longer periods of time both is not only an important prerequisite for learning and achievement but also an important educational goal (Spinath, 2010). Motivation is too an important component of self-regulation, for example when initiating (motivating oneself) and maintaining learning. It can also be beneficial for evaluating one's own success and failure in order to keep on learning (Landmann, Perels, Otto, & Schmitz, 2009). Motivation has a lot of positive effects. It fosters learning success and achievement, and helps students to deal with learning contents over long periods of time (e.g., in the context of school and university) (Schiefele, 2009). Moreover, lessons with motivated students are usually experienced as smoother, more enjoyable, and also more efficient, which in turn has positive effects on students' learning success (Schiefele, 2009). Interestingly, motivation was shown to be influenced and fostered through educational and psychological interventions (Harackiewicz, Canning, Tibbetts, Priniski, & Hyde, 2016; Midgley, Anderman, & Hicks, 1995; Yeager & Walton, 2011). Therefore, motivation plays an important role in educational psychology and education research.

In the past, a great amount of studies examined the relationship between motivation and school achievement. It has been shown that motivation is an important predictor of school achievement (e.g., Möller, Pohlmann, Köller, & Marsh, 2009; Spinath, Eckart, & Steinmayr, 2014; Valentine, DuBois, & Cooper, 2004). Even though there is extensive research on motivation as a predictor in the school context, there are still open questions that are addressed in this dissertation. This lack of research relates to the interplay of motivation with other student characteristics such as intelligence and SES when predicting school achievement. For example, only a few studies tested motivation and intelligence together as predictors of school achievement. Whereas most studies found that intelligence is the stronger predictor (Gagné & St. Père, 2001), the relative importance of motivation was shown to be comparably high or even higher than intelligence under certain conditions (Steinmayr & Meißner, 2013; Steinmayr & Spinath, 2009). Until now, it has been unclear how much of the explained variance in school achievement can be attributed to motivation and intelligence, both individually and together. Another student characteristic that is associated with school achievement is their SES (e.g., OECD, 2007; Sirin, 2005). It is still unclear whether motivation can explain this relationship. To advance research on motivation as a predictor in the school context, one should focus not only on school achievement, but also on other measures of students' abilities (e.g., teachers' judgments of students' aptitude). To this date, longitudinal effects of students' motivation on teachers' judgments of students' aptitude were not analyzed sufficiently. Moreover, there are many motivational constructs in the achievement motivation literature but only few studies examined which of these predicted school achievement best. It remains important to look at possible differences in the predictive power of several motivational constructs in order to examine their relative importance for school achievement or teachers' judgments. Generally, there is a lack of research examining the relative importance of motivation predicting school achievement. The interplay of motivation with other student characteristics such as intelligence and SES as well as the prediction of teachers' judgments need further attention. Therefore, the present dissertation will address these open questions to create new insights to this field of research.

In the following, I will begin with a chapter introducing two important motivational constructs from Expectancy-Value-Theory, which is a fundamental and prominent theory in the achievement motivation literature. In the next chapter, I will shift the focus to important criteria of students' academic abilities such as school achievement and teachers' judgments of students' aptitude. Findings on the predictive power and relative importance of motivation for school achievement and teachers' judgments in addition to intelligence and social background are presented. I will then address open questions and state the aims of this dissertation. As its core, three studies about single aspects of motivation as a predictor in the school context will be presented: the relative importance of motivation and intelligence for school achievement (1st Paper: Kriegbaum, Becker, & Spinath, 2018), motivation as a mediator of the relationship between parents' SES and students' standardized test achievement (2nd Paper: Kriegbaum & Spinath, 2016), and motivation as a predictor of subsequent teachers' judgments of students' aptitude (3rd Paper: Kriegbaum, Steinmayr, & Spinath, 2019). I will end this dissertation with a general discussion on the role of motivation as a predictor in the school context and will also mention its implications for theory, future research, as well as for practice.

2 Motivation

The achievement motivation literature holds a variety of motivational constructs. Among the most prominent constructs are expectancies, such as academic self-concept (e.g., Marsh, Byrne, & Shavelson, 1988) and self-efficacy (Bandura, 1997), as well as values from Expectancy-Value-Theory (EVT; Eccles et al., 1983), intrinsic and extrinsic motivation from Self-Determination-Theory (Deci & Ryan, 1985), goal orientations (Elliot & McGregor, 2001), achievement motives (McClelland, Atkinson, Clark, & Lowell, 1953), and interest (Hidi & Renninger, 2006; Krapp, 1999).

Study 1 of this dissertation is a meta-analysis that included all of these motivational constructs to give an overview on their predictive power for school achievement. Study 2 and 3 only involved motivational constructs from EVT. For this reason, EVT from Eccles and colleagues (1983) will be described in more detail. The most recent version of this model is depicted in Figure 1.

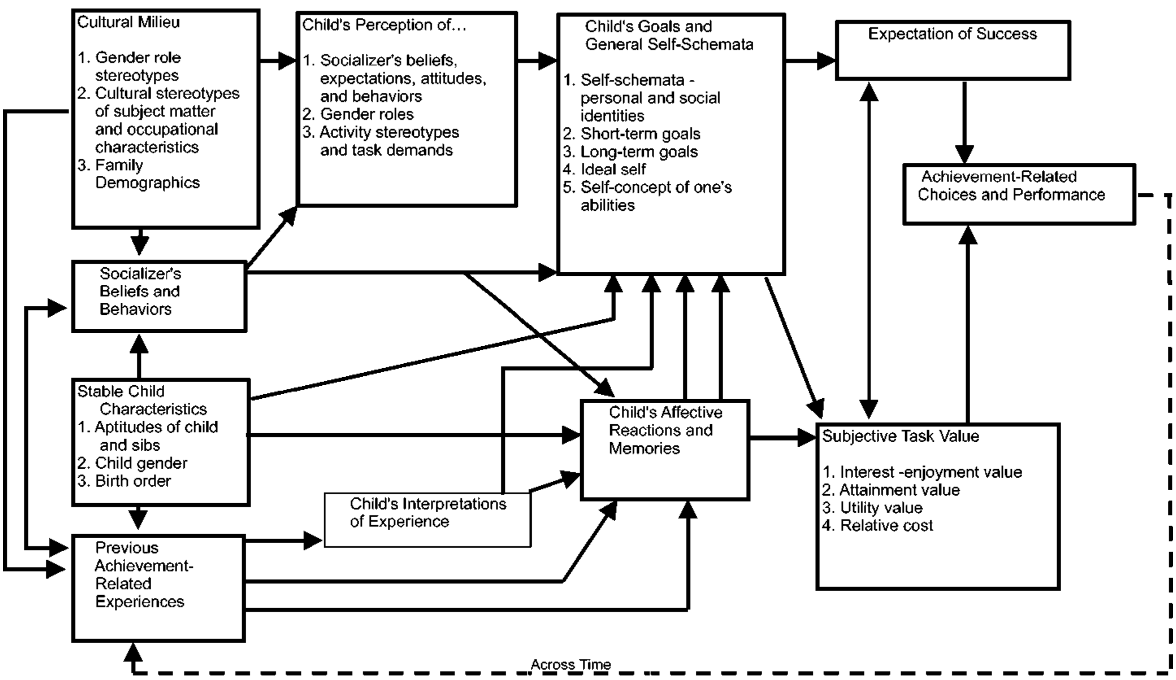

Figure 1. Expectancy-Value-Model from Eccles and Wigfield (2002).

The first motivational construct within the framework of EVT, namely expectancies for future success, is defined as “children’s beliefs about how well they will do on an upcoming task” (e.g., *How well do you think you will do in math next year?)* (Wigfield, Tonks, & Klauda, 2016, p. 57). This expectancy is very similar to the motivational construct of self-efficacy which is defined as individual expectancy about future success (i.e., one’s belief about solving a specific task in the future) (Bandura, 1997). Self-efficacy is often domain-specifically or task-specifically operationalized. On a conceptual level, the model differentiates between expectancies of future success and the self-concept of one’s abilities. This self-concept is defined as an individuals’ perception of one’s own competence or ability in a certain domain (Marsh & Martin, 2011; Marsh & Seaton, 2013). Academic self-concepts are typically assessed by asking students how good they think they are in a certain domain such as math and are therefore domain-specifically operationalized (Eccles et al., 1983; Wigfield & Eccles, 2000). It is important to note that there is a close theoretical relation between both constructs. Empirical studies have shown that self-efficacy and academic self-concept are highly associated with each other and both are used as important predictors of school achievement (Eccles & Wigfield, 2002).

The second motivational construct within the framework of EVT, namely the subjective task values, is defined as the quality of a specific task that contributes to an increasing or decreasing probability that an individual will do the task. The quality of these task values is divided into four components. The attainment value (1) refers to the importance of doing well on a specific task. The intrinsic value (2) is related to the joy that individuals experience while doing a specific task. This component is very similar to intrinsic motivation from the Self-Determination-Theory and interest. The utility value (3) refers to the usefulness of a specific task for one’s future career.

The costs associated with task values (4) can be seen as a negative component when individuals are confronted with negative consequences of a specific task such as anticipated effort or giving up an alternative task. In the school context, task values are typically assessed domain-specifically. Research on the four value components has shown rather high intercorrelations despite their theoretical separation (Trautwein et al., 2012). Interestingly, most empirical studies on task values only considered the first three components with costs not further examined.

It is how expectancies and values as well as their antecedents influence achievement-related choices, persistence, and academic achievement that constitute the main idea of the model. Expectancies of future success and task values have been hypothesized to directly influence achievement-related choices and academic achievement. Expectancies and values can be seen as proximal variables to influence school achievement. Intelligence (as part of stable child characteristics) and SES (being part of cultural milieu) can both be seen as distal variables that influence school achievement via previous achievement-related experiences.

Expectancies and values themselves are meant to be affected by an individuals' task-specific beliefs (e.g., academic self-concept), personal goals, affective reactions, and memories of achievement-related events. There are also other factors that influence expectancies and values rather indirectly through goals and an individuals' task-specific beliefs such as the cultural milieu, socializer's beliefs and behaviors, personal characteristics, as well as children's perceptions of these components (Eccles et al., 1983).

To conclude, EVT is a prominent model in the achievement motivation literature holding that expectancies and task values as motivational constructs predict academic achievement. Academic achievement is also determined by stable child characteristics such as intelligence and students' cultural milieu such as SES.

3 Criteria of Students' Academic Abilities

Schools are important learning environments. They provide the framework for learning and knowledge acquisition but also opportunities to quantify students' academic abilities. While different criteria allow the measurement or assessment of students' academic abilities, two distinct pathways can be distinguished. On the one hand, students' school achievement serves as a rather direct criterion of students' academic abilities. This is typically assessed via school grades and standardized test achievement. On the other hand, teachers' judgments make up a rather indirect criterion of students' academic abilities. These judgments typically refer to students' aptitude, their actual achievement, or expectations about students' future achievement. Both criteria will receive closer consideration in the following.

Even though school achievement is one of the most examined student outcomes in educational psychology, there exists no consistent theory about the construct itself (Köller & Baumert, 2002). Thus, school achievement is mostly described on a content-related level. School achievement can be defined as a student's performance in all domains that are taught at school. While varying between students, it is relatively stable over time on an intraindividual level (Heller & Hany, 1997; Spinath, 2012). School achievement also is a criterion that results from preparing, practicing, and overall learning endeavors (Heller & Hany, 1997). At the same time, school achievement does not only consist of behaviors that a student might show in a specific achievement situation (e.g., in an exam). It is also a result of longitudinally effective and hierarchically organized mental processes (Heller & Hany, 1997).

When measuring school achievement, it is important that the construct manifests itself in observable behaviors within two categories: solving specific tasks in the written domain (e.g., a student's score on a certain test) or solving them in the verbal domain (e.g., a student's answer on a certain question) (Schrader & Helmke, 2001). School achievement is typically assessed with school grades or standardized test scores. School grades are given by teachers that not only take a student's achievement into account but also other aspects such as motivation, discipline, effort, and achievement development over one school year (e.g., McMillan, Myran, & Workman, 2002; Zimmermann, Schütte, Taskinen, & Köller, 2013). Additionally, school grades are given in class and teachers use the achievement of all students in a given class as a frame of reference. By contrast, standardized test achievement is a more pure measure of students' achievement that can be seen as more objective. Such measures only include students' achievement and evaluate it within the framework of a representative norm sample (Arens et al., 2016). Therefore, school grades and standardized test achievement can be considered as two side-by-side measures. Many empirical studies have demonstrated that school grades and standardized test achievement show moderate to high positive associations with $.34 \leq r \leq .62$ (e.g., Gustafsson & Balke, 1993; Schütte, Frenzel, Asseburg, & Pekrun, 2007).

Teachers' judgments can take different aspects into account such as single characteristics that are judged and the specific timeframe. One facet is teachers' expectations that can be understood as teachers' predictions of students' achievement for future events (e.g., Brattesani, Weinstein, & Marshall, 1984; Rubie-Davies, 2006). A second facet of teachers' judgments is usually conceptualized as teachers' estimations of students' past or current achievement (Hoge & Coladarci, 1989). These are mostly operationalized as an estimation of students' achievement on a standardized test (Südkamp, Kaiser, & Möller, 2012). A third facet often is operationalized as teachers' estimations of students' current aptitude in a specific subject such as math (Dickhäuser & Stiensmeier-Pelster, 2003; Rubie-Davies et al., 2014; Tiedemann, 2000). In this context, students' aptitude can be defined as the potential to learn and achieve (e.g., general cognitive ability as measured by intelligence tests). It is therefore a prerequisite for achievement outcomes such as school grades. Interestingly, students' aptitude is not always reflected by actual achievement (e.g., underachievers). Because students' aptitude is not a directly observable measure, it can be seen as an indirect criterion of students' academic abilities.

On another note, school achievement has a selective function for subsequent educational paths (i.e., getting access to university or certain jobs). There is ample evidence that school achievement is a strong and valid predictor of occupational careers and socio-economic prosperity (e.g., Schuler, Funke, & Baron-Boldt, 1990; Cohen, 1984; Roth, BeVier, Switzer, & Schippmann, 1996; Spinath, 2012). Given the fact that school achievement is such an important antecedent of individual careers, it is worthwhile to examine which factors have a significant impact on school achievement. Also, teachers' judgments of students' aptitude can have far-reaching consequences for students. For example, teachers give recommendations for secondary school at the end of elementary school that can impact students' future motivation and achievement (Steinmayr, Michels, & Weidinger, 2017). Research on the determinants of school achievement and teachers' judgments has thus become increasingly important in educational psychology.

4 Motivation as an Important Predictor in the School Context

Given that school achievement and teachers' judgments of students' aptitude are very important for students' future careers, it is worthwhile to examine whether motivation as a student characteristic serves as a significant predictor of these constructs. Recent evidence suggests that the prediction of school achievement seems rather complex. For example, school achievement is not merely determined by one student characteristic alone, but is influenced by multiple factors such as intelligence, motivation, and social background (Hattie, 2009; Helmke & Weinert, 1997; Wang, Haertel, & Walberg, 1993). Nevertheless, many studies have focused on one specific student characteristic such as motivation and examined its predictive power for school achievement. Only few studies have considered several student characteristics such as motivation and intelligence and have explored both their interplay and unique contribution.

The next sections will highlight the role of motivation as a sole predictor of school achievement and teachers' judgments. Empirical findings on the importance of motivation in predicting school achievement will be presented. These findings will take other student characteristics such as intelligence and social background into account to help examine whether motivation predicts school achievement over and beyond intelligence and social background.

4.1 Motivation as a Predictor of School Achievement

EVT has inspired research in many educational domains. There is an extensive and increasing literature on the relationship between academic self-concept, self-efficacy, task values, and school achievement. Moderate to high positive relationships between academic self-concept and school achievement ($.30 \leq r \leq .60$) were found by numerous primary studies as well as meta-analyses in different domains (e.g., Guay, Marsh, & Boivin, 2003; Möller et al., 2009). It has also been shown that academic self-concepts predict school achievement, not only cross-sectionally, but also longitudinally and even over prior achievement (e.g., Bong, Cho, Ahn, & Kim, 2012; Helmke & van Aken, 1995; Huang, 2011; Marsh, Trautwein, Lüdtke, Köller, & Baumert, 2005; Valentine et al., 2004). Moderate to high positive associations have also been found between self-efficacy and school achievement (e.g., Bong & Clark, 1999; Bong et al., 2012; Kriegbaum, Jansen, & Spinath, 2015; Robbins et al., 2004; Schunk & Schwartz, 1993; Stevens, Olivarez, Lan, & Tallent-Runnels, 2004; Stevens, Olivarez, & Hamman, 2006; Zimmermann, 2000). The relationship between task values and school achievement has been demonstrated to be weak to moderate (e.g., Kriegbaum et al., 2015; Ozel, Caglak & Erdogan, 2013; Steinmayr & Spinath, 2009; Trautwein et al., 2012). Furthermore, current evidence suggests that academic self-concepts and self-efficacy are better predictors of school achievement compared to task values (Chamorro-Premuzic, Harlaar, Greven, & Plomin, 2010; Helmke, 1992; Kriegbaum et al., 2015; Steinmayr & Meißner, 2013; Steinmayr & Spinath, 2009; Zaunbauer, Retelsdorf, & Möller, 2009). Taken together, all this research supports expectancies for future success, academic self-concepts, and task values to be prominent motivational constructs that are important predictors of school achievement.

4.2 Motivation as a Predictor of Teachers' Judgments

EVT holds that socializer's beliefs are influenced by three variables: cultural milieu (such as SES), stable child characteristics (such as intelligence), and previous achievement (Eccles et al., 1983). Empirical findings have shown that teachers' judgments of students' aptitude can be predicted by students' actual achievement (Dickhäuser & Stiensmeier-Pelster, 2003; Rubie-Davies et al., 2014; Tiedemann, 2000), general cognitive ability (Baudson, Fischbach, & Preckel, 2016), and SES (Baudson et al., 2016).

Other groups of researchers found that even students' engagement (as a proxy of their motivation) had an influence on teachers' judgments of students' achievement (Kaiser, Retelsdorf, Südkamp, & Möller, 2013). Students' reading engagement showed an effect on teachers' judgments of students' reading achievement (β = .24 / .19) in both a field study as well as in an experimental setting (simulated classroom). The authors argued that students' engagement (especially in form of classroom participation) could be considered as an indicator of students' knowledge. For example, more pronounced student engagement could lead to more careful homework completion which are then followed by more positive teachers' judgments. Apart from that, teachers could also be influenced by the so-called halo effect in a way that a positive evaluation of one specific student characteristic could lead to a positive evaluation overall (Thorndike, 1920). A positive evaluation of a student's engagement would then lead to a more positive evaluation of this student's reading achievement. However, this can be identified as an overestimation of the student's actual reading achievement, because the positive evaluation of this student's engagement outshined that reading achievement. A shortcoming of this study was that it only assessed students' engagement as a proxy of their motivation (Kaiser et al., 2013).

In a study by Madon and colleagues (2001), students' self-concept at the beginning of 6th grade predicted teachers' judgments of students' talent in math at the end of 6th grade. Although there was a longitudinal effect of previous self-concept on subsequent teachers' judgments, the study only included two measurement occasions over one school year. Further research would do well to explore whether these effects can also be found over longer time periods and whether other motivational variables can predict teachers’ judgments longitudinally.

In this context, it would be possible that motivation in form of expectancies and values shows an effect on teachers’ judgments. First, a student with a high self-concept in a specific subject (i.e., he or she believes that he or she has a high aptitude in this subject) might convince the teacher of his or her high aptitude and could therefore be evaluated as more talented. Second, a student with a high intrinsic motivation (i.e., interest in a specific subject) might actively participate in class and would thereby show more desirable behavior for teachers. This positive impression of a student’s interest in the subject might in turn influence the teacher’s judgment of this student’s aptitude. Such a situation would make a classic example of the halo effect. Up until now, no study has examined the effects of self-concepts and intrinsic motivation on teachers’ judgments.

4.3 Motivation and Intelligence as Predictors of School Achievement

Intelligence is one of the most investigated personality constructs in psychology. It also belongs to the most examined student characteristics in the school context (Hattie, 2009; Roth et al., 2015). Despite the fact that there are many studies that have assessed intelligence, psychology still lacks a universal definition of the construct. One reason for this might be that existing psychological sub-disciplines focused on different aspects of intelligence. While differential psychology has mostly examined individual differences and heritability, educational psychology has rather focused on the development of intelligence and at its predictive power for school achievement. Nonetheless, two definitions of intelligence gained popularity within psychological literature. Binet and Simon (1905) defined intelligence as the ability to master situations well, but also to understand, judge, and act well. The task force of the American Psychological Association defined intelligence as “the ability to understand complex ideas, to adapt effectively to the environment, to learn from experience, to engage in various forms of reasoning, [and] to overcome obstacles by taking thought” (Neisser et al., 1996, p. 77). Besides these definitions of intelligence, different theories about the structure of intelligence exist. Whereas it is well established that there seems to be a general factor of intelligence called *g*, verbal, figural, and numerical intelligence have been stated to be specific intelligence factors (Brody, 2000). When predicting school achievement in certain school subjects or domains, these specific intelligence factors are often involved. Evidence suggests that intelligence is relatively stable once children reach school age (Deary, 2014; Sternberg, Grigorenko, & Bundy, 2001). Furthermore, intelligence has also been shown to be a strong predictor of school achievement as early as in elementary school (for an overview see Helmke & Weinert, 1997).

Empirical studies and meta-analyses have reported strong positive correlations between students’ intelligence and their school achievement with a mean correlation of $r = .50$ (e.g., Gottfredson, 2002; Gustafsson & Undheim, 1996; Kuncel, Hezlett, & Ones, 2004; Neisser et al., 1996; Roth et al., 2015). Higher correlations were found between intelligence and students’ standardized test achievement ($.61 \leq r \leq .90$) compared to school grades (e.g., Deary, Strand, Smith, & Fernandes, 2007; Duckworth, Quinn, & Tsukayama, 2012; Frey & Dettermann, 2004; Steinmayr & Meißner, 2013). The reason for this might be that standardized test achievement constitutes a more pure measure of achievement compared to grades. School grades also take students’ motivation, discipline, and achievement development into account and typically accumulate these over one year (Steinmayr & Meißner, 2013; Steinmayr & Spinath, 2009). Intelligence and standardized test achievement are also measured on an absolute scale whereas grades are given according to social norms and reference groups (Trautwein & Baeriswyl, 2007). To conclude, intelligence was repeatedly shown to be a strong predictor of school achievement.

At this point the question about the relative importance of intelligence and motivation for school achievement arises. The previous sections outlined the extensive body of research including meta-analyses that supported both intelligence and motivation to be important predictors of school achievement (Möller et al., 2009; Roth et al., 2015; Valentine et al., 2004). Importantly, existing meta-analyses have either examined intelligence or motivation as a predictor of school achievement. There is no meta-analysis so far that has combined both intelligence and motivation within one model to predict school achievement.

Only a few primary studies have analyzed the extent to which variance in school achievement can be explained by intelligence and motivation together. Also, only few studies examined whether motivation predicts school achievement over and beyond intelligence. The following motivational constructs have been shown to predict school achievement over and beyond intelligence, both in form of grades and standardized test achievement: academic self-concept, self-efficacy, intrinsic motivation, task values, and learning goals (Chamorro-Premuzic et al., 2010; Freudenthaler, Spinath, & Neubauer, 2008; Greven, Harlaar, Kovas, Chamorro-Premuzic, & Plomin, 2009; Helmke, 1992; Kriegbaum et al., 2015; Lloyd & Barenblatt, 1984; Luo, Haworth, & Plomin, 2010; Schicke & Fagan, 1994; Spinath, Spinath, Harlaar, & Plomin, 2006; Spinath, Freudenthaler, & Neubauer, 2010; Steinmayr, Bipp, & Spinath, 2011; Steinmayr & Meißner, 2013; Steinmayr & Spinath, 2009). Only few of these studies looked at the specific portions of variance in school achievement, both explained by intelligence and motivation in order to quantify which predictor is "better". In most cases, research has shown that intelligence explained a higher portion of variance in school achievement (Kriegbaum et al., 2015; Spinath et al., 2006; Steinmayr & Spinath, 2009). Some findings highlighted that academic self-concept appears to be an equally strong predictor of school achievement (Helmke, 1992; Steinmayr & Meißner, 2013; Steinmayr & Spinath, 2009). In contrast, one particular study did not find any incremental validity for motivation when predicting school achievement over intelligence, which made the authors question whether motivation would predict school achievement independently from intelligence (Gagné & St. Père, 2001). To conclude, there exist only few empirical studies that have examined the predictive power of intelligence and motivation for school achievement. Their findings also differed with regard to the relative importance attributed to motivation and intelligence for school achievement. Therefore, it remains to be analyzed which portions of variance in school achievement can be explained by either intelligence or motivation alone and both constructs together.

4.4 Motivation and Socio-Economic Status as Predictors of School Achievement

The socio-economic status (SES) of a family determines the available economic and material resources within the family and therefore the possibility to provide supportive context for a given student's learning and achieving (Ehmke, Hohensee, Heidemeier, & Prenzel, 2004). A student's social background can be measured by its parents' SES, which is often indicated by their education (i.e., scholastic and vocational / educational attainment), occupation and income, or a combination of these three factors (Bradley & Corwyn, 2002; Steinmayr, Dinger, & Spinath, 2012). In order to assess parents' SES, different indices exist. First, there is the international socio-economic index (ISEI) that includes parents' occupation. The ISEI is based on international data related to education and income in different professions (Ganzeboom, De Graaf, & Treiman, 1992; Ganzeboom & Treiman, 1996). This index is used to assess an individual SES of each parent (i.e., the ISEI of the mother and the ISEI of the father). Second, there is the highest international socio-economic index (HISEI) that applies the same criteria to assess parents' SES as ISEI. The HISEI uses the information of the parent with the higher SES (i.e., either the mother's or father's SES) as an index of a family's SES (Ehmke & Siegle, 2005; Marks, 2008). Third, there is the index of parents' economic, social, and cultural status (ESCS) that became popular within the Programme for International Student Assessment (PISA). The ESCS is a composite of three variables: the highest level of education in the family, the HISEI, and the number of possessions at home (e.g., number of books) (Ramm et al., 2006).

In recent years, many studies have shown positive associations between SES and students' school achievement (e.g., Ehmke et al., 2004; Ehmke, Hohensee, Siegle, & Prenzel, 2006; OECD, 2007; Sirin, 2005; White, 1982). There were two meta-analyses that integrated a lot of evidence and reported mean correlations of r = .25 and r = .29 between SES and students' achievement (Sirin, 2005; White, 1982). Moderate positive relationships (.35 ≤ r ≤ .40) were found within the framework of PISA when SES and students' competencies were examined for OECD average (OECD, 2007). Depending on the SES index that was used to assess parents' SES, there were also differences found in the association between parents' SES and students' school achievement. Fathers' SES was shown to be more strongly related with students' achievement in science than mothers' SES (Marks, 2008). PISA illustrated that ESCS (as an index of families' SES) was more strongly associated with students' competencies in reading, math, and science compared to HISEI (Ehmke & Siegle, 2005). For this reason, it might be worthwhile to both assess families' SES with different indices and to explore possible differences in their predictive power for school achievement.

The positive association between SES and school achievement has often been interpreted as educational or social inequity (Ehmke & Jude, 2010; OECD, 2014a, 2014b). According to this logic, every student should have the chance to be successful in school no matter what social background he or she has. This is why it is important to study the extent to which students' social backgrounds are associated with other student characteristics such as intelligence and motivation. Both intelligence and motivation appear to have a significant impact on school achievement and might therefore explain social disparities in school achievement. Mechanisms behind the association between parents' SES and students' characteristics will be described first. Empirical results about motivation and intelligence as mediators of the relationship between SES and school achievement are reported later.

Both the environment parents provide and their genetic endowment have been shown to influence students' school achievement (e.g., Plomin, DeFries, Knopik, & Neiderhiser, 2012). Parents' SES can be seen as result of their achievement-related behaviors and choices, which were in turn determined by their intelligence and motivation. For example, parents with a higher intelligence and motivation are more likely to have a high-income job and to pursue a successful career. Therefore, it can be assumed that such parents will transmit these beneficial and achievement-related prerequisites in the following ways. First, parents provide their children with a more educationally stimulating environment, which might then lead to better school achievement. Second, as intelligence and even motivation are also heritable, parents transmit these characteristics to their children genetically (Plomin & Spinath, 2002; Johnson et al., 2007). Third, a gene-environment interaction would make it likely that children from such parents benefit from more stimulating environments because their genetic potential fits the actual environment (Bradley, Corwyn, Burchinal, Pipes

McAdoo, & García Coll, 2001; Bronfenbrenner & Ceci, 1994). Therefore, intelligence and motivation might serve as mediators of the relationship between SES and school achievement.

Indeed, empirical studies have demonstrated that the relationship between SES and students' school achievement (i.e., school grades and standardized test achievement) is mediated by parents' intelligence (Baumert, Watermann, & Schümer, 2003; Hecht, Burgess, Torgesen, Wagner, & Rashotte, 2000; Johnson et al., 2007; Lloyd & Barenblatt, 1984; Steinmayr et al., 2010, 2012). In a study from Steinmayr and colleagues (2012), intelligence accounted for 64% of the relationship between fathers' SES and students' school achievement. An amount of 41% of the relationship between mothers' SES and students' achievement in school was explained by students' intelligence (Steinmayr et al., 2012). Within the study, however, intelligence could not explain the entire covariance between SES and school achievement. It is likely that other student characteristics mediate this relationship. Looking for further mediators, Steinmayr and colleagues (2012) identified motivation in form of academic self-concepts and task values to significantly mediate the relationship between fathers' SES and students' achievement in math, physics, and chemistry. For the relationship between mothers' SES and students' school achievement in chemistry, only academic self-concept showed a significant mediation effect.

Taken together, these findings underline that both motivation and intelligence appear to partially mediate the relationship between SES and school achievement. Research has shown differences in the mediating effects depending on the applied SES indicator. To the best of my knowledge, however, there is only one study that examined the role of motivation as a mediator of the relationship between SES and school achievement.

4.5 Conclusion

School achievement as well as teachers' judgments of students' aptitude have been shown to influence students' careers and their socio-economic prosperity. Consequently, studying the determinants of school achievement and teachers' judgments themselves became a crucial research topic in educational psychology.

It is well established by now that motivation predicts school achievement over and beyond intelligence. However, only few studies looked at the specific and common portions of variance in school achievement explained by intelligence and motivation. While these studies assessed school achievement using school grades or standardized test achievement, they missed the systematic examination of differences in the predictive power of students' characteristics for these achievement measures.

Furthermore, studies have supported a significant interplay between SES, motivation, and intelligence when predicting school achievement. The positive association between SES and school achievement was particularly mediated by students' motivation and intelligence. This interplay was only explored for school grades but remains to be studied for standardized test achievement.

In addition, students' engagement predicted teachers' judgments. There is a lack of research that examined longitudinal effects of students' motivation on teachers' judgments of students' aptitude. Both students' academic self-concepts and intrinsic motivation were not yet considered as predictors of teachers' judgments. Finding empirical evidence for the underlying processes would advance the understanding of important determinants that play a role for teachers' judgments.

Even though numerous studies highlighted the role of motivation in the school context, there are still fundamental research gaps. This dissertation aimed at closing these gaps by providing empirical findings to open research questions.

5 Specification of This Dissertation Project

The following sections form the core of this dissertation. Based on the previous chapters, open research questions will be stated first. Second, the aims of this dissertation will be specified. Third and last, an overview is given on each of the three studies that examined single aspects of motivation as a predictor in the school context.

5.1 Open Research Questions

Even though there is a huge body of research with countless empirical studies that have examined motivation as a predictor of school achievement, open questions still remain. Many researchers who were interested in the determinants of school achievement missed to study the interplay of motivation with other student characteristics such as intelligence and SES. Very few studies have tested how well motivation, intelligence, and SES predict school achievement together. It is still unclear how much of the explained variance in school achievement can be attributed to students' intelligence and motivation, both individually and together. It is also unknown whether the predictive power of these student characteristics differs depending on the applied achievement measures (school grades or standardized test achievement). Another open question is whether different motivational constructs and SES indices vary in their predictive power for school achievement. Moreover, the extent to which students' motivation predicts teachers' judgments of students' aptitude is still unclear. One should examine whether students' academic self-concepts and their intrinsic motivation predict not only students' school achievement, but also teachers' judgments of students' aptitude. This dissertation addresses all of these open questions and further specifies them with the following aims.

5.2 Aims of This Dissertation

The primary and most important aim of this dissertation was to expand the knowledge about the power of motivation in predicting relevant constructs in the school context (e.g., school achievement and teachers' judgments of students' aptitude). It aimed at understanding the role of motivation, both relative to other well-established predictors such as intelligence and SES, as well as a potential mediating and explaining factor. This has been essential to advance the field of research of educational psychology and school practice.

The first specific aim of this dissertation was to systematically examine the relative importance of motivation and intelligence for school achievement from a meta-perspective. Existing primary studies were integrated in order to conduct a meta-analysis that included motivation and intelligence as combined predictors of school achievement. This followed the objective to provide the specific and common portions of variance in school achievement explained by students' motivation and intelligence. The relative importance of these two student characteristics for school achievement could therefore be compared.

The second specific aim of this dissertation was to study the extent to which SES, motivation, and intelligence interplay when predicting school achievement. It was set to examine whether the association between SES and school achievement (standardized test achievement) was mediated by students' motivation and intelligence. SES indices and motivational constructs were included due to their negligible consideration in recent studies.

The third specific aim of this dissertation was to explore whether students' motivation predicted not only school achievement but also teachers' judgements. This followed the purpose to examine the effects of students' motivation on teachers' judgments of students' aptitude over time. Up until now, longitudinal effects in elementary school have rarely been studied.

Besides these specific aims, there were also overarching objectives of this dissertation. By including different measures of motivation, namely both expectancies and values, it was possible to analyze potential differences in their predictive power for school achievement and teachers' judgments of students' aptitude. Also, different criteria to measure students' academic abilities were considered. On the one hand, students' school achievement was used as a rather direct criterion. This was assessed via school grades and standardized test achievement. On the other hand, teachers' judgments of students' aptitude were included as a rather indirect criterion. This allowed to examine whether motivation is a stronger predictor for either one or both criteria.

Regarding statistical methods, this dissertation pursued to challenge recent practice in educational psychology in that all three studies applied structural equation modeling (SEM). SEM has several advantages over traditional regression analyses that will be outlined in the following. First, the use of latent variables and the inclusion of measurement errors in the model make up a representative character of SEM that are not considered in other methods (Jeon, 2015). For mediation analyses (Study 2), it has been shown that SEM is superior to regression analysis methods. This is because a simultaneous estimation of all parameters (direct, indirect, and total effects) can be calculated at once and standard errors are reduced (Iacobucci, Saldanha, & Deng, 2007). Another benefit of SEM is the estimation of reciprocal effects between two or more variables over different measurement occasions (Study 3). Even the meta-analysis (Study 1) used SEM to examine the relative importance of motivation and intelligence for school achievement in a systematic approach. This method is called meta-analytic structural equation modeling (MASEM) and was only recently introduced by Cheung (2015). MASEM enables the computation of several structural equation models on a meta-analytic level.

The following section summarizes the foci and research questions of the three studies included in this dissertation.

5.3 Overview of the Studies

Study 1 ("*The relative importance of intelligence and motivation as predictors of school achievement: A meta-analysis*") is a meta-analysis that summarized 74 primary studies (N = 80,145) to examine the relative importance of students' intelligence and motivation when predicting school achievement. It is a clear advantage of a meta-analysis that it systematically examines and integrates existing empirical studies in the field. Another strength of a meta-analysis is that it puts potential moderators, which might have an influence on the predictive power of intelligence and motivation, to a systematic test. For example, this meta-analysis analyzed the extent to which the relative importance of intelligence and motivation depended on the achievement measures, the motivational constructs, and other factors that the actual paper describes in more detail. This meta-analysis applied the emerging methodological approach of meta-analytic structural equation modeling (MASEM; Cheung, 2015). It contributed to the existing research by providing insights into specific and common portions of variance in school achievement explained by intelligence and motivation. This meta-analytical perspective eventually made it possible to compare the relative importance of intelligence and motivation for school achievement.

Study 2 ("*Explaining social disparities in mathematical achievement: The role of motivation*") examined the role of students' motivation and intelligence as mediators of the relationship between SES and school achievement in math. This study went beyond existing research by using standardized test achievement as an achievement measure, more motivational constructs, as well as different indices of SES. A longitudinal dataset from PISA 2003 / 2004 was used including two measurement occasions and a representative sample of German students (N = 6,020). Structural equation modeling was applied to analyze whether the relationship between SES and standardized test achievement was mediated by students' motivation and intelligence. This study contributed to existing research by providing deeper insights into the relationship between SES and school achievement and its mediators. The study also showed that the mediation effects differed depending on the applied SES index and motivational constructs.

Study 3 ("Longitudinal reciprocal effects between teachers' judgments of students' aptitude, students' motivation, and grades in math") examined the effects of math-specific motivation and students' math grades on teachers' subsequent judgments of students' aptitude and vice versa. This study went one step further and looked whether students' motivation not only predicted school achievement but also external evaluations of students' aptitude in form of teachers' judgments. A sample of N = 519 elementary students was drawn at four measurement occasions (end of 3rd grade until end of 4th grade). Students completed a questionnaire about their math-specific self-concept and intrinsic task values. Teachers (N = 27) evaluated students' aptitude in math and provided their math grades. Cross-lagged panel models were computed to examine potential reciprocal effects between students' motivation, math grades, and teachers' judgments of students' aptitude. This study contributed to the literature by being the first study that examined whether students' motivation predicts teachers' judgments of students' aptitude over two school years. Also, it provided deeper insights into the factors that determine teachers' judgments of students' aptitudes.

Table 1

Overview of the three studies within this dissertation and its characteristics

Study	Kind of study	Design	Predictor	Criterion	Motivational constructs	Academic ability measure	Type of analysis
1	Methodological review / meta-analysis	Cross-sectional	Motivation, intelligence	School achievement	Academic self-concept, self-efficacy, intrinsic and extrinsic motivation, interest, task values, goal orientations, achievement motives	School achievement (school grades and standardized test achievement)	MASEM
2	Primary empirical study	Longitudinal (two measurement occasions)	SES Mediators: motivation, intelligence, prior math achievement	School achievement	Math-specific self-concept, self-efficacy, interest	School achievement (standardized test achievement in math)	SEM (mediation)
3	Primary empirical study	Longitudinal (four measurement occasions)	Motivation, school achievement, teachers' judgments of students' aptitude	Teachers' judgments of students' aptitude, school achievement, motivation	Math-specific self-concept, intrinsic task values in math	Teachers' judgments of students' aptitude	SEM (cross-lagged)

Notes. SEM = Structural Equation Modeling; SES = Socio-Economic Status.

6 Empirical Research

6.1 Study 1: The Relative Importance of Intelligence and Motivation as Predictors of School Achievement: A Meta-Analysis

Note: This is the first author's version of a study that was published in *Educational Research Review*. The following manuscript does not exactly replicate the final version that was published in the journal. It is neither a copy of the original article nor a suitable citation.

