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A Meta-Analysis on the Relationship between School Characteristics and Student Outcomes in Science and Math – Evidence from Large-Scale Studies

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A meta-analysis on the relationship between school characteristics and student outcomes in science and math – evidence from large-scale studies

Abstract

In the present meta-analysis, we examine how secondary school characteristics—such as schools’ academic press, school climate, material resources, personnel resources, classroom climate, instructional practices, out-of-school activities, and socioeconomic status (SES) composition — provide opportunities for students to engage in science and math, and how these matter with regard to students’ cognitive and motivational-affective outcomes. The meta-analysis includes 71 (international) articles from large-scale studies with a total of 3,960,281 students, 260,390 schools, and 285 effect sizes that were transformed to correlation coefficients. Multilevel meta-analyses were performed. Results identified a number of school variables that can be regarded as relevant for making a difference in student outcomes and at the same time be influenced by education. These refer to school variables such as schools’ academic press, classroom climate, instructional practices, and out-of-school activities. Moreover, SES composition was significantly related to student outcomes. Material and personnel resources as well as school climate yielded a close to zero effect. No differences were found between cognitive and motivational-affective outcome variables or between science and math. The results point to the most promising school characteristics for promoting students’ outcomes and emphasise schools’ potential for students’ engagement in science and math.

Keywords: meta-analysis; school characteristics; school effectiveness; large-scale studies; student outcomes, science education

Introduction

From economic, societal, and political perspectives, students' skills in science and mathematics are undeniably important (Bosworth, Lyonette, Wilson, Bayliss, & Fathers, 2013; Mullis & Martin, 2016). However, students still lack proficiency as well as engagement with science (Krapp & Prenzel, 2011; National Research Council, 2011a, 2013; OECD, 2016). Therefore, many stakeholders in education question how to promote students' outcomes in science and education, and research is concerned with determining the variables that predict these outcomes. While 'internal' factors such as students' personal backgrounds (e.g., family characteristics, socioeconomic status [SES], and cultural capital) have repeatedly and consistently been shown to predict student science outcomes (Archer et al., 2012; Fouad et al., 2010; George & Kaplan, 1997; Nugent et al., 2015; Taskinen, Schütte, & Prenzel, 2013), these personal background characteristics cannot easily be influenced or changed. Therefore, when searching for factors that can be actively manipulated and developed, schools are regarded as valuable resource. Science education research on school-related opportunities and their relationships with student outcomes has been expanding (e.g., Basl, 2011; Belland, Walker, & Kim, 2017; Belland, Walker, Kim, & Lefler, 2017; D'Agostino, 2000; Hogrebe & Tate, 2010; Ma & Klinger, 2000). Basl (2011), for example, found that students attending schools that offer preparation for science-related careers showed higher career orientations; Hogrebe and Tate (2010) investigated the influence of SES composition, and D'Agostino (2000), Belland, Walker, and Kim (2017) and Belland, Walker, Kim, and Lefler (2017) analysed whether instructional characteristics predicted students' achievement (in STEM). Although schools characteristics are rather distal with regard to the concrete learning activities necessary for acquiring knowledge and reaching certain learning developments, schools do promote student outcomes by offering and expanding learning opportunities and by providing a specific learning environment than can enable necessary learning activities (Seidel & Shavelson, 2007). Therefore, school characteristics interact with

classroom variables and affect teaching (e.g., Maag Merki, Emmerich, & Holmeier, 2015; Reynolds et al., 2014). The learning opportunities schools provide are manifold and a large variety of school variables is under research. Multiple frameworks intend to integrate these various school variables into one model. Although these frameworks do not have a specific focus on science or math, they are useful for categorising the multitude of school variables that are under investigation. Opdenakker and van Damme (2006), for example, distinguish between school composition, school context, and school practice, which, in turn, affect the classroom as well as students' achievement. While school composition (e.g., student population, teaching staff, school leader) and school context (e.g., location, resources, sizes) are – at least at the school level – difficult to change, school practice (e.g., organization and management, work and learning climate) can be developed. Scheerens (2015) also provides a framework of school variables and differentiates between school antecedents (e.g., higher level policies, school neighborhood), school ecology (e.g., student composition, resources, extracurricular activities), and school leadership, policies, and organizations (e.g., curriculum, achievement orientation, cooperation among staff). Although the two models differ in terminology as well as in grouping different variables into categories, both assume that these school characteristics form the environment for actual learning opportunities in the classroom with relationships to students' outcomes, particularly, to students' achievement.

Previous meta-analyses and reviews in the field of school characteristics examine single variables only, such as school climate (e.g., Thapa & Cohen, 2013), school resources (Greenwald, Hedges, & Laine, 1996; Hanushek, 1997; Hedges et al., 2016), school SES composition (e.g., Mickelson, Bottia, & Lambert, 2013; mathematics outcomes), extracurricular activities (e.g., Holland & Andre, 1987), teacher-student relationship (e.g., Quin, 2017), or teaching methods (e.g., Furtak, Seidel, Iverson, & Briggs, 2012; science education) and their relationship with student outcomes. These meta-analyses have three open challenges: First, the meta-analyses do not focus on a specific discipline (e.g., are not