Kriegbaum, K., Becker, N., & Spinath, B. (2018). The relative importance of intelligence and motivation as predictors of school achievement: A meta-analysis. *Educational Research Review, 25,* 120–148. doi:10.1016/j.edurev.2018.10.001

Abstract

This meta-analysis summarizes 74 studies (*N* = 80,145) that simultaneously examined the predictive power of intelligence and motivation for school achievement. First, we found average correlations between intelligence (*r* = .44) and motivation (*r* = .27) with school achievement and between intelligence and motivation (*r* = .17). Moderator analyses showed that the correlation between motivation and school achievement was higher for expectancies than for values. No moderator effects were found for grade level, school form or gender. Second, in a path model, 24% of variance in school achievement was explained overall. From this overall explained variance in school achievement, 66.6% was uniquely explained by intelligence and 16.6% uniquely by motivation, whereas the two predictors commonly explained 16.6%. Thus, the results show that both intelligence and motivation contribute substantial, unique shares to the prediction of school achievement as well as an additional share of commonly explained variance.

Keywords: motivation, intelligence, school achievement, meta-analysis

1. Introduction

The question about the relative importance of different prerequisites for school achievement is one of the oldest in psychology. Over many decades, it has been shown that school achievement is strongly influenced by students' individual prerequisites such as cognitive and motivational factors (Hattie, 2009). In this article, we focus on two of the most important individual factors of students predicting school achievement that is intelligence and motivation. There is an extensive body of research indicating that intelligence and motivation are both important predictors of school achievement. Meta-analyses and reviews can be found for each of these two predictors (e.g., Möller, Pohlmann, Köller, & Marsh, 2009; Robbins et al., 2004; Roth et al., 2015; Schiefele, Krapp, & Schreyer, 1993; Spinath et al., 2014; Valentine et al., 2004). A close look at the underlying studies shows that these typically stem from different psychological sub-disciplines: Whereas motivation as a predictor of school achievement is usually investigated in educational psychology, the predictive power of intelligence is the focus in the psychology of personality and individual differences. Therefore, there is a lack of integration of these findings and there are contradicting conclusions in the literature obscuring the picture of the relative importance of these factors. Only a few studies have investigated motivation and intelligence at the same time and have delivered diverging results regarding the relative importance of motivation and intelligence. On the one hand, some authors have concluded that intelligence is the only important predictor of school achievement, whereas motivation is negligible and summarized "the results question the belief of most educators about the crucial role of motivation as a determinant of scholastic achievement" (Gagné & St. Père, 2001, p. 71). On the other hand, studies have found that motivation was as important as, if not even more important than intelligence for school achievement (e.g., Helmke, 1992; Steinmayr & Meißner, 2013;

Steinmayr & Spinath, 2009). In this vein, the authors (2009, p. 87) concluded, “Motivation is a predictor of school performance whose relative importance is at least comparable to intelligence irrespective of the considered domain”. Reasons for these differences in the relative importance attributed to intelligence and motivation for school achievement might depend on the operationalization of achievement, motivation and intelligence, whether the constructs are measured domain-specific or domain-general, subject domains, students’ grade level and school form, students’ gender, the country the study was conducted in, and the year of publication.

The present meta-analysis goes beyond prior studies by examining the predictive power of intelligence and motivation on the basis of studies comparing the relative importance of these two predictors for school achievement. Moreover, our meta-analysis investigates whether the predictive power of intelligence and motivation depends on potential moderators such as the achievement measure, the motivational construct considered, intelligence measure, subject domain, students’ grade level, school form, gender, country or year the study was conducted.

1.1 School achievement as criterion

The term school achievement summarizes performance outcomes in all domains taught at school. School achievement is an important research issue, because it serves as an indicator of an individual’s competencies and, learning success and forms the basis for career decisions of serious consequence. School achievement functions as a selection criterion for subsequent education and jobs. Moreover, school achievement is also a valid predictor of individuals’ occupational careers and socio-economic prosperity (e.g., Schuler, Funke, & Baron-Boldt, 1990; Cohen, 1984; Roth, BeVier, Switzer, & Schippmann, 1996; Spinath, 2012).

Therefore, what determines school achievement is a crucial question in psychological research.

School achievement is typically operationalized via school grades or standardized tests. The correlation between school grades and standardized test achievement (e.g., as examined in large scale assessment studies of school achievement) varies from moderate to high with $.34 \leq r \leq .62$ (e.g., Gustafsson & Balke, 1993; Schütte, Frenzel, Asseburg, & Pekrun, 2007). The following reasons explain why the relationship between school grades and standardized test achievement is not even stronger: First, in comparison to standardized test achievement, school grades also serve other functions, like motivating students (Spinath, 2012). Second, school grades are given in the context of classes, meaning that teachers use the achievement of all students in a given class as a frame of reference. Therefore, the same student with an objective achievement could get different grades depending on the average achievement in the respective class (e.g., Arens et al., 2016). Third, school grades do not purely assess achievement: teachers take additional information about students into account when grading their performance, such as their motivation, how their performance developed over a school year, their invested effort and so on (e.g., McMillan, Myran, & Workman, 2002; Zimmermann, Schütte, Taskinen, & Köller, 2013), whereas standardized tests assess students' knowledge and abilities more directly. Therefore, it can be concluded that standardized test achievement is a purer measure of students' achievement than grades are, but school grades can be seen as a highly ecologically valid measure of school achievement, because they are good predictors of future academic success and are used as allocation and selection criteria for higher education and jobs.

1.2 Intelligence as a predictor of school achievement

There are many definitions of intelligence. An APA task force (Neisser et al., 1996, p. 77) defined intelligence as the ability “to understand complex ideas, to adapt effectively to the environment, to learn from experience, to engage in various forms of reasoning, to overcome obstacles by taking thought”. Concerning the structure of intelligence, it is widely accepted that both a general intelligence factor (*g*) and specific intelligence factors such as verbal, non-verbal, and numerical intelligence exist. These specific intelligence factors are often used in studies to predict school achievement in specific subjects such as reading and math, because these specific factors might have special relevance for certain domains and might explain a higher amount of variance than general intelligence.

It is well established that the general factor of intelligence, *g*, is a strong predictor of school achievement, with a mean correlation of around r = .50 (e.g., Gottfredson, 2002; Gustafsson & Undheim, 1996; Kuncel, Hezlett, & Ones, 2004; Neisser et al., 1996). A recent meta-analysis (Roth et al., 2015) found a population correlation of ρ = .54 between general intelligence and school grades. This correlation was significantly lower for nonverbal intelligence tests (ρ = .44) in contrast to verbal (ρ = .53) or mixed intelligence tests (ρ = .60). Because verbal skills are very important for both the active collaboration in class and performance on written achievement tests and exams, it is not surprising that verbal and mixture intelligence tests were found to be more strongly associated with school achievement.

Moreover, it has also shown that the magnitude of the association between intelligence and school achievement depends on the achievement measure used. When using standardized test achievement as an achievement measure in comparison to school grades, higher correlations with intelligence can be found, namely .61 ≤ r ≤ .90 (e.g., Deary, Strand, Smith & Fernandes, 2007; Duckworth et al., 2012; Frey & Dettermann, 2004; Steinmayr & Meißner, 2013). Possible explanations for this might be inter alia the different conceptualization of standardized test achievement and school grades. This will be described in more detail in section 1.5 about potential moderators.

Based on these findings, we expected the achievement measure and intelligence measure to be moderators of the relationship between intelligence and achievement, such that the correlation between intelligence and school achievement is higher when standardized tests are used as achievement measures rather than grades, *g* or verbal intelligence is measured instead of nonverbal intelligence.

1.3 Motivation as a predictor of school achievement

In the achievement motivation literature, a large variety of motivational constructs is described. Because of this, it is not possible to include all of them in one meta-analysis. We selected those constructs for which we expected to find a sufficient number of studies meeting our inclusion criteria. Following Eccles and colleagues' (1983) Expectancy-Value-Theory, we divided the motivational constructs into expectancies and values. This classification was chosen because there are not a sufficient number of studies for each motivational construct to examine the effects separately. Academic self-concept and self-efficacy were assigned to expectancies and intrinsic/extrinsic motivation, task values, achievement motive, achievement goals and interest were assigned to values. In the following section, we first define these motivational constructs and then report their relationships with achievement measures.

1.3.1 Academic Self-concept

Academic self-concept is defined as an individual's perception of their competence in a specific domain (Marsh & Martin, 2011). The construct is typically operationalized by asking students how good they think they are in a specific domain such as Mathematics or Biology (Eccles et al., 1983; Wigfield & Eccles, 2000). There are countless studies, including meta-analyses, reporting moderate to high positive correlations ($.30 \leq r \leq .60$) between academic self-concept and school achievement (e.g., Guay, Marsh, & Boivin, 2003; Helmke & van Aken, 1995; Huang, 2011; Marsh et al., 2005; Möller et al., 2009; Valentine et al., 2004). There is some evidence that one's academic self-concept develops over time and therefore that the correlation with school achievement increases when students get older (e.g., Spinath & Spinath, 2005). The correlation between academic self-concept and school achievement is typically higher when both are operationalized as domain-specific rather than domain-general (e.g., Marsh & Craven, 2006; Steinmayr & Spinath, 2009) and in cross-sectional studies compared to longitudinal studies (e.g., Guay, Marsh, & Boivin, 2003; Marsh & Yeung, 1997; Valentine et al., 2004). Valentine (2001) showed that the relation between academic self-concept and school achievement became weaker when the time interval between the measurement occasions increased. Furthermore, multiple research groups have found that academic self-concept predicts school achievement over and above intelligence and that academic self-concept is a better predictor of school grades than other motivational constructs such as task values (e.g., Chamorro-Premuzic, Harlaar, Greven, & Plomin, 2010; Helmke, 1992; Kriegbaum et al., 2015; Steinmayr & Meißner, 2013; Steinmayr & Spinath, 2009; Zaunbauer, Retelsdorf, & Möller, 2009). On the basis of these findings, we expected motivation to be a better predictor of school achievement when expectancies such as academic self-concept are used compared to other motivational constructs such as values. Also, the correlation between motivation and school achievement should be higher when both are operationalized domain-specifically and cross-sectional compared to longitudinal and when samples from higher grades are investigated.

1.3.2 Self-efficacy

Self-efficacy is defined as individual expectancies about future performance and is typically measured as one's conviction about how well one will be able to solve a certain task in the future (Bandura, 1997). Thus, self-efficacy is more closely related to specific tasks than academic self-concept. Findings from different studies have revealed moderate to high positive correlations between self-efficacy and school achievement (e.g., Bong & Clark, 1999; Schunk & Schwartz, 1993; Zimmermann, 2000). In their meta-analysis, Robbins and colleagues (2004) found an average correlation between self-efficacy and grade point average (GPA) of r = .38. Moreover, they reported that math-specific self-efficacy predicts math achievement over and above intelligence (e.g., Kriegbaum et al., 2015; Stevens et al., 2004, 2006). Those studies also found self-efficacy to be a more powerful predictor of standardized test achievement over and above intelligence than other motivational constructs such as task values. Based on these results, we expect the relation between motivation and school achievement to be higher when expectancies, such as self-efficacy and academic self-concept, are assessed rather than other motivational constructs such as values.

1.3.3 Task values

The value attributed to a certain task comprises different components, namely intrinsic value (enjoyment of the task, interest), importance value (importance of doing well on a certain task), utility value (utility of a certain task for one's future) and a cost component (Eccles et al., 1983; Wigfield & Eccles, 2000). Only the first three value components are normally assessed, and they are typically assessed domain-specifically. Positive associations between values and school achievement have repeatedly been reported. The results are consistent in that the relationship between values and school achievement (both grades and standardized test achievement) is typically weak to moderate (e.g., Ozel, Caglak & Erdogan, 2013; Trautwein et al., 2012). Steinmayr and Spinath (2010) found that the correlations with school grades were higher when values were assessed domain-specifically than domain-generally. A few studies showed that values predict school grades (Steinmayr & Spinath, 2009) as well as standardized test achievement in math and English over and above intelligence (Trautwein et al., 2012). On the basis of these results and as reported above in the section about academic self-concept, we expect the correlation between motivation and school achievement to be higher when both are operationalized domain-specifically, and to be lower for values as motivational constructs compared to expectancies.

1.3.4 Interest

Interest can be defined, on the one hand, as a personality-specific trait, such as a relatively stable preference for a specific learning topic (Hidi & Renninger, 2006). It can also be defined as a situation-specific state related to the attraction of a specific learning condition (Krapp, 1999). The relationship between domain-specific interest and school achievement is typically weak to moderate, with a meta-analysis by Schiefele, Krapp, and Schreyer (1993) finding a mean correlation of r =. 30. Correlations with interest have been found to be similar for school grades and standardized test achievement ($.15 \leq r \leq .40$; Köller, Baumert & Schnabel, 2001; Marsh et al., 2005; Ozel et al., 2013). Moreover, it has been shown that reading interest predicts reading competence over and above intelligence (Retelsdorf, Köller, & Möller, 2011). The correlation between interest and school achievement is similar to the correlation between task values and school achievement, but lower than the correlation between expectancies (academic self-concept and self-efficacy) and school achievement. Therefore, we expect the correlation between motivation and school achievement to be lower for values than for expectancies.

1.3.5 Intrinsic Motivation and Extrinsic Motivation

Intrinsic motivation and extrinsic motivation are two constructs embedded in Self-Determination Theory (Deci & Ryan, 2002). These constructs already have been introduced earlier by deCharms (1968) and have been examined in other research traditions as well, but the integration of intrinsic and extrinsic motivation in Self-Determination Theory is the most prominent embedding approach in Educational Psychology. Whereas intrinsic motivation is defined as engaging in something for its own sake and for enjoyment, extrinsic motivation is defined as doing something for its consequences, such as obtaining a reward or avoiding punishment (instrumental gain or loss; Deci & Ryan, 2002). Intrinsic motivation is usually operationalized by asking how much a person likes doing a certain activity. Extrinsic motivation is usually operationalized as the degree to which a person completes a task or goes to school for external reasons. In the school context, intrinsic and extrinsic motivation can be operationalized both domain-specifically (for example math-specific) and globally (for example intrinsic motivation for school in general). Two meta-analyses found relationships between intrinsic motivation and school achievement of r = .21 and r = .27 (Cerasoli et al., 2014; Taylor et al., 2014), whereas the relationship between extrinsic motivation and school achievement was negative, with r = -.22 (Taylor et al., 2014). Neither of these meta-analyses revealed any moderator effects.

Findings concerning the incremental power of intrinsic motivation to predict school achievement over and above intelligence are inconsistent. Whereas some studies have found that intrinsic motivation explained additional variance in school achievement over and above intelligence (e.g., Gottfried, 1990; Lloyd & Barenblatt, 1984; Murayama et al., 2013; Schaffner & Schiefele, 2013; Spinath et al., 2006), other research groups could confirm the incremental validity of intrinsic motivation for male students only (e.g., Freudenthaler et al., 2008; Gagné & St. Père, 2000). Therefore, gender was included in our meta-analysis as a moderator variable to test whether the relative importance of motivation for school achievement depends on gender.

1.3.6 Achievement goals

Achievement goal theory focuses on a person's individual goals with regard to learning and performance. The 2 x 2 model of achievement goals identifies four different goals (Elliot & McGregor, 2001): mastery-approach goals focus on the positive development of one's own competence, whereas mastery-avoidance goals tap the fear of losing competence. Performance-approach goals focus on demonstrating one's own competence and performing better than others, whereas performance-avoidance goals focus on hiding supposed incompetence and striving not to perform worse than others. A further component of achievement goals, namely work avoidance (Nicholls, 1984), is also well-established. Persons with high work avoidance motivation try to invest minimal effort. Achievement goals can be considered traits, are stable over time and are mostly operationalized domain-generally. Two meta-analyses by Huang (2011) and Wirthwein and colleagues (2013) showed that mastery goals (r = .10/.13), performance-approach goals (r = .13/.08), performance-avoidance goals (r = -.13/-.12) and work avoidance (r = -.11) were all significantly associated with school achievement. The country where the primary studies were conducted was a significant moderator, with the relation between mastery goals and school achievement significantly different from 0 in the United States compared to other countries (Huang, 2011). Moreover, a few studies found that while mastery goals contributed to predicting school achievement, performance goals and work avoidance did not (Kriegbaum et al., 2015; Steinmayr & Spinath, 2009; Steinmayr et al., 2011). Based on the findings reported above, we included the country of residence as a moderator in our meta-analysis in order to investigate whether the predictive power of motivation for school achievement differs across countries.

1.3.7 Achievement motive (hope for success and fear of failure)

McClelland and colleagues (1953) distinguished the achievement motive into an approach component (hope for success) and an avoidance component (fear of failure). Hope for success refers to a positive attitude towards performance, the belief that one can succeed, and positive emotions in achievement situations. Fear of failure refers to a negative, fearful attitude towards performance and negative emotions in corresponding situations. These two components tend to be operationalized domain-generally. The relationship between achievement motive and school achievement is typically weak to moderate. A meta-analysis by Robbins and others (2004) found a mean correlation between hope for success and academic achievement of $r = .26$. It has also been shown that both hope for success and fear of failure explain variance in math grades and GPA independently of intelligence, whereas only hope for success had incremental power in predicting German grades (Steinmayr & Spinath, 2009; Wach et al., 2015). No specific moderator hypotheses can be generated at this point.

1.4 Summary of the previous research and open questions

Both intelligence and motivation have been shown to predict school achievement, with intelligence typically being the stronger predictor. There is evidence that motivational variables predict school grades and standardized test achievement over and above intelligence. Moreover, several potential moderators of the association between intelligence and motivation as predictors and school achievement as criterion can be identified from previous research, such as the operationalization of school achievement (grades vs. tests), kind of motivational construct (expectancies vs. values) and others. However, all these aforementioned moderators have not been investigated systematically yet. Moreover, most of the studies examining the incremental power of motivation did not determine specific and common portions of the variance in school achievement explained by intelligence and motivation in order to investigate their relative importance. This obscures the true predictive power of the less strong predictor (in this case motivation) because the variance explained by both predictors alike is attributed to the stronger predictor. Furthermore, most of these studies assessed either school grades or standardized test achievement and did not compare these two achievement measures. In addition, the studies usually focused on whether one or two motivational constructs predict school achievement over and above intelligence, meaning that which motivational construct is the best predictor of school achievement remains an open question. In sum, there is a lack of a systematic meta-analysis examining the relative importance of motivation and intelligence in predicting school achievement as well as potential moderators.

1.5 Potential Moderators

Because of inconsistent findings about the relative importance of intelligence and motivation for school achievement, which led to notions that motivation is negligible for the prediction of school achievement on one side (Gagné & St. Père, 2001) and that motivation is as important as intelligence for school achievement on the other side (Helmke, 1992; Steinmayr & Meißner, 2013; Steinmayr & Spinath, 2009), we sought to identify relevant moderator variables that might explain these inconsistent findings. In the theoretical background, differences in the predictive power of intelligence and motivation for achievement were already noted and underlined with empirical findings, which led to our moderator hypotheses. At this point, we want to give an overview of all moderators included in our meta-analysis and argue more theoretically, why these moderators were investigated. Some moderators were worth considering for theoretical reasons (e.g., achievement measure, motivational construct, intelligence measure) whereas other moderators needed to be investigated for methodological reasons (e.g., study design, school form, publication year).

Our first three moderators were related to the measurement / operationalization of achievement as our criterion and to the measurement of intelligence and motivation as predictors. Regarding the achievement measure, standardized test achievement is conceptualized as a purer measure of students' abilities and school grades contain information about factors aside from students' achievement such as motivation (e.g., Steinmayr & Meißner, 2013; Steinmayr & Spinath, 2009). Empirically, it has been shown that intelligence is a stronger predictor for standardized test achievement compared to school grades (e.g., Deary, Strand, Smith & Fernandes, 2007; Duckworth et al., 2012; Frey & Dettermann, 2004; Steinmayr & Meißner, 2013), whereas motivation is a better predictor for school grades (Helmke, 1992; Steinmayr & Meißner, 2013). Possible explanations for this might be the different conceptualization of standardized test achievement and school grades mentioned above. Moreover, grades are given in the reference frame of school classes, whereas intelligence and standardized test achievement are both measured on an absolute scale. Due to these theoretical considerations and prior findings, it is supposed that the kind of achievement measure might be a moderator for the relationship between intelligence and school achievement. We suppose that intelligence will explain a higher portion of the variance in standardized test achievement than in school grades, but that the relative importance of motivation is higher when predicting school grades than test achievement. Concerning the relative importance of different motivational construct, Expectancy-Value Theory (Eccles et al., 1983; Eccles & Wigfield, 2002) predicts that expectancies should be more important for the prediction of school achievement compared to values, which in turn should be more predictive for achievement-related choices. Findings from various research groups are consistent with these assumptions (e.g., Steinmayr & Spinath, 2009; Trautwein et al., 2012). Regarding the measurement of intelligence, intelligence tests that measure general intelligence or verbal intelligence include tasks that are similar to tasks that measure achievement compared to intelligence tests that measure non-verbal intelligence with figural tasks. Roth et al. (2015) found in their meta-analysis that the correlation between intelligence and school achievement was higher for verbal intelligence tests or mixed intelligence tests compared to non-verbal intelligence tests. Therefore, the relative importance of intelligence for school achievement should differ depending on the intelligence measure.

The subject domain of school achievement such as Mathematics, Science and Languages was examined as a potential moderator. I can be argued that

Mathematics and Science compared to Languages and other subjects rely more on logical thinking and the production of unambiguously correct solutions, which is also the case in intelligence tests. In a recent meta-analysis (Roth et al., 2015), it has been shown that the population correlation between intelligence and achievement was higher for Mathematics and Science compared to Language and other subjects. Therefore, it was expected that intelligence would be a stronger predictor of achievement in Mathematics and Science compared to other subject domains.

Moreover, we expect specificity versus generality of measures to be a moderator in the prediction of school achievement. Whereas the predictive power of intelligence is usually strongest for the general factor of intelligence (Roth et al., 2015), motivational constructs are more predictive when measured domain-specifically (e.g., math- or biology-specific interest; (e.g., Marsh & Craven, 2006; Steinmayr & Spinath, 2009). Moreover, from a developmental perspective, it can be argued that motivational constructs develop over the school years in the sense that they become more differentiated and stable (e.g., Spinath & Spinath, 2005). Therefore, it was expected that motivation would become a stronger predictor of school achievement in higher grade levels.

A moderator, which was included for theoretical and methodological reasons, was the study design, namely if a study was cross-sectional or longitudinal. Because of a long time interval between measurement occasions, changes in motivation or achievement during that time and other variables also influencing these relationship between motivation and achievement, it might be interesting to test whether the correlation between motivation and achievement is higher in cross-sectional studies. Furthermore, it was important to investigate, whether the correlations between intelligence and motivation with school achievement are significant in longitudinal studies as well, which can be seen as a first indication of an influence.

From a methodological perspective, the school form was a moderator worth examining. In secondary school, students are preselected according to their prior achievement level. Because intelligence is most closely related to school achievement, the variance of intelligence should be lower within secondary schools compared to elementary school.

Moreover, in the meta-analysis of Roth and colleagues (2015), it has been found that the year of publication significantly moderated the association between intelligence and school grades. In the period before 1983, the population correlation was higher (ρ = .68) than after 1983 (ρ = .47). It can be argued that this moderator effect was due to grade inflation over time (e.g., Kostal, Kuncel, & Sackett, 2016) in the way that better grades are given in the last decades and a range restriction in school grades might lead to lower correlations between achievement and predictors. Students' gender was included as a moderator less because of theoretical reasons but more because of different findings from various studies. For example, Vecchione and colleagues (2014) found that intrinsic motivation was a stronger predictor for school achievement for girls compared to boys. Wach et al. (2015) found that academic self-concept and fear of failure were more relevant for the school achievement of girls compared to boys. As different countries use different instruments to assess intelligence, motivation and school achievement, the country, where the primary study was conducted in, was included as a moderator in order to test cross-cultural or cross-national generalizability of our results.

1.6 The present study

The purpose of the present meta-analysis was to summarize findings from the literature in order to investigate the relative importance of motivation and intelligence in predicting school achievement.

The first novel aspect of our meta-analysis is a conceptual aspect, namely that two important predictors of school achievement will be included at once. While prior meta-analyses have examined either intelligence or motivation as predictors of school achievement, this meta-analysis is the first to compare the relative importance of motivation and intelligence in predicting school achievement.

The second novel aspect of our meta-analysis is methodological, namely its usage of an emergent approach: meta-analytic structural equation modeling (MASEM; Cheung, 2015). This approach allows structural equation models to be applied on a meta-analytic level. More specifically, we first specified a path model that included intelligence and motivation as predictors of school achievement on a meta-analytic level. We then used this model to compute the specific and common portions of the variance in school achievement explained by intelligence and motivation in order to investigate and compare their relative importance, which no other meta-analysis has done before.

Furthermore, it was a purpose to identify relevant moderator variables to examine whether the relative importance of motivation and intelligence in predicting school achievement depends on factors such as the kind of achievement measure, motivational construct, intelligence measure, subject domain, study design, grade level, school form, gender, country, and year of publication.

On a related note, our meta-analysis focuses on intelligence and motivation as predictors of school achievement and does not examine other student characteristics such as emotion (e.g., test anxiety) and personality (e.g., conscientiousness).

1.7 Research Questions and Hypotheses

Specifically, we addressed the following research questions and hypotheses:

1) How are the two predictors intelligence and motivation related to each other? The correlation between intelligence and motivation is expected to be weak.
2) How are the two predictors related to the criterion of school achievement? The correlation between intelligence and school achievement is expected to be high, whereas the correlation between motivation and school achievement is expected to be moderate.
3) What is the relative importance of intelligence and motivation in predicting school achievement? What is the portion of variance in school achievement explained only by intelligence (specific share intelligence) and only by motivation (specific share motivation) and by both predictors alike (common share)? Intelligence is expected to explain a higher specific portion of variance in school achievement than motivation, but the portion of variance explained by motivation specifically is also expected to be substantial. The same is expected for the shared portion of variance explained by both predictors alike.
4) Moderator hypotheses

   As reported in the theoretical background, different characteristics may moderate the relative importance of motivation and intelligence in predicting school achievement. The following list provides an overview of the moderators tested in our meta-analysis and our specific moderator hypotheses for the correlations between intelligence (r_{IA}) and motivation (r_{MA}) with school achievement:

   a. Achievement measure: for r_{IA} grades < standardized test achievement and for r_{MA} grades > standardized test achievement.
   b. Motivational constructs: for r_{MA} expectancies > values.
   c. Intelligence measure: for r_{IA} *g*/verbal intelligence > nonverbal intelligence.

d. Subject domains: for r_{IA} mathematics/science > languages and other subjects.
e. Domain-specificity: for r_{MA} domain-specific > domain-general.
f. Study design: for r_{MA} cross-sectional > longitudinal.
g. Grade level: for r_{MA} higher grades > lower grades.
h. School form: for r_{IA} not preselected > preselected.
i. Gender: No specific hypothesis was generated, but gender was included as a moderator variable, because a few studies found different results for male and female students.
j. Country: No specific hypothesis was generated, but the country, where the primary studies were conducted in, was included as a moderator variable to test the cross-national generalizability of our findings.
k. Language of publication: No specific hypothesis was generated, but language of publication was included as a moderator variable to make allowance for the fact that publications in English or German but no other language were included in the meta-analysis and to examine if there are differences in the correlations depending on the language of publication.
l. Year of publication: for r_{IA} and r_{MA} older studies > more recent studies.

2. Method

2.1 Inclusion criteria

The primary studies had to fulfill the following criteria to be included into the meta-analysis: (1) The dependent variable, school achievement, was measured using either standardized tests or school grades (GPA or grades in specific subjects). (2) The independent variable intelligence was measured with standardized intelligence tests. (3) The independent variable motivation was measured with standardized motivation tests or specific items as a short version of a standardized motivation test. The following motivational constructs were considered: academic self-concept, self-efficacy, intrinsic and extrinsic motivation, values, achievement motive (hope for success and fear of failure), achievement goals (mastery and performance goals) and interest. (4) The sample consisted of students from primary or secondary school. University students were not included. (5) The sample size of the primary study was reported. (6) The primary study reported the correlations between the three following variables: intelligence, motivation and school achievement. (7) The primary study was available in German or English. (8) The primary study did not have any methodological flaws, such as unreliable instruments, biased or very small samples (no study had to be excluded for methodological reasons).

2.2 Literature search

We used two strategies to identify relevant studies for the present meta-analysis: (1) We conducted a literature search via electronic databases (PsycINFO, ERIC, Web of Knowledge, Science Direct, Google Scholar and PSYNDEX). The following search terms were used: intelligence or cognitive ability, motivation or self-concept or self-efficacy or expectancy or achievement goals or interest or value, and academic achievement or school grades or standardized test achievement. The literature search covered all articles published before April 2016. Using this strategy, we found 157 studies that seemed relevant on the basis of their title and abstract. (2) To reduce publication bias and identify unpublished studies, we contacted mailing lists of psychological societies. Members were asked to send us unpublished studies that included correlations between intelligence, motivation, and school achievement. Four at that time unpublished studies were sent to us.

2.3 Exclusion of studies

Some primary studies did not fulfill our inclusion criteria for various reasons and had to be excluded. Examples of excluded studies were studies that had missing information related to the correlations (for example the correlation between intelligence and school achievement was reported, but not the correlation between motivation and school achievement). We excluded studies focusing on the importance of intelligence and motivation for achievement in other contexts than school (e.g., university). We also excluded qualitative studies. Figure 1 following a PRISMA flow diagram (Moher et al., 2009) shows the flow of information through the different phases of our meta-analysis, namely the number of records identified, number of records included and excluded and reasons for the exclusion of studies. Also, studies with missing information were excluded from our meta-analysis. The main reasons for excluding studies were that correlation coefficients between intelligence, motivation and school achievement were not reported and could not be sent to us upon request. Moreover, a study was excluded if the same dataset was already included from another publication. In the end, a total of 74 published and unpublished studies remained and were included in the present meta-analysis.

2.4 Coding of studies

The following section provides an overview of all coded variables that were essential for the current meta-analysis. If information on a given variable was not available in a certain study, it was coded as missing.

2.4.1 Bibliographic information. The following pieces of bibliographic information from the primary studies were documented: the complete reference of the article, name(s) of the author(s), publication year and language of publication (English or German).

2.4.2 Achievement measures. The school achievement measure was categorized as either school grades or standardized test achievement. Also, we noted whether or not school achievement was measured domain-specifically. If school achievement was measured domain-specifically, the domain was coded.

2.4.3 Motivation measures. We first specified which motivational construct was measured (academic self-concept, self-efficacy, intrinsic or extrinsic motivation, values, achievement goals, achievement motive, or interest). Second, whether the motivational construct was assessed domain-specifically or domain-generally was coded. If motivation was measured domain-specifically, the domain was coded. In all studies, motivation was assessed with questionnaires, except for three studies that measured the achievement motive with a projective test such as TAT (Caplehorn & Sutton, 1965; Morgan, 1953; Sewell et al., 1982).

2.4.4 Intelligence measures. The intelligence measure was categorized as either a measure of general intelligence (g-factor) or a specific intelligence dimension (e.g., verbal or non-verbal). By general intelligence (g), we mean the first factor that is extracted in an intelligence test including different subtests / dimensions such as vocabulary, arithmetic computation and matrices. By specific intelligence dimensions, we mean an intelligence measure that is assessed with just one specific subtest dimension, such as only verbal or non-verbal tasks.

2.4.5 Sample characteristics. A variety of sample-level characteristics were coded. Students' grade level, mean age and school form(s) were coded. In terms of the latter, we also noted whether all students at this level attended the same school form (for example, comprehensive elementary schools) or students were separated according to their performance level (for example "Gymnasium", "Realschule" and "Hauptschule" as different secondary school tracks in Germany). Afterwards, the sample size, gender composition (if a sample contained more female than male students, it was coded as female), and country the study was conducted in were coded.

2.4.6 Study Design. For each study, it was coded if the design was cross-sectional, longitudinal with a distance between the measurement occasions up to 12 months or longitudinal with a distance between the measurement occasions from 13 months or more.

2.4.7 Correlations between the variables. For each study, we noted the correlation between intelligence and school achievement, the correlation between motivation and school achievement, and the correlation between intelligence and motivation. Several primary studies reported multiple correlation coefficients for a single sample (e.g., separate correlation coefficients for diverse motivational constructs or intelligence tests). To avoid violating the independence assumption for study coefficients (see Hunter & Schmidt, 2004) without losing information, we decided to average them using Fisher's z-transformation and included this single coefficient for each sample.

2.5 Coding procedure. A standardized coding sheet, where all coded variables could be entered, was prepared in order to ensure high clarity and accuracy. The first author, who was also the first coder, created a coding manual documenting all information about the coding process and the coded variables. The second coder received this coding manual and instructions on how to code the primary studies. Both coders coded all of the primary studies independently, with an interrater agreement of 98%. Moreover, we reached an average interrater agreement of Cohens $\kappa = 0.93$. Because the interrater agreement was so high, it can be assumed that the coding process was straightforward. In the few cases in which the data were unclear, the two coders discussed their divergent codes and came to a unanimous decision.

2.6 Data Analysis

2.6.1 Meta-analytic procedure

Meta-analytic path modeling (see e.g., Viswesvaran & Ones, 1995; Landis, 2013; Cheung, 2015) was used to integrate the results of the primary studies. The analyses were carried out in two consecutive steps: (1) integrating the correlation matrices of the primary studies into a pooled correlation matrix and (2) fitting path models on the basis of the pooled correlation matrix.

Following the meta-analytic strategy of Hedges and Vevea (1998), we employed a random-effects model in Step 1 since it can be assumed that true correlations may vary between primary studies due to different measures of intelligence, motivation, and school achievement or differences between samples (e.g., different grade levels and school forms). If a study reported more than one correlation between a predictor and school achievement (for example different correlations between several expectancies as motivational construct and school achievement), these correlations were z-transformed, averaged and retransformed in order to have one effect size for the three correlations. For each of the three correlations between measures, we computed the mean weighted correlation [*M(r)*] as an estimator of the population correlation, the estimated variance of the population correlation (τ^2) as an indicator of the variability of the population correlation, the corresponding 95% confidence intervals (95% CI_u; 95% CI_l) as an indicator of the significance of the population correlation, and the *Q* statistic as an indicator of the homogeneity of the distribution of correlations in the primary studies. We also computed the I^2 statistic (Higgins, Thompson, Deeks, & Altman, 2003) as a second homogeneity estimate. I^2 represents the ratio of the real differences in correlations to the observed variance (signal-to-noise ratio). Values on the order of 25%, 50% and 75% are considered to be low, moderate and high, respectively. Furthermore, we conducted outlier analyses to identify study results that significantly deviated from the results of the other studies (Viechtbauer & Cheung, 2010). We computed standardized deleted residuals (SDRs) which represent the deviation of the correlation of a single study from the mean correlation of all other studies expressed in standard deviations. Studies with SDRs above 1.96 or below -1.96 were regarded as significant outliers. Subsequently, we reran the meta-analysis without the outliers to evaluate the influence of outliers on the meta-analytical results. All analyses in Stage 1 were conducted using the package metafor (Viechtbauer, 2010) in R 3.3.2 (R Core Team, 2016).

On the basis of the pooled correlation matrix estimated, we specified three path models to analyze the specific and shared portions of the variance in school achievement explained by intelligence and motivation: two baseline models in which school achievement was predicted solely on the basis of intelligence (model 1) and solely on the basis of motivation (model 2) yielding the absolute portion of variance explained by only one of these predictors, as well as an extended model in which school achievement was predicted on the basis of intelligence and motivation (model 3), yielding the portion of variance explained by both predictors. The specific portion of variance explained by intelligence and motivation was calculated by subtracting the portion of variance explained by the other predictor from the portion of variance explained by both predictors. The portion of explained variance of school achievement shared by the two predictors (R^2_{shared}) was calculated by subtracting the specific portions of variance of the predictors from the amount of variance explained by both predictors. These analyses were carried out using the package lavaan

(Rosseel, 2012) in R 3.3.2 (R Core Team, 2016). Following Landis (2013), the harmonic mean of the sample sizes of the primary studies was used as the sample size for the meta-analytic path models, since it tends to limit the influence of large studies and leads to more conservative results. The significance of the specific portions of variance explained by the two predictors was assessed with a partial F-test (Tabachnick & Fidell, 2001). On a related note, the words “predict”, “importance / relevance of x for y” are used in the sense of a statistically prediction / regression and are not meant to be causal.

2.6.2 Moderator Analyses

Moderator analyses were conducted in both Step 1 and Step 2. To test for moderating effects in Step 1, we split the study results according to the moderator variables and computed separate analyses for each subgroup using metafor. We inspected the 95% confidence intervals to test the significance of the mean correlations between the subgroups, as recommended by Hunter and Schmidt (2002) and Whitener (1990). A substantial difference between the mean correlations on the moderator level as well as non-overlapping confidence intervals were regarded as indicators of a moderating effect. In our moderator analyses each moderator was treated as independent. However, as covariance of moderators across studies is possible, we analyzed the extent to which our moderators were confounded. Therefore, we computed pairwise Kendall’s τ coefficients between moderator dimensions. Correlations between dimensions within one moderator (for example general and verbal intelligence) were not computed, as only one dimension within one moderator applied for each study.

2.6.3 Publication Bias

As the majority of the studies included in our analyses were published, the possibility of publication bias had to be considered. Publication bias refers to the phenomenon that significant results are more likely to be published than insignificant ones. This might lead to an overestimation of the effects found in meta-analyses. The possibility of publication bias in the current study was evaluated with three analyses. (1) As recommended by Begg and Mazumdar (1994), we analyzed the association between correlations and standard errors using Kenndal's τ and regarded positive values as an indicator of publication bias. (2) Following Light and Pillemer (1984), we generated funnel plots in which the correlations of the primary studies were plotted against their standard errors. Asymmetry in the funnel plot due to missing studies on the left tail can be regarded as an indicator of publication bias. We corrected for missing studies using the trim and fill method (Duval & Tweedie, 2000), which supplements studies to achieve symmetry in the funnel plot. The difference between the uncorrected and corrected mean correlations can be regarded as an estimate of the magnitude of the publication bias. (3) Following the recommendations of Hunter and Schmidt (2004), we computed fail-safe Ns using the formula by Orwin (1983). In our results, the fail-safe N corresponds to the number of studies with null effects it would take to reduce the mean correlations to a trivial size of $M(r) = .10$.

2.6.4 Correction of statistical artifacts

The correlations presented in the primary studies might be attenuated due to statistical artifacts. Following the recommendations of Hunter and Schmidt (2004) we decided to additionally correct the main meta-analyses for measurement error and range restriction. We used a correction for attenuation (i.e., division of the correlation by the product of the square roots of the reliabilities) to correct for measurement error (see Hunter & Schmidt, 2004). If studies did not report the reliabilities of the employed measures we decided to use the mean reliabilities of the measures in all other studies. Range restriction in the independent variables was corrected using the formula presented by Callender and Osburn (1980). None of the primary studies reported information on range restriction in the employed samples and there was no possibility to estimate these coefficients. Therefore, we decided to simulate the correction for range restriction in two scenarios: A conservative scenario, in which the sample variance was 80% of the population variance and a liberal scenario, in which the sample variance was 60% of the population variance. First, we corrected each artifact separately to observe the effect of the correction of single artifacts. Furthermore, we combined the correction of both artifacts to observe the joint effect.

3. Results

3.1 Overview of the results of the primary studies

74 primary studies were included in the final data set of our meta-analysis. Each of these primary studies corresponds to one independent sample (k = 74). Table 1 gives an overview of the included primary studies and their characteristics. 70 of these studies were published between 1953 and 2016, while four studies had been presented at international conferences with manuscripts in preparation. The overall sample size was N = 80,145, whereas the sample sizes of the primary studies varied from 44 to 25,875. The gender distribution was provided for 60 samples. One sample only included male students and one sample only included female students. Overall, the percentage of female students in the included samples was 50.9%. The primary studies were conducted in 23 countries: Australia (k = 1), Austria (k = 4), Belgium (k = 1), Canada (k = 4), China (k = 1), Finland (k = 2), Germany (k = 31), Greece (k = 1), India (k = 1), Italy (k = 1), the Netherlands (k = 1), Nicaragua (k = 1),

Nigeria (*k* = 1), Norway (*k* = 1), Poland (*k* = 1), Russia (*k* = 1), Slovenia (*k* = 1), Spain (*k* = 3), Switzerland (*k* = 1), Taiwan (*k* = 1), Turkey (*k* = 1), the United Kingdom (*k* = 2) and the United States of America (k = 15).

Forrest plots with correlation coefficients for all primary studies can be seen in Figure 2. The correlations for the relationship between intelligence and school achievement were positive and significant in all primary studies. The correlations for the relation between motivation and school achievement and between intelligence and motivation were also significant and positive in all studies except one each.

3.2 Meta-analytic correlational results

The results of the main meta-analyses are presented in Table 2. The mean correlation corrected for sampling error between intelligence and school achievement was *M(r)* = .44 (.41 ≤ *M(r)* ≤ .48), whereas the corrected average correlations between motivation and school achievement and between intelligence and motivation were *M(r)* = .28 (.24 ≤ *M(r)* ≤ .31) and *M(r)* = .17 (.15 ≤ *M(r)* ≤ .20) respectively. All three correlations were significant. The correction for error of measurement resulted in a corrected average correlation between intelligence and school achievement of *M(r)* = .52 (.48 ≤ *M(r)* ≤ .56), between motivation and school achievement of *M(r)* = .33 (.28 ≤ *M(r)* ≤ .37), and between intelligence and motivation of *M(r)* = .20 (.17 ≤ *M(r)* ≤ .24). After a conservative correction for range restriction, we found the following mean correlations: *M(r)* = .53 (.48 ≤ *M(r)* ≤ .55) for intelligence and school achievement, *M(r)* = .33 (.28 ≤ *M(r)* ≤ .37) for motivation and school achievement and *M(r)* = .21 (.18 ≤ *M(r)* ≤ .24) for intelligence and motivation. After a liberal correction for range restriction, we found the following mean correlations: *M(r)* = .62 (.58 ≤ *M(r)* ≤ .65) for intelligence and school achievement, *M(r)* = .41 (.36 ≤ *M(r)* ≤ .46) for motivation and school achievement and *M(r)* = .27 (.23 ≤ *M(r)* ≤ .31) for intelligence and motivation. Results for the correction for both error of measurement and range restriction can be found in Table 2. The homogeneity index *Q* was significant for all three average correlations, indicating that the heterogeneity in the correlation coefficients was not only due to sampling error. Additionally, the homogeneity index I^2 indicated substantial heterogeneity in the examined correlation coefficients. The results of the outlier analysis are presented in Figure 4. The critical SDR values were exceeded in three cases (Studies 7, 19, 21) for the correlation between intelligence and school achievement, in three cases (Studies 33, 41, 69) for the correlation between motivation and school achievement, in only one case for correlation between intelligence and motivation (Study 33). Most of the study results did not exceed the critical SDR values and therefore cannot be regarded as significant outliers. The exclusion of outliers had only a negligible influence on the mean correlations, population correlations, and 95% confidence intervals. Therefore, the results of the main meta-analysis can be regarded as rather homogeneous. However, due to the significant *Q* statistics and high I^2 values, we nevertheless decided that moderator analyses were needed to clarify whether these moderator variables can explain the heterogeneity in the examined correlations.

3.3 Moderator results

Correlational results for the moderator analyses can be seen in Table 2 and will be reported for each moderator separately.

3.3.1 Achievement measures. Contrary to our expectations, the kind of achievement measure was no significant moderator. On a descriptive level, the average correlation between intelligence and school achievement was higher when standardized test achievement was used as the achievement measure, with *M(r)* =

.47 (.41 ≤ *M(r)* ≤ .53), in contrast to school grades, *M(r)* = .42 (.38 ≤ *M(r)* ≤ .47), but the difference did not reach significance.

3.3.2 Motivational constructs. To investigate the effect of type of motivational construct, we divided the examined motivational constructs into expectancies and values. The moderator analysis showed that, in line with our assumption, the average correlation between motivation and school achievement was significantly higher for expectancies, with *M(r)* = .40 (.34 ≤ *M(r)* ≤ .46), than for values with *M(r)* = .22 (.15 ≤ *M(r)* ≤ .28). This classification was chosen because there were not a sufficient number of studies for each motivational construct to examine the effects separately. The majority of studies measured motivation explicitly, and only three primary studies used implicit measures of motivation. Whereas one study did not find significant associations between motivation assessed with TAT and school achievement (Sewell et al., 1982), two studies found significant positive correlations between need for achievement as motivational measure and school achievement (Caplehorn & Sutton, 1965: *r* = .50/.56; Morgan, 1953: *r* = .15 - .47). In the following, studies with explicit and implicit measures of motivation were combined, as separate analyses for explicit versus implicit measures would not have been reasonable because of the small number of studies assessing motivation implicitly.

3.3.3 Intelligence measures. The average correlation between intelligence and school achievement was significantly different for various intelligence measures, such that the correlation was higher when *g* was assessed, with *M(r)* = .49 (.45 ≤ *M(r)* ≤ .54), compared to nonverbal intelligence, with *M(r)* = .38 (.34 ≤ *M(r)* ≤ .43). The relation between intelligence and motivation was higher for *g,* with *M(r)* = .22, in comparison to nonverbal intelligence, with *M(r)* = .14, but the difference was not significant, even though the 95% confidence intervals only marginally overlapped (g: .17 ≤ *M(r)* ≤ .28; nonverbal: .11 ≤ *M(r)* ≤ .17).

3.3.4 Subject domains and Domain-specificity. The average correlation between motivation and school achievement was higher when both variables were assessed domain-specifically, with *M(r)* = .33, in comparison to domain-generally, with *M(r)* = .23, but the difference was not significant, even though the 95% confidence intervals only marginally overlapped (domain-specific: .28 ≤ *M(r)* ≤ .37; domain-general: .17 ≤ *M(r)* ≤ .28). Moreover, the average correlation between motivation and school achievement was significantly higher for the languages domain, with *M(r)* = .39 (.32 ≤ *M(r)* ≤ .46), compared to mathematics *M(r)* = .22 (.14 ≤ *M(r)* ≤ .30) or science *M(r)* = .23 (.18 ≤ *M(r)* ≤ .28). Domain-specificity or subject domains were no significant moderator of the average correlations between intelligence and school achievement or between intelligence and motivation.

3.3.5 Study Design. For the average correlation between intelligence and school achievement, we did not find differences depending on the study design. The average correlation between motivation and school achievement was significantly higher for studies with a cross-sectional design with *M(r)* = .29 (.25 ≤ *M(r)* ≤ .33) compared to studies with a longitudinal design having a distance between the measurement occasions from 13 months on with *M(r)* = .15 (.08 ≤ *M(r)* ≤ .23). But there was no difference in the average correlation between motivation and school achievement for studies with a cross-sectional design compared to studies with a longitudinal design having a distance between the measurement occasions up to 12 months. Also, the average correlation between intelligence and motivation was higher in studies with a cross-sectional design with *M(r)* = .18 (.15 ≤ *M(r)* ≤ .21) compared to studies with a longitudinal design having a distance between the measurement occasions from 13 months on with *M(r)* = .05 (.00 ≤ *M(r)* ≤ .10).

3.3.6 Grade level/age. Students' grade level was no significant moderator of the average correlations between intelligence and school achievement, motivation and school achievement or intelligence and motivation.

3.3.7 School form. School form was no significant moderator of the average correlations between intelligence and motivation with school achievement. Contrary to our expectations, no differences in the average correlation between intelligence and school achievement were found between schools where students are not preselected on the basis of achievement level versus schools where they are. On a descriptive level, the average correlation between intelligence and school achievement was higher in schools where students were not preselected, but the difference was not significant.

3.3.8 Gender. Gender did not explain the heterogeneity in the correlation coefficients. The relations between intelligence and motivation and school achievement did not differ between male and female students, nor did the relationship between intelligence and motivation.

3.3.9 Country. Due to the small number of studies for many countries, primary studies were classified as belonging to one of the following continents: Asia, Europe or North America. No significant differences in correlations between continents were found.

3.3.10 Language of publication. No significant differences in average correlations between intelligence and school achievement as well as intelligence and motivation were found for the language of publication.

3.3.11 Year of publication. The primary studies' year of publication did not account for significant variance in the average correlations.

3.3.12 Independence of moderators. The correlations (pairwise Kendall's τ coefficients) between our moderator dimensions are reported in Table 4. The results showed no homogeneous cluster of moderator dimensions, but a few significant correlations between moderator dimensions. We found that studies examining school grades assessed general intelligence and achievement in math more frequently. Studies that assessed school achievement with a standardized test measured verbal intelligence and English school achievement more frequently. Studies that investigated motivation in form of expectancies assessed this domain-specifically and focused on reading more frequently. Moreover, studies that were conducted in Europe examined students in schools where they were preselected because of their prior achievement more frequently than studies that were conducted in North America. Also, European studies were more often published in German language.

3.4 Publication bias

Kendall's τ between the correlations and the corresponding standard errors was negative for all main meta-analyses (τ = -.23 for the correlations between intelligence and school achievement, τ = -.17 for the correlations between motivation and school achievement, τ = .04 for the correlations between intelligence and motivation), indicating the opposite of a publication bias, i.e., if anything, correlations above the mean correlation are missing. These results are strengthened by the funnel plots presented in Figure 3, where the distribution of correlations around the mean correlation is skewed to the left side. The results of the trim and fill analyses indicated that missing studies have to be added to the right side of the distribution for all three correlations (13 for the correlation between intelligence and school achievement, 9 for the correlation between motivation and school achievement, and 8 for the correlation between intelligence and motivation). Consequently, adding missing studies led to higher correlations in all analyses [*M(r)* = .49 for the correlation between intelligence and school achievement, *M(r)* = .30 for the correlation between motivation and school achievement, and *M(r)* = .19 for the correlation between intelligence and motivation]. In our analysis, we found the fail-safe N to be 250 for the correlation between intelligence and school achievement, 127 for the correlation between motivation and school achievement, and 53 for the correlation between intelligence and motivation.

3.5 Meta-analytic regression

As expected, when only one predictor was entered into the meta-analytic regression model, intelligence strongly (β = .44) predicted and motivation moderately (β = .28) predicted school achievement. When both predictors were entered, intelligence still strongly (β = .41) predicted and motivation still moderately (β = .20) predicted school achievement. Overall, 24% of the variance in school achievement was explained by intelligence and motivation. Moreover, 66.6% of the overall explained variance in school achievement was uniquely explained by intelligence, whereas motivation uniquely accounted for 16.6%, and 16.6% was explained in common by intelligence and motivation. These results are in line with our predictions that the portion of variance in school achievement explained by intelligence alone is higher in comparison to the portion of variance in school achievement explained by motivation alone and the common portion of variance in school achievement explained by intelligence and motivation together. F-tests indicated that both intelligence and motivation explain a significant portion of variance in school achievement above and beyond the other predictor. When correcting the results for error of measurement, overall 32% of the variance in school achievement was explained by intelligence and motivation. Intelligence was still the stronger predictor

(β = .47) and explained 65.6 % alone of the overall explained variance in school achievement compared to motivation (β = .23), which was a moderate predictor and explained 15.6 % alone of the overall explained variance in school achievement. The predictors together explained 18.8 % of the overall explained variance in common. Results for the correction for range restriction in our predictors showed that 32% (conservative) and 44% (liberal) variance of school achievement were explained. Intelligence was always the better predictor for school achievement (conservative: β = .47; liberal: β = .55), but also motivation incrementally predicted school achievement with (conservative: β = .23; liberal: β = .26). When correcting for both, namely error of measurement and range restriction, even 43% (conservative) and 58% (liberal) of variance in school achievement were explained.

4. Discussion

The purpose of this meta-analysis was to examine the relative importance of intelligence and motivation in predicting school achievement, because previous studies had reported inconsistent findings and researchers from different psychological sub-disciplines had come in some cases to diametrically opposed conclusions. Whereas previous meta-analyses had included only either intelligence or motivation as a predictor of school achievement, the present meta-analysis focused on studies including both predictors, allowing us to investigate the share of variance in school achievement specifically explained by intelligence and motivation as well as the share commonly explained by both predictors. A further goal of the present meta-analysis was to identify potential moderators influencing the relations between intelligence, motivation, and school achievement.

4.1 Relative importance of intelligence and motivation for school achievement

A central finding of our meta-analysis is that intelligence and motivation are only weakly positively associated with one another (*M(r)* = .17) and commonly explained 16.6% of the overall explained variance in school achievement. That the correlation between intelligence and motivation was weak is in line with our hypothesis and results from previous studies (e.g., Friedrich et al., 2015; Preckel et al., 2008; Zaunbauer et al., 2009). It can be assumed that intelligence and motivation mutually reinforce one another, such that students with higher intelligence are likely to develop a higher academic self-concept, higher self-efficacy and higher intrinsic values, which in turn enhance knowledge acquisition and the improvement of one's abilities (Spinath et al., 2006). This suggests that the interplay of intelligence and motivation is also important for predicting school achievement, and that including both constructs in the prediction of school achievement will lead to a higher proportion of overall explained variance.

Moreover, our results indicate that intelligence is a strong predictor of school achievement, with an average correlation of *M(r)* = .44. Moreover, in line with our hypothesis, the portion of the overall explained variance in school achievement specifically predicted by intelligence (66.6%) was higher than for motivation (16.6%) or the share commonly explained by intelligence and motivation together (16.6%). This finding is in line with previous results from meta-analyses showing the importance of intelligence for predicting school achievement (e.g., Gottfredson, 2002; Gustafsson & Undheim, 1996; Kuncel, Hezlett, & Ones, 2004; Neisser et al., 1996; Roth et al., 2015). The fact that intelligence alone accounted for 66% of the overall explained variance in school achievement underlines that intelligence is a strong and very important predictor of school achievement.

One reason for the strong predictive power of intelligence tests for school achievement is content and measurement overlap between the two constructs. Regarding content overlap, in intelligence tests that include verbal and math subtests, tasks are very similar to those in standardized achievement tests and also to tasks in written exams as the basis of school grades. The content overlap of intelligence and school achievement also becomes clear when using the intelligence measure as a moderator of the relationship between intelligence and achievement in our meta-analysis. These results showed that the relationship between intelligence and school achievement was closer for tests using verbal and math subscales, compared to nonverbal tasks such as measured with “culture-fair” tests. Concerning measurement overlap, both intelligence and school achievement are measured with tests – either standardized or ad-hoc tests - and, therefore, share common method variance. In contract, motivation is mostly assessed with questionnaires that are not similar to the task format in school achievement tests or school exams. Thus, these factors disadvantage motivation for the prediction of achievement in contrast to intelligence.

Shifting the focus now to motivation as a predictor of school achievement, a central finding of our meta-analysis is that the average correlation between motivation and school achievement is moderate and positive, with $M(r)$ = .28. The path model showed that motivation specifically accounted for 16.6 % of the overall explained variance in school achievement. In comparison to the specific portion of variance in school achievement explained by intelligence, this specific portion of explained variance by motivation is smaller. Even though intelligence explained a greater portion of the variance of school achievement, it must be emphasized that motivation incrementally predicted school achievement above and beyond intelligence on both the main level and on each moderator level. The present result that motivation explained school achievement over and beyond intelligence in our meta-analysis clearly attests the relevance of motivation for school achievement.

Also, after correcting the results for error of measurement (reliability), the same pattern of findings was revealed: intelligence was a strong predictor and motivation was a moderate predictor of school achievement with both predictors being weakly associated.

As the school setting is a strong situational context that determines and restricts students' motivation as well as other predictors such as intelligence, we corrected for range restriction in our predictors. Therefore, we simulated two scenarios, namely one conservative correction (sample variance was 80% of the population variance) and a more liberal correction (sample variance was 60% of the population variance). When using this approach, the results showed that 32% / 44% of variance in school achievement were explained. Also, intelligence still was a strong and motivation a moderate predictor of school achievement which confirm the robust findings of this meta-analysis. When correcting for error of measurement and range restriction at the same time, we found that intelligence and motivation explained not more than 58% of variance in school achievement. It should be noted that this amount of variance might only be explained under optimal conditions with highly reliable measures and no variance restriction in the predictors. Such conditions seem too idealistic when doing research in this field, however.

In sum, the present meta-analysis contributes to the scientific literature with integrating findings from different primary studies and analyzing the importance of intelligence and motivation for school achievement. Findings in the literature about the relevance of intelligence and motivation for the prediction of school achievement stem from different psychological sub-disciplines and led different research groups to doubt that either intelligence is not important for school achievement and its' development or that motivation is negligible for the prediction of school achievement. This was used as a starting point for the present meta-analysis. Our results showed that both intelligence and motivation are important when predicting school achievement, as they both accounted for a specific portion of variance in school achievement and also share a portion of variance in school achievement.

4.2 Moderators of the relationship between intelligence, motivation and school achievement

One aim of the present study was to find reasons for the diverging results regarding the relative importance of intelligence and motivation for school achievement. One explanation might be moderators contributing to the heterogeneity in findings.

Contrary to our expectations, we found no significant differences in the average correlation between intelligence and school achievement depending on the achievement measure used. Based on the results of previous empirical studies, especially when modeling intelligence and standardized achievement as latent and using large-scale assessment data, high correlations between these constructs were found with r = .61 - .90 (Deary et al., 2007; Frey & Detterman, 2004; Rindermann, 2006). Therefore, we expected that the average correlation between intelligence and standardized test achievement would be higher than the average correlation between intelligence and school grades. On a descriptive level, we indeed found a higher average correlation between intelligence and standardized test achievement ($M(r)$ = .47) than between intelligence and school grades ($M(r)$ = .42), but the difference was not significant. One possible reason for this might be that most of the primary studies that assessed school achievement with a standardized test did not examine general intelligence as intelligence measure. As reported above, g was a stronger predictor of school achievement than verbal or non-verbal intelligence, because g as general intelligence is measured with different tasks that are more closely related to the measurement of achievement compared to non-verbal intelligence, which is just one intelligence dimension and measured with figural tasks (e.g., matrices), which are not similar to tasks in exams to assess school achievement. This might have lead to an underestimation of the average correlation between intelligence and standardized test achievement. Another reason for the higher correlation between standardized tests achievement and intelligence in other studies (e.g., Rindermann, 2006) compared to our result could be that intelligence was modeled latent.

Moderator analyses showed that the average correlation between motivation and school achievement was higher for expectancies (*M(r)* = .40) than for values (*M(r)* = .22). This finding is in line with the prediction of Expectancy-Value Theory (Eccles et al., 1983; Wigfield & Eccles, 2000) that expectancies such as academic self-concept and self-efficacy are better predictors of school achievement than values such as intrinsic motivation, interest, achievement motive and achievement goals, which in turn are better predictors of achievement-related choices in the school context. Evidence in support of this has been found in many studies (Huang, 2011; Meece, Wigfield, & Eccles, 1990; Möller et al., 2009; Nagengast et al., 2011). In our current meta-analysis we also found strong support that motivation in the form of expectancies is an especially important predictor of school achievement.

The moderator analyses showed that the relation between intelligence and school achievement was stronger when g (*M(r)* = .49) was assessed compared to nonverbal intelligence (*M(r)* = .38). Roth and colleagues (2015) also found in their meta-analysis that the association between intelligence and school grades was higher for g than for nonverbal intelligence. This might be explained by the fact that intelligence tests that measure g also assess verbal skills, which are important for school success, whereas nonverbal skills are not that important for success in school. Moreover, this result provides strong support for the assumption that intelligence and achievement have a content overlap. Whereas general intelligence and school achievement are both assessed with verbal and math tasks, nonverbal intelligence tests include tasks that include more figural material and are not closely content-related to achievement tasks, which appears in a significantly lower correlation with achievement.

Furthermore, the moderator analyses showed a significantly higher average correlation between motivation and school achievement for cross-sectional studies compared to studies with a longitudinal design having a time interval between the measurement occasions from 13 months or more. This is in line with previous findings that for example the relation between academic self-concept and school achievement is higher when assessing cross-sectionally compared to longitudinally (Guay, Marsh, & Boivin, 2003; Valentine, 2001; Valentine et al., 2004). Reasons for the lower correlation between motivation and achievement in longitudinal studies with a time interval of 13 months or more might be changes in motivation and achievement during this time or other variables that have an influence and impinge in the relation between motivation and achievement. As a difference in the correlation with school achievement between studies with a cross-sectional design compared to a longitudinal design with a time interval of 13 months or more was only found for motivation, but not for intelligence, this can be attributed to the fact that intelligence is pretty stable over time but motivation changes over time and is malleable (Jacobs et al., 2002; Watt, 2004; Spinath & Steinmayr, 2008). It should be also noted that only three primary studies had a longitudinal design with 13 months or more time interval between the measurement occasions, wherefore this finding should be interpreted with caution.

Moreover, we did not find significant differences in the correlations between intelligence, motivation, and school achievement for different grade levels, school forms, gender, continents, publication years and language of publication. The fact that publication year was not a significant moderator is inconsistent with findings from previous meta-analyses by Roth et al. (2015) and Möller and colleagues (2009), who found the average correlations between intelligence / academic self-concept and school achievement to be higher in older studies than in more recent studies.

In order to test whether our moderators were confounded, we looked at correlations between the moderator sub-dimensions. Only a few of all possible correlations were significant and mostly weak to moderate. When looking at the results for different related moderator sub-dimensions explicitly, we did not find consistent patterns in a way that these moderator sub-dimensions led to the same correlations between intelligence and motivation with school achievement. Also, we did not find any homogeneous clusters of confounded moderator sub-dimensions, but only a few associations. For example, studies assessing school achievement with school grades applied general intelligence as an intelligence measure more frequently. This can be explained by the fact that many studies used school grades as an achievement measure based on the grade point average (GPA) of many subjects, which is considered a domain-general measure of achievement. Therefore, it is reasonable to relate GPA to general intelligence as a broad measure of intelligence. Moreover, European studies investigated school forms more often where students were pre-selected due to their prior achievement levels than studies from North America. This can be explained by different school systems: secondary schools in most European countries are divided into different school forms depending on students' achievement levels in elementary school, whereas high schools in North America are open to all students without taking their prior achievement into account.

In general, our results provide strong support for our model in which intelligence and motivation predict school achievement, and indicate that these effects are not restricted to specific subgroups.

Furthermore, the funnel plots showed no publication bias in our data such that only studies with high significant correlations are published in peer-reviewed journals. Additionally, the fail-safe *N*s reveal that it would take a large number of primary studies with non-significant correlations to reduce the average correlations between intelligence, motivation, and school achievement to a trivial size.

4.3 Limitations and directions for further research

One shortcoming of this meta-analysis is the cross-sectional design, as most primary studies assessed the predictors and the criterion at the same time. Therefore, we were not able to examine longitudinal relations between intelligence, motivation, and school achievement. As a result, the data remain correlational and conclusions concerning causality cannot be drawn. The following three causal directions are possible due to our findings of cross-sectional correlations. Intelligence and motivation can influence achievement, achievement can influence intelligence and motivational development as well as third variables can generate these correlations. Future studies would do well to identify such third variables that influence intelligence and motivation on the one hand side and school achievement on the other hand side. Our meta-analysis cannot investigate which one of these directions is true. To do so, a more elaborated longitudinal design is needed. But our moderator analyses showed that when looking at primary studies with a longitudinal design, intelligence and motivation still are correlated with school achievement. These findings can be carefully seen as first hints for influences of intelligence and motivation on school achievement. Because prior school achievement is typically the best predictor of subsequent achievement (e.g., Kriegbaum et al., 2015; Steinmayr & Spinath, 2009), another shortcoming of the present meta-analysis is that we did not include prior achievement as a predictor in our model. Unfortunately, this was impossible as only a few primary studies assessed prior school achievement. Future research (in form of a meta-analysis) would do well to examine the relative importance of prior school achievement, intelligence and motivation for subsequent school achievement and look at their interactions.

Because our meta-analysis only focused on achievement in the school context, it would also be interesting for future research to examine the relative importance of intelligence and motivation for achievement in the context of university or apprenticeships. One might suppose that motivation is more important for academic achievement in university study programs with restricted admission, because students in these programs are pre-selected for intelligence and prior achievement (i.e., school grades and aptitude tests). A future meta-analysis should shed light on these research questions.

In the motivation literature, various constructs are defined as motivation. Even though it is difficult to measure pure motivation in the sense of the mental force that energizes and directs behavior, as some constructs refer to things that generate this power such as expectancies and values and other constructs are already an outcome of this power such as effort. In our meta-analysis, we focused on constructs that are central to leading motivation theories in educational contexts. As expectancies and values are part of the prominent Expectancy-Value Theory and called as the most proximal determinants of achievement-related behavior (Eccles & Wigfield, 2002), we decided to include these motivational constructs in our meta-analysis. Nevertheless, it would be interesting for future research to examine the relative importance of other constructs that are more an outcome of the motivational power such as effort.

Moreover, in our meta-analysis we focused on intelligence and motivation as predictors of school achievement. It would also be interesting to investigate the relative importance of other student characteristics such as personality for school achievement. Some studies have shown that especially conscientiousness as a personality factor predicts school achievement (Arbabi, Vollmer, Dörfler, & Randler, 2015; Dumfart & Neubauer, 2016) and as facets of this construct can be interpreted as an indicator of motivation, it would be interesting for future studies to compare the relative importance of intelligence, motivation and personality for school achievement.

4.4 Implications for research and practice

Intelligence and motivation are two very important predictors that should both be considered when predicting school achievement. Our results indicate that specific constructs such as expectancies and g or verbal intelligence are stronger predictors of school achievement than others. Therefore, future research should use these constructs, which explain greater proportions of variance, to predict school achievement in order to explain as much variance in the criterion as possible. Another important finding of our meta-analysis is that motivation predicts school achievement above and beyond intelligence. This means that out of two equally intelligent students, the one who is more motivated will have higher achievement. Since motivation is easier to influence and foster through instructional characteristics, feedback, learning contexts and situational factors (Midgley, Anderman, & Hicks, 1995), teachers should be aware of their power to motivate their students toward higher achievement. Especially as recent minimal intervention studies showed to effectively promote students' motivation (Gaspard et al., 2015; Harackiewicz et al., 2016; Hulleman, Godes, Hendricks, & Harackiewicz, 2010), teachers could integrate such minimal interventions in their lessons in order that students are and stay motivated.

Our results show that motivational constructs such as expectancies were especially important predictors of school achievement. Therefore, students should develop positive expectancies for success in their future assignments and exams and a realistic, yet positive ability self-concept. Teachers should support their students in developing a realistic academic self-concept, for example when varying the difficulty of tasks, setting short-term goals and by providing clear, specific and informative feedback (Stipek, 2002). Also parents might support their students in becoming and remaining motivated.

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Table 1

Overview of studies included in the meta-analysis

Author (Year)	**Achievement measure**	**Motivational construct(s)**	**Intelligence measure**	**Subject domain**	***N***	**Grade level**	**School form**	**Gender (% Female)**	***r* IA**	***r* MA**	***r* IM**	**Country**
Arbabi et al. (2015)	Grades	Achievement goals	nonverbal	-	1125	4	Elementary school	47.6	.37	.06	.07	Germany
Ayotola & Adedeji (2009)	stand. Test	Self-efficacy	nonverbal	Mathematics	1099	n.a.	High School	46.0	.18	.37	.15	Nigeria
Caplehorn & Sutton (1965)	stand. Test	Achievement motive	g	-	59	6	n.a.	0	.59	.53	.39	Australia
Castejon & Vera-Munoz (1996)	Grades	Self-concept	g	-	1925	n.a.	High School	n.a.	.41	.16	.06	Spain
Chen et al. (2012)	Grades	Self-concept	numeric, verbal	Mathematics, Chinese	1080	10	High School	41.9	.19	.43	.22	Taiwan
del Rosal et al. (2012)	Grades	Intrinsic motivation, extrinsic motivation	n.a.	-	492	n.a.	n.a.	61.4	.30	.16	.05	Spain
Dermitzaki & Efklides (2000)	stand. Test	Self-concept, self-efficacy	verbal	Language	512	7; 9; 11	Gesamtschule	51.0	.75	.19	.11	Greece
Dumfart & Neubauer (2016)	Grades	Self-efficacy, intrinsic motivation, extrinsic motivation	g	-	361	8	Gesamtschule	47.4	.55	.21	.15	Austria
Ferrando et al. (2011)	Grades	Self-concept	g	-	290	n.a.	Elementary School	46.9	.43	.24	.17	Spain
Freudenthaler et al. (2008)	Grades	Self-concept, intrinsic motivation, achieve-ment goals, interest	g, numeric, verbal	Mathematics, German, English, Average	1353	8	Hauptschule	59.2	.37	.16	.07	Austria
Friedrich et al. (2015)	Grades, stand. Test	Self-concept	nonverbal	Mathematics	1289	5	Hauptschule	48.0	.28	.25	.08	Germany
Gagné & St. Père (2002)	Grades	Intrinsic motivation, extrinsic motivation	g	-	208	8	High School	100.0	.45	.01	.00	Canada
Gottschling et al. (2012)	Grades	Self-concept	g	Mathematics, German	560	n.a.	n.a.	52.0	.46	.42	.15	Germany
Gralewski & Karwowski (2013)	Grades	Intrinsic motivation	nonverbal	-	589	n.a.	High School	51.8	.15	.03	.13	Poland

Author (Year)	Achievement measure	Motivational construct(s)	Intelligence measure	Subject domain	*N*	Grade level	School form	Gender (% Female)	r_{IA}	r_{MA}	r_{IM}	Country
Harty et al. (1985)	Grades, stand. Test	Self-concept, interest	numeric, verbal	Science	105	5; 6; 7; 8	High School	52.4	.37	.28	.19	USA
Helmke (1992)	Grades, stand. Test	Self-concept	g	Mathematics	813	5	Hauptschule	n.a.	.48	.54	.36	Germany
Hintsanen et al. (2012)	Grades	Values	g	-	309	9	Gesamtschule	46.6	.61	.46	.25	Finland
Hornstra et al. (2013)	stand. Test	Self-efficacy, achievement goals	g	-	722	3	Elementary School	50.0	.43	.11	.09	Netherlands
Jurecska et al. (2012)	stand. Test	Self-efficacy	g	-	90	n.a.	Elementary School, High School	48.9	.75	.08	.21	USA, Nicaragua
Katzir et al. (2009)	stand. Test	Self-concept	verbal	Reading	67	4	Elementary School	49.3	.50	.45	.30	USA
Keith & Cool (1992)	stand. Test	Interest	verbal	-	25875	n.a.	High School	n.a.	.74	.26	.21	USA
Kirby et al. (2011)	stand. Test	Interest	verbal, nonverbal	Reading	117	1	Elementary School	52.3	.50	.14	.04	Canada
Korkmaz (2016)	Grades	Achievement goals	nonverbal	-	123	5	Elementary School	52.8	.55	.16	.15	Turkey
Kriegbaum, Jansen & Spinath (2015)	stand. Test	Self-concept, self-efficacy, values, achievement goals, interest	nonverbal	Mathematics	6020	10	Gymnasium, Realschule, Gesamtschule	55.4	.55	.18	.12	Germany
Lau & Roeser (2002)	Grades, stand. Test	Self-efficacy, values	g	Science	491	10; 11	High School	50.9	.49	.30	.28	USA
Levpušček et al. (2013)	Grades, stand. Test	Self-efficacy	nonverbal	Mathematics	416	8	High School	51.9	.53	.38	.33	Slovenia
Liew et al. (2008)	stand. Test	Self-efficacy	nonverbal	-	733	1	Elementary School	45.4	.32	.10	.02	USA
Llloyd & Barenblatt (1984)	stand. Test	Intrinsic motivation	n.a.	-	450	10	High School	60.9	.68	.37	.27	USA
Lotz, Schneider & Sparfeldt (2018)	Grades, stand. Test	Self-concept	g	Mathematics, German	496	n.a.	Gymnasium, Gesamtschule	53.0	.59	.52	.26	Germany
Lu et al. (2011)	stand. Test	Self-concept, intrinsic motivation	nonverbal	Mathematics, Chinese	171	4	Elementary School	n.a.	.45	.13	.06	China

Author (Year)	Achievement measure	Motivational construct(s)	Intelligence measure	Subject domain	*N*	Grade level	School form	Gender (% Female)	*r* IA	*r* MA	*r* IM	Country
Lyon & MacDonald (1990)	Grades, stand. Test	Self-concept	verbal	-	122	6	High School	54.9	.69	.32	.40	USA
Manger & Eikeland (1998)	stand. Test	Self-concept	visual/ spatial	Mathematics	409	6	Elementary School	45.7	.45	.41	.22	Norway
Marsh & O'Mara (2010)	Grades	Self-concept	g	-	2213	10; 11	High School	n.a.	.54	.65	.62	USA
McCann et al. (1986)	Grades	Achievement motive	n.a.	-	445	11; 12	High School	n.a.	.51	.22	.07	Canada
McElvany et al. (in prep)	stand. Test	Self-efficacy, intrinsic motivation	verbal, nonverbal	Mathematics, Reading	1307	7	Gymnasium, Hauptschule, Gesamtschule	51.1	.66	.24	.17	Germany
Meier et al. (2014)	stand. Test	Self-concept, achievement goals, interest	nonverbal	Mathematics, Reading	920	5	Gymnasium	41.0	.54	.11	.09	Germany
Meißner, McElvany & Steinmayr (in prep)	Grades, stand. Test	Self-concept	g	Reading	458	6	Elementary School	46.9	.43	.41	.12	Germany
Meißner & Steinmayr (in prep)	Grades, stand. Test	Self-concept	nonverbal	Mathematics, German	1067	8	Gymnasium, Realschule, Gesamtschule	52.2	.43	.42	.17	Germany
Morgan (1953)	Grades	Achievement motive	g	-	62	n.a.	High School	n.a.	.46	.31	.23	USA
Moss & St. Laurent (2001)	Grades	Achievement goals	n.a.	-	108	n.a.	Elementary School	55.6	.18	.04	.01	Canada
Preckel & Brüll (2010)	Grades	Self-concept	g	Mathematics	722	5	Gymnasium	52.0	.43	.63	.35	Germany
Preckel et al. (2008)	Grades, stand. Test	Self-concept, achievement goals, interest	nonverbal	Mathematics	362	6	Gymnasium, Realschule, Hauptschule, Gesamtschule	n.a.	.33	.28	.10	Germany
Preckel et al. (2006)	Grades	Achievement motive	g	-	93	7; 8; 9; 10	Gymnasium	49.5	.31	.34	.07	Germany
Preckel et al. (2013)	Grades	Achievement goals	nonverbal	-	272	9; 10	Gymnasium, Realschule, Hauptschule, Gesamtschule	46.7	.44	.00	.06	Germany

Author (Year)	**Achievement measure**	**Motivational construct(s)**	**Intelligence measure**	**Subject domain**	***N***	**Grade level**	**School form**	**Gender (% Female)**	r_{IA}	r_{MA}	r_{IM}	**Country**
Putwain et al. (2012)	Grades	Intrinsic and extrinsic motivation	nonverbal	English	122	8	High School	49.2	.37	.32	.26	UK
Reimann et al. (2013)	stand. Test	Intrinsic motivation	g	-	567	n.a.	Elementary School, Gymnasium, Realschule, Hauptschule, Gesamtschule	53.4	.56	.22	.31	Germany, Austria, Switzerland
Retelsdorf & Möller (2008; Study 1)	stand. Test	Self-concept, intrinsic motivation, interest	nonverbal	Reading	392	4,5	Elementary School, Gymnasium, Realschule, Hauptschule, Gesamtschule	51.5	.42	.26	.10	Germany
Retelsdorf & Möller (2008; Study 2)	stand. Test	Self-concept, intrinsic motivation, interest	nonverbal	Reading	1455	5	Gymnasium, Realschule, Hauptschule, Gesamtschule	50.6	.37	.20	.08	Germany
Retelsdorf et al. (2011)	stand. Test	Self-concept, intrinsic motivation, extrinsic motivation, interest	nonverbal	Reading	1508	5	Gymnasium, Realschule, Hauptschule, Gesamtschule	49.0	.41	.21	.09	Germany
Roberts et al. (2015)	stand. Test	Values	verbal	English (Reading)	156	3	Elementary School	55.8	.18	.20	.08	USA
Sauer & Gamsjäger (1996)	Grades	Achievement motive	g	-	651	4	Elementary School	47.8	.68	.42	.32	Austria
Schaffner & Schiefele (2013)	stand. Test	Intrinsic motivation	nonverbal	Reading	820	8; 9	Gymnasium, Realschule, Gesamtschule	n.a.	.43	.40	.18	Germany
Scherer et al. (2015)	Grades	Achievement goals	g	-	2000	9	High School	51.0	.47	.21	.13	Finland
Schick & Phillipson (2009)	Grades	Self-concept	g	-	1512	9	Gymnasium	60.0	.57	.38	.30	Germany
Schicke & Fagan (1994)	Grades, stand. Test	Self-concept	n.a.	-	121	4; 6; 8	Elementary School	54.5	.70	.30	.11	USA

Author (Year)	Achievement measure	Motivational construct(s)	Intelligence measure	Subject domain	*N*	Grade level	School form	Gender (% Female)	r_{IA}	r_{MA}	r_{IM}	Country
Schrader & Helmke (1990)	Grades	Self-concept	g	Mathematics	690	6	Hauptschule	n.a.	.34	.49	.34	Germany
Sewell et al. (1982)	stand. Test	Achievement motive	nonverbal	-	49	7; 8	High School	49.0	.28	.16	.03	USA
Shcheblanova (2009)	Grades	Self-concept, achievement motive	g	-	360	5; 7; 9	High School	50.0	.54	.15	.32	Russia
Sparfeldt et al. (2009)	Grades, stand. Test	Self-concept, interest	nonverbal	Mathematics	498	4	Elementary School	46.6	.37	.49	.24	Germany
Spinath et al. (2006)	Grades	Self-concept, intrinsic motivation	g	Mathematics, Science	1678	6	Elementary School	n.a.	.45	.24	.16	UK
Stang et al. (2014)	stand. Test	Self-concept, self-efficacy, achievement motive, interest	nonverbal	Biology, Chemistry	44	10; 11; 12; 13	Gymnasium, Realschule, Hauptschule, Gesamtschule	47.0	.22	.10	.10	Germany
Steinmayr et al. (2011)	Grades	Achievement goals	nonverbal	-	520	11; 12	Gymnasium	58.3	.22	.05	.02	Germany
Steinmayr & Meißner (2013)	Grades, stand. Test	Self-concept	nonverbal	Mathematics	463	8	Gymnasium, Realschule	48.8	.35	.46	.19	Germany
Steinmayr & Spinath (2009)	Grades	Self-concept, values, achievement motive, achievement goals	g, numeric, verbal	Mathematics, German, Average	342	11; 12	Gymnasium	59.6	.30	.29	.16	Germany
Stevens et al. (2006)	stand. Test	Self-efficacy, intrinsic motivation, interest	nonverbal	Mathematics	666	4; 8; 10	High School	n.a.	.34	.21	.16	USA
Stevens et al. (2004)	stand. Test	Self-efficacy	nonverbal	Mathematics	417	9; 10	High School	n.a.	.56	.47	.36	USA
Stoeger et al. (2014)	Grades	achievement goals	nonverbal	-	976	4	Elementary School	50.9	.47	.05	.06	Germany
Stutz et al. (2016)	stand. Test	Intrinsic motivation, extrinsic motivation	g	-	1075	2; 3	Elementary School	52.3	.23	.16	.08	Germany
Trama (2002)	Grades	Self-concept	nonverbal	-	947	5; 6; 9; 10	Elementary School, High School	44.1	.46	.57	.31	India
van de Gaer et al. (2007)	stand. Test	Achievement motive	g	-	4340	8	Gymnasium, Realschule, Hauptschule, Gesamtschule	52.9	.54	.13	.03	Belgium

Author (Year)	Achievement measure	Motivational construct(s)	Intelligence measure	Subject domain	*N*	Grade level	School form	Gender (% Female)	r_{IA}	r_{MA}	r_{IM}	Country
Vecchione et al. (2014)	Grades	Intrinsic and extrinsic motivation	nonverbal	-	102	11; 12	High School	47.1	.12	.24	.24	Italy
Wach et al. (2015)	Grades	Self-concept, achievement motive	numeric, verbal, visual/spatial	Mathematics, German	325	5	Gymnasium, Realschule, Hauptschule, Gesamtschule	56.9	.35	.12	.09	Germany
Zaunbauer & Möller (2007)	stand. Test	Self-concept, interest	nonverbal	Mathematics, German	139	1	Elementary School	46.0	.45	.23	.06	Germany
Zaunbauer et al. (2009)	Grades, stand. Test	Self-concept, interest	nonverbal	English	710	5	Gymnasium, Realschule	51.0	.23	.23	.11	Germany

Notes. r_{IA}: correlation between intelligence and achievement; r_{MA}: correlation between motivation and achievement; r_{IM}: correlation between intelligence and achievement.