specifically restricted to science and math education) but rather include student outcomes in various disciplines. Scheerens and Blömeke (2016) noted, however, that it is not yet clear how school characteristics are related to subject-specific outcomes. Second, the comparison of multiple school learning opportunities at the same time has not yet been considered. Meta-analyses on single school variables are worthwhile with respect to the question how one variable is related to student outcomes. However, without comparing these absolute effect sizes to other school characteristics, these absolute values are difficult to interpret. They do not allow inferences on the relevance of the variable conglomerate. Therefore, it is not yet clear which of the school's learning opportunities are most relevant. Finally, most of the present literature reviews focus on cognitive outcomes. However, a narrow view on students' achievement as a cognitive outcome has been criticised and it has been claimed that non-cognitive student outcomes should also be considered (e.g., Grossman, Cohen, Ronfeldt, & Brown, 2014; Reynolds et al., 2014; Seidel & Shavelson, 2007), particularly, in the field of science (Fredericks, Hofkens, Wang, Mortenson, & Scott, 2017; Greenfield, 1997; Lamb, Anneta, Meldrum, & Vallett, 2012; Logan & Skamp, 2013). Non-cognitive outcomes encompass, for example, motivational-affective outcomes. In their review of motivational constructs, Murphy and Alexander (2000) differentiated between goals, interest, (intrinsic and extrinsic) motivation, and self-schema, such as self-efficacy or self-concept. In addition to motivational orientations, affective outcomes defined as emotions (e.g., enjoyment, anxiety) can be examined as student outcomes (Shuell, 1996). Motivational-affective constructs are usually conceptualised as context- and discipline-specific, and this, in turn, should be reflected in their measurement. Also, with the multitude of school variables, different processes may apply in predicting students' cognitive and motivational-affective variables. While schools' extracurricular activities may rather be related with motivational-affective variables, students' cognitive outcomes may be predicted by high learning expectations.

The Present Study

In light of previous meta-analyses, the present meta-analysis aims to summarise international research on the relationship between school variables (as learning opportunities) and student cognitive and non-cognitive outcomes in science and math in secondary schools, and examines whether different processes on the school-level apply (Eisenhart et al., 2015). Therewith, the present study advances previous research by (a) including multiple school variables concurrently, (b) investigating differences in cognitive and non-cognitive outcome variables, and (c) addressing subject-specific relationships. In particular, we examined the following research question: How does the effect size for the relationship between school variables and student outcomes differ for (a) different groups for school characteristics (e.g., material resources, school climate), (b) cognitive and motivational-affective outcomes, and (c) science and math?

Therewith, we aim to identify those school-related variables that seem to be most promising (a) when promoting students' outcomes in science and math. Contrary to previous meta-analyses that focused on single school variables, the present study expands the knowledge about the specific relevance of different school variables and enables recommendations about initiatives on the promotion of science and math outcomes based on the relative importance of school characteristics. By comparing cognitive and motivational-affective outcome variables (b), we gain information about whether, for instance, school variables are more strongly related to motivational-affective variables than to cognitive variables. Testing the generalizability of effects across science and math (c) will contribute to the knowledge of whether the effects differ depending on the discipline and will provide insights on what constitutes a science- and math-supportive school environment.

With our goal to compare multiple school characteristics and multiple student outcome variables in the meta-analysis, we face the challenge of a meta-analysis that needs to guarantee the comparability of included studies. In order to have similar operationalization of the variables under investigation, we analysed the instruments of large-scales studies and

found comparable measures across studies. Therefore, we decided to focus on large-scale studies only. Moreover, large-scale studies are characterised by surveying a large sample with a wide range of participants (e.g., students, teachers, principals) and measures (e.g., standardized achievement tests, background questionnaire) with a high degree of standardisation. With their wide range of instruments and our goal to compare multiple school variables concurrently, large-scale studies were particularly appropriate for the present study.

Method

Literature Search

To answer our research questions, we conducted a meta-analysis. Our literature search process involved two steps. First, we searched subject-specific databases ERIC (Education) and Web of Science (social sciences – general/ interdisciplinary, pedagogy, philosophy, political science, psychology, law, sociology, economic sciences). The search in both databases yielded mostly distinct results with only few duplicates (see below). We used keyword combinations concerning (1) school variables, (2) student outcomes (cognitive and motivational-affective), and (3) the disciplines science and math. Detailed search terms are presented in Table 1. As we intended to cover a broad range of variables characterised as school variables, studies that claimed to investigate school variables were eligible. Our search included all appropriate synonyms. The Boolean terms 'AND' and 'NEAR' separated the search terms, resulting in the following search construction: school variables AND (student outcomes [two separate searches for cognitive and motivational-affective variables] NEAR/1 science and math).¹ As outlined above, we limited our search to articles based on large-scale studies. With the key international large-scale study Programme for International Student Assessment (PISA) starting in 2000, we limited our search to articles published since 2000, resulting in a time period from 2000 to 2016. The database search resulted in 1,567 articles (889 from ERIC; 889 from Web of Science).

¹ Please note that ERIC uses N1 instead of NEAR/1.

As a second step, we scanned reference lists of articles matching our inclusion criteria in order to complement our search. However, we did not find any publications additionally to the database matches.

(Please add Table 1 here)

After removing duplicate references, a total number of 1,353 studies remained from the initial search. Following the PRISMA statement (Moher, Liberati, Tetzlaff, & Altman, 2009) Figure 1 presents an overview of the literature search and coding process as described below.

(Please add Figure 1 here)

Inclusion Criteria and Study Selection

In addition to search criteria such as publication period, we established further criteria for inclusion: studies were eligible if (a) they addressed a relationship between school variables and student outcomes (thematic fit), (b) the dependent variable under investigation was related to at least science or math, (c) the sample was located at the secondary education level², (d) they were empirical quantitative studies, (e) they reported all relevant parameters to calculate or transform the effect size necessary for the meta-analysis (see section 'Effect sizes' for further details), (f) they were published in the English language, (g) they were published in peer-reviewed journals, and (h) they