Table 2

Meta-analytic correlational results

Moderator	*Analysis*	*k*	*N*	*M(r)*	τ^2	*95%-CI*	I^2	*Q(df)*	*p(Q)*	N_{FS}
All studies	I-A	74	80,145	.44	.02	.41 ≤ M(r) ≤ .48	97.57%	4,956.17(73)	< .01	250
	M-A	74	80,145	.28	.02	.24 ≤ M(r) ≤ .31	96.51%	2,424.23(73)	< .01	127
	I-M	74	80,145	.17	.01	.15 ≤ M(r) ≤ .20	92.96%	1,704.42(73)	< .01	53
Correction for attenuation	I-A	74	80,145	.52	.03	.48 ≤ M(r) ≤ .56	98.95%	11,981.47(73)	< .01	303
	M-A	74	80,145	.33	.03	.28 ≤ M(r) ≤ .37	97.95%	5,046.53(73)	< .01	165
	I-M	74	80,145	.20	.02	.17 ≤ M(r) ≤ .24	95.30%	3,476.82(73)	< .01	76
Conservative correction for range restriction	I-A	74	80,145	.53	.02	.48 ≤ M(r) ≤ .55	98.43%	6,157.60(73)	< .01	306
	M-A	74	80,145	.33	.03	.28 ≤ M(r) ≤ .37	97.69%	3,797.61(73)	< .01	167
	I-M	74	80,145	.21	.02	.18 ≤ M(r) ≤ .24	95.32%	2,815.37(73)	< .01	81
Liberal correction for range restriction	I-A	74	80,145	.62	.02	.58 ≤ M(r) ≤ .65	99.12%	7,341.93(73)	< .01	378
	M-A	74	80,145	.41	.04	.36 ≤ M(r) ≤ .46	98.67%	6,437.12(73)	< .01	225
	I-M	74	80,145	.27	.03	.23 ≤ M(r) ≤ .31	97.29%	5,316.73(73)	< .01	125
Conservative correction for range and attenuation	I-A	74	80,145	.60	.03	.56 ≤ M(r) ≤ .64	99.58%	17,790.21(73)	< .01	367
	M-A	74	80,145	.39	.04	.34 ≤ M(r) ≤ .44	98.89%	10,227.50(73)	< .01	213
	I-M	74	80,145	.25	.02	.21 ≤ M(r) ≤ .29	97.17%	7,477.93(73)	< .01	109
Liberal correction for range and attenuation	I-A	74	80,145	.71	.03	.67 ≤ M(r) ≤ .76	99.97%	16,418.57(73)	< .01	450
	M-A	74	80,145	.49	.06	.43 ≤ M(r) ≤ .54	99.75%	30,381.66(73)	< .01	283
	I-M	74	80,145	.32	.04	.28 ≤ M(r) ≤ .37	98.87%	25,700.84(73)	< .01	161
Without outliers	I-A	68	49,786	.43	.02	.40 ≤ M(r) ≤ .46	95.36%	1,282.28(67)	< .01	220
	M-A	68	49,786	.26	.02	.23 ≤ M(r) ≤ .30	93.89%	1,086.19(67)	< .01	109
	I-M	68	49,786	.16	.01	.13 ≤ M(r) ≤ .18	86.08%	464.90(67)	< .01	41
Achievement measure: School grades	I-A	33	22,645	.42	.02	.38 ≤ M(r) ≤ .47	95.28%	529.41(32)	< .01	106
	M-A	33	22,645	.26	.03	.19 ≤ M(r) ≤ .32	96.82%	1,521.97(32)	< .01	50
	I-M	33	22,645	.18	.02	.13 ≤ M(r) ≤ .23	93.16%	1,183.42(32)	< .01	25
Achievement measure: Stand. test achievement	I-A	27	50,089	.47	.02	.41 ≤ M(r) ≤ .53	98.57%	2,327.40(26)	< .01	97
	M-A	27	50,089	.24	.01	.20 ≤ M(r) ≤ .29	94.49%	282.66(26)	< .01	39
	I-M	27	50,089	.14	.01	.11 ≤ M(r) ≤ .18	90.33%	260.30(26)	< .01	12
Motivational constructs: Expectancies	I-A	24	17,999	.46	.02	.40 ≤ M(r) ≤ .52	95.88%	464.22(23)	< .01	87
	M-A	24	17,999	.40	.02	.34 ≤ M(r) ≤ .46	95.99%	752.18(23)	< .01	71
	I-M	24	17,999	.24	.02	.19 ≤ M(r) ≤ .30	94.19%	937.46(23)	< .01	34
Motivational constructs: Values	I-A	22	39,706	.46	.03	.39 ≤ M(r) ≤ .53	98.30%	1,467.74(21)	< .01	78
	M-A	22	39,706	.22	.02	.15 ≤ M(r) ≤ .28	96.01%	313.60(21)	< .01	26
	I-M	22	39,706	.14	.01	.10 ≤ M(r) ≤ .19	90.50%	226.63(21)	< .01	10
Intelligence measure: g	I-A	26	22,745	.49	.01	.45 ≤ M(r) ≤ .54	94.13%	328.96(25)	< .01	102
	M-A	26	22,745	.32	.03	.25 ≤ M(r) ≤ .39	97.22%	1,371.81(25)	< .01	58
	I-M	26	22,745	.22	.02	.17 ≤ M(r) ≤ .28	95.01%	1,248.07(25)	< .01	32
Intelligence measure: verbal	I-A	6	26,781	.54	.05	.34 ≤ M(r) ≤ .74	98.66%	71.85(5)	< .01	26
	M-A	6	26,781	.25	< .01	.21 ≤ M(r) ≤ .29	21.87%	8.07(5)	.15	10
	I-M	6	26,781	.19	.01	.09 ≤ M(r) ≤ .30	80.03%	16.22(5)	< .01	6
Intelligence measure: nonverbal	I-A	29	23,965	.38	.02	.34 ≤ M(r) ≤ .43	93.50%	439.08(28)	< .01	81
	M-A	29	23,965	.24	.02	.19 ≤ M(r) ≤ .30	95.52%	655.10(28)	< .01	41
	I-M	29	23,965	.14	.01	.11 ≤ M(r) ≤ .17	83.96%	144.25(28)	< .01	12
Subject: Mathematics	I-A	22	40,429	.48	.03	.40 ≤ M(r) ≤ .55	98.52%	1,622.90(21)	< .01	82
	M-A	22	40,429	.21	.03	.14 ≤ M(r) ≤ .30	98.01%	1,361.74(21)	< .01	26
	I-M	22	40,429	.19	.02	.12 ≤ M(r) ≤ .26	96.85%	1,108.34(21)	< .01	20

Moderator	*Analysis*	*k*	*N*	*M(r)*	*τ²*	*95%-CI*	*I²*	*Q(df)*	*p(Q)*	N_{FS}
Subject: Reading	I-A	15	14,740	.43	.01	.36 ≤ M(r) ≤ .49	95.08%	321.03(14)	< .01	49
	M-A	15	14,740	.39	.02	.32 ≤ M(r) ≤ .46	95.53%	509.51(14)	< .01	44
	I-M	15	14,740	.24	.01	.18 ≤ M(r) ≤ .29	89.65%	164.92(14)	< .01	21
Subject: English	I-A	10	7,064	.44	.01	.36 ≤ M(r) ≤ .51	92.90%	154.53(9)	< .01	34
	M-A	10	7,064	.27	.01	.19 ≤ M(r) ≤ .34	90.59%	87.56(9)	< .01	18
	I-M	10	7,064	.12	< .01	.08 ≤ M(r) ≤ .17	65.43%	24.28(9)	< .01	4
Subject: Science	I-A	4	1,433	.33	.02	.18 ≤ M(r) ≤ .48	89.35%	36.94(3)	< .01	9
	M-A	4	1,433	.23	< .01	.18 ≤ M(r) ≤ .28	< 0.01%	1.41(3)	.70	6
	I-M	4	1,433	.11	< .01	.06 ≤ M(r) ≤ .16	0.01%	3.99(3)	.26	2
Domain-specificity: Domain-general	I-A	35	49,886	.47	.03	.42 ≤ M(r) ≤ .53	98.22%	2,433.87(34)	< .01	128
	M-A	35	49,886	.23	.03	.17 ≤ M(r) ≤ .28	97.14%	1,603.41(34)	< .01	44
	I-M	35	49,886	.17	.02	.12 ≤ M(r) ≤ .22	95.78%	1,402.81(34)	< .01	25
Domain-specificity: Domain-specific	I-A	36	28,239	.42	.02	.38 ≤ M(r) ≤ .47	95.10%	865.03(35)	< .01	115
	M-A	36	28,239	.33	.02	.28 ≤ M(r) ≤ .37	94.15%	744.64(35)	< .01	80
	I-M	36	28,239	.18	.01	.15 ≤ M(r) ≤ .21	84.92%	220.22(35)	< .01	28
Study Design: Cross-sectional	I-A	57	34,147	.44	.02	.40 ≤ M(r) ≤ .48	95.53%	1,249.20(56)	< .01	193
	M-A	57	34,147	.29	.02	.25 ≤ M(r) ≤ .33	94.22%	1,129.57(56)	< .01	104
	I-M	57	34,147	.18	.01	.15 ≤ M(r) ≤ .21	83.10%	342.50(56)	< .01	46
Study Design: Longitudinal (up to 12 months)	I-A	14	40,042	.45	.02	.38 ≤ M(r) ≤ .53	98.41%	1,472.71(13)	< .01	50
	M-A	14	40,042	.26	.03	.17 ≤ M(r) ≤ .35	98.54%	1,136.86(13)	< .01	22
	I-M	14	40,042	.17	.03	.08 ≤ M(r) ≤ .26	98.40%	1,111.19(13)	< .01	9
Study Design: Longitudinal (13 months or more)	I-A	3	5,956	.39	.03	.20 ≤ M(r) ≤ .59	97.95%	42.00(2)	< .01	9
	M-A	3	5,956	.15	< .01	.08 ≤ M(r) ≤ .23	78.66%	9.03(2)	.01	1
	I-M	3	5,956	.05	< .01	.00 ≤ M(r) ≤ .10	56.33%	4.21(2)	.12	0
Grade level: 1-4	I-A	14	8,500	.42	.01	.35 ≤ M(r) ≤ .48	92.24%	220.27(13)	< .01	45
	M-A	14	8,500	.21	.02	.14 ≤ M(r) ≤ .29	92.43%	190.12(13)	< .01	17
	I-M	14	8,500	.12	.01	.07 ≤ M(r) ≤ .17	79.80%	64.08(13)	< .01	3
Grade level: 5-9	I-A	31	24,757	.46	.01	.41 ≤ M(r) ≤ .49	93.62%	468.77(30)	< .01	109
	M-A	31	24,757	.30	.02	.25 ≤ M(r) ≤ .36	95.25%	750.98(30)	< .01	62
	I-M	31	24,757	.18	.01	.14 ≤ M(r) ≤ .22	89.51%	315.91(30)	< .01	27
Grade level: 10-13	I-A	10	11,707	.40	.03	.28 ≤ M(r) ≤ .51	98.16%	272.37(9)	< .01	29
	M-A	10	11,707	.29	.03	.18 ≤ M(r) ≤ .41	97.53%	824.18(9)	< .01	19
	I-M	10	11,707	.22	.03	.10 ≤ M(r) ≤ .33	97.30%	874.14(9)	< .01	11
School form: not pre-selected	I-A	43	49,595	.45	.02	.40 ≤ M(r) ≤ .50	97.59%	3,013.33(42)	< .01	149
	M-A	43	49,595	.26	.02	.22 ≤ M(r) ≤ .31	95.59%	1,376.39(42)	< .01	68
	I-M	43	49,595	.18	.01	.14 ≤ M(r) ≤ .22	93.35%	1,228.42(42)	< .01	33
School form: pre-selected	I-A	10	8,254	.39	.01	.32 ≤ M(r) ≤ .46	94.04%	170,88(9)	< .01	29
	M-A	10	8,254	.33	.04	.21 ≤ M(r) ≤ .45	97.61%	401.74(9)	< .01	23
	I-M	10	8,254	.19	.02	.10 ≤ M(r) ≤ .28	94.06%	155.76(9)	< .01	9
Gender: Female	I-A	35	29,636	.46	.02	.40 ≤ M(r) ≤ .51	97.40%	829.02(34)	< .01	124
	M-A	35	29,636	.24	.02	.19 ≤ M(r) ≤ .29	95.05%	761.06(34)	< .01	47
	I-M	35	29,636	.15	.01	.12 ≤ M(r) ≤ .19	87.95%	269.78(34)	< .01	18
Gender: Male	I-A	26	15,565	.41	.02	.36 ≤ M(r) ≤ .46	94.01%	493.79(25)	< .01	80
	M-A	26	15,565	.32	.03	.25 ≤ M(r) ≤ .38	95.61%	955.61(25)	< .01	56
	I-M	26	15,565	.19	.02	.13 ≤ M(r) ≤ .24	92.29%	1,013.81(25)	< .01	23

Moderator	*Analysis*	*k*	*N*	*M(r)*	*τ²*	*95%-CI*	*I²*	*Q(df)*	*p(Q)*	N_{FS}
Continent: Asia	I-A	4	2,558	.41	.02	.26 ≤ M(r) ≤ .56	94.98%	70.97(3)	< .01	13
	M-A	4	2,558	.33	.04	.12 ≤ M(r) ≤ .54	97.44%	81.83(3)	< .01	9
	I-M	4	2,558	.24	.01	.14 ≤ M(r) ≤ .34	84.15%	13.25(3)	< .01	6
Continent: Europe	I-A	49	43,934	.43	.02	.39 ≤ M(r) ≤ .47	95.94%	1,082.96(48)	< .01	159
	M-A	49	43,934	.27	.02	.22 ≤ M(r) ≤ .31	95.76%	1,192.96(48)	< .01	81
	I-M	49	43,934	.16	.01	.13 ≤ M(r) ≤ .18	87.65%	396.54(48)	< .01	27
Continent: North America	I-A	19	32,495	.50	.03	.42 ≤ M(r) ≤ .58	97.31%	723.90(18)	< .01	74
	M-A	19	32,495	.27	.02	.19 ≤ M(r) ≤ .34	96.14%	939.48(18)	< .01	30
	I-M	19	32,495	.20	.02	.12 ≤ M(r) ≤ .28	96.02%	937.54(18)	< .01	17
Language of publication: English	I-A	61	71,420	.44	.02	.41 ≤ M(r) ≤ .48	97.73%	4,358.06(60)	< .01	208
	M-A	61	71,420	.26	.02	.22 ≤ M(r) ≤ .29	96.49%	2,111.26(60)	< .01	94
	I-M	61	71,420	.17	.01	.14 ≤ M(r) ≤ .20	93.60%	1,608.52(60)	< .01	41
Language of publication: German	I-A	13	8,725	.44	.02	.36 ≤ M(r) ≤ .52	95.57%	339.76(12)	< .01	43
	M-A	13	8,725	.37	.02	.29 ≤ M(r) ≤ .44	93.91%	203.92(12)	< .01	33
	I-M	13	8,725	.20	.01	.14 ≤ M(r) ≤ .26	86.38%	95.42(12)	< .01	13
Year of publication: 1980-1989	I-A	4	1,049	.49	.02	.32 ≤ M(r) ≤ .66	91.54%	29.68(3)	< .01	15
	M-A	4	1,049	.28	< .01	.18 ≤ M(r) ≤ .38	55.56%	7.10(3)	.07	7
	I-M	4	1,049	.16	.01	.04 ≤ M(r) ≤ .28	66.98%	10.69(3)	.01	2
Year of publication: 1990-1999	I-A	8	30,606	.56	.02	.45 ≤ M(r) ≤ .67	98.29%	571.05(7)	< .01	37
	M-A	8	30,606	.37	.02	.27 ≤ M(r) ≤ .46	96.48%	232.05(7)	< .01	21
	I-M	8	30,606	.25	.01	.17 ≤ M(r) ≤ .34	94.59%	99.55(7)	< .01	13
Year of publication: 2000-2009	I-A	23	18,482	.42	.02	.36 ≤ M(r) ≤ .47	95.57%	552.14(22)	< .01	72
	M-A	23	18,482	.27	.02	.21 ≤ M(r) ≤ .33	94.30%	469.18(22)	< .01	38
	I-M	23	18,482	.16	.01	.11 ≤ M(r) ≤ .20	89.02%	226.04(22)	< .01	13
Year of publication: 2010-2016	I-A	33	26,559	.41	.02	.36 ≤ M(r) ≤ .46	95.78%	586.60(32)	< .01	102
	M-A	33	26,559	.24	.03	.18 ≤ M(r) ≤ .29	96.47%	1,584.05(32)	< .01	43
	I-M	33	26,559	.16	.01	.12 ≤ M(r) ≤ .21	92.81%	1,264.09(32)	< .01	20
Year of publication: in prep	I-A	4	3,328	.53	.01	.41 ≤ M(r) ≤ .64	95.35%	77.93(3)	< .01	18
	M-A	4	3,328	.40	.01	.28 ≤ M(r) ≤ .51	93.47%	50.15(3)	< .01	12
	I-M	4	3,328	.18	< .01	.13 ≤ M(r) ≤ .22	41.89%	5.57(3)	< .01	4

Notes. I-A = intelligence with school achievement; M-A = motivation with school achievement; I-M = intelligence with motivation; k = number of studies; *N* = number of participants; *M(r)* = mean correlation; τ^2 = population variance; 95%-CI = 95% confidence interval of population correlation; I^2 = I^2-value; *Q(df)* = Q-statistic with degrees of freedom; *p(Q)* = significance of Q-statistic; N_{FS} = fail-safe N.

Table 3

Results of meta-analytic regression models showing for intelligence and motivation specific (ΔR^2_I, ΔR^2_M) and common shares (R^2_{shared}) of explained variance in school achievement

Predictors	*Intelligence (Model 1)*		*Motivation (Model 2)*		*Intelligence and Motivation (Model 3)*									
Analysis	β	R^2	β	R^2	β_I	β_M	R^2	ΔR^2_I	ΔR^2_M	R^2_{shared}	$F_I(df)$	$p(F_I)$	$F_M(df)$	$p(F_M)$
All studies	.44	.20	.28	.08	.41	.20	.24	.16	.04	.04	52.44(1;247)	< .01	13.11(1;247)	< .01
Correction for attenuation	.52	.27	.33	.11	.47	.23	.32	.21	.05	.06	76.03(1;247)	< .01	18.53(1;247)	< .01
Conservative correction for range restriction	.52	.27	.33	.11	.47	.23	.32	.21	.05	.06	76.64(1;247)	< .01	18.39(1;247)	< .01
Liberal correction for range restriction	.62	.38	.41	.17	.55	.26	.44	.28	.06	.10	122.91(1;247)	< .01	27.94(1;247)	< .01
Conservative correction for range and attenuation	.60	.36	.39	.15	.54	.26	.43	.27	.06	.09	116.52(1;247)	< .01	26.73(1;247)	< .01
Liberal correction for range and attenuation	.71	.51	.49	.24	.62	.29	.58	.35	.07	.16	206.56(1;247)	< .01	43.81(1;247)	< .01
School grades	.42	.18	.26	.07	.39	.19	.21	.15	.03	.03	50.40(1;268)	< .01	11.42(1;268)	< .01
Stand. Test achievement	.47	.22	.24	.06	.44	.18	.25	.18	.03	.03	52.38(1;208)	< .01	8.72(1;208)	< .01
Expectancies	.46	.21	.40	.16	.39	.31	.30	.14	.09	.07	64.67(1;325)	< .01	41.21(1;325)	< .01
Values	.46	.21	.22	.05	.44	.15	.23	.18	.02	.02	44.46(1;181)	< .01	5.38(1;181)	.02
g	.49	.24	.32	.10	.44	.22	.29	.18	.05	.06	73.33(1;277)	< .01	18.68(1;277)	< .01
verbal	.54	.29	.25	.06	.51	.15	.31	.25	.02	.04	40.80(1;112)	< .01	3.74(1;112)	.06
non-verbal	.38	.15	.24	.06	.36	.20	.18	.12	.04	.02	44.56(1;294)	< .01	13.37(1;294)	< .01
Mathematics	.48	.23	.21	.05	.45	.13	.25	.20	.02	.03	62.92(1;239)	< .01	5.39(1;239)	.02
Reading	.43	.18	.39	.15	.35	.31	.27	.12	.09	.06	89.73(1;560)	< .01	67.88(1;560)	< .01
English	.44	.19	.27	.07	.41	.22	.24	.16	.05	.03	60.34(1;279)	< .01	16.85(1;279)	< .01
Science	.33	.11	.23	.05	.31	.20	.15	.09	.04	.01	23.24(1;215)	< .01	9.85(1;215)	< .01
Domain-general	.47	.22	.23	.05	.45	.15	.25	.19	.02	.03	54.56(1;212)	< .01	6.08(1;212)	.01
Domain-specific	.42	.18	.33	.11	.38	.26	.25	.14	.07	.04	51.43(1;282)	< .01	24.64(1;282)	< .01

Predictors	Intelligence (Model 1)		Motivation (Model 2)		Intelligence and Motivation (Model 3)									
Analysis	β	R^2	β	R^2	β_I	β_M	R^2	ΔR^2_I	ΔR^2_M	R^2_{shared}	$F_I(df)$	$p(F_I)$	$F_M(df)$	$p(F_M)$
Cross-sectional	.44	.20	.29	.08	.41	.21	.24	.16	.04	.04	46.98(1;224)	< .01	12.93(1;224)	< .01
Longitudinal (up to 12 months)	.45	.21	.36	.07	.42	.19	.24	.17	.04	.03	89.85(1;379)	< .01	18.51(1;379)	< .01
Longitudinal (13 months or more)	.39	.16	.15	.02	.39	.13	.17	.15	.02	.01	52.64(1;291)	< .01	6.13(1;291)	.01
1-4	.42	.17	.21	.05	.40	.17	.20	.15	.03	.02	48.62(1;250)	< .01	8.61(1;250)	< .01
5-9	.46	.21	.30	.09	.41	.23	.26	.17	.05	.04	59.53(1;268)	< .01	17.83(1;268)	< .01
10-13	.40	.16	.29	.09	.35	.22	.20	.12	.05	.04	31.28(1;216)	< .01	12.34(1;216)	< .01
Not pre-selected	.45	.20	.26	.07	.42	.19	.24	.17	.03	.03	48.68(1;220)	< .01	9.63(1;220)	< .01
Pre-selected	.39	.15	.33	.11	.34	.26	.22	.11	.07	.04	31.47(1;220)	< .01	18.44(1;220)	< .01
Female	.46	.21	.24	.06	.43	.17	.24	.18	.03	.03	61.03(1;254)	< .01	9.80(1;254)	< .01
Male	.41	.17	.32	.10	.36	.25	.23	.13	.06	.04	31.00(1;188)	< .01	14.63(1;188)	< .01
Asia	.41	.17	.33	.11	.35	.24	.22	.12	.06	.05	55.25(1;373)	< .01	26.64(1;373)	< .01
Europe	.43	.19	.27	.07	.40	.21	.23	.16	.04	.03	71.18(1;355)	< .01	18.91(1;355)	< .01
North America	.50	.25	.27	.07	.46	.17	.28	.21	.03	.04	40.62(1;142)	< .01	5.66(1;142)	.02
English	.44	.20	.26	.07	.41	.19	.23	.16	.03	.03	52.33(1;242)	< .01	10.60(1;242)	< .01
German	.44	.19	.37	.14	.38	.29	.28	.13	.08	.05	52.99(1;275)	< .01	30.83(1;275)	< .01
1980-1989	.49	.24	.28	.08	.45	.21	.28	.20	.04	.04	31.29(1;112)	< .01	6.62(1;112)	.01
1990-1999	.56	.31	.37	.13	.50	.24	.37	.23	.05	.08	123.91(1;344)	< .01	28.09(1;334)	< .01
2000-2009	.42	.17	.27	.07	.39	.21	.22	.14	.04	.03	55.40(1;301)	< .01	16.10(1;301)	< .01
2010-2016	.41	.17	.24	.06	.39	.17	.20	.15	.03	.03	48.23(1;266)	< .01	9.70(1;266)	< .01
in prep	.53	.28	.40	.16	.47	.31	.37	.22	.09	.06	234.09(1;674)	< .01	101.22(1;674)	< .01

Notes. β_I = regression coefficient of intelligence; β_M = regression coefficient of motivation; ΔR^2_I = incremental validity of intelligence; ΔR^2_M = incremental validity of motivation; R^2_{shared} = explained variance shared by motivation and intelligence; F_I(df) = F-statistic of incremental validity of intelligence with degrees of freedom; $p(F_I)$ = significance of F-statistic of incremental validity of intelligence; F_M(df) = F-statistic of incremental validity of motivation with degrees of freedom; $p(F_M)$ = significance of F-statistic of incremental validity of motivation.

Table 4

Correlations between the moderators (Kendall's τ)

Moderator	Mot	I g	I v	I nv	Math	Reading	English	Science	Domain-specific	SD cross	SD long (12 m)	SD long (13 m)	Grade level	School type	Gender	Asia	Europe	North America	PL	PY 1980 – 1989	PY 1990 - 1999	PY 2000 - 2009	PY 2010 - 2016	PY in prep
Achievement measure	.07	**-.44**	**.36**	.22	**-.72**	.27	**.63**	-.05	**.47**	-.18	.14	.10	-.26	-.25	-.04	-.10	-.13	.20	.19	.10	-.03	.10	-.17	.14
Motivational construct (Mot)		-.08	.11	.01	.17	**-.39**	.10	.26	**-.50**	-.02	-.10	.22	-.11	-.20	-.08	-.21	.01	.08	-.24	.28	-.21	-.14	.17	-.25
Intelligence: g (I g)					.20	-.10	-.05	-.23	**-.35**	.04	-.06	.03	.06	.15	-.07	-.04	.06	-.04	-.09	-.11	.16	-.11	-.09	.11
Intelligence: verbal (I v)					.04	-.20	.06	.23	-.01	.04	-.01	-.06	-.16	-.19	-.06	-.08	**-.43**	**.50**	-.16	**.39**	**.26**	.04	-.20	-.08
Intelligence: non-verbal (I nv)					-.23	.22	.02	.10	**.35**	-.07	.07	.01	.03	-.02	.10	.09	.20	**-.26**	.19	-.12	**-.31**	.10	.21	-.07
Domain: Math									**-.80**	.12	-.15	.04	.07	-.11	.04	.23	-.16	.07	-.25	-.21	.18	-.10	.05	-.12
Domain: Reading									**.50**	-.03	.09	-.12	.08	**.37**	.06	-.12	**.28**	-.24	.20	-.15	.09	.07	-.01	-.09
Domain: English									.22	-.06	-.10	.16	-.28	-.17	-.08	-.10	.07	-.03	.07	.09	-.20	.02	.03	**.29**
Domain: Science									.16	-.17	.21	-.06	.04	-.12	.12	-.06	-.08	.11	.08	.24	-.12	-.02	.02	-.04
Domain-specificity										.01	.03	-.07	-.06	.15	-.04	-.01	.16	-.17	**.39**	-.13	-.09	.15	-.07	**.24**
Study design: cross-sectional													-.06	-.06	-.04	.14	.11	-.19	-.01	-.01	-.02	-.12	.04	.13
Study Design: Longitudinal (to 12 months)													.05	.09	.07	-.12	-.12	.18	.05	.04	.05	.05	-.02	-.12
Study Design: Longitudinal (13 months or more)													.03	-.07	-.04	-.05	-.01	.03	-.10	-.05	-.07	.16	-.05	-.05
Grade level														.26	-.14	.02	-.06	.05	-.14	.23	-.05	-.17	.04	.03
School type															-.12	-.12	**.40**	**-.36**	.17	-.14	.07	.08	-.02	-.07
Gender																.23	-.01	-.09	-.06	-.04	.04	.02	-.05	-.09
Continent: Asia																			-.11	-.06	-.09	.10	.02	-.06
Continent: Europe																			**.32**	**-.35**	-.04	-.13	**.27**	.17
Continent: North America																			**-.28**	**.41**	.09	.08	**-.30**	-.15
Publication language (PL)																				-.11	.18	.07	**-.27**	**.36**

Note. Coefficients printed in bold are significant ($p < .05$).

Figure 1. Flow Diagram

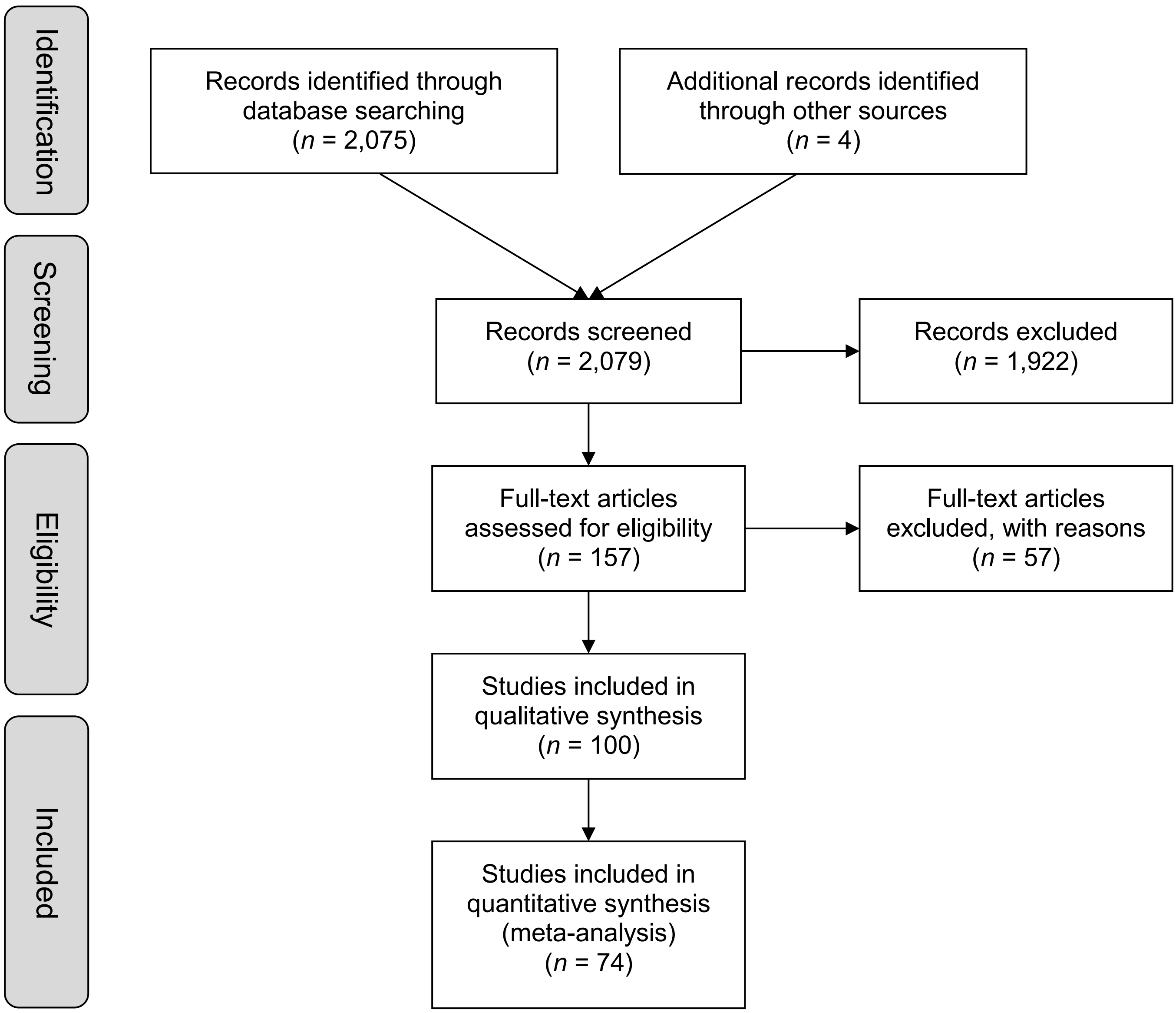


Figure 2. Forrest plots

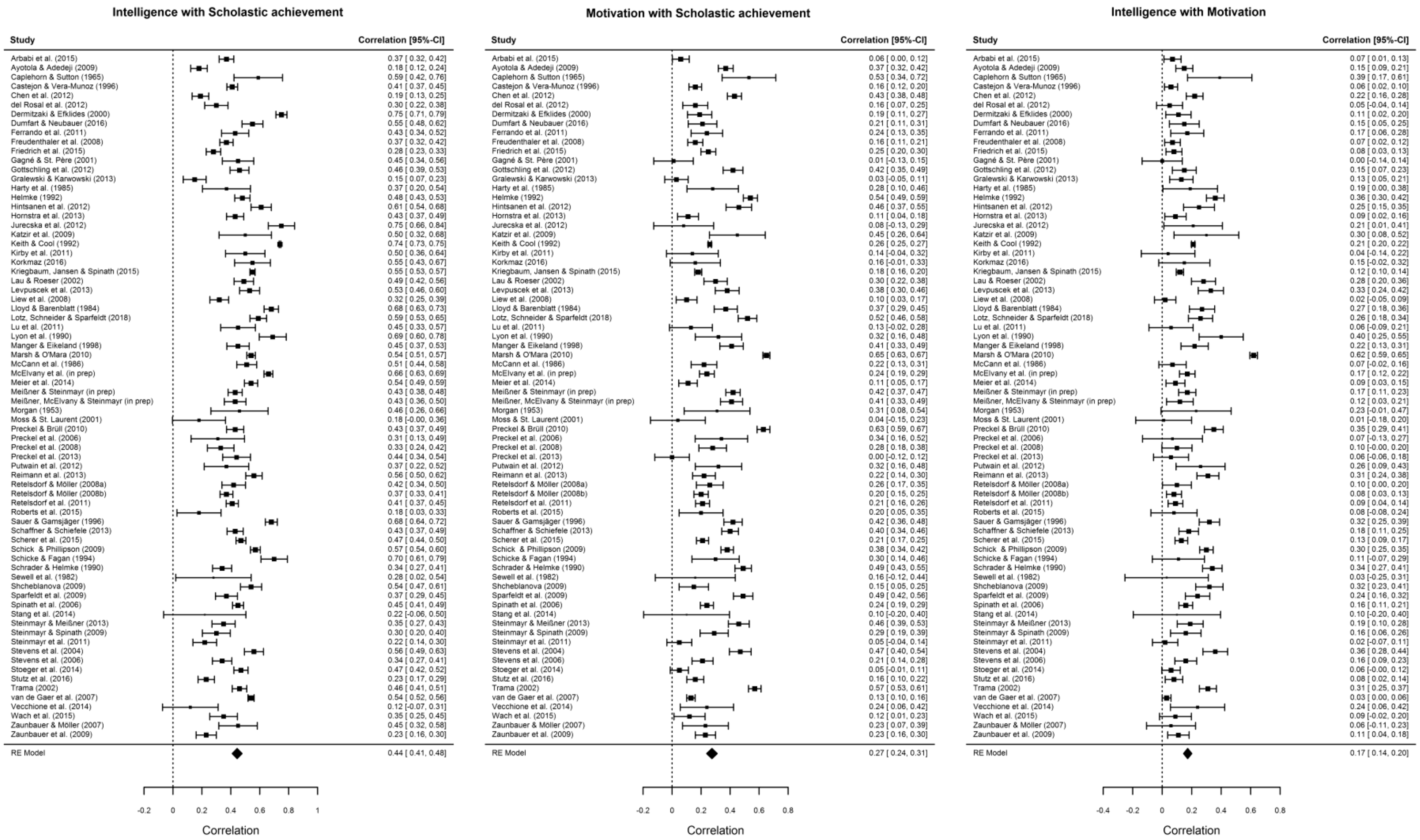


Figure 3. Outlier analyses

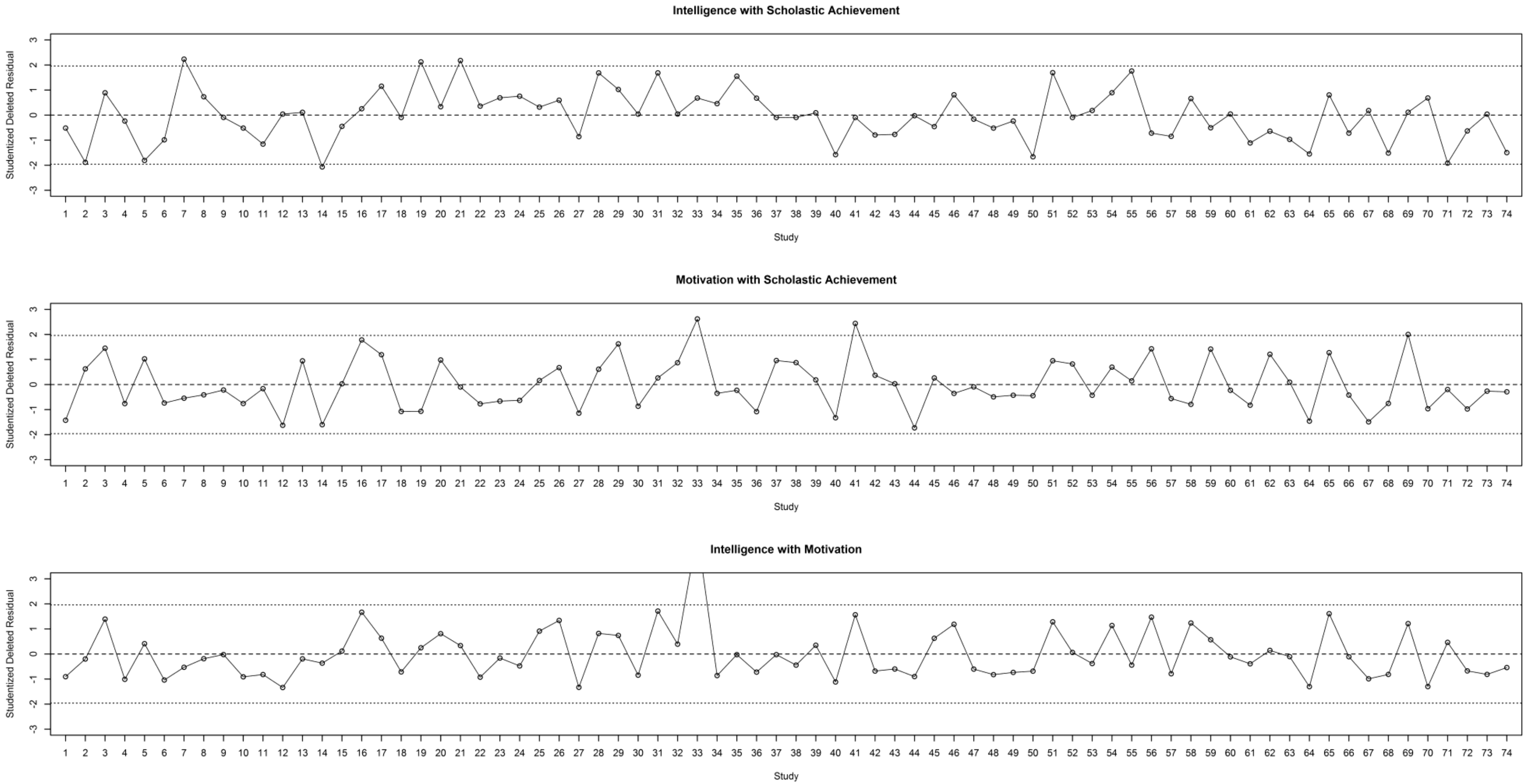
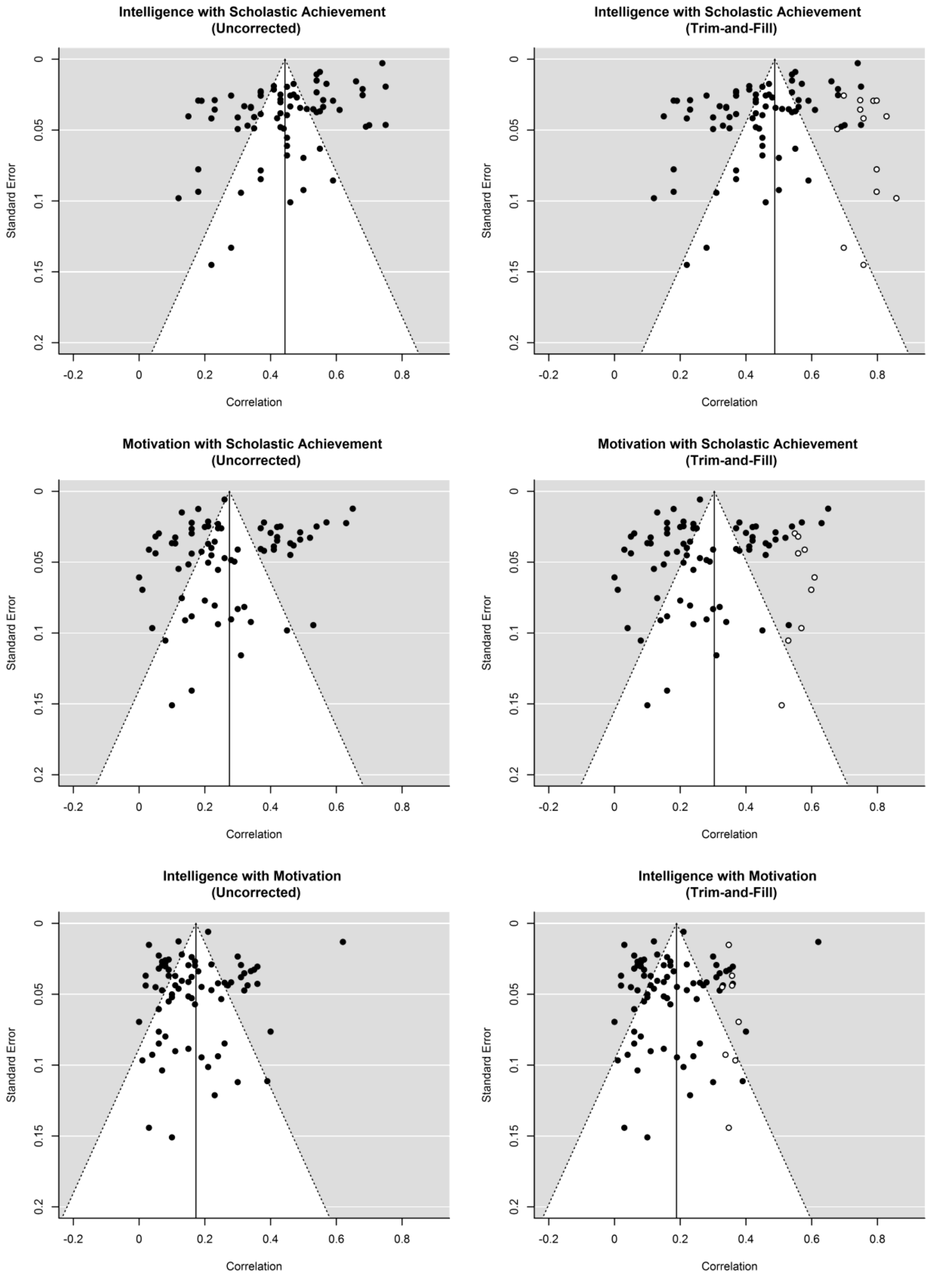


Figure 4. Funnel plots



6.2 Study 2: Explaining Social Disparities in School Achievement: The Role of Motivation

Note: This is the first author's version of a study that was published in *European Journal of Personality*. The following manuscript does not exactly replicate the final version that was published in the journal. It is neither a copy of the original article nor a suitable citation.

Kriegbaum, K. & Spinath, B. (2016). Explaining Social Disparities in Mathematical Achievement: The Role of Motivation. *European Journal of Personality, 30,* 45–63. doi: 10.1002/per.2042

Abstract

This study examined the role of motivation as a mediator of the relationship between parents' socio-economic status (SES) and children's standardized test achievement in math. We employed a one-year longitudinal approach using PISA 2003 and a follow-up exam in 2004. The sample consisted of N = 6,020 German students (mean age 15.5 years, *SD* = .55) who continued school after Grade 9 (PISA 2003) and were in Grade 10 at the time of PISA 2004. Children completed measures related to their parents' SES, math-specific self-concept, task-specific and global self-efficacy, and interest, intelligence and mathematical competence. We found a small to moderate correlation between parents' SES and children's achievement. All motivational constructs partially mediated the relationship between father's SES as well as a family index for SES (ESCS) and children's mathematical competence, but only math-specific self-concept and self-efficacy were significant mediators for mother's SES. Even when simultaneously considering the mediating effect of children's intelligence and prior achievement, the mediation effects of motivation remained significant. These results are important for our understanding of educational equality.

Keywords: socio-economic status, PISA, mathematical competence, motivation

1. Introduction

A positive association between parents' SES and children's school achievement is often interpreted as an indicator of educational inequity (e.g., Ehmke & Jude, 2010; OECD, 2014a, b). Underlying this line of reasoning is the notion that every child should have the same chances to succeed in the educational system, independent of their family background. However, if family background is systematically linked to important individual prerequisites for school achievement, such as intelligence and motivation, it does not seem reasonable to expect children from families with different SES to have equal school outcomes. Instead, it might be argued that in an equitable educational system, better individual prerequisites should lead to better achievement. If this notion of educational equity is accepted, then a positive association between family SES and children's school achievement might even be interpreted as a sign of an equitable educational system. This is true to the extent that the association between parents' SES and children's school achievement is mediated by individual characteristics of children such as intelligence and motivation, which are known to be important for school achievement. The present study investigated the extent of this potential mediation.

The current study extends the nascent body of work on factors mediating the relationship between social background and academic achievement in a number of important ways. First, we used the PISA-I-Plus dataset, which is fully representative of the population of German secondary school students who continue attending school after Grade 9. Having a population-representative sample on the population level is important because otherwise pre-selection of students according to criteria such as prior achievement restricts the variance of some predictors more than that of others, thus leading to distorted results when analyzing their comparative predictive power. Second, we operationalized school achievement in terms of standardized achievement tests instead of grades, which has not been done before when investigating these research questions. Third, we investigated the role of several motivational constructs, i.e. math-specific self-concept, task-specific and global self-efficacy and interest, which have also not been investigated before in this context. Fourth, we examined mediational effects both cross-sectionally and longitudinally. This allowed us to examine the extent to which changes in standardized test achievement are predicted by SES and how this relationship was mediated by motivational constructs. Fifth, we first considered the mediation effects of intelligence and prior achievement and then tested the incremental predictive power of motivation.

1.1 The role of parents' SES in children's academic achievement

Parents' SES is frequently indicated by parents' education (scholastic and vocational educational attainment), occupation, income (Bradley & Corwyn, 2002; Steinmayr et al., 2012) or a combination of these. The International Socio-Economic Index (ISEI; Ganzeboom, De Graaf, & Treiman, 1992; Ganzeboom & Treiman, 1996) is frequently used to quantify parents' SES. This index includes reports of parents' occupation and is based on international data concerning the education and income of members of different professions. Nevertheless, there are different approaches to measuring parents' SES: The first approach is the individual approach and comprises separate measures for each parent (father's and mother's SES). A second approach, a dominance or power model, is to use the measures of the parent with the higher status as an indicator for the family's overall socioeconomic position (Marks, 2008; Ehmke & Siegle, 2005). In this case, the highest international socio-economic index (HISEI) score is used to determine family SES (Ramm et al., 2006). A third approach to assessing parents' SES was used in recent waves of the international large-scale study PISA, namely, an index of parents' economic, social and cultural status (ESCS) (Ramm et al., 2006). This index is a composite of three variables referring to family background: the highest level of education in the family, highest ISEI of the family, and the number of possessions in the home (including the number of books).

There exists a large and growing literature on social disparities in children's academic achievement. Positive associations between parents' SES and children's academic achievement have repeatedly been reported both for school grades and standardized test achievement (e.g., Ehmke, Hohensee, Heidemeier, & Prenzel, 2004; Ehmke, Hohensee, Siegle, & Prenzel, 2006; OECD, 2007; Sirin, 2005; White, 1982). Two meta-analyses found average correlations between SES and school grades of r = .25 and .29, respectively (Sirin, 2005; White, 1982). In this context, it has also been shown that the strength of the association between SES and academic achievement depends on which indicator of social background is used. The association was the lowest when only parents' education was used as an indicator of SES (r = .19), moderate when only parents' occupation was used (r = .20), and highest when parents' education, occupation and income were used to indicate SES (r = .32) (White, 1982).

As part of PISA, parents' SES was assessed using an even more sophisticated measure and linked to children's competencies in reading, math and science in international comparison for the first time. Using standardized test achievement as a performance indicator, substantial associations between parents' SES and children's competencies in reading, math, and science were found for PISA 2003 (OECD average: r = .39/.41/.40) and PISA 2006 (OECD average: r = .35/.35/.38; OECD, 2007, pp. 127, 129, 131). These relationships apply for the population of students in the last compulsory school year, i.e. a non-selective sample representing the complete range of school-related ability. That the correlations between parents' SES and PISA competencies are higher than the correlations reported in the aforementioned meta-analyses might be due to the specific SES indicator used in PISA. This is in line with the finding that ESCS accounts for more variance in mathematical competence than HISEI, which only takes parents' occupation into account, and can be seen as a valid index of social background (Ehmke & Siegle, 2005).

Furthermore, there is some evidence that father's occupation is more strongly related to children's achievement in science compared to mother's SES (for a review, see Marks, 2008). One possible explanation for this might be that fathers often have a stronger attachment to the labor market than mothers (Marks, 2008), whereas mothers are often more family and less career oriented and might choose to stay at home with their children rather than taking a high-powered job, even they have a high level of education. This would lead to a range restriction in mother's SES, which also might have an impact on the relationship between mother's SES and children's achievement. Another explanation for this might be that men are more frequently employed in jobs related to math and science than women (Marks, 2008), are more likely to address math and science topics at home and might play a more important part in motivating their children when it comes to math and science.

Based on the approaches reported above, we examined both father's and mother's SES via each person's ISEI in order to look for differences between these indicators. We also assessed ESCS as an index of family SES, because it has been shown to be more strongly associated to children's academic achievement than each parent's ISEI.

1.2 The importance of intelligence and motivation for academic achievement

What are the most promising candidates for explaining differences in academic achievement? Interestingly, different psychological sub-disciples have focused on different constructs when investigating this question. Whereas intelligence is a construct which is primarily investigated in the context of the psychology of personality and individual differences, educational psychologists tend to examine motivation as an important reason for achievement differences. In the present study, these two lines of research are brought together to analyze potential reasons for social disparities in math achievement.

The literature on intelligence contains many different theories, but there is a consensus that one general factor, the g-factor, is a representation of several kinds of intelligent behaviors, such as good reasoning and the ability to adapt to new demands (Neisser et al., 1996). It has been shown that general intelligence is one of the best predictors of children's academic achievement (Gustafsson & Undheim, 1996; Kuncel, Hezlett, & Ones, 2004). Therefore, intelligence is one of the most promising constructs when it comes to explaining social disparities in academic achievement.

Regarding motivation, one widely-used and well-established model is expectancy-value theory (EVT; Eccles et al., 1983; Wigfield & Eccles, 2000), in which two groups of motivational constructs are supposed to be proximal determinants of achievement-related behavior: expectancies of success and task values. Expectancies of success refer to a person's perception of their ability to successfully solve specific tasks as well as their evaluation of their ability in specific domains. Expectancies are typically assessed via self-efficacy and academic self-concept. Task values can be specified in terms of intrinsic or interest value, attainment value, utility value and cost. Several studies have shown that both expectancies and task values are positively related to academic achievement, but this correlation is stronger for expectancies than task values (Trautwein et al., 2012; Wigfield & Eccles, 2000). Moreover, EVT supposes that children's social background has an influence on their academic achievement via their motivational prerequisites.

1.3 Mediators of the relationship between parents' SES and children's academic achievement

Several possible mediators of the relationship between parents' SES and children's academic achievement have been considered. Because intelligence is positively related to both parents' SES (*r* = .40; White, 1982) and children's academic achievement (*r* = .50; Kuncel, Hezlett & Ones, 2004), it fulfills the prerequisites of a mediator. Several research groups have found that intelligence partially mediates the relationship between parents' SES and children's academic achievement. This was also the case for standardized test achievement in reading (Baumert, Watermann, & Schümer, 2003; Hecht et al., 2000; Lloyd & Barenblatt, 1984). For example, one study found that SES explained 16% of the variance in the growth of decoding skills from kindergarten to second grade, but only explained 8% after intelligence and prior decoding skills were included as mediators (Hecht et al., 2000). Intelligence was also found to be a mediator of the relationship between parents' SES and children's school grades (Johnson, McGue, & Iacono, 2007; Steinmayr et al., 2010; Steinmayr et al., 2012). For example, the effect of SES on children's school grades dropped from *b* = .19 to *b* = .07 after including children's intelligence, gender and parental expectations about education, and IQ accounted for one-third of the total effect (Johnson et al., 2007). Furthermore, intelligence has been shown to explain 43% of the relationship between parents' education and children's school grades (Steinmayr et al., 2010). In another study, intelligence explained 64% of the relationship between father's SES and children's school grades in math and 41% of the relationship between mother's SES and children's school grades in chemistry (Steinmayr et al., 2012). Because intelligence does not explain the entire covariance in the relationship between social background and academic achievement, it is worthwhile to look for other individual-related factors that have an influence on this relationship.

In order to explain the relationship between social background and reading competence, Baumert and colleagues (2003) investigated the role of psychological and institutional factors as mediators using a German PISA dataset. These authors found intelligence, enjoyment of reading, decoding skills, and school type to be significant mediators of this relationship. Nevertheless, even after considering these factors, social background still had a significant effect on children's reading competence.

Regarding student characteristics, motivation is another important variable that has been shown to be associated with children's academic achievement. Typically, correlations between task values and academic achievement are about $r = .30$ and the associations between expectancies and academic achievement vary between $r = .40$ and $.50$ (Kriegbaum, Jansen & Spinath, 2015; Steinmayr & Spinath, 2009). Moreover, children's motivation is associated with parents' SES ($r = .05$ - $.10$; Dotterer et al., 2009), rendering motivation a potential mediator of the relationship between parents' SES and children's academic achievement.

In a prior study investigating the potential mediating effects of motivation, Steinmayr et al. (2012) focused on motivational constructs such as academic self-concept and scholastic values and examined whether these constructs mediated the aforementioned relationship. The results showed that both academic self-concept and scholastic values were significant mediators of the relationship between father's SES and children's grades in mathematics, physics and chemistry. Academic self-concept explained between 50% (physics) and 92% (math) and scholastic values explained between 38% (physics) and 41% (math) of the relationship between parents' SES and children's grades. When using mother's SES as an indicator of children's social background, only academic self-concept partially mediated the association with grades in chemistry. Furthermore, it has been demonstrated that intelligence (see above) and prior achievement are significant mediators of the relationship between father's and mother's SES and children's grades in science, technology, engineering and mathematics (STEM). Because past performance is both related to SES and a strong predictor of subsequent performance (Prenzel, Carstensen, Schöps, & Maurischat, 2006; Kriegbaum et al., 2015), it is not surprising that prior achievement was found to mediate the aforementioned relationship. In the study by Steinmayr and colleagues (2012), prior achievement explained between 43% and 83% (depending on the investigated subject and SES indicator) of the relationship between parents' SES and children's school grades in STEM domains. Even after controlling for prior school grades, academic self-concept and scholastic values were still significant mediators of the relationship between father's SES and children's grades in STEM subjects. Nevertheless, it is important to note that the sample in this study only included eleventh-graders from the highest school type in Germany ("Gymnasium"), meaning that SES and intelligence were significantly higher than in the general population and restricted in range.

1.4 Mechanisms behind associations between parents' and children's characteristics

The debate about educational inequality typically takes little to no notice of findings regarding the genetic bases of individual differences. However, to understand why parents resemble their children with respect to certain characteristics, it is vital to acknowledge that parents influence their children not only by way of the environment they provide, but also via genetic endowment (see Plomin, DeFries, Knopik, & Neiderhiser, 2012). Parents' SES can be seen as a result of their achievement-related choices and behavior, which in turn is a result of individual characteristics such as intelligence and motivation. Thus, parents' SES might be interpreted as a proxy of parents' intelligence, motivation and other prerequisites for achievement. More intelligent and motivated parents are more likely to reach a higher level of education, have better jobs and earn a higher income. They transmit these better achievement prerequisites to their children, which renders their children more likely to attain better achievement results as well. This transmission occurs in three different ways: a better genetic make-up, a more intellectually stimulating environment, and interaction effects between genes and environment (see Plomin et al., 2012).

There is ample evidence that individual differences in intelligence have a strong genetic basis (see Plomin & Spinath, 2002). Much less research has investigated the extent to which motivation is heritable (e.g., Johnson, McGue, & Iacono, 2007). With respect to constructs based on EVT, moderate genetic influences of approximately 40% on ability self-concept and intrinsic values were found in a UK-based sample (Spinath, Spinath & Plomin, 2008). Using the same motivational constructs, a German study came to similar heritability estimates (Spinath, Toussaint, Spengler, & Spinath, 2008).

Theoretical and empirical work suggests that SES-related disparities in school achievement may emerge from an interaction of genes and environmental effects (Bradley & Corwyn, 2001; Bronfenbrenner & Ceci, 1994): Children from families with a high SES will be provided with environmental experiences that allow them to tap into their genetic potential. In contrast, children from families with a low SES will probably not grow up in a highly stimulating environment, will have less access to a variety of learning material and thus will not be able to tap into their genetic potential. Furthermore, empirical studies have provided evidence of a genetic influence on differences in children's academic achievement and its association with parents' SES (Krapohl & Plomin, 2015; Trzaskowski et al., 2014). What was striking was that one-third of this reported genetic effect extended to children's intelligence, but two-thirds of the genetic effect on the relationship between parents' SES and children's academic achievement was independent of intelligence (Krapohl & Plomin, 2015). These findings suggest that there is a shared genetic variance between parents' SES and children's achievement that is not only due to manifested differences in children's intelligence, but may also be due to other genetically influenced factors such as academic self-concept and self-efficacy (Krapohl & Plomin, 2015).

1.5 Conclusions from literature review and open questions

Summing up, prior literature supports the notion that children's characteristics, such as intelligence and motivation, partially explain the relationship between social background and academic achievement. These studies have predominantly used school grades as measures of achievement rather than standardized tests. Moreover, it has been shown that the role of motivation as a mediator depends on the SES indicator used. Whereas almost all motivational constructs examined have mediated the relationship between father's SES and children's school grades, not all motivational variables explain the association between mother's SES and children's grades in STEM. For this reason, we also investigated both father's and mother's SES separately in order to examine to what extent the power of motivation differs in explaining social disparities in the standardized test achievement context.

Additional empirical work is needed to analyze the role of different motivational constructs mediating the relationship between SES and standardized test achievement as a performance measure in a representative sample, while simultaneously considering the mediating effect of intelligence and prior achievement. This can only be done in a longitudinal approach. With a longitudinal design, it is also possible to examine the statistical effects of parents' SES on the development of their children's competence in math and whether these effects are mediated by motivational constructs. Moreover, self-efficacy and interest are two motivational constructs that are important components of the EVT and have not been examined before as a factor explaining social disparities. These issues were addressed in the current study.

1.6 The present study: Research questions and hypotheses

The aim of the present study was to determine the extent to which different motivational constructs mediate the relationship between parents' SES and children's standardized test achievement. In addition, we investigated whether the mediating effects of motivation remain significant when simultaneously considering the mediating effects of children's intelligence and prior achievement.

On the basis of the literature mentioned above, the following hypotheses were investigated:

1) Children's motivation (math-specific self-concept, task-specific and global self-efficacy and interest) will partially mediate the association between parents' SES and children's mathematical competence.
2) Children's intelligence will partially mediate the association between parents' SES and children's mathematical competence.

3) The mediating effects of children's motivation will remain significant when simultaneously considering the mediating effect of children's intelligence.
4) The effect of SES on the development of children's mathematical competence will be mediated by children's motivation (math-specific self-concept, self-efficacy and interest) as well as by children's intelligence.

Moreover, we raised the exploratory research question of whether the mediating effects of motivation and intelligence differ depending on the indicator used for SES (mother's ISEI, father's ISEI or family's ESCS).

2. Method

The PISA-I-Plus dataset, a one-year longitudinal approach with German PISA data from 2003 and 2004, was used in this study. The data was created under the direction of the Leibniz-Institut für die Pädagogik der Naturwissenschaften und Mathematik (IPN) and was provided from the Forschungsdatenzentrum (FDZ) at the Institute for Educational Quality Improvement (IQB) (Prenzel et al., 2006).

2.1 Sample and Procedure

The PISA-I-Plus dataset is based on a sample which is fully representative of the German secondary student population that continued school after Grade 9. In the PISA framework, the target population refers to students in the last compulsory school year (Grade 9). The sampling process and the recovery of a representative sample are described in detail in Baumert, Stanat, and Demmrich (2001) and Prenzel et al. (2006). The participating schools were drawn at random from all types of secondary schools in Germany. Within each school that was drawn, one or two randomly drawn classes of ninth-grade students participated in the study. For all public schools, participation was mandatory. Students included in the present analyses were in Grade 9 at the first measurement time point and were tested again one year later in Grade 10. Only students who transferred from Grade 9 into 10 during the 2003/2004 school year were included in the sample (Prenzel, 2006). The sample for the two measurement time points comprised 6,020 students enrolled in 275 schools: 42.6% *Gymnasium* (grammar school), 10.6% comprehensive school, 35.1% *Realschule*, and 11.7% schools with multiple courses of education. Students' mean age was 15.50 years (*SD* = 0.55) at the first measurement occasion. Because more girls continue school after Grade 9 and more boys end their school careers after Grade 9, 55% of the students in the sample were female. Testing took place on three consecutive days (Day 1: test for international comparison; Days 2 and 3: test with national items for math achievement, motivation and intelligence) (Ramm et al., 2006). All of the constructs used in our study were taken on the same day and as part of the regular PISA assessment. All predictors were assessed in 2003, whereas mathematics achievement was assessed both in 2003 and 2004. For students, participation was mandatory for the math achievement test and voluntary for the student questionnaire.

2.2 Measures

2.2.1 SES father and SES mother (ISEI). To assess the SES of both parents in a family, the International Socio-Economic Index (ISEI; Ganzeboom et al., 1992; Ganzeboom & Treiman, 1996) was used in PISA 2003. Children gave reports on their parents' current occupation. Statements about parents' occupations were classified in all countries that participated in PISA based on the International Standard Classification of Occupation of 1988 (ISCO-88; International Labor Office, 1990).

2.2.2 Index for economic, social and cultural status (ESCS). This index represents parents' economic, social and cultural resources and is a composite of the following three variables referring to family background: highest level of education in the family (pared), highest socio-economic status in the family (hisei), and the number of possessions at home including the number of books in the home (homeposs) (Ramm et al., 2006).

2.2.3 Standardized achievement. Children's mathematical competence was measured using the standardized mathematics achievement test during the regular PISA 2003 wave as well as one year later in a longitudinal framework (for a detailed description, see Frey et al., 2010).

2.2.4 Intelligence. The Cognitive Abilities Test 5-12+R (Heller, Gaedike, & Weinläder, 1976) is an established instrument to assess children's intelligence. This test includes nine subtests that can be assigned to the following ability dimensions: verbal thinking, numerical abilities and figural thinking. In the framework of PISA, children's intelligence was only assessed with one subscale (figural analogies) of the dimension figural thinking. This subtest belongs to the non-verbal part of the test and consists of 25 items in a multiple-choice format, has an internal consistency of α = .85 in the normative sample and serves as a proxy for fluid intelligence (Wilhelm & Engle, 2004).

2.2.5 Motivation. The participating children were given a self-report questionnaire assessing mathematics-specific motivational constructs.

2.2.5.1. Math-specific self-concept. Academic self-concept is defined as a self-evaluation of one's competence in a given domain (Marsh & Martin, 2011). Children's math-specific self-concept was assessed with five items on a 4-point scale. These items assessed how well students thought they could take on various math tasks (α = .92; e.g., “I learn quickly in math.”).

2.2.5.2 Self-efficacy (task-specific). Self-efficacy is commonly defined as one’s perception of one’s ability to successfully solve a specific task (Pajares, 1996). Children’s task-specific self-efficacy was assessed with eight items on a 4-point scale. Children were asked to indicate how well they thought they could solve various math tasks (α = .79; e.g., “How sure are you that you can successfully complete the following tasks: Solve the equation 3x + 5 = 17.”).

2.2.5.3. Self-efficacy (global). This measure of self-efficacy does not refer to a specific task but to math in general. Children’s global self-efficacy was assessed with four items on a 4-point scale (adapted for math from Kunter et al., 2002). Children’s were asked to indicate how convinced they were that they can perform well in math (α = .88; e.g., “I am convinced that I can understand the most difficult subject matter in math.”).

2.2.5.4. Interest. Children’s interest was assessed with four items on a 4-point scale. Children were asked how much they like and are interested in math, an example being, “I am interested in the things I learn in mathematics” (α = .90).

2.3 Statistical analysis

2.3.1 Structural equation models. We conducted structural equation modeling using the Mplus software (Version 6.1, Muthén & Muthén, 2011) to examine the extent to which the relationship between parent’s SES and children’s standardized test achievement was mediated by motivation. Because each motivational construct was measured with more than two items per scale, we specified these constructs as latent variables. For intelligence and mathematical competence, we used weighted likelihood estimates for each child (Warm, 1989). We ran separate analyses to test each of our hypotheses. First, only one mediator was included in the model. Figure 1 illustrates the model in which children's task-specific self-efficacy mediates the relationship between ESCS and mathematical competence. Second, each motivational construct was tested as a mediator of the relationship between social background and academic achievement while simultaneously including the mediating effect of children's intelligence (see Figure 2). And third, the restrictive motivational construct and intelligence were tested as mediators of the relationship between ESCS and math achievement while simultaneously considering the mediating effect of prior achievement (see Figure 3).

2.3.2 Evaluation of model fit. To evaluate the fit of the structural equation models, we assessed the Comparative Fit Index (CFI) and the Root Mean Square Error of Approximation (RMSEA). Values greater than .95 for the CFI and less than .05 for the RMSEA are regarded as excellent model fits (Hu & Bentler, 1999). The χ^2 value was also taken into account, but it is well established that the χ^2 value strongly depends on the sample size and is highly sensitive in large samples, often leading to significant χ^2 values (Ullmann, 2007). Therefore, it should be interpreted carefully.

2.3.3 Handling of missing data. The proportion of missing values varied between 0% and 14% for parents' SES, 1.89% for children's intelligence, 4.27% for children's mathematical competence and varied between 1.40% and 1.48% for the motivational variables. Because standardized math achievement was significantly associated with missingness in children's motivational constructs (d = 0.11), it appeared reasonable to assume the missing-at-random mechanism. The full-information-maximum-likelihood method (FIML) in Mplus was used to handle missing data because this approach is unbiased under the missing-at-random (MAR) assumption and typically produces less biased results than listwise deletion while also maintaining statistical power (Enders, 2010).

2.3.4 Weighting and handling selection bias. The “TYPE = COMPLEX” option in Mplus was used to adjust for the effects of sampling error and to correct for the clustering of the data (i.e., students in classes and schools).

2.3.5 Computing confidence intervals. In order to test the significance of the mediated effect, confidence intervals (95%) were computed for each mediator using the RMediation Package (Tofoghi & MacKinnon, 2011). The mediation effect is significantly different from zero if the confidence intervals do not contain zero.

2.3.6 Computing the explained variance of the mediated relationship. The amount of variance in the relationship between parents’ SES and mathematical achievement explained by respective mediator was calculated. To this purpose, the indirect effect was divided by the direct effect. Concretely, the product of the a path (effect of the independent variable on the mediator) and b path (effect of the mediator on the dependent variable) was divided by the c path (effect of the independent on the dependent variable in the basic model).

3. Results

3.1 Descriptive statistics and intercorrelations

Means (M), standard deviations (SD), internal consistencies (α), and intercorrelations for all measures are presented in Table 1. Internal consistencies for children’s motivational measures were very good. Because weighted likelihood estimates were used for the SES, intelligence and mathematical competence measures, we cannot provide an internal consistency value for these measures. Parents' SES was positively associated with mathematical competence at both measurement points (r = .24 for father's SES, r = .21 for mother's SES and r = .30 for ESCS). Father's SES was significantly positively related to all motivational measures, whereas mother's SES was only significantly related to children's math-specific self-concept and self-efficacy (task-specific). Furthermore, we found ESCS to be associated with all measures of children's motivation. The associations between motivational constructs and mathematical competence ranged from r = .23 for interest and r = .49 for task-specific self-efficacy. Children's intelligence was positively associated with all SES measures (r = .14 - .22), motivational constructs (r = .17 - .31) and mathematical competence (r = .55).

3.2 Single mediator models

Our first hypothesis postulated that motivation, intelligence and prior achievement would partially mediate the relationship between SES and mathematical competence. Results for father's SES are shown in Table 2a, for mother's SES in Table 2b, and for ESCS in Table 2c. In the first step, a basic model was computed in which SES predicted academic achievement (b = .21-.30). In a second step, motivation, intelligence or prior achievement were included as mediators of the association between SES and academic achievement. All models had an excellent or good model fit. The results for father's SES provide strong support for our hypothesis. All motivational constructs, intelligence, and prior achievement partially mediated the relationship between father's SES and children's mathematical competence (see Table 2a). Motivation explained between 5% (interest) and 47% (self-efficacy), intelligence explained 41% and prior achievement 68% of the relationship between SES and mathematical competence. When considering mother's SES as an indicator of children's social background, math-specific self-concept, task-specific self-efficacy, intelligence and prior achievement were significant mediators, whereas global self-efficacy and interest did not mediate the association between SES and academic achievement (see Table 2b). Motivation explained between 12% (math-specific self-concept) and 40% (self-efficacy), intelligence 38% and prior achievement 75% of this relationship. When using ESCS as an indicator of SES, all motivational constructs, intelligence and prior achievement partially mediated the relationship between children's social background and their academic achievement (see Table 2c). Motivation explained between 5.4% (interest) and 48% (self-efficacy), intelligence 37% and prior achievement 70% of this relationship. The amount of variance in 2004 mathematical competence explained was the highest in all models with prior achievement as a mediator (R^2 = .54). It is also important to note that task-specific self-efficacy as a mediator explained a greater share of the variance in the relationship between social background and math achievement than intelligence. Even though motivation, intelligence and prior achievement functioned as significant mediators, these effects should be interpreted carefully. The large sample size renders even very small changes in coefficients significant. The association between parents' SES and math achievement was sometimes only minimally - although still significantly - reduced when including a mediator. This was true for math-specific self-concept, global self-efficacy and interest in terms of father's SES, math-specific self-concept for mother's SES and global self-efficacy and interest with regard to ESCS. Furthermore, the investigated mediators only partially explained the relationship at hand, because SES was still significantly associated with academic achievement in all models (b = .08-.29).

3.3 Motivation as mediator when simultaneously considering the mediating effect of intelligence

In our second hypothesis, we postulated that the mediating effect of children's motivation would still be present when simultaneously considering the mediating effect of children's intelligence. Table 3a shows the results of the mediation analyses for father's SES, Table 3b for mother's SES, and Table 3c for ESCS. All models had an excellent or good model fit. When looking at father's SES as an indicator of children's social background, we found that the mediating effect of children's motivation on the relationship between social background and mathematical competence was still significant even when simultaneously considering the mediating effect of intelligence. The same was true for ESCS as an indicator of SES. For mother's SES, math-specific self-concept and task-specific self-efficacy were still significant mediators of the association between SES and academic achievement when simultaneously considering the mediating effect of intelligence. The total explained variance in mathematical competence in 2004 ranged from R^2 = .34 (interest) to .43 (task-specific self-efficacy). In sum, the results were in line with our hypothesis. However, it is important to note that SES still had a significant impact on math achievement in all models.

3.4 Motivation and intelligence as mediators of competence development

Our third hypothesis stated that children's motivation and intelligence would partially mediate the relationship between SES and achievement development in mathematics. We included motivation, intelligence and prior achievement as mediators of the relationship between social background and mathematical competence in the models. Results of these mediation analyses are shown in Table 4a for father's SES, Table 4b for mother's SES, and Table 4c for ESCS. All models had a very good model fit. Prior mathematical competence significantly mediated the relationship between SES and subsequent mathematical competence in 2004 in all models. Moreover, intelligence also mediated this relationship in all models. With regard to father's SES, all motivational constructs except for global self-efficacy functioned as significant mediators. The relationship between mother's SES and standardized test achievement was significantly mediated by math-specific self-concept and task-specific self-efficacy. When investigating ESCS as an indicator of children's social background, we found that all motivational constructs significantly mediated the relationship between SES and standardized test achievement. All variables considered simultaneously explained 57% and 58% of mathematical competence at the second measurement point. Thus, the mediating effects of children's motivation still remained significant when simultaneously considering the mediating effects of prior achievement and intelligence. Nevertheless, the effect of SES on math achievement was small, but still significant, in all models (b = .04-.08).

4. Discussion

The purpose of this investigation was to determine the extent to which motivational constructs mediate the relationship between parents' SES and children's standardized test achievement in mathematics as well as their competence development over one year. The results of the present study, based on a fully representative sample of German students continuing school after Grade 9, provide strong support for the hypothesized framework and emphasize that motivation can partially explain the association between social background and academic achievement. In the following section, we discuss the implications of our results with respect to our hypotheses and look at some of the limitations of our study and opportunities for future research.

4.1 Motivation as mediator of the relationship between SES and academic achievement

In line with our first hypothesis, motivational constructs such as math-specific self-concept, task-specific and global self-efficacy, and interest partially mediated the association between social background and children's mathematical competence. Going beyond the existing literature, these results indicate that motivation is not only a significant mediator of the relationship between SES and academic achievement when using school grades in STEM subjects as achievement criteria (Steinmayr et al., 2012), but also when using standardized test achievement as an achievement criterion. Children of parents with a higher SES also have a more positive academic self-concept, greater self-efficacy and a greater interest in math, which in turn contributes to higher achievement in standardized mathematics tests. Therefore, the present study supports theoretical considerations that children from families with higher SES have better individual performance prerequisites that partially explain their better school performance.

We investigated motivational mediation effects for different indicators of SES. We focused on father's SES, mother's SES, and ESCS as indicators of children's social background, because previous studies had reported divergent results for these indicators. We found different results for motivation mediating the relationship between SES and academic achievement depending on the indicator of social background used. Whereas all motivational constructs significantly mediated the relationships between father's SES and ESCS, respectively, and mathematical competence, only math-specific self-concept and task-specific self-efficacy were significant mediators when mother's SES was used. These results correspond to findings that math-specific self-concept and values significantly mediate the relationship between father's SES and children's school grades in STEM domains, but only academic self-concept mediates the relationship between mother's SES and school grades in chemistry (Steinmayr et al., 2012). Children from homes in which fathers have a high SES typically have higher self-efficacy, academic self-concept and interest in mathematics. One possible explanation might be that fathers use different communication styles compared to mothers, and therefore have a higher influence on children's motivation. A study from Korat, Ron and Klein (2008) investigated mothers' and fathers' interactions with their child while reading an unfamiliar book as well as their verbal expressions. The participants were divided into two groups depending on their parents' SES. The results showed that parents with a lower SES only paraphrased the text, whereas parents with a higher SES used higher cognitive levels of mediation. Moreover, it has been shown that mothers also discussed topics not related to the story with their child, whereas fathers used higher cognitive levels of mediation and discussed the content beyond the text. Another study showed that fathers use more cognitively demanding speech when talking to their sons about science and that this was related to children's interest and self-efficacy in science (Tenenbaum & Leaper, 2003). Against this background, it seems plausible that it is fathers with a high SES, in particular, who use cognitively demanding language and communication styles, familiarize their children with topics in math and science, attract their interest and shape their motivation. Future studies should investigate the extent to which these results extend to other domains like language or social sciences.

Consistent with our second hypothesis, intelligence also partially mediated the relationship between children's social background and their mathematical competence. This empirical finding is also in line with previous studies suggesting that intelligence is a significant mediator of the relationship between parents' SES and children's academic achievement (Baumert et al., 2003; Hecht et al., 2000;

Johnson et al., 2007; Lloyd & Barenblatt, 1984; Steinmayr et al., 2010; Steinmayr et al., 2012). In this context, it is important to note that most of these studies used school grades as achievement criterion. Our study provides strong support for the idea that intelligence is also a significant mediator when using standardized test achievement as the achievement criterion. Moreover, we found that prior achievement partially mediates the relationship between SES and subsequent achievement in math. This is in line with the findings of Steinmayr and colleagues (2012), who showed that prior school grades in STEM subjects significantly mediated the relationship between parents' SES and children's subsequent school grades in STEM domains.

Third, we found strong evidence that math-specific self-concept, self-efficacy and interest partially mediate the relationship between father's SES and children's mathematical competence even when simultaneously considering the mediating effect of intelligence. Again, this was the case not only when father's SES was used as an indicator of children's social background, but also when ESCS was used. When using mother's SES as an indicator of children's social background, only math-specific self-concept and task-specific self-efficacy were significant mediators when simultaneously considering the mediating effect of intelligence. These results are in line with a previous study by Steinmayr and colleagues (2012), who showed that motivation was a significant mediator of the relationship between SES and school grades in STEM domains even when simultaneously considering the mediating effect of intelligence. In fact, motivation and intelligence are mediators of the relationship between SES and academic achievement not only when school grades are used as the achievement measure, but also when standardized test achievement is focused on. These findings also show that it can be beneficial to bring two constructs together which are primarily investigated in two different psychological sub-disciplines.

Moreover, the results of the present study confirm the supposition of EVT (Eccles et al., 1983; Wigfield & Eccles, 2000) that children's social background has an influence on their academic achievement via expectations for success and task values.

Contrary to the findings of Steinmayr et al. (2012), in our study, the path from intelligence to achievement remained significant in all cases even after including motivation as a mediator. This is in line with findings that intelligence is a stronger predictor of standardized test achievement than of school grades and that motivation, especially academic self-concept, is more strongly related to school grades than to standardized test achievement (Steinmayr et al., 2012; Steinmayr & Meißner, 2013).

Fourth, in line with our hypothesis, motivation and intelligence partially mediated the relationship between children's social background and their mathematical competence even when simultaneously considering the mediating effect of prior test achievement. This confirms that intelligence and motivation are important in explaining changes in mathematical competence from ninth to tenth grade. This finding is in line with the results of Steinmayr et al. (2012), who demonstrated that motivation still mediated the relationship between parents' SES and children's grades when controlling for prior school achievement. Indeed, intelligence no longer mediated the relationship between children's social background and their school grades when controlling for prior school grades. Because intelligence was still a significant mediator when using a standardized test as an achievement measure, it suggests once more that intelligence has a greater effect on standardized test achievement than on school grades (see also Helmke, 1992; Steinmayr & Meißner, 2013). One reason for this is the content and methodological overlap of tasks used in intelligence and standardized math achievement tests. However, it has been convincingly shown that math achievement in the framework of PISA is different from intelligence in a theoretical and empirical sense and measures more than just general cognitive ability (Baumert et al., 2007; Prenzel, Walter, & Frey, 2007). In addition, we found parents' SES to be positively related to children's achievement development in math.

Furthermore, the results suggest that children from families with a lower SES might also have a lower academic self-concept, self-efficacy and a lower interest in math. From a practical perspective, teachers should enhance the motivation of such students, which may also affect their math achievement. Compared to intelligence, motivation can be more easily influenced by situational factors such as teaching characteristics (e.g., Midgley, Anderman, & Hicks, 1995). New findings confirm the efficacy of even 90-minute interventions based on EVT that foster students' beliefs in their abilities in the classroom (Gaspard et al., 2015). Such motivational interventions could be especially targeted at children from families with low SES.

4.2 Practical implications for evaluating educational equity

Our findings also have practical implications for the evaluation of educational equity. On the basis of the present findings, we argue that it is not justified to interpret a positive association between family SES and children's school achievement as an indication of an inequitable educational system. The focus on SES or on families' financial resources, to which SES is often reduced in the media, blurs our sight to what is actually driving the association in question. In accordance with prior studies (Steinmayr et al., 2010, 2012), the present study shows that the association between family background and children's school achievement can be partially explained by children's individual characteristics such as motivation and intelligence. This is in line with a meritocratic notion of educational equity: better individual perquisites for achievement should lead to better achievement results. We are aware that there are other possible definitions of educational equity. For example, a compensatory notion holds that because students come with different individual prerequisites, an equitable educational system should try and compensate for these differences. It is true that education not only aims to raise students' competence levels (qualification), but also to level out or at least avoid increasing differences in students' achievement results (equalization). However, in light of the fact that both individual prerequisites of achievement and achievement as such have a strong genetic basis (e.g., Johnson, McGue, & Iacono, 2006; Spinath, Spinath & Plomin, 2008; Walker et al., 2004), it is obvious that no educational system can reach complete equalization of student outcomes and that complete equalization is neither a realistic nor a desirable aim for education. Instead, a good educational system helps students realize their potential. To the extent that this potential is heritable, helping students reach their potential will lead to different educational outcomes. Also, to the extent that students' potential is heritable, an educational system helps students realize their potential will see a positive correlation between parents' characteristics, i.e. SES, intelligence, motivation, and their children's educational achievement. Thus, it is a practical implication of the present results that a positive association between family SES and children's school achievement should no longer be considered an indicator of educational inequity.

4.3 Strengths and limitations of this study

The current study has a number of important strengths. One strength of this study is its large, representative sample of German students who continue school after Grade 9. Another strength of our study is the combined use of cross-sectional and longitudinal analyses, which enabled us to examine the power of intelligence and motivation in mediating the relationship between SES and changes in mathematical competence over one school year. Nevertheless, the results must be interpreted in light of a few limitations. One limitation specific to our study is that we cannot draw causal conclusions because of the correlational design. When we speak of the “effects” of one variable on another, this is meant in a statistical sense, not in a causal one. Second, and also a consequence of the correlational design, there might be alternative explanations for the mediating effects. We cannot exclude the possibility that other variables can explain the same amount or more variance than the variables investigated here. Third, we investigated the relationship between SES, motivation and achievement on a phenotypic level, because this is the level on which questions of educational inequity are usually discussed. Our study does not include genetic data. However, it is well established that phenotypic relationships between such traits and academic achievement are mediated genetically and that genes play an important role, meaning that they are possible causes for the mediating role of motivation and intelligence.

4.4 Future research

One direction for future research is to investigate not only children’s characteristics with regard to motivation and intelligence, but also parents’ characteristics and characteristics of the home environment as mediators of the relationship between social background and academic achievement. Some studies have used PISA data to examine the role of cultural influences like cultural property, the numbers of books at home, education-related resources, cultural communication, and attendance at cultural events as possible mediators (Ehmke et al., 2006; Jungbauer-Gans, 2004; Watermann & Baumert, 2006). It has been shown that these variables could not completely explain the relationship between parents’ SES and students’ academic achievement. It would also be worthwhile to investigate parents’ motivation and intelligence as possible mediators.

Another direction for future research concerns whether our results can be generalized to other competence domains in PISA, like reading or science. It would also be interesting to investigate whether motivation and intelligence mediate the relationship between SES and academic achievement in other age groups, as we only tested students from Grades 9 to 10. Further research is warranted to explore whether the impact of SES on academic achievement remains stable or decreases with age and whether motivation can partially explain the association with academic achievement. As motivation and intelligence only partially mediated the relationship between parents' SES and children's academic achievement, additional empirical work is also needed to explore other factors as possible mediators. This may help provide a better understanding of the underlying processes through which social disparities affect academic achievement.

As our study indicates that motivation helps explain social disparities in the achievement context, the question arises as to *why* motivation explains the relationship between social background and academic achievement and why children from families with a lower socio-economic status are less motivated, have a lower academic self-concept and lower self-efficacy. Future research should examine the following factors as possible causes: genes, early childhood development, parental care, academic education, and psychosocial factors, and clarify how our results came into being. Specifically, it is a potentially important research topic to investigate the extent to which genes determine the relationship between parents' SES and children's academic achievement as well as the role of motivation as a mediator of this relationship.

4.5 Conclusion

Our results indicate that the association between social background and academic achievement is complex and partially explained by children's prior achievement, intelligence and motivation. These mediating processes contribute to social disparities in competency acquisition in the school context. On the basis of the data presented, we question the common notion that a positive association between family SES and academic achievement is an indicator of educational inequity per se. Instead, it is important to understand the causes of this relationship. If educational equity is defined in terms of an educational system in which better achievement prerequisites lead to better academic achievement, then a positive association between family SES and children's school achievement is to be interpreted as an indicator of an equitable educational system, if the association is mediated by such factors as children's intelligence and motivation.

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Acknowledgements

We would like to thank the Research Data Centre (FDZ) at the Institute for Educational Quality Improvement for providing the PISA-I-Plus dataset.

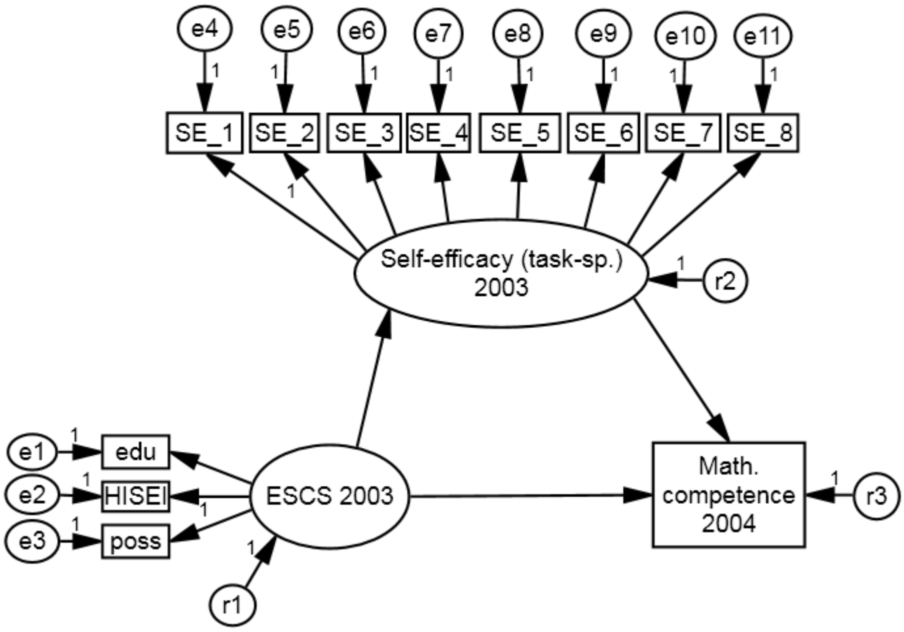

Figure 1. Structural equation model specified to test children's self-efficacy (task-specific) in math as a mediator of the relationship between family's ESCS and children's standardized test achievement in math. Children's mathematical competence was explained by family's ESCS (indicated by family's highest level of education and highest SES as well as by number of possessions at home) and children's self-efficacy (indicated by eight items). The depicted model is an example for all models testing one mediator at a time.

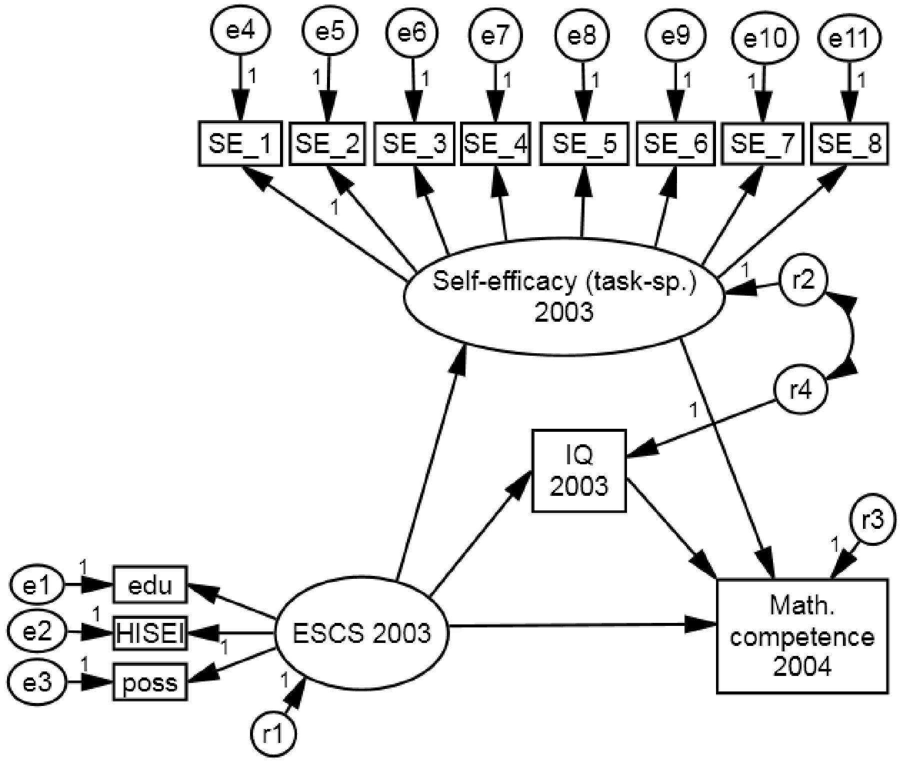

Figure 2. Structural equation model specified to test children's self-efficacy (task-specific) in math as a mediator of the relationship between family's ESCS and children's standardized test achievement in math while simultaneously considering the mediating effect of children's intelligence. Children's mathematical competence was explained by family's ESCS (indicated by family's highest level of education and highest SES as well as by number of possessions at home), children's self-efficacy (indicated by eight items) and their intelligence. The depicted model is an example for all models testing the motivational constructs as mediators while simultaneously considering the mediating effect of children's intelligence.

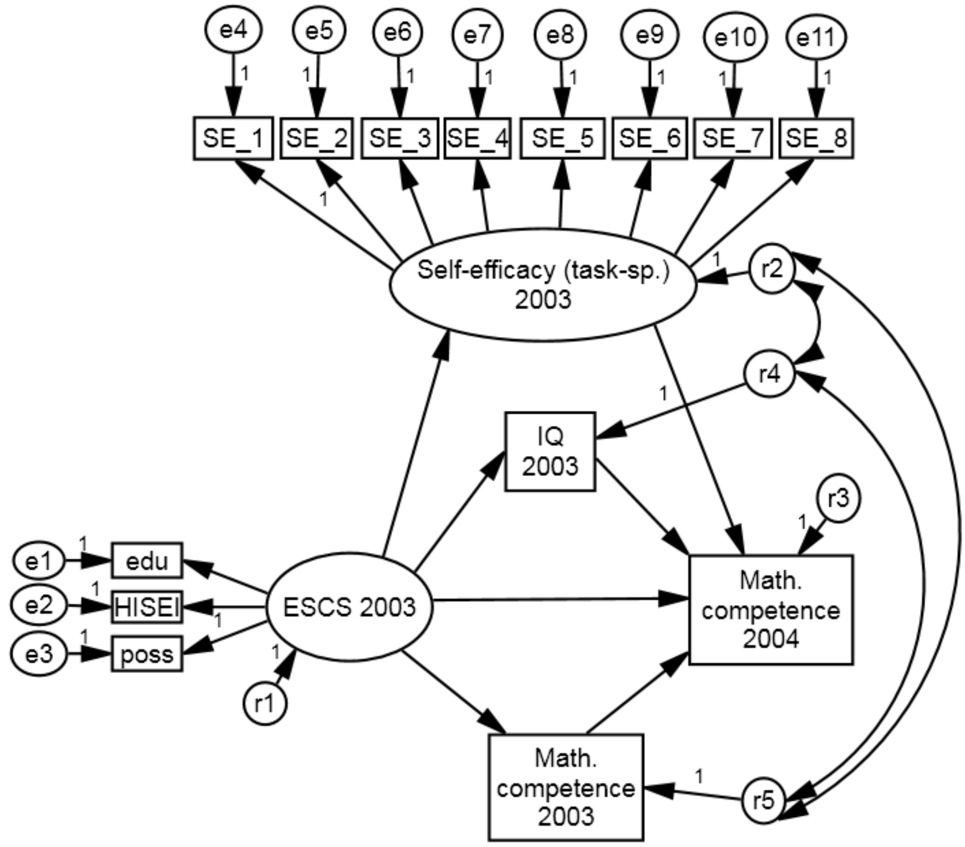

Figure 3. Structural equation model specified to test children's self-efficacy (task-specific) in math as a mediator of the relationship between family's ESCS and children's standardized test achievement in math while simultaneously considering the mediating effects of children's intelligence and their prior math achievement. Children's mathematical competence was explained by family's ESCS (indicated by family's highest level of education and highest SES as well as by number of possessions at home), children's self-efficacy (indicated by eight items), their intelligence and prior mathematical competence (one year ago). The depicted model is an example for all models testing the motivational constructs as mediators while simultaneously considering the mediating effects of children's intelligence and prior achievement.

Table 1

Means (M), Standard deviations (SD), internal consistencies (α) and intercorrelations among mothers' and fathers' socio-economic status and children's mathematical competence, intelligence and motivation

	Descriptives			Intercorrelations								
	M	*SD*	α	fSES	ESCS	IQ	SC	SEtask	SEglob	Int	MC03	MC04
Mother's SES (mSES)	46.33	15.26	-	.39**	.60**	.14**	.07**	.15**	.02	.02	.21**	.21**
Father's SES (fSES)	49.44	17.70	-		.76**	.18**	.07**	.20**	.05*	.05**	.23**	.24**
ESCS	.55	.85	-			.22**	.09**	.27**	.06**	.07**	.30**	.30**
Intelligence (IQ)	49.76	10.52	-				.27**	.31**	.19**	.17**	.55**	.55**
Math-specific self-concept (MSC)	2.51	.82	.92					.53**	.76**	.73**	.35**	.34**
Self-efficacy (task-specific) (SEtask)	3.15	.51	.79						.48**	.42**	.49**	.45**
Self-efficacy (global) (SEglob)	2.81	.78	.88							.60**	.25**	.26**
Math-specific Interest (Int)	2.22	.82	.90								.23**	.24**
Math. Competence 2003 (MC03)	546.40	84.66	-									.73**
Math. Competence 2004 (MC04)	569.77	81.40	-									

Notes. ** $p < .01$, * $p < .05$.

Table 2a

Results of structural equation modeling (full-information-maximum-likelihood estimations) testing children's motivation (academic self-concept, self-efficacy and interest), intelligence and prior achievement as mediators of the relationship between fathers' socio-economic status and children's subsequent mathematical competence as well as confidence intervals for the mediated effects

Model	Fit Indices				R^2	Standardized coefficients			CIs of mediated effect
	χ^2	df	CFI	RMSEA	Model	SES ➔ MC04	SES ➔ Med	Med ➔ MC04	Med
Basic	0.00	0	1.00	.000	.06	.24***			
MSC	297.67	13	.982	.060	.18	.22***	.08***	.34***	**[.016; .036]**
SEtask	442.06	31	.965	.047	.28	.13***	.23***	.49***	**[.094; .130]**
SEglob	140.76	8	.973	.053	.13	.23***	.05*	.26***	**[.002; .024]**
Interest	130.26	8	.990	.050	.12	.23***	.05**	.24***	**[.004; .019]**
IQ	0.00	0	1.00	.000	.32	.15***	.19***	.52***	**[.080; .112]**
MC03	0.00	0	1.00	.000	.54	.08***	.23***	.71***	**[.141; .187]**

Notes. df = model degrees of freedom; CFI = comparative fit index; RMSEA = root mean square error of approximation; ➔ = path weight; SES = socio-economic status; MSC = math-specific self-concept; SEtask = task-specific self-efficacy; SEglob = global self-efficacy; IQ = Intelligence; MC03 = mathematical competence 2003; MC04 = mathematical competence 2004; CI = 95% interval; CIs not including zero indicate a significant mediation effect; **p* < .05; ***p* < .01; ****p* < .001.

Table 2b

Results of structural equation modeling (full-information-maximum-likelihood estimations) testing children's motivation (academic self-concept, self-efficacy and interest), intelligence and prior achievement as mediators of the relationship between mothers' socio-economic status and children's subsequent mathematical competence as well as confidence intervals for the mediated effects

Model	Fit Indices				R^2	Standardized coefficients			CIs of mediated effect
	χ^2	df	CFI	RMSEA	Model	SES ➔ MC04	SES ➔ Med	Med ➔ MC04	Med
Basic	0.00	0	1.00	.000	.05	.21***			
MSC	283.69	13	.982	.059	.16	.19***	.07***	.35***	**[.014; .034]**
SEtask	427.89	31	.966	.046	.29	.13***	.17***	.50***	**[.069; .104]**
SEglob	142.97	8	.972	.053	.12	.20***	.03	.27***	[-.004; .019]
Interest	132.21	8	.990	.051	.10	.21***	.03	.24***	[-.002; .014]
IQ	0.00	0	1.00	.000	.32	.14***	.15***	.53***	**[.060; .092]**
MC03	0.00	0	1.00	.000	.54	.06***	.22***	.72***	**[.131; .179]**

Notes. df = model degrees of freedom; CFI = comparative fit index; RMSEA = root mean square error of approximation; ➔ = path weight; SES = socio-economic status; MSC = math-specific self-concept; SEtask = task-specific self-efficacy; SEglob = global self-efficacy; IQ = Intelligence; MC03 = mathematical competence 2003; MC04 = mathematical competence 2004; CI = 95% interval; CIs not including zero indicate a significant mediation effect; *p < .05; **p < .01; ***p < .001.

Table 2c

Results of structural equation modeling (full-information-maximum-likelihood estimations) testing children's motivation (academic self-concept, self-efficacy and interest), intelligence and prior achievement as mediators of the relationship between ESCS and children's subsequent mathematical competence as well as confidence intervals for the mediated effects

Model	Fit Indices				R^2	Standardized coefficients			CIs of mediated effect
	χ^2	df	CFI	RMSEA	Model	SES ➔ MC04	SES ➔ Med	Med ➔ MC04	Med
Basic	0.00	0	1.00	.000	.09	.30***			
MSC	300.50	13	.982	.061	.20	.27***	.10***	.33***	**[.023; .042]**
SEtask	468.27	31	.964	.048	.30	.16***	.30***	.48***	**[.127; .162]**
SEglob	141.78	8	.975	.053	.16	.28***	.07***	.26***	**[.007; .029]**
Interest	131.08	8	.990	.051	.14	.29***	.07***	.23***	**[.009; .024]**
IQ	0.00	0	1.00	.000	.33	.19***	.22***	.50***	**[.095; .128]**
MC03	0.00	0	1.00	.000	.54	.09***	.30***	.70***	**[.186; .232]**

Notes. df = model degrees of freedom; CFI = comparative fit index; RMSEA = root mean square error of approximation; ➔ = path weight; SES = socio-economic status; MSC = math-specific self-concept; SEtask = task-specific self-efficacy; SEglob = global self-efficacy; IQ = Intelligence; MC03 = mathematical competence 2003; MC04 = mathematical competence 2004; CI = 95% interval; CIs not including zero indicate a significant mediation effect; **p* < .05; ***p* < .01; ****p* < .001.

Table 3a

Results of structural equation modeling (full-information-maximum-likelihood estimations) testing children's motivation (academic self-concept, self-efficacy and interest) as mediators of the relationship between fathers' socio-economic status and children's subsequent mathematical competence as well as confidence intervals for the mediated effects, simultaneously considering the mediating effects of children's intelligence

Model	Fit Indices				R^2	Standardized coefficients						CIs of mediated effect
	χ^2	df	CFI	RMSEA	Model	SES ➔ MC04	SES ➔ Mot	Mot ➔ MC04	SES ➔ IQ	IQ ➔ MC04	Mot ←➔ IQ	Mot; IQ
MSC + IQ	304.45	17	.985	.053	.37	.15***	.08***	.22***	.19***	.46***	.28***	**[.010; .024]** **[.071; .100]**
SEtask + IQ	502.83	38	.967	.045	.43	.09***	.23***	.36***	.19***	.40***	.33***	**[.069; .096]** **[.062; .088]**
SEglob + IQ	154.62	11	.982	.047	.35	.15***	.05*	.17***	.19***	.49***	.19***	**[.001; .015]** **[.075; .105]**
Interest + IQ	145.83	11	.992	.045	.34	.15***	.05**	.15***	.19***	.49***	.18***	**[.002; .012]** **[.076; .107]**

Notes. df = model degrees of freedom; CFI = comparative fit index; RMSEA = root mean square error of approximation; ➔ = path weight; SES = socio-economic status; MSC = math-specific self-concept; SEtask = task-specific self-efficacy; SEglob = global self-efficacy; IQ = Intelligence; MC04 = mathematical competence 2004; Mot = motivational variable; CI = 95% interval; CIs not including zero indicate a significant mediation effect; **p* < .05; ***p* < .01; ****p* < .001.

Table 3b

Results of structural equation modeling (full-information-maximum-likelihood estimations) testing children's motivation (academic self-concept, self-efficacy and interest) as mediators of the relationship between mothers' socio-economic status and children's subsequent mathematical competence as well as confidence intervals for the mediated effects, simultaneously considering the mediating effects of children's intelligence

Model	Fit Indices				R^2	Standardized coefficients						CIs of mediated effect
	χ^2	df	CFI	RMSEA	Model	SES ➔ MC04	SES ➔ Mot	Mot ➔ MC04	SES ➔ IQ	IQ ➔ MC04	Mot ←➔ IQ	Mot; IQ
MSC + IQ	292.51	17	.985	.052	.36	.13***	.07***	.22***	.15***	.47***	.28***	**[.009; .021]**
												[.053; .082]
SEtask + IQ	490.98	38	.968	.044	.43	.09***	.17***	.37***	.15***	.40***	.34***	**[.050; .076]**
												[.046; .071]
SEglob + IQ	157.56	11	.981	.047	.35	.14***	.03	.18***	.15***	.49***	.19***	[-.003; .013]
												[.057; .087]
Interest + IQ	147.58	11	.992	.045	.34	.14***	.02	.16***	.15***	.50***	.18***	[-.001; .009]
												[.057; .088]

Notes. df = model degrees of freedom; CFI = comparative fit index; RMSEA = root mean square error of approximation; ➔ = path weight; SES = socio-economic status; MSC = math-specific self-concept; SEtask = task-specific self-efficacy; SEglob = global self-efficacy; IQ = Intelligence; MC04 = mathematical competence 2004; Mot = motivational variable; CI = 95% interval; CIs not including zero indicate a significant mediation effect; **p* < .05; ***p* < .01; ****p* < .001.

Table 3c

Results of structural equation modeling (full-information-maximum-likelihood estimations) testing children's motivation (academic self-concept, self-efficacy and interest) as mediators of the relationship between ESCS and children's subsequent mathematical competence as well as confidence intervals for the mediated effects, simultaneously considering the mediating effects of children's intelligence

Model	Fit Indices				R^2	Standardized coefficients						CIs of mediated effect
	χ^2	df	CFI	RMSEA	Model	SES ➔ MC04	SES ➔ Mot	Mot ➔ MC04	SES ➔ IQ	IQ ➔ MC04	Mot ←➔ IQ	Mot; IQ
MSC + IQ	308.00	17	.985	.053	.38	.18***	.10***	.22***	.22***	.45***	.27***	**[.014; .027]** **[.083; .114]**
SEtask + IQ	529.70	38	.967	.046	.43	.11***	.30***	.35***	.22***	.40***	.31***	**[.092; .120]** **[.074; .102]**
SEglob + IQ	156.50	11	.983	.047	.36	.19***	.07***	.17***	.22***	.47***	.18***	**[.004; .019]** **[.088; .121]**
Interest + IQ	146.99	11	.992	.045	.35	.19***	.07***	.15***	.22***	.48***	.17***	**[.006; .016]** **[.090; .122]**

Notes. df = model degrees of freedom; CFI = comparative fit index; RMSEA = root mean square error of approximation; ➔ = path weight; SES = socio-economic status; MSC = math-specific self-concept; SEtask = task-specific self-efficacy; SEglob = global self-efficacy; IQ = Intelligence; MC04 = mathematical competence 2004; Mot = motivational variable; CI = 95% interval; CIs not including zero indicate a significant mediation effect; **p* < .05; ***p* < .01; ****p* < .001.

Table 4a

Results of structural equation modeling (full-information-maximum-likelihood estimations) testing children's motivation (academic self-concept, self-efficacy and interest) as mediators of the relationship between fathers' socio-economic status and children's subsequent mathematical competence as well as confidence intervals for the mediated effects, simultaneously considering the mediating effects of children's intelligence and prior mathematical competence (MC03)

Model	Fit Indices				R^2	Standardized coefficients										CIs of mediated effect
	χ^2	df	CFI	RMSEA	Model	SES ➔ MC04	SES ➔ Mot	Mot ➔ MC04	SES ➔ IQ	IQ ➔ MC04	SES ➔ MC03	MC03 ➔ MC04	Mot ←➔ IQ	Mot ←➔ MC03	IQ ←➔ MC03	Mot; IQ; MC03
MSC + IQ + MC03	318.28	21	.989	.048	.57	.07***	.08***	.09***	.19***	.19***	.24***	.58***	.28***	.36***	.53***	**[.004; .010]** **[.028; .042]** **[.116; .154]**
SEtask + IQ + MC03	529.14	45	.977	.042	.58	.06***	.23***	.15***	.19***	.19***	.24***	.53***	.33***	.54***	.53***	**[.026; .041]** **[.029; .043]** **[.107; .142]**
SEglob + IQ + MC03	155.37	14	.991	.041	.57	.07***	.05*	.08***	.19***	.19***	.24***	.58***	.19***	.26***	.53***	[.000; .008] **[.029; .043]** **[.118; .157]**
Interest + IQ + MC03	147.34	14	.995	.040	.57	.07***	.05**	.07***	.19***	.20***	.24***	.59***	.18***	.24***	.53***	**[.001; .006]** **[.029; .044]** **[.119; .158]**

Notes. df = model degrees of freedom; CFI = comparative fit index; RMSEA = root mean square error of approximation; ➔ = path weight; SES = socio-economic status; MSC = math-specific self-concept; SEtask = task-specific self-efficacy; SEglob = global self-efficacy; IQ = Intelligence; MC03 = mathematical competence 2003; MC04 = mathematical competence 2004; Mot = motivational variable; CI = 95% interval; CIs not including zero indicate a significant mediation effect;**p* < .05; ***p* < .01; ****p* < .001.

Table 4b

Results of structural equation modeling (full-information-maximum-likelihood estimations) testing children's motivation (academic self-concept, self-efficacy and interest) as mediators of the relationship between mothers' socio-economic status and children's subsequent mathematical competence as well as confidence intervals for the mediated effects, simultaneously considering the mediating effects of children's intelligence and prior mathematical competence (MC03)

Model	Fit Indices				R^2	Standardized coefficients										CIs of mediated effect
	χ^2	df	CFI	RMSEA	Model	SES $\rightarrow$ MC04	SES $\rightarrow$ Mot	Mot $\rightarrow$ MC04	SES $\rightarrow$ IQ	IQ $\rightarrow$ MC04	SES $\rightarrow$ MC03	MC03 $\rightarrow$ MC04	Mot $\leftrightarrow$ IQ	Mot $\leftrightarrow$ MC03	IQ $\leftrightarrow$ MC03	Mot; IQ; MC03
MSC + IQ + MC03	308.08	21	.989	.048	.57	.05***	.07***	.09***	.15***	.19***	.22***	.58***	.28***	.36***	.54***	[**.003; .009**] [**.022; .035**] [**.105; .145**]
SEtask + IQ + MC03	515.78	45	.978	.042	.58	.04***	.17***	.15***	.15***	.19***	.22***	.53***	.34***	.55***	.54***	[**.020; .033**] [**.022; .035**] [**.096; .133**]
SEglob + IQ + MC03	159.23	14	.991	.042	.57	.05***	.03	.08***	.15***	.20***	.22***	.59***	.19***	.26***	.54***	[-.001; .006] [**.022; .036**] [**.106; .147**]
Interest + IQ + MC03	149.09	14	.995	.040	.57	.05***	.02	.07***	.15***	.20***	.22***	.59***	.18***	.24***	.54***	[.000; .004] [**.022; .036**] [**.107; .148**]

Notes. df = model degrees of freedom; CFI = comparative fit index; RMSEA = root mean square error of approximation; $\rightarrow$ = path weight; SES = socio-economic status; MSC = math-specific self-concept; SEtask = task-specific self-efficacy; SEglob = global self-efficacy; IQ = Intelligence; MC03 = mathematical competence 2003; MC04 = mathematical competence 2004; Mot = motivational variable; CI = 95% interval; CIs not including zero indicate a significant mediation effect;**p* < .05; ***p* < .01; ****p* < .001.

Table 4c

Results of structural equation modeling (full-information-maximum-likelihood estimations) testing children's motivation (academic self-concept, self-efficacy and interest) as mediators of the relationship between ESCS and children's subsequent mathematical competence as well as confidence intervals for the mediated effects, simultaneously considering the mediating effects of children's intelligence and prior mathematical competence (MC03)

Model	Fit Indices				R^2	Standardized coefficients										CIs of mediated effect
	χ^2	df	CFI	RMSEA	Model	SES ➔ MC04	SES ➔ Mot	Mot ➔ MC04	SES ➔ IQ	IQ ➔ MC04	SES ➔ MC03	MC03 ➔ MC04	Mot ↔ IQ	Mot ↔ MC03	IQ ↔ MC03	Mot; IQ; MC03
MSC + IQ + MC03	322.37	21	.989	.049	.57	.08***	.10***	.09***	.22***	.19***	.30***	.57***	.27***	.36***	.52***	**[.006; .012]** **[.034; .050]** **[.150; .189]**
SEtask + IQ + MC03	557.51	45	.976	.043	.58	.06***	.30***	.14***	.22***	.19***	.30***	.53***	.31***	.52***	.52***	**[.034; .053]** **[.035; .050]** **[.139; .176]**
SEglob + IQ + MC03	157.48	14	.991	.041	.57	.08***	.07***	.08***	.22***	.19***	.30***	.58***	.19***	.26***	.52***	**[.002; .010]** **[.035; .051]** **[.153; .192]**
Interest + IQ + MC03	148.12	14	.995	.040	.57	.08***	.07***	.07***	.22***	.19***	.30***	.58***	.17***	.23***	.52***	**[.002; .007]** **[.035; .051]** **[.155; .194]**

Notes. df = model degrees of freedom; CFI = comparative fit index; RMSEA = root mean square error of approximation; ➔ = path weight; SES = socio-economic status; MSC = math-specific self-concept; SEtask = task-specific self-efficacy; SEglob = global self-efficacy; IQ = Intelligence; MC03 = mathematical competence 2003; MC04 = mathematical competence 2004; Mot = motivational variable; CI = 95% interval; CIs not including zero indicate a significant mediation effect;**p* < .05; ***p* < .01; ****p* < .001.

6.3 Study 3: Longitudinal Reciprocal Effects Between Teachers' Judgments of Students' Aptitude, Students' Motivation, and Math Grades

Note: This is the first author's version of a study that was published in *Contemporary Educational Psychology*. The following manuscript does not exactly replicate the final version that was published in the journal. It is neither a copy of the original article nor a suitable citation.

Kriegbaum, K., Steinmayr, R., & Spinath, B. (2019). Longitudinal reciprocal effects between teachers' judgments of students' aptitude, students' motivation, and grades in math. *Contemporary Educational Psychology*. Advance online publication. doi: 10.1016/j.cedpsych.2019.101807

Abstract

We investigated whether teachers' judgments of students' aptitude had reciprocal effects on students' motivation and math grades. We expected that teachers' judgments of students' aptitude would predict students' grades and motivation, and that teachers' judgments would also be predicted by these two aspects. A sample of *N* = 519 elementary school students was investigated at four measurement occasions from the end of third until the end of fourth grade. Students reported their self-concepts and intrinsic task values in math. Teachers (*N* = 27) judged students' aptitude in math and provided students' math grades. Cross-lagged panel analyses revealed that students' prior grades and prior self-concepts (but not intrinsic task values) had positive effects on teachers' subsequent judgments of student aptitude. Also, teachers' prior judgments of student aptitude predicted students' subsequent grades but not motivation. The findings underscore the importance of teachers' judgments for students' achievement development and give insights into which students' motivational variables influence teachers' perceptions of students' aptitude.

Keywords: academic self-concept, intrinsic task values, teachers' judgments

1. Introduction

Teachers' judgments of students' aptitude or general cognitive ability are important because they have been shown to influence students' development as early as elementary school and beyond (e.g., Alvidrez & Weinstein, 1999; Friedrich, Flunger, Nagengast, Jonkmann, & Trautwein, 2015; Rubie-Davies et al., 2014; Smith, Jussim, & Eccles, 1999; Tiedemann, 2000; Trouilloud, Sarrazin, Martinek, & Guillet, 2002). Effects of teachers' judgments of students' aptitude on students' motivation (e.g., academic self-concept), which in turn influences students' achievement, can be interpreted as a self-fulfilling prophecy (Brophy & Good, 1970). These effects are also suggested in Eccles et al.'s (1983) expectancy-value theory of achievement motivation. It can be argued that teachers, on the basis of their judgments of students' aptitude, treat students differently and that students react to this treatment and might develop higher or lower motivation, which may improve or impair their achievement in the long run. Some studies have examined effects of teachers' judgments on different student outcomes such as achievement and motivation (Kaiser, Retelsdorf, Südkamp, & Möller, 2013; Rubie-Davies et al., 2014; Smith et al., 1999; Tiedemann, 2000; Trouilloud et al., 2002). Whereas a few studies have investigated the effects of teachers' judgments on students' ability self-concept, to our knowledge, no study has yet examined the effects of teachers' judgments of students' aptitude on students' intrinsic task values in elementary school. Elementary school is an important stage for the development of school-related motivation (Spinath & Steinmayr, 2008; Wigfield et al., in press). Longitudinal studies in which each construct is assessed at several time points can contribute to uncovering the process of how teachers' judgments might influence students' motivation and achievement development and vice versa.

Little is known about the student variables that teachers take into account when judging students' aptitude. Studies have demonstrated that students' achievement (Dickhäuser & Stiensmeier-Pelster, 2003; Rubie-Davies et al., 2014; Tiedemann, 2000), general cognitive ability (Baudson, Fischbach, & Preckel, 2016), and socioeconomic status (Baudson et al., 2016) predict teachers' judgments. Moreover, one study showed that students' engagement as a proxy for students' motivation had an influence on teachers' judgments of students' achievement (Kaiser et al., 2013). To our knowledge, no empirical studies have investigated how prominent motivational constructs, such as students' academic self-concept and intrinsic task values, predict teachers' judgments of students' aptitude.

Given these results, it is worthwhile to look into whether teachers' judgments of students' aptitude predict students' achievement and motivation longitudinally, and in reverse, how students' motivation (e.g., students' academic self-concept and their intrinsic task values in a specific domain) also predict teachers' judgments of students' aptitude. It seems likely that students with a high academic self-concept in a specific domain can convince their teachers of their high ability and would then be judged as having high aptitude by the teacher. Also, it might be possible for a teacher to judge an active student who shows high subject-specific intrinsic task values as having a high aptitude.

Therefore, we aimed to achieve two goals with this study. First, we examined the effects of teachers' judgments of students' aptitude on students' achievement and motivation development. Second and in reverse, we investigated the extent to which students' achievement and academic motivation predicted teachers' judgments of students' aptitude. Because these effects might already be important in the early school years, we focused on elementary school children. We used a longitudinal design with four measurement occasions from the end of the third grade until the end of the fourth grade and computed cross-lagged models. Models of this kind allow longitudinal reciprocal effects to be estimated between teachers' judgments of students' aptitude and students' achievement as well as students' motivation.

The findings of our study will lead to a deeper understanding not only of the importance of teachers' judgments of students' aptitude for students' achievement and motivation development in elementary school but also of the importance of students' motivation when teachers judge students' aptitude.

1.1 Definition and operationalization of teachers' judgments

In the last 50 years, a large number of studies have examined the role of teachers' judgments in determining student outcomes. Because different kinds of teachers' judgments have been investigated, it is important to define these constructs and to clarify how these constructs are operationalized. Teachers' judgments can be seen as an umbrella term with different facets that depend on which student characteristics are being judged and which time frame the judgment refers to. One facet, which is called teachers' expectations, is defined as inferences teachers make about students' future behavior and achievement (Good, 1987) and is measured as teachers' predictions of students' achievement in the near future (e.g., Brattesani, Weinstein, & Marshall, 1984; Rubie-Davies, 2006; Rubie-Davies, Hattie, & Hamilton, 2006; Trouilloud et al., 2002) or regarding their graduation (de Boer, Bosker, & van der Werf, 2010; Gregory & Huang, 2013).

Another facet is typically conceptualized as teachers' estimations of students' past or current achievement (Hoge & Coladarci, 1989) and is not future-related in contrast to teachers' expectations. In many studies, teachers' judgments were operationalized as an estimation of students' achievement on a standardized test (e.g., Hoge & Butcher, 1984; Hoge & Coladarci, 1989; see the meta-analysis by

Südkamp, Kaiser, & Möller, 2012; Zhu & Urhahne, 2015; Zhu, Urhahne, & Rubie-Davies, 2018) or as ratings of students' competence in specific domains such as reading (e.g., Begeny, Eckert, Montarello, & Storie, 2008; Brophy & Good, 1970; Kaiser et al., 2013). These studies typically examined the accuracy of teachers' judgments by computing correlations between teachers' judgments of students' achievement on a standardized test and students' actual achievement on this test.

A third facet of teachers' judgments that was examined in some studies was operationalized as teachers' estimations of students' current aptitude in a specific subject such as mathematics (Baker, Tichovolsky, Kupersmidt, Voegler-Lee, & Arnold, 2015; Dickhäuser & Stiensmeier-Pelster, 2003; Rubie-Davies et al., 2014; Tiedemann, 2000; Trouilloud et al., 2002) or as an estimation of students' general cognitive ability/intelligence (Alvidrez & Weinstein, 1999; Baudson et al., 2016; Hoge & Butcher, 1984; Rubie-Davies et al., 2014). Aptitude is defined as an individual's capacity for learning and proficiency in a specific domain (Snow, 1992; Stemler & Sternberg, 2013). Students' aptitude is the potential to learn and achieve. It is a prerequisite for achievement outcomes such as school grades, but is not always reflected by actual achievement (e.g., underachievers). Therefore, students' aptitude is not as directly observable by teachers as students' actual achievement is. However, teachers' judgments of students' aptitude can have far-reaching consequences for students in elementary school concerning students' motivation, students' achievement, and teachers' recommendations for secondary school (Steinmayr, Michels, & Weidinger, 2017). In the following, we focus on teachers' judgments of students' current aptitude both in our study and in the literature review.

1.2 The effects of teachers' judgments of students' aptitude on students' achievement and motivation

When examining the effects of teachers' judgments of students' aptitude on student outcomes, many empirical studies have focused on the prediction of students' achievement and its development. Furthermore, few studies have examined the effects of teachers' judgments on students' motivation.

Because all of the studies presented in the following section focused on expectancies and task values as motivational constructs, the underlying expectancy-value theory should be described. According to the expectancy-value theory of achievement motivation (Eccles et al., 1983), motivation can be described as expectancies and task values. Expectancies are defined as beliefs about future success in a specific task, and these beliefs are supposed to be influenced by an individual's academic self-concept. Even though these two constructs are differentiated in expectancy-value theory, many empirical studies have shown that they are highly correlated and have used them interchangeably (Wigfield & Eccles, 2002). Also, a most recent study by Marsh and colleagues (2019) showed that academic self-concept, outcome expectancies and generalized self-efficacy are highly correlated (r = .88 - .97) and apparently reflect a similar construct, even though the constructs have different labels. Therefore, academic self-concept, which is typically assessed domain-specifically, can be seen as an expectancy component. For achievement task values, Eccles et al. (1983) defined four different aspects: intrinsic value, attainment value, utility value, and cost. Intrinsic value is defined as the enjoyment of doing a task and subjective interest in a task/subject. This intrinsic task value is similar in certain respects to intrinsic motivation, but it is important that these two constructs stem from different theoretical traditions. Intrinsic motivation is a construct embedded in Self-Determination Theory, and is defined as engaging in something for its’ own sake and for enjoyment (Deci & Ryan, 2002). Attainment value is defined as the importance of doing well in a specific task. Utility value refers to how useful a task is for future goals or activities, and cost is a negative component that refers to the costs that emerge from doing a task. These task values are typically assessed domain-specifically (e.g., in relation to the domain of math). In the present study, we focused on students’ academic self-concept and intrinsic task value for math as motivational constructs.

Theoretically, in their expectancy-value theory of achievement motivation, Eccles et al. (1983) explicitly assumed an influence of socializers’ beliefs such as teachers’ beliefs about students’ characteristics (e.g., aptitude in a specific domain, general cognitive ability) on students’ academic self-concept, which in turn is supposed to influence students’ achievement.

Moreover, the effects of teachers’ judgments on students’ achievement can be the result of self-fulfilling prophecy effects (Brophy & Good, 1970). This approach originated in the field of research on teachers’ expectations but has been transferred to research on teachers’ judgment several times (e.g., Friedrich et al., 2015; Rubie-Davies et al., 2014; Zhu et al., 2018). The mechanisms behind these effects of teachers’ judgments on students’ achievement might be the following: On the basis of their judgments of students’ aptitude, teachers treat their students differently such as providing more support, more challenging tasks, and more feedback to students with greater judged aptitudes. Students react to this different treatment and develop higher motivation for school or a specific subject and this subsequently leads to an improvement in students’ achievement in the long run. These positive changes are recognized by teachers and provide support for teachers’ prior judgments.

Jussim (1989) described that a correlation between teachers’ judgments and students’ grades can indicate teacher accuracy, teacher expectancy effects (such as self-fulfilling prophecy as mentioned above) or a perceptual bias such as measurement overlap as teachers make judgments and also assign grades. But given that teachers judge students' aptitude in the form of potential that might or might not be reflected by their actual achievement (Steinmayr et al., 2017), a correlation between teachers' judgments and students' achievement, would not indicate accuracy in the sense the term is usually used. Therefore, it is worthwhile to examine the extent to which teachers' judgments of students' aptitude predict students' grades longitudinally. Moreover, some studies have also assessed students' achievement on a standardized test as the dependent variable, and such a test would not be affected by teachers' perceptual biases.

Cross-sectionally, studies have found strong positive correlations between teachers' judgments of students' aptitude in a specific domain and general cognitive ability with students' achievement operationalized as grades or GPA (Dickhäuser & Stiensmeier-Pelster, 2003; Fischbach, Baudson, Preckel, Martin, & Brunner, 2013). Tiedemann (2000) showed that teachers' judgments of students' aptitude in math still significantly predicted students' math grades after students' prior math grades in elementary school were controlled for. Furthermore, several studies have shown that teachers' judgments of students' aptitude or general cognitive ability longitudinally predicted students' achievement across multiple school years. A study by Trouilloud et al. (2002) showed that teachers' judgments of students' aptitude for swimming predicted students' final score on a swimming test 10 weeks later in junior high school. Smith et al. (1999) found that teachers' judgments of students' achievement, aptitude, and effort from Grades 6 and 7 significantly predicted students' achievement development in math up to Grade 12 (β = .13 to .33). A study by Alvidrez and Weinstein (1999) showed that teachers' judgments of students' general cognitive ability from preschool significantly predicted both students' grade point average and standardized achievement test scores in high school after students' intelligence at age 4 was controlled for. Teachers' judgments of students' general cognitive ability in Grade 1 indirectly predicted students' achievement in Grade 4 (Rubie-Davies et al., 2014).

Moreover, small to moderate positive associations between teachers' judgments of students' aptitude and students' academic self-concept, interest, and utility value have been reported (Dickhäuser & Stiensmeier-Pelster, 2003; Smith et al., 1999; Tiedemann, 2000), but it must be noted that these variables were all assessed at the same time, and it was not possible to investigate whether teachers' judgments predicted students' motivation across several school years.

Trouilloud et al. (2002) found that teachers' judgments of students' aptitude in swimming predicted students' perceived ability 10 weeks later. Moreover, in a study by Madon et al. (2001) it has been shown that teachers' judgments of students' talent in math at the beginning of 6^{th} grade predicted students' math-specific self-concept at the end of 6^{th} grade ($\beta = .12$). Whereas no other studies examining longitudinal effects of teachers' judgments of students' aptitude on students' motivation exist, some studies have investigated the extent to which teachers' judgments of students' achievement, which is another possible way to operationalize teachers' judgments (see Section 1.1), predict students' motivation longitudinally. It has been shown that teachers' judgments of students' achievement in math weakly predicted students' academic self-concept in math 4 months later (Friedrich et al., 2015). Zhu et al. (2018) showed that teachers' judgments of students' achievement in English in Grade 5 significantly predicted students' expectancies for success (what students thought which grade they will get in their next English test) in Grade 6 but not students' academic self-concept in Grade 6.

To conclude, these reported findings support the assumption that teachers' judgments of students' aptitude have significant effects on students' achievement and its development. By contrast, only a few studies have investigated the effects of teachers' judgments of students' aptitude on students' motivation, and most of these studies were cross-sectional. Longitudinal studies that have examined effects of teachers' judgments on students' subsequent motivation have assessed teachers' judgments as estimations of students' current achievement. Therefore, it remains unclear whether teachers' judgments of students' aptitude can predict students' motivation longitudinally. Given the strong association between teachers' evaluations of students' aptitude and teachers' evaluations of students' current achievement (Steinmayr et al., 2017), we expected to find the same effects for teachers' judgments of students' aptitude as were previously found for teachers' judgments of students' current achievement.

1.3 Effects of students' achievement and motivation on teachers' judgments of students' aptitude

Theoretically, it is plausible not only that teachers' judgments of students' aptitude predict student outcomes but also that students' achievement and motivation have effects on teachers' judgments. First, the model of academic achievement by Eccles and colleagues (e.g., Eccles & Wigfield, 2002) depicts a dynamic path from academic achievement to socializers' beliefs concerning students' ability or aptitude. Second, students' grades are readily available to teachers because they themselves have graded the students, and students' aptitude is reflected in students' grades. For these reasons, grades as an indicator of academic achievement may influence teachers' beliefs about students' aptitude. This assumption has been supported by some studies. For teachers' judgments of students' general cognitive ability, studies have shown that both students' general cognitive ability (β = .56) and their socioeconomic status (β = .35) had effects on teachers' judgments of students' intelligence (Baudson et al., 2016). In a longitudinal study from kindergarten to Grade 4, Rubie-Davies et al. (2014) found that students' prior achievement had significant effects on teachers' subsequent judgments of students' general cognitive ability. When investigating the effects of students' grades on teachers' judgments of students' aptitude, Tiedemann (2000) showed that students' prior math grades had a significantly strong effect (β = .71) on teachers' subsequent judgments of students' aptitude in math.

Whereas a few studies have found effects of students' actual achievement on teachers' judgments, to our knowledge, only two studies investigated whether students' motivation also impacted teachers' judgments. A study by Kaiser et al. (2013) showed that even students' engagement (as a proxy for motivation) influenced teachers' judgments of students' achievement. The authors conducted a field study as well as an experiment in a simulated classroom and showed that students' reading engagement had a significant effect (β = .24 and β = .19, respectively) on teachers' judgment of students' achievement. Kaiser et al. (2013) argued that engagement might be an indicator of students' knowledge with higher engagement leading for instance, to more careful homework completion. Through this, teachers might judge students' achievement better. Moreover, in the simulated classroom the correlation between students' actual achievement and engagement was constrained to zero. This implies that teachers' inaccurately based part of their judgments of students' achievement come about students' displayed behavioral engagement. The authors also argued that the teachers might also have been influenced by a halo-effect (Thorndike, 1920) such that one positive evaluation of a certain student characteristic could have influenced other evaluations of students' characteristics. This would also lead to an overestimation of students' achievement. Precisely, a teacher may form a positive evaluation of a student's engagement, and this positive evaluation will influence the teacher's judgment of this student's achievement. The teacher may then overestimate the student's achievement on the basis of the teacher's evaluation of the student's engagement. The aforementioned study assessed only students' engagement as a proxy for motivation and focused on teachers' judgments of students' achievement but not students' aptitude, which is a different operationalization of teachers' judgments.

Furthermore, in a study by Madon and colleagues (2001) it has been shown that students' math-specific self-concept at the beginning of 6th grade significantly predicted teachers' judgments of students' talent in math at the end of 6th grade (β = .04). The authors argue that this effect can be interpreted as self-verification in a way that students try to increase the likelihood that information, which are consistent with their self-concepts, will be forthcoming (better recall of information that are self-consistent, retain this information more accurately, search interaction partners providing feedback that is more consistent with their self-concept). Although a longitudinal effect was found of previous self-concept on subsequent teachers' judgment, the study only included two measurement occasions. Further research is needed to explore whether these effects can be found over a longer period of time in school and whether other motivational variables can predict teachers' judgments longitudinally.

Referring to this the following scenario might be possible: A student with a high academic self-concept who thinks that he or she has a high aptitude in a specific subject may convince the teacher of his or her high aptitude. Social psychological evidence has suggested that people who are convinced of something are better at persuading others to agree with them (Hovland, Harvey, & Sherif, 1957). Therefore, the teacher might rate the aptitude of this student as high. Another possible scenario is the following: A student with a high interest and intrinsic task values in a specific subject may show active oral involvement, which is a desirable student behavior. The teachers' positive impression of this interest and intrinsic task values might then influence the teachers' judgment in the form of a halo-effect. The halo-effect (Thorndike, 1920) would then be defined as a bias such that a person's positive impression of one characteristic will outshine other characteristics (leading to a more positive evaluation of other characteristics). In our example, the teacher's positive impression of the student's motivation will positively predict the teacher's judgment such that the teacher will rate the student's aptitude as higher as a result of the student's high intrinsic task values.

To summarize, there is a lack of research that has examined longitudinal effects of students' motivation on teachers' judgments of students' aptitude with respect to students' academic self-concept and intrinsic task values in particular. Obtaining empirical evidence of these underlying processes would not only advance the understanding of which information teachers take into account when judging their students' aptitude but would also make teachers more aware of such mechanisms.

2. Research questions and expectations

In this study, we aimed to examine the effects of teachers' judgments of students' aptitude on students' achievement and motivation development in math and also to examine the reverse effect, that is, whether teachers' judgments can be predicted by students' math-specific grades and motivation. On the basis of the findings reported above, we derived the following research questions and expectations:

1) Effects of teachers' judgments of students' aptitude on students' achievement and motivation development

   Research questions 1a to 1c. Do teachers' prior judgments of students' aptitude predict (a) students' subsequent grades in math, (b) students' subsequent academic self-concept in math, or (c) students' subsequent intrinsic task values in math while prior math grades, self-concepts and intrinsic task values are controlled for?

   Expectations 1a to 1c. Teachers' prior judgments of students' aptitude will predict (a) students' subsequent grades in math after prior math grades are controlled for, (b) students' subsequent academic self-concept in math after prior math-specific self-concepts and math grades are controlled for, and (c) students' subsequent intrinsic task values in math after prior math-specific intrinsic task values and math grades are controlled for.

2) Effects of students' achievement and motivation on teachers' judgments

   Research questions 2a to 2c. Do (a) students' prior math grades, (b) students' prior math-specific self-concepts, or (c) students' prior intrinsic task values in math predict teachers' subsequent judgments of students' aptitude in math while teachers' prior judgments and math grades are controlled for?

   Expectations 2a to 2c. (a) Students' prior math grades, (b) students' prior self-concepts in math, or (c) students' prior intrinsic task values in math will predict teachers' subsequent judgments of students' aptitude in math after teachers' prior judgments of students' aptitude in math and math grades are controlled for.

3. Method

3.1 Sample and procedure

The sample consisted of a total of *N* = 519 students (49.9% girls) and *N* = 27 teachers (100% women). Data were collected in 27 classes at 11 elementary schools in the German state of Baden-Württemberg across seven measurement occasions (cf. authors). Because teachers' judgments were assessed at only four measurement occasions, we focused on these four measurement occasions, which were spaced 4 months apart (t1: at the end of third grade; t2: at the beginning of fourth grade; t3: in the middle of fourth grade; t4: at the end of fourth grade). Students were 8.28 years old (*SD* = 0.54) at t1 and 9.93 years old (*SD* = 0.72) at t4. 76.7% of the students indicated that German was their native language. When comparing our current data with those from the Federal Statistical Office (2009), we found that the students in our sample were representative for the population in their federal state concerning gender ratio (χ^2= .004, *df* = 1, *p* = .950) and immigration background (χ^2 = .220, *df* = 1, *p* = .639) (see authors). All students answered questions about their motivation in mathematics in their classrooms on a regular school day. Trained research assistants administered the questionnaire and read all items aloud in order to ensure that all students worked at the same speed. Overall, the assessments took about 45 min. Meanwhile, teachers provided information about students' grades and indicated their judgments of students' aptitude. All students had the same teacher throughout grades 3 and 4. This means that teachers knew their students for at least one year at the measurement occasions. Because we did not preregister our study, this study can be seen as a kind of exploratory study despite the fact that we had clear hypotheses.

3.2 Measures

3.2.1 Students' math-specific academic self-concept

Students' math-specific academic self-concept was assessed with three items: "How good are you at math?" with a response format ranging from 1 (*very good*) to 5 (*very bad*), "How easy is it for you to learn new things in math?" ranging from 1 (*very easy*) to 5 (*very hard*), and "To which group of students do you belong in your class in math?" ranging from 1 (*the best*) to 5 (*the worst*). These items were based on a questionnaire for assessing students' academic self-concept according to expectancy-value theory (Eccles & Wigfield, 1995) and established in previous studies (e.g., Spinath & Steinmayr, 2008; Weidinger, Steinmayr, & Spinath, 2018) that supported the construct validity of academic self-concept. To estimate the reliability of the scale, we calculated McDonald's Omega (ω), which varied from ω = .907 to ω = .928 (see Table 1). In order to present the values of this scale more intuitively, the items were recoded so that higher values stood for higher academic self-concept.

3.2.2 Students' math-specific intrinsic task values

Students' intrinsic task values for math was measured with three items, each with a 5-point response format ranging from 1 (*not at all*) to 5 (*really a lot*): "How much do you like mental arithmetic?"; "How much do you like doing calculations?"; and "How much do you like solving math problems?" These items were based on a questionnaire for assessing intrinsic task values in the context of expectancy-value theory (Eccles & Wigfield, 1995) and established in previous studies (e.g., Spinath & Steinmayr, 2008; Weidinger et al., 2018). To estimate the reliability of the scale, we calculated McDonald's Omega (ω), which varied from ω = .844 to ω = .872 (see Table 1).

3.2.3 Teachers' judgments of students' aptitude in math

Teachers' judgments of students' aptitude in mathematics were assessed with one item, namely, "In your opinion, how talented is the following student in math?". Teachers' judgments were given on a 5-point response format ranging from 1 (*not talented*) to 5 (*very talented*). In German language, the wording of the item "how talented…in math" explicitly refers to students' aptitude / giftedness in math. Because the construct of teachers' judgments of students' aptitude is a very narrow construct, and additional items would be phrased in the same way, it was assessed with only one item. Moreover, researchers examining teachers' judgments of students' aptitude and achievement have assessed these constructs with single-item measures (Dickhäuser & Stiensmeier-Pelster, 2003; Fischbach et al., 2013; Hoge & Butcher, 1984; Kuklinski & Weinstein, 2001; Tiedemann, 2000).

3.2.4 School grades

Teachers reported the grades that students had earned in math as noted in their report cards. Teachers used the same grading practices and assignments (e.g., both students' written and verbal performance were considered for final grades). For a better interpretation of the effects of math grades on other variables in our models, we reversed the polarity such that higher values indicated better math achievement ranging from 1 = *insufficient/fail* (minimum) to 6 = *excellent* (maximum).

3.2.5 Control variables

We controlled for students' sex (1 = male, 2 = female) and students' native language (1 = German as native language, 2 = other language than German as native language).

3.3 Statistical analyses

3.3.1 Structural equation models

To examine the effects of teachers' judgments of students' aptitude in math on students' grades, math-specific self-concept, and intrinsic task values as well as to investigate the effects of students' characteristics on teachers' judgments of students' aptitude in math, we used structural equation modeling in Mplus 7.11 (Muthén & Muthén, 1998 - 2013). Two cross-lagged panel models were computed: The first model included cross-lagged effects between teachers' judgments of students' aptitude in math, students' math grades, and students' math-specific self-concept (as an indicator of students' motivation). The second model included cross-lagged effects between teachers' judgments of students' aptitude in math, students' math grades, and their intrinsic task values (as an indicator of students' motivation). Both motivational constructs were assessed with three items each, so we specified these variables as latent variables. Students' grades in math and teachers' judgments of students' aptitude were measured with only one item each, so we specified these variables as manifest variables. In both structural equation models, we examined the stabilities of all three constructs and also looked at cross-lagged effects between teachers' prior judgments of students' aptitude and students' subsequent grades and motivation and vice versa. Also, we included cross-lagged effects between students' grades in math and their math-specific motivation. Moreover, we included the correlations between all three variables within one measurement occasion and item-specific method factors. Students' sex and native language were included as control variables in both models as additional predictor variables. Figure 1 exemplifies one of our cross-lagged panel models.

To correct for the clustering in our data (students nested in different classes and schools) and sampling error, we used the "TYPE = COMPLEX" option in Mplus.

On a related note, the word "effect" is used in the sense of a statistical prediction in a cross-lagged panel model (one prior variable predicts another subsequent variable) with different measurement occasions and is not meant to be causal.

Moreover, we tested measurement invariance of students' math-specific self-concept and intrinsic task values over our four measurement occasions. We evaluated the measurement invariance using different criteria, namely the significance of the change in χ^2 for two nested models, changes in the Comparative Fit Index (CFI) as well as changes in the Root Mean Square Error of Approximation (RMSEA). According to Chen (2007) changes in CFI should not be higher than -.01 and changes in RMSEA should not be higher than .015.

Furthermore, two Monte Carlo studies with 10.000 replications were performed in Mplus in order to test the power post-hoc. For the first post-hoc power analysis model, we followed the effect sizes of previous studies that examined the effects between teachers' judgments and students' engagement (Kaiser et al., 2013) or students' self-concept (Madon et al., 2001). These two studies found small effect sizes. In our study, we also found the effects of students' self-concepts on teachers' judgments to be small. Therefore, the observed and hypothesized parameters based on previous findings are similar / the same. For the second post-hoc power analysis model, we used the estimated parameter values as our study was the first one that examined the effects of students' intrinsic motivation on teachers' judgments. Therefore, no other study could be used as indication for hypothesized parameters. Results of these Monte Carlo studies can be found in Table 5 and 6. The significance coefficients show the proportion of replications for which the null hypothesis, that an effect in our model is equal to zero, is rejected at the .05 level (Muthén & Muthén, 2002). For effects with population values different from zero, the significance coefficient is an estimate of power (the probability of rejecting the null hypothesis when it is false). For effects with population values equal to zero, the significance coefficient is an estimate of Type I error (the probability of rejecting the null hypothesis when it is true).

3.3.2 Evaluation of model fit

For the model fit of the two structural equation models, we considered the χ^2 value with degrees of freedom, the Comparative Fit Index (CFI), Tucker-Lewis-Index (TLI), the Root Mean Square Error of Approximation (RMSEA) as well as Standardized Root Mean Square Residual (SRMR). Because the χ^2 value depends on the sample size and can easily become significant in large samples (Ullman, 2007), this value must be interpreted with caution. For the CFI and TLI, values higher than .95, and for the RMSEA as well as SRMR, values lower than .05 are considered excellent. Such an excellent fit occurs when the model fits the data well. If the values for the CFI and TLI are lower than .90 and the values for RMSEA and SRMR are higher than .10, then the model is not acceptable (Hu & Bentler, 1999; Marsh, Dowson, Pietsch, & Walker, 2004).

3.3.3 Handling missing data

As in every longitudinal study, we had to deal with missing data in the present study. The main reason for missing data was illness, whereby some students missed one or more measurement occasions. These missing data ranged from 11.4% (t2) to 24.7% (t1) for teachers' judgments of students' talent, from 9.8% (t1) to 14.1% (t4) for academic self-concept, from 9.6% (t1) to 13.7% (t3, t4) for intrinsic task values, and from 11.4% (t2) to 19.5% (t3) for math grades. In order to examine whether students with missing data at one measurement occasion differed in our study variables from students without missing data, multivariate analyses of variance were computed.

Students with missing data at t1 did not differ in math-specific motivation, math grades, teacher judgments' at t2, t3 and t4 from students without missing data ($F(12,337) = 0.95$, $p = .49$. The same results were found for the comparison between students with missing data at t2 and students without missing data ($F(12,264) = 1.39$, $p = .17$. Students with missing data at t3 had significantly lower math grades compared to students without missing data, but we did not find significant differences for the other examined variables ($F(12,302) = 1.95$, $p = .03$, $\eta^2 = .07$. For students with missing data to t4 we found that they had a significantly lower intrinsic task values compared to students without missing data ($F(12,274) = 2.41$, $p = .01$, $\eta^2 = .09$, but no differences were found on the other variables.

To handle missing data in Mplus, we used the full information maximum likelihood (FIML) method. This is an approach that typically yields less biased estimates under the missing at random assumption than traditional approaches such as listwise or pairwise deletion. Also, this method takes all information into account (i.e., cases with missing values) when estimating the model parameters and maintains statistical power at the same time (Enders, 2010; Schafer & Graham, 2002). In order to make the missing-at-random more plausible, both models in Mplus were estimated using the AUXILIARY function. The so-called auxiliary variables are considered as missing data correlates in addition to the analysis variables (Graham, 2003). Following Enders (2010) we examined mean differences across missing data patterns as well as correlations between the analysis variables with missing data and other variables in the data set. Two variables (i.e., students' perceived teachers' judgments of their aptitude and students' self-reported ability self-concept about school in general[1]) were identified as correlates of missingness and included as auxiliary variables in both models.

4. Results

4.1 Descriptive statistics and longitudinal measurement invariance

Means (*M*), standard deviations (*SD*), reliabilities (McDonald's Omega ω), minimum, maximum, skewness, kurtosis and intra-class correlations on class level of the examined variables across four measurement occasions are reported in Table 1. A closer look showed that students' academic self-concept and intrinsic task values in math were relatively high. The correlations between all variables can be found in Table 2. Teachers' judgments were strongly related to students' grades in math (r = .68 to .82), moderately to strongly related to students' academic self-concept (r = .43 to .61), and weakly related to students' intrinsic task values in math (r = .22 to .34). Students' grades in math were moderately to strongly associated with their academic self-concept (r = .42 to .61) and weakly to moderately associated with their intrinsic task values (r = .19 to .31). Finally, students' academic self-concept and their intrinsic task values were moderately to strongly related to each other (r = .45 to .62).

Results of the model comparisons regarding measurement invariance testing for students' math-specific self-concept are reported in Table 3 and for intrinsic task values in Table 4. For both constructs, the model fit did not significantly decline when constraining the factor loadings to be invariant over time. The model fit did also not significantly decline when setting the intercepts to be invariant over time. Therefore, we can conclude that strong factorial longitudinal invariance was achieved for both students' math-specific self-concepts and intrinsic task values, which means that

[1] Students' perceived teachers' judgments of their aptitude was measured with three items, each with a 5-point response format with an example item "My teacher beliefs that I am talented in Math". Students' self-reported ability self-concept about school in general was measured with three items, each with a 5-point response format with an example item "I am good at school".

students interpreted the items and used the response scale in the same way over the four measurement occasions.

4.2 Effects of teachers' judgments of students' aptitude on students' grades and motivation

The results for our first cross-lagged panel model with teachers' judgments of students' aptitude in math, students' math grades, and their math-specific self-concepts are reported in Table 5. The model fit was good, $\chi^2(138, N = 508) = 250.79$, $p < .001$; CFI = .980; TLI = .967; RMSEA = .040; SRMR = .038. All three constructs were relatively stable over time, whereas on a descriptive level, students' math-specific self-concept and math grades were more stable than teachers' judgments. We also found moderate to high concurrent intercorrelations between teachers' judgments and students' grades in math. The intercorrelation between students' academic self-concept and teachers' judgments of students' aptitude was high at t1 but no longer significant at t2 to t4 (see Table 7). Effects of students' sex and native language on students' math-specific self-concept, math grades and teachers' judgments can be found in Table 8.

In line with Expectation 1a, we found significant positive effects from teachers' prior judgments of students' aptitude in math on students' subsequent math grades ($\beta = .13$ to $.27$) after controlling for prior math grades. In contrast with our Expectation 1b, we did not find significant positive effects from teachers' prior judgments of students' aptitude in math on students' subsequent math-specific self-concept after controlling for prior math-specific self-concept, except for an effect of teachers' judgments at t2 on students' self-concept at t3 ($\beta = .11$). Furthermore, we found one significant effect from students' math grades at t2 on students' math-specific self-concept at t3 ($\beta = .16$). Also, we found that prior math-specific self-concepts had significant positive effects on subsequent math grades (β = .08 to .18). The post-hoc power analysis showed that the power for population values different from zero was high enough while ranging from .835 to 1.000, except for one effect from students' self-concept to t3 on teachers' judgments to t4 with power of .561. The estimates of Type I error for population values equal to zero were small ranging from .057 to .198.

The results for our second cross-lagged panel model with teachers' judgments of students' aptitude in math, students' math grades, and their math-specific intrinsic task values are reported in Table 6. The model fit was acceptable, $\chi^2(138, N = 508) = 340.07$, $p < .001$; CFI = .969; TLI = .948; RMSEA = .053; SRMR = .053. Students' grades and their intrinsic task values were highly stable, whereas teachers' judgments of students' aptitude were moderately stable from t1 to t4. Consistent with the first model, we found moderate to high concurrent intercorrelations between teachers' judgments of students' aptitude and students' math grades. The intercorrelation between teachers' judgments of students' aptitude and students' intrinsic task values was moderate at t1 but no longer significant at t2 to t4 (see Table 7). In line with the results from the first model and our Expectation 1a, we found significant positive effects from teachers' prior judgments of students' aptitude on students' subsequent math grades (β = .17 to .32) after controlling for prior math grades. In contrast to our Expectation 1c, we did not find significant positive effects from teachers' prior judgments of students' aptitude in math on students' subsequent intrinsic task values in math after controlling for prior intrinsic task values in math. No significantly reciprocal effects were found between students' prior math grades and their intrinsic task values in math. The results of post-hoc power analysis showed that power for population values different from zero were 1.000 except for one effect of math grades to t3 on students' intrinsic task values to t4 with power of .405. The estimates for Type I error for population values equal to zero were small ranging from

.059 to .380 except for on effect from teachers' judgments to t2 on students' intrinsic values to t3 with type I error of .697.

4.3 Effects of students' grades and motivation on teachers' judgments of students' aptitude

Tables 5 and 6 show not only effects from teachers' prior judgments of students' aptitude in math on students' outcomes but also effects of students' prior math grades, their math-specific self-concept, and intrinsic task values on teachers' subsequent judgments of students' aptitude in math. The model fits, stabilities of the included variables across four measurement occasions, as well as correlations between these variables within one measurement occasion were already mentioned in the previous section. In line with our Expectation 2a, we did indeed find significant positive effects of prior grades in math on teachers' subsequent judgments of students' aptitude in math (β = .22 to .35) after controlling for teachers' prior judgments. Consistent with our Expectation 2b, students' prior math-specific self-concepts had significant positive effects on changes in teachers' judgments of students' aptitude in math (β = .07 to .14). In line with the results from our first model and in line with our Expectation 2a, we found significant positive effects of students' prior math grades on teachers' subsequent judgments of students' aptitude in math (β = .26 to .37) after controlling for teachers' prior judgments of students' aptitude in math (Expectation 2a). In contrast to our Expectation 2c, we did not find significant effects of students' prior intrinsic task values on changes in teachers' judgments of students' aptitude in math. Post-hoc power for population values different from zero was high (.995-1.000), except for one effect of math-specific self-concept to t3 on teachers' judgments to t4 with power of .699 and one effect of students' intrinsic task values to t2 on teachers' judgments to t3 with power of .477. Estimates for Type I error ranged from .059 to .071 with one exception for the effect of students' intrinsic values to t1 on teachers' judgments to t2 with an estimate of .280.

5. Discussion

The first goal of this study was to investigate how teachers' judgments of students' aptitude in math longitudinally predicted students' math grades and motivation. The second goal of this study was to determine the extent to which teachers' judgments of students' aptitude were predicted by students' grades as an indicator of their academic achievement and motivation, such as academic self-concept and intrinsic task values. The results are discussed with regard to our expectations. We will then discuss some limitations, make suggestions for future research, and outline some practical implications of our study.

5.1 Effects of teachers' judgments of students' aptitude on students' achievement and motivation

In line with our prediction in Expectation 1a, we found that teachers' prior judgments of students' aptitude in math had significant positive effects on students' subsequent math grades after we controlled for prior math grades, students' sex and native language. Precisely, teachers' judgments of students' aptitude predicted change in students' math grades across 1 year of elementary school. This result is consistent with results from previous studies showing that teachers' judgments of students' aptitude or general cognitive ability predicted students' subsequent achievement (Alvidrez & Weinstein, 1999; Rubie-Davies et al., 2014; Smith et al., 1999; Tiedemann, 2000; Trouilloud et al., 2002). Considered together, these findings indicate that teachers' judgments of students' aptitude have significant effects on students' achievement development. These effects can have long-lasting and negative consequences, especially when a teacher underestimates a student's aptitude.

Contrary to the predictions made in Expectations 1b and 1c, we did not find that teachers' prior judgments of students' aptitude in math had significant effects on students' math-specific motivation (self-concept and intrinsic task values), except for one effect of teachers' judgements at t2 on students' self-concept at t3. At this point, our results mostly indicate that teachers' judgments of students' aptitude did not predict students' motivation and their motivation development in elementary school when students' grades, sex and native language were controlled for. By contrast, Dickhäuser and Stiensmeier-Pelster (2003), Smith et al. (1999), and Tiedemann (2000) showed that teachers' judgments of students' aptitude in math significantly predicted students' self-concept. But these studies had a cross-sectional design and did not test for the effects of teachers' judgments of students' aptitude on students' self-concepts longitudinally. Only a study by Madon et al. (2001) found a significant effect of teachers' judgments on students' self-concept over one school year, but they did not control for students' grades. It can be assumed that the effects of teachers' prior judgments of students' aptitude on students' subsequent self-concepts were non-significant in our study because we focused on the longitudinal effects and controlled for prior self-concepts as well as grades when looking at the effects of teachers' judgments of students' aptitude on students' subsequent self-concepts. It might be the case that the effects of teachers' prior judgments of students' aptitude on subsequent self-concepts were non-significant in our study because prior grades and prior self-concepts were stronger predictors of students' subsequent self-concepts. Teachers' judgments of students' aptitude did not incrementally predict students' subsequent self-concepts over their prior self-concepts and grades.

In contrast, teachers' judgments of students' aptitude in swimming predicted students' perceived ability 10 weeks later (Trouilloud et al., 2002) and in a study by Friedrich and colleagues (2015) teachers' judgments of students' achievement, which is another form of teachers' judgments, predicted students' self-concept in Math four months later. Rubie-Davies et al. (2014) did not find a significant effect of teachers' prior judgments of students' general cognitive ability on students' academic self-concept, a result that is in line with our findings. Whereas teachers' judgments of students' aptitude did not significantly predict students' development of their math-specific self-concept, we found one significant effect of students' math grades at t2 on change in students' math-specific self-concept from t2 to t3. The longitudinal influence of students' achievement in the form of grades on students' ability self-concepts has been found in many previous studies (Guay, Marsh, & Boivin, 2003; Marsh, Gerlach, Trautwein, Lüdtke, & Brettschneider, 2007; Weidinger et al., 2018). It might be possible that teachers' judgments of students' aptitude do not directly predict students' motivation development but rather indirectly predict this development through students' grades. Furthermore, given the high cross-sectional correlations between teachers' judgments of students' aptitude and grades, it might also well be the case that the effect of teachers' judgments of students' aptitude on students' ability self-concept was underestimated in the proposed model (cf. Marsh et al., 2004).

5.2 Effects of students' achievement and motivation on teachers' judgments of students' aptitude

In line with our prediction in Expectation 2a, we found that students' prior math grades had positive moderate effects on teachers' subsequent judgments of students' aptitude in math. This result is consistent with previous findings from empirical studies showing that students' grades are positively associated or predict teachers' judgments of students' aptitude (Dickhäuser & Stiensmeier-Pelster, 2003; Tiedemann, 2000). Moreover, our study demonstrated that not only are grades positively associated, but they indeed predict change in teachers' judgments of students' aptitude. These results are in line with the dynamic component of the Eccles model (Eccles & Wigfield, 2002), which states that teachers' (socializers') perceptions predict students' academic achievement, which, in turn, influences students' ability perceptions. Furthermore, the high cross-sectional correlations in combination with the effects of grades on the change in teachers' judgments of students' aptitude strongly indicated that teachers mainly used students' observed achievement as the basis for their judgments. In the literature, Jussim (1989) described that correlations between teachers' judgments and students' achievement can be interpreted as teacher accuracy, expectancy effects or perceptual bias. In our case, these effects cannot be interpreted as teacher accuracy, as we did not assess students' objective aptitude in math and therefore we could not examine the relationship between teachers' judgments of students' aptitude and students' objective aptitude. But it might be possible that teachers' judgments of students' aptitude and math grades are prone to the same perceptual biases and have measurement overlap (Jussim, 1989), because both were provided by the same teachers. But given that students' aptitude in the form of potential does not always manifest in achievement measures such as grades, it was worthwhile to examine the extent to which students' previous grades predicted teachers' subsequent judgments of students' aptitude. Thus, underachievers (i.e., students with high potential and low performance) were not likely to be detected as already demonstrated in other studies (e.g., Fischbach et al., 2013). Because we did not apply an objective measure of mathematical achievement, we could not identify underachievers in the present study. Future studies should look at how a possible misconception of students' abilities might impact students' future grades and their motivation.

In line with our prediction in Expectation 2b, we found that students' prior academic self-concepts in math had positive effects on change in teachers' judgments of students' aptitude. Even though these effects were weak, they were significant across all measurement occasions. This finding is in line with a study by Madon et al. (2001), who also found a significant longitudinal effect of students' math-specific self-concepts on teachers' judgments. By contrast, we did not find that students' prior intrinsic task values predicted teachers' subsequent judgments of students' aptitude. This indicates that in our study the effects of students' motivation on teachers' judgments occur through students' academic self-concepts rather than through students' intrinsic task values in class (cf. the halo-effect). The result that students' intrinsic task values did not predict teachers' judgments of students' aptitude can be interpreted positively. Teachers do not seem to be deceived by students' high intrinsic task values and their high participation in class such that this single positive impression would have an influence on teachers' judgments of students' aptitude. Maybe, students' intrinsic task values could have had positive effects when teachers had to judge students' actual competence in math, which is - in contrast to students' aptitude in form of giftedness - also determined by students' engagement. Moreover, our post-hoc power analysis showed that the estimate of power for one effect of students' intrinsic task values on teachers' judgments was rather low with .477. Maybe, this effect could have been significant in a larger sample. The finding that students' self-concept in math had positive effects on teachers' judgments of students' aptitude suggests that students with a high academic self-concept can convince their teachers of their high aptitude and will be rated as having a high aptitude. This result is in line with findings from social psychology studies in which people could persuade others better when they were convinced of a particular fact themselves (Hovland et al., 1957).

5.2 Limitations and future research

The results of our study should be interpreted in the light of some limitations. We chose a longitudinal design with four measurement occasions to detect longitudinally reciprocal effects of teachers' judgments of students' aptitude and students' grades as well as students' motivation. These longitudinal effects cannot be interpreted causally, it is also possible that teachers' judgments and students' self-concept in math are influenced by a third variable. Therefore, future research would do well to investigate the influence of students' motivation on teachers' judgments in an experimental study, for example, in the framework of a simulated classroom. In this kind of setting, a teacher would interact with virtual students. Students' achievement, operationalized as the proportion of correct answers, and students' intrinsic task values, operationalized as participation in class or having fun working on math tasks, could be experimentally manipulated. Students' math self-concept could also be experimentally manipulated by providing students' self-reports of how good they think they are at math. Moreover, researchers could provide information about students' results on a numeric intelligence test. After interacting with these virtual students and posing questions to the students, teachers could be asked to judge students' aptitude in math. The simulated classroom has some advantages, whereby findings from this kind of study can contribute to insights regarding the importance of teachers' judgments for students' achievement and motivation and the other way around. First, in a simulated classroom, students' motivation is more transparent and clearly observable for teachers, whereas in a real classroom setting, it can sometimes be difficult to perceive students' motivation (Kaiser et al., 2013).

Second, students' characteristics such as socio-economic status or gender could be randomized in a simulated classroom, thus eliminating their influence on teachers' judgments. And third, because of the nature of an experiment, effects can be interpreted as causal, whereas findings from a longitudinal study can be interpreted only as hints about an influence because both variables could also be influenced by a third variable.

As reported above, in this study, a single-item measure was used to assess teachers' judgments of students' aptitude. Because we used this single item, we could not compute internal consistency as a measure of reliability. Instead, the correlation coefficients between teachers' judgments across different measurement occasions can be interpreted as hinting at retest-reliability ($.77 < r < .82$), which can be interpreted as good and functional. Moreover, many other studies have also used single-item measures to assess teachers' judgments of students' aptitude (Dickhäuser & Stiensmeier-Pelster, 2003; Fischbach et al., 2013; Hoge & Butcher, 1984; Kuklinski & Weinstein, 2001; Tiedemann, 2000) because this construct is narrow, and additional items would be worded in the same way.

In our study, we focused on students' motivation and teachers' judgments of students' aptitude in the math domain. More research is needed to investigate the effects of teachers' judgments of students' aptitude on student characteristics (e.g., achievement and motivation) and vice versa to generalize these findings to other domains.

Another shortcoming of our study is the fact that we did not assess objective performance but instead used grades as an achievement indicator. Especially in Germany, grades are the most salient indicators of academic achievement, and students very rarely if ever receive performance feedback based on objective performance tests (cf. Hertel, Hochweber, Steinert, & Klieme, 2010), and thus their teachers also do not get to see students' scores on such tests. Therefore, grades were the most ecologically valid achievement measure that could be obtained. However, as indicated above, future studies should also assess objective performance indicators to clarify how the reciprocal effects of students' motivation, grades, and teachers' judgments work for underachieving students or students whose aptitudes are not correctly judged by their teachers. Furthermore, our sample consisted of elementary school students. At an elementary-school level, teachers' judgments of students' aptitude play an important role and have far-reaching consequences when teachers provide recommendations for secondary school, for example. It is also worth investigating whether teachers take students' motivation into account when they judge students' aptitude in secondary school. Consequently, future research should elaborate on this issue in secondary school, also in order to generalize the findings across different school samples.

Finally, we assessed two of the most prominent motivational constructs (students' academic self-concept in math and intrinsic task values) to examine the effects of students' motivation on teachers' judgments. It would also be interesting to consider students' performance-approach goals as a motivational construct. Students with high performance-approach goals who want to both show that they are good students and perform better than others could possibly be evaluated as having high aptitude by teachers. Therefore, in future research, researchers would do well to also look at the effect of students' performance-approach goals on teachers' judgments.

5.3 Practical implications

Next to some suggestions for future research, there are also a number of practical implications of our findings. We found evidence that suggests that teachers' judgments of students' aptitude predicted students' achievement development in elementary school. These effects can have long-lasting effects on students' school careers, especially at the end of elementary school and for the transition to secondary school. A teacher's underestimation of a student's aptitude in math can lead to negative achievement development in elementary school and moreover to a worse recommendation for secondary school than would be expected on the basis of the student's real aptitude. Therefore, it is very important to make teachers aware of the influence of their judgments of students' aptitude on students' achievement development and to foster teachers' ability to judge students' aptitude correctly.

Furthermore, the results clearly demonstrate that teachers take other student characteristics other than achievement (e.g., academic self-concept) into account when judging students' aptitude. This finding has far-reaching consequences, for example, if a teacher judges a student with a low academic self-concept as having low aptitude, even though the student's real aptitude is high, then this judgment has negative effects on offering the student tasks with an appropriate level of difficulty and the teacher's recommendation for secondary school. Also, if a teacher rates a student as having a higher aptitude than he or she really has just because of the students' high academic self-concept, the teacher will not be able to foster the student appropriately. The teacher will offer more difficult tasks and will give a better recommendation for secondary school even though the student might not have the appropriate aptitude. Both the over- and underestimation of students' aptitudes because of their own ability self-concepts will lead to decreases in students' motivation. This is because the teacher will interact with the student in a way that is not in line with the student's actual aptitude.

When considering educational practice, it would be worthwhile to offer workshops that focus on teachers' judgments. First, teachers could be introduced to research on teachers' judgments and findings on the accuracy of teachers' judgments of students' aptitude, which shows that they are accurate but not perfect (Alvidrez & Weinstein, 1999; Baudson et al., 2016). Further, with respect to psychoeducation, it is important to make teachers aware of their judgment process and the finding that they might easily take other student characteristics into account when evaluating students' aptitudes. Teachers should be informed that they might take students' academic self-concept into account even though they should be judging students' aptitude instead. Moreover, it is important to present findings on the effects of teachers' judgments on students' achievement and motivation development and that judgments have long-lasting effects. Down the line, it will be helpful to train teachers to evaluate students' aptitude in order to prevent such biases. For example, teachers could learn how to administer a standardized test in order to assess students' aptitude in math. Moreover, a video analysis could be conducted on teachers to detect teachers' verbal and nonverbal behaviors when interacting with students in order to visually represent whether a teacher treats students differently after judging them with different aptitudes.

5.4 Conclusion

This study provides new insights into the effects of teachers' judgments of students' aptitude on student outcomes and how these teachers' judgments of students' aptitude are predicted by student achievement and motivation. The study emphasizes that teachers' judgments of students' aptitude predicts students' achievement development in elementary school and that both students' grades and academic self-concepts but not their intrinsic task values have significant effects on teachers' judgments of students' aptitude.

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Table 1

Means (M), standard deviations (SD), reliabilities (McDonald's ω), minimum, maximum, skewness, kurtosis and intra-class correlations of all variables

	Descriptives								
	M	*SD*	ω	Min	Max	Skewness	Kurtosis	*ICC*	*n*
Teachers' judgments (TJM) t1	3.61	1.01	-	1	5	-.37	-.38	.048	391
Teachers' judgments (TJM) t2	3.68	.99	-	1	5	-.39	-.40	.043	460
Teachers' judgments (TJM) t3	3.72	.96	-	1	5	-.41	-.40	.041	418
Teachers' judgments (TJM) t4	3.77	.97	-	1	5	-.38	-.55	.077	453
Math Grade (MG) t1	4.62	1.00	-	1	6	-.65	.13	.165	432
Math Grade (MG) t2	4.66	.92	-	2	6	-.60	-.01	.093	460
Math Grade (MG) t3	4.67	.90	-	2	6	-.55	-.11	.097	418
Math Grade (MG) t4	4.65	.87	-	1	6	-.60	.61	.101	453
Academic self-concept (ASC) t1	3.80	.82	.91	1	5	-.44	.13	.046	468
Academic self-concept (ASC) t2	3.92	.76	.92	1	5	-.46	.11	.007	451
Academic self-concept (ASC) t3	3.84	.78	.92	1	5	-.29	-.11	.002	449
Academic self-concept (ASC) t4	3.78	.74	.93	1	5	-.17	-.06	.016	446
Intrinsic task values (IV) t1	3.80	1.07	.84	1	5	-.66	-.36	.058	469
Intrinsic task values (IV) t2	3.87	1.03	.87	1	5	-.76	-.06	.060	451
Intrinsic task values (IV) t3	3.84	.95	.87	1	5	-.70	-.09	.009	448
Intrinsic task values (IV) t4	3.69	1.03	.87	1	5	-.57	-.28	.026	448

Table 2

Intercorrelations among all variables

	TJM t2	TJM t3	TJM t4	MG t1	MG t2	MG t3	MGt4	ASC t1	ASC t2	ASC t3	ASC t4	IV t1	IV t2	IV t3	IV t4
Teachers' judgments (TJM) t1	.77	.74	.71	.76	.72	.73	.68	.49	.43	.53	.51	.27	.27	.25	.25
Teachers' judgments (TJM) t2		.79	.77	.70	.82	.77	.71	.52	.47	.56	.59	.29	.27	.29	.32
Teachers' judgments (TJM) t3			.82	.71	.79	.82	.76	.54	.50	.59	.61	.30	.30	.33	.34
Teachers' judgments (TJM) t4				.71	.75	.80	.79	.52	.44	.55	.58	.22	.25	.26	.32
Math Grade (MG) t1					.76	.80	.79	.52	.42	.55	.56	.26	.26	.23	.28
Math Grade (MG) t2						.87	.81	.54	.50	.58	.61	.28	.31	.29	.35
Math Grade (MG) t3							.87	.53	.47	.61	.61	.26	.29	.30	.34
Math Grade (MG) t4								.49	.43	.57	.60	.19	.27	.26	.30
Academic self-concept (ASC) t1									.74	.72	.71	.59	.52	.52	.56
Academic self-concept (ASC) t2										.75	.72	.55	.62	.54	.54
Academic self-concept (ASC) t3											.81	.45	.48	.58	.53
Academic self-concept (ASC) t4												.44	.45	.53	.60
Intrinsic task values (IV) t1													.77	.69	.69
Intrinsic task values (IV) t2														.71	.73
Intrinsic task values (IV) t3															.79
Intrinsic task values (IV) t4															

Note. All correlations were significant on the *p* < .01 level.

Table 3

Model fit statistics for testing the longitudinal measurement invariance of math-specific self-concepts

Model tested	χ^2 (df)	*p*	$\Delta\chi^{2\ corr}$ (df)	*p*	CFI	RMSEA	ΔCFI	ΔRMSEA	Pass?
Configurally invariant model	28.91 (30)	.32	-	-	.999	.015	-	-	
Weak invariant model	42.89 (36)	.20	13.60 (6)	.192	.998	.019	.001	.004	Yes
Strong invariant model	55.45 (42)	.08	11.15 (6)	.084	.995	.025	.003	.006	Yes

Table 4

Model fit statistics for testing the longitudinal measurement invariance of intrinsic task values

Model tested	χ^2 (df)	*p*	$\Delta\chi^{2\ corr}$ (df)	*p*	CFI	RMSEA	ΔCFI	ΔRMSEA	Pass?
Configurally invariant model	45.57 (30)	.03	-	-	.995	.032	-	-	
Weak invariant model	54.14 (36)	.03	8.69 (6)	.192	.994	.031	.001	.001	Yes
Strong invariant model	57.90 (42)	.05	5.14 (6)	.527	.995	.027	.001	.004	Yes

Table 5

Standardized stability and cross-lagged effects with standard errors and confidence intervals as well as significance coefficients from post-hoc power analysis for teachers' judgments of students' aptitude in math (TJM), students' math grades (MG) and their math-specific self-concept (MSC)

	Stability effects			Cross-lagged effects					
Waves	TJM	MG	MSC	TJM → MG	MG → TJM	TJM → MSC	MSC → TJM	MG → MSC	MSC → MG
t 1-2	.53*** (.06) [.43; .63] 1.000	.46*** (.07) [.36; .57] 1.000	.87*** (.07) [.76; .98] 1.000	.27*** (.06) [.18; .37] 1.000	.22*** (.06) [.13; .31]. .999	.05 (.05) [-.04; .14]. .198	.14** (.05) [.07; .22]. .978	.01 (.08) [-.15; .12] .057	.18*** (.05) [.10; .25]. .999
t 2-3	.46*** (.06) [.37; .55] 1.000	.71*** (.05) [.63; .78] 1.000	.73*** (.05) [.65; .82] 1.000	.14*** (.04) [.07; .21] .998	.35*** (.06) [.26; .44]. 1.000	.11* (.05) [.03; .19]. .909	.13** (.04) [.06; .20]. .987	.16** (.05) [.07; .25] .996	.08* (.04) [.02; .14] .835
t 3-4	.51*** (.06) [.42; .60] 1.000	.69*** (.06) [.59; .79] 1.000	.81*** (.06) [.71; .91] 1.000	.13** (.04) [.06; .20] .984	.32*** (.06) [.22; .42]. 1.000	.11 (.06) [.01; .21] .892	.07* (.05) [.01; .15] .561	.03 (.07) [-.08; .14] .143	.12* (.05) [.03; .20] .970

Notes. TJM = Teachers' judgments of students' aptitude in math; MG = Math grade; MSC = Math-specific self-concept; students' perceived teachers' judgments of their aptitude and students' self-reported ability self-concept about school in general were included as auxiliary variables;
*** $p < .001$; ** $p < .01$, * $p < .05$.

Table 6

Standardized stability and cross-lagged effects with standard errors and confidence intervals as well as significance coefficients from post-hoc power analysis for teachers' judgments of students' aptitude in math (TJM), students' math grades (MG) and their intrinsic task values in math (IV)

	Stability effects			Cross-lagged effects					
Waves	TJM	MG	IV	TJM → MG	MG → TJM	TJM → IV	IV → TJM	MG → IV	IV → MG
t 1-2	.57*** (.06) [.46; .67] 1.000	.52*** (.07) [.41; .64] 1.000	.91*** (.03) [.86; .96] 1.000	.32*** (.06) [.22; .42] 1.000	.26*** (.06) [.16; .36]. 1.000	-.02 (.06) [-.11; .08] .079	.03 (.04) [-.04; .10] .174	.03 (.06) [-.08; .13] .114	.03 (.04) [-.04; .09] .183
t 2-3	.49*** (.06) [.39; .58] 1.000	.72*** (.06) [.63; .81] 1.000	.82*** (.04) [.76; .89] 1.000	.17*** (.04) [.10; .24] 1.000	.37*** (.06) [.28; .47] 1.000	.09 (.06) [-.01; .19] .697	.04 (.03) [-.01; .09] .327	-.01 (.09) [-.14; .14] .059	.01 (.03) [-.04; .05] .073
t 3-4	.53*** (.05) [.45; .62] 1.000	.70*** (.06) [.60; .81] 1.000	.88*** (.02) [.85; .91] 1.000	.17** (.05) [.08; .26] 1.000	.36*** (.05) [.27; .45] 1.000	-.01 (.04) [-.08; .07] .064	.01 (.03) [-.06; .05] .069	.06 (.04) [.01; .12] .405	.04 (.03) [-.01; .10] .380

Notes. TJM = Teachers' judgments of students' aptitude in math; MG = Math grade; IV = Intrinsic task values; students' perceived teachers' judgments of their aptitude and students' self-reported ability self-concept about school in general were included as auxiliary variables;
*** *p* < .001; ** *p* < .01.

Table 7

Time-point specific (residual) correlation coefficients between the examined variables

Variables	t1	t2	t3	t4
TJM - MG	.76***	.55***	.40***	.30***
TJM – MSC	.53***	.01	.05	.07
TJM – IV	.28***	.04	.09	.15
MSC - MG	.58***	.11	.19***	.18**
IV - MG	.29***	.19*	.07	.03

Notes. TJM = Teachers’ judgments of students’ aptitude in math; MG = Math grade; MSC = Math-specific self-concept; IV = Intrinsic task values; t1 = measurement occasion 1; t2 = measurement occasion 2; t3 = measurement occasion 3; t4 = measurement occasion; *** p < .001; * p < .05.

Table 8

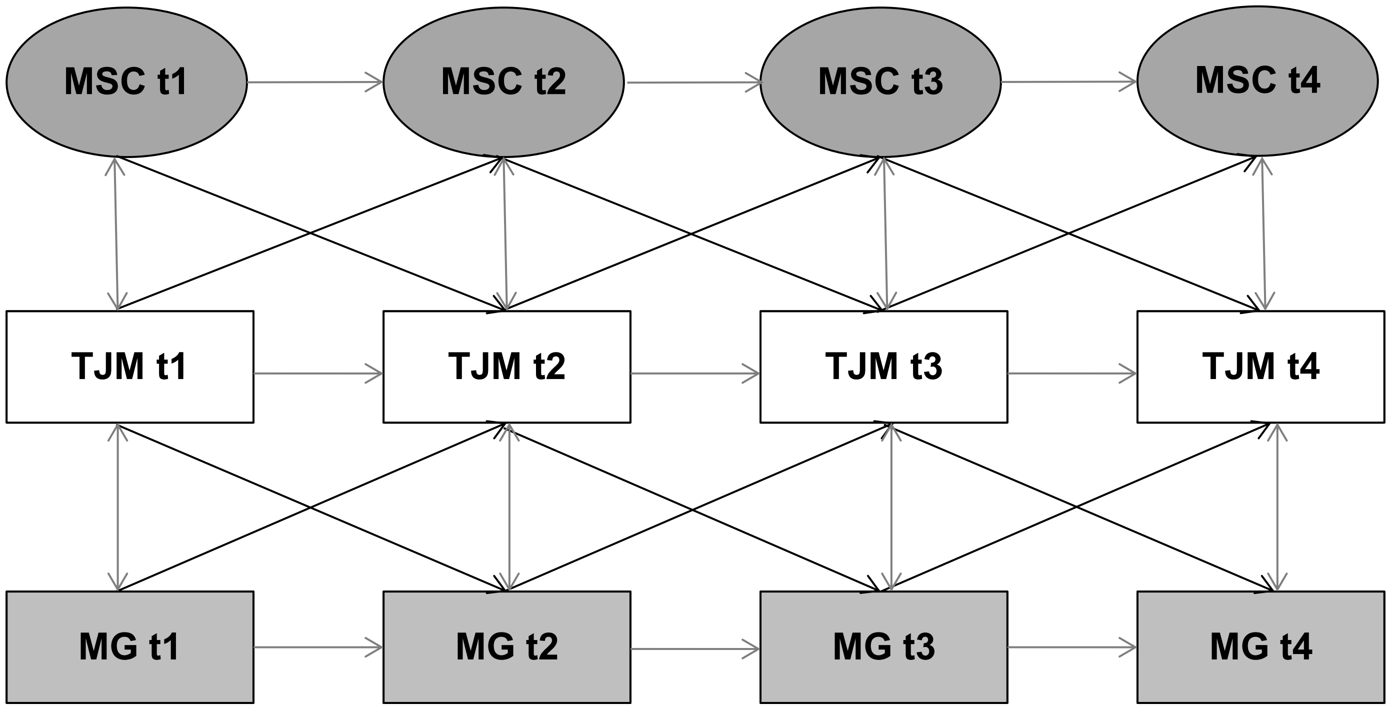
Standardized effects (standard errors) and confidence intervals from control variables (sex and native language) on teachers' judgments, students' math grades and their motivation

Variables	Sex	Native language
TJM t1	-.09 (.05) [-.18; -.01]	-.22*** (.06) [-.32; -.13]
TJM t2	-.04 (.04) [-.10; .02]	-.03 (.03) [-.09; .02]
TJM t3	.04 (.04) [-.02; .10]	.04 (.03) [-.01; .09]
TJM t4	-.05 (.03) [-.09; .01]	-.04 (.04) [-.11; .02]
MG t1	-.03 (.05) [-.10; .05]	-.22** (.08) [-.35; -.08]
MG t2	-.01 (.03) [-.05; .04]	-.02 (.03) [-.06; .03]
MG t3	.02 (.02) [-.01; .06]	-.02 (.03) [-.07; .03]
MG t4	.05* (.03) [.01; .10]	-.04 (.03) [-.09; .02]
MSC t1	-.27*** (.05) [-.34; -.20]	.01 (.05) [-.08; .10]
MSC t2	.02 (.03) [-.03; .07]	.02 (.04) [-.04; .09]
MSC t3	.02 (.03) [-.03; .07]	-.01 (.04) [-.07; .07]
MSC t4	-.12*** (.03) [-.17; -.08]	-.05 (.04) [-.12; .02]
IV t1	-.15** (.05) [-.22; -.07]	.07 (.05) [-.02; .16]
IV t2	.09** (.03) [.03; .14]	.03 (.04) [-.04; .09]
IV t3	-.07* (.03) [-.13; -.02]	.05 (.05) [-.04; .13]
IV t4	-.06* (.02) [-.10; -.02]	-.04 (.04) [-.10; .03]

Notes. TJM = Teachers' judgments of students' aptitude in math; MG = Math grade; MSC = Math-specific self-concept; IV = Intrinsic task values; t1 = measurement occasion 1; t2 = measurement occasion 2; t3 = measurement occasion 3; t4 = measurement occasion 4; *** $p < .001$; * $p < .05$.

Figure 1

Cross-lagged panel model with teachers' judgments of students' aptitude in math, students' math grades and their math-specific self-concept



Notes. MSC = Math-specific self-concept; TJM = Teachers' judgments of students' aptitude in math; MG = Math grade.

For greater clarity, indicators of latent constructs (items), method factors and control variables are not depicted in this figure.

7 General Discussion

The overarching aim of this dissertation was to examine the relative importance of motivation in the context of school. Three different studies looked at single aspects of motivation as a predictor of both school achievement and teachers' judgments. In the following, the findings of this dissertation will be summarized and embedded into the corresponding research literature. Then, strengths and limitations of the presented studies will be discussed. Finally, implications for theory, future research, and practice are outlined.

7.1 Summary of Empirical Findings and General Aspects

7.1.1 Motivation as a Predictor of School Achievement

One purpose of this dissertation was to determine the extent to which motivation predicts school achievement both relative to other well-established predictors and as a potential mediating and explaining factor.

Study 1 is a meta-analysis that has shown both intelligence and motivation to be important predictors of school achievement. Even though intelligence was the stronger predictor, motivation incrementally contributed to the prediction of school achievement. This finding is in line with results from other primary empirical studies and could now also be shown on a meta-level (e.g., Helmke, 1992; Gottfried, 1990; Kriegbaum et al., 2015; Lloyd & Barenblatt, 1984; Schicke & Fagan, 1994; Spinath et al., 2006; Steinmayr & Spinath, 2009; Trautwein et al., 2012). The meta-analysis also provided empirical support that intelligence and motivation explained a common amount of variance in school achievement. It can therefore be derived that both intelligence and motivation are important predictors of school achievement that lead to a higher portion of overall explained variance in school achievement together. It is likely that intelligence and motivation mutually reinforce each other for the following reason: more intelligent students are likely to be the ones that also develop higher academic self-concepts and higher self-efficacy, which may then lead to improved knowledge acquisition and enhanced school achievement. These findings highlight the essential interplay that seems to exist between intelligence and motivation that impacts the prediction of school achievement.

Study 2 has shown that all three measures of SES (i.e., fathers' and mothers' ISEI as well as ESCS) were significantly positively associated with students' motivation (in form of academic self-concept, self-efficacy, and interest). The relationship between parents' SES and students' standardized test achievement in math was mediated by students' motivation. The mediation effects of motivation still remained significant after including students' intelligence as an additional mediator. This suggests that students from parents with a higher SES might have better individual performance prerequisites (i.e., higher intelligence and higher motivation) that could explain their superior school achievement. This is also in line with EVT that states students' social background to influence their motivation which may also affect their achievement (Eccles et al., 1983). It can be argued that parents' SES might serve as a proxy for parents' motivation influencing students' motivation via genetic, environmental, or a combination of both factors (Steinmayr et al., 2010, 2012). These findings suggest an interplay between parents' SES and students' motivation as well as between parents' SES and students' intelligence. All three constructs taken together could therefore be beneficial for predicting school achievement. Moreover, motivation incrementally explained the relationship between parents' SES and students' standardized test achievement even after including intelligence as an additional mediator. This is supportive to the idea that motivation can make an important difference over and beyond intelligence.

Looking at Study 1 and 2, motivation did not only predict school achievement, but also explained the association between parents' SES and students' school achievement. Both studies clearly demonstrated that motivation makes up a crucial student characteristic that is capable of explaining differences in school achievement.

7.1.2 Motivation as a Predictor of Teachers' Judgments

Study 1 and 2 focused on school achievement as a rather direct criterion of students' academic abilities (i.e., school grades and standardized test achievement). Study 3 went one step further and assessed a rather indirect criterion of students' academic abilities, namely teachers' judgments of students' aptitude. It examined whether students' motivation can predict teachers' judgments of students' aptitude over time. It has indeed been shown that students' prior academic self-concepts in math had significant effects on teachers' subsequent judgments of students' aptitude over and beyond students' math grades. In other words, students' self-concepts predicted teachers' judgments of students' aptitude longitudinally. Students' intrinsic task values, however, did not significantly predict teachers' judgments of students' aptitude. It can therefore be derived that students with a high academic self-concept might convince their teachers of their higher aptitude and could in turn be evaluated as more talented by their teachers.

The EVT assumes that socializer's beliefs can have effects on students' motivation (Eccles et al., 1983; Wigfield & Eccles, 2000). Study 3 revealed a reversed effect in that students' motivation (in form of academic self-concepts) had a significant effect on teachers' subsequent judgments of students' aptitude. Importantly, this appears to be the first study that has demonstrated students' motivation to predict socializer's beliefs in elementary school. This effect is in line with findings from social psychology showing that people can persuade others better when they are convinced of a particular fact themselves (Hovland, Harvey, & Sherif, 1957).

Taken together, the findings of Study 3 provided strong support that motivation (in form of academic self-concept or expectancies) does not only significantly contribute to students' school achievement (in form of grades or standardized test achievement), but also predicts teachers' judgments of students' aptitude.

7.1.3 Differences in the Predictive Power Depending on Motivational Constructs

Besides the single contributions of each study within this dissertation, all studies share important similarities that should also be discussed. All three studies operationalized motivation as expectancies and values which made it possible to examine differences in their predictive power. Study 1 showed that the correlation between students' motivation and school achievement was significantly higher for expectancies (such as academic self-concept and self-efficacy) compared to values (such as intrinsic motivation, interest, and task values). In Study 2, the effects of motivation on standardized test achievement were also stronger for expectancies (academic self-concept and self-efficacy) compared to values (interest). Study 3 showed that academic self-concept, but not intrinsic task values, predicted teachers' judgments of students' aptitude. All these findings are in line with the EVT assumption that expectancies compared to values are more strongly related to school achievement (Eccles et al., 1983; Wigfield & Eccles, 2000). This can be explained by the fact that expectancies are primarily determined by achievement information and thus predict achievement outcomes. Values concern students' levels of interest in an activity and whether this activity is important and useful. This extends beyond whether or not students feel competent in the activity, which makes values better predictors of choices.

7.1.4 Differences in the Predictive Power of Motivation Depending on Students' Outcomes in the School Context

It should also be discussed whether the predictive power of motivation differs for various outcomes (i.e., school grades, standardized test achievement, and teachers' judgments of students' aptitude). In all three studies there were significant small to moderate effects of students' motivation on their school achievement and teachers' judgments of students' aptitude. Only Study 1 was able to systematically examine whether the predictive power of motivation differed depending on the applied achievement measures. There were no significant differences found in the predictive power of motivation for school grades in comparison to standardized test achievement. One reason for this might be that the correlation between motivation and school grades or standardized test achievement included not just one but various motivational constructs. For example, there are motivational constructs (such as academic self-concept) that were shown to be more strongly related to school grades (Steinmayr & Meißner, 2013). Other motivational constructs (such as task-specific self-efficacy) were found to be associated with standardized test achievement (Ferla, Valcke, & Cai, 2009; Frenzel, Pekrun, & Zimmer, 2006). Considering all motivational constructs together results in a relatively equal relationship with both school grades and standardized test achievement. Only splitting up motivation into its different constructs makes it possible to examine whether a different relationship exists.

7.2 Strengths and Limitations of This Dissertation

The present dissertation has several strengths. One major strength is that different motivational constructs were examined within three studies. This made it possible to study the extent to which these motivational constructs differed in their predictive power for school achievement. Also, this allowed to check whether the results were generalizable over different motivational constructs. A second major strength is that different measures of school achievement (such as school grades and standardized test achievement in different domains) were included. This allowed the exploration of school grades as an achievement measure and standardized test achievement and whether they could equally be determined by student characteristics. A third major strength was its combination of primary empirical studies as well as one meta-analysis. The primary studies applied a longitudinal design to examine the effects of motivation on different criteria of students' academic abilities over time. The meta-analysis summarized a great amount of primary studies in order to examine the effects of motivation and intelligence on school achievement and test for their generalizability.

Furthermore, all three studies included different student samples. One particular sample of students came from elementary school (Study 3). Another representative sample was drawn from the German secondary student population who continued school after 9th grade (Study 2). The meta-analysis benefited from several samples that ranged from the beginning of elementary school until the end of high school (Study 1). Adding just another strength, the sophisticated data analysis method of SEM was applied in all three studies. By using this approach, latent variables including measurement errors could be computed. Study 1 even applied MASEM as an advanced technique for modeling data on a meta level. Study 2 added a mediation model in which all parameters (direct and indirect effects) could be estimated simultaneously. Study 3 applied a cross-lagged panel model with four measurement occasions to look at reciprocal effects.

However, the findings within this dissertation must be interpreted in light of some limitations. Despite the longitudinal designs, the data remain correlational. Therefore, definitive conclusions about causal influences or relationships cannot be drawn and any detected effects should be understood as describing predictions (such as regression effects). Another shortcoming was that students' motivation got always assessed via self-report using questionnaires. However, this approach was in line with the research questions that aimed to assess students' subjective perceptions of their math ability and their subjective values. This can be best captured by asking students what they think on how good they are in math or how much they like math. Motivation is also typically assessed via self-reports in most empirical studies. Another drawback is that the results might be biased due to mechanisms of social desirability. It would be valuable to assess students' motivation via observational data or external reports. Lastly, all studies of this dissertation focused on motivation in the context of school and therefore conclusions cannot be generalized to other educational settings.

7.3 Implications

This section will give an overview on general implications for theory, future research, and practice that go beyond the specific implications already mentioned in the three studies included in this dissertation.

7.3.1 Theory

The present research contributes to the literature and theory in multiple ways. First, Study 1 and 2 replicated an assumption of EVT that expectancies and values as motivational constructs predict school achievement (Eccles et al., 1983). The meta-analysis provided strong evidence for the assumption that expectancies are more strongly related to school achievement compared to values. Second, parents' SES (as an indicator of students' social background) was shown to be not only associated with students' expectancies (as assumed in EVT), but also with students' values (such as their interest in a specific subject) (Study 2). Both expectancies and values mediated the relationship between parents' SES and students' school achievement. Third, and in contrast to an assumption of EVT, there was no evidence for an effect of socializer's beliefs on students' academic self-concept. There was evidence for a reversed effect, namely that students' academic self-concepts predicted teachers' judgments of students' aptitude over time (Study 3). It was the first time that this effect was examined over several measurement occasions. This suggests that EVT would benefit from an additional path which relates to the aforementioned effect (i.e., students' academic self-concepts on socializer's beliefs). The current version of the model proposes an unidirectional effect of socializer's beliefs on students' academic self-concepts. However, a major finding of Study 3 was that students' academic self-concepts could predict socializer's beliefs over time. Therefore, the effect should be considered in a bidirectional manner. To conclude, while many assumptions of EVT (Eccles et al., 1983) were replicated within this dissertation, there was also a new effect that emerged which should be integrated in an updated version of the model.

7.3.2 Future Research

Two studies of this dissertation (Study 2 and 3) examined longitudinal effects between motivation and criteria of students' academic abilities. Even though no causal inferences could be drawn from these correlational data, it marks a first approach on how one motivational variable influences another over time. In this context, future research should focus on designing genuine experiments to examine the causal influence of motivation on both school achievement and teachers' judgments. Such experiments allow for the manipulation of students' motivation and can also test its influence on different outcomes in the school context (such as achievement measures and teachers' judgments).

Furthermore, Study 2 and 3 focused on school achievement in the math domain. The meta-analysis (Study 1) showed that the association between motivation and school achievement was significantly stronger for languages compared to math. It would therefore be interesting to further explore whether motivation mediates the relationship between SES and students' competence in reading, for example. One should also test for reciprocal effects between motivation and teachers' judgments of students' aptitude in other subjects (such as the first language or foreign languages).

Eventually, the present dissertation focused on motivation as an important student characteristic when predicting school achievement and teachers' judgments. There are also other student characteristics that are important to look at. Future studies should also address the predictive power of variables such as personality factors.

7.3.3 Practice

The results of the present dissertation clearly demonstrate that motivation is an important predictor of school achievement as well as teachers' judgments of students' aptitude. This means that motivation is an important prerequisite to perform well at school. It has been shown that motivation is relatively easy to influence and foster through different approaches such as feedback or instructional characteristics (e.g., Harackiewicz et al., 2016; Midgley et al., 1995; Yeager & Walton, 2011). Due to these promising findings, both teachers and parents should make use of such approaches and strategies in order to motivate students. Also, academic self-concepts and self-efficacy as expectations were more strongly associated with school achievement and teachers' judgments than other motivational constructs such as values. From another practical perspective, it is important for students to develop realistic and positive expectations for success. This can not only help them to perform well, but also to develop a higher motivation for future learning. At this point, teachers could support their students in developing realistic and positive expectations for success while providing more differentiated feedback (Stipek, 2002). Study 2 showed that motivation partly explained social disparities in school achievement in that students from a rather disadvantaged social background appeared to be less motivated compared to more privileged students. Therefore, teachers should particularly promote the motivation of students from less privileged families.

7.4 General Conclusion

The aim of this dissertation was to examine the relative importance of motivation in the context of school, both relative to other well-established predictors and as a potential mediating and explaining factor. Based on three studies, single aspects of motivation as a predictor in the school environment were analyzed with different methodological approaches. Both empirical primary studies (Study 2 and 3) and one meta-analysis (Study 1) were conducted using structural equation modeling analyses. The findings showed the following: (1) motivation predicted school achievement over and beyond intelligence, (2) motivation mediated the relationship between SES and standardized test achievement in math, and (3) motivation in form of math-specific self-concepts predicted teachers' judgments of students' aptitude over time. These results clearly highlight the special role of motivation in that motivation was powerful enough to explain differences in school achievement even though other strong achievement predictors such as intelligence and SES were considered within the analyses.

The findings of the single studies not only contribute to educational psychology and its related fields but also give practical advice to a broader audience that is more directly engaged with students such as teachers and parents. Coming back to the exemplary scenarios from the very beginning of this dissertation, there is now better understanding why some students perform better than others. The first scenario based on Study 1 where one of two equally intelligent students would receive better grades in a certain subject. This dissertation showed that a higher motivation can certainly be a valuable explanation for this achievement difference. The second scenario aligned with Study 2 where one student with a higher SES outperformed another student with a lower SES. This dissertation demonstrated that motivation is also able to explain the relationship between SES and achievement. Finally, the third scenario belonged to Study 3 where one highly motivated student was judged as more talented by the teacher than a less motivated student in that particular subject. Again, this dissertation clearly supported the notion that motivation in form of students' self-concepts predict teachers' judgments of students' aptitude over time. In conclusion, motivation functions as an important predictor in the school context that plays a significant role not only for individual achievement, but also serves as an important goal for education on a large scale.

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List of Abbreviations

Abbreviation	Long Version
ISEI	International Socio-Economic Index of Occupational Status
ESCS	Index of Economic, Social, and Cultural Status
EVT	Expectancy-Value-Theory
HISEI	Highest International Socio-Economic Index of Occupational Status
MASEM	Meta-Analytic Structural Equation Modeling
PISA	Programme for International Student Assessment
SEM	Structural Equation Modeling
SES	Socio-economic status

Description of Personal Contribution for the Publications of This Dissertation

1st Publication:

The relative importance of intelligence and motivation as predictors of school achievement: A meta-analysis.

Katharina Kriegbaum and Prof. Dr. Birgit Spinath developed the research questions and hypotheses together. Katharina Kriegbaum conducted the literature search. She and her research assistant Rahel Milla coded the primary studies. Dr. Nicolas Becker and Katharina Kriegbaum analyzed the data. Katharina Kriegbaum wrote the whole article except for section 2.6 Data analysis which was written by Dr. Nicolas Becker. Prof. Dr. Birgit Spinath supervised the manuscript.

2nd Publication:

Explaining Social Disparities in Mathematical Achievement: The Role of Motivation.

Katharina Kriegbaum and Prof. Dr. Birgit Spinath developed the research questions and hypotheses together. Katharina Kriegbaum analyzed the data that stem from the research data center (FDZ) from the institute for educational quality improvement (IQB) in Berlin. Katharina Kriegbaum wrote the whole article except for the section "Practical implications for evaluating educational equity" that is part of the discussion section which was written by Prof. Dr. Birgit Spinath. The work was supervised by Prof. Dr. Birgit Spinath.

3rd Publication:

Longitudinal reciprocal effects between teachers' judgments of students' aptitude, students' motivation, and grades in math.

Katharina Kriegbaum and Prof. Dr. Birgit Spinath developed the research questions and hypotheses together. Katharina Kriegbaum analyzed the data stemming from the project MEGA (Development of motivation in elementary school) that was led by Prof. Dr. Birgit Spinath and Prof. Dr. Ricarda Steinmayr. Katharina Kriegbaum wrote the article. The work was supervised by Prof. Dr. Birgit Spinath and Prof. Dr. Ricarda Steinmayr.

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**FAKULTÄT FÜR VERHALTENS-
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**Promotionsausschuss der Fakultät für Verhaltens- und Empirische Kulturwissenschaften
der Ruprecht-Karls-Universität Heidelberg**
Doctoral Committee of the Faculty of Behavioural and Cultural Studies of Heidelberg University

Erklärung gemäß § 8 (1) c) der Promotionsordnung der Universität Heidelberg für die Fakultät für Verhaltens- und Empirische Kulturwissenschaften
Declaration in accordance to § 8 (1) c) of the doctoral degree regulation of Heidelberg University, Faculty of Behavioural and Cultural Studies

Ich erkläre, dass ich die vorgelegte Dissertation selbstständig angefertigt, nur die angegebenen Hilfsmittel benutzt und die Zitate gekennzeichnet habe.
I declare that I have made the submitted dissertation independently, using only the specified tools and have correctly marked all quotations.

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Ich erkläre, dass ich die vorgelegte Dissertation in dieser oder einer anderen Form nicht anderweitig als Prüfungsarbeit verwendet oder einer anderen Fakultät als Dissertation vorgelegt habe.
I declare that I did not use the submitted dissertation in this or any other form as an examination paper until now and that I did not submit it in another faculty.

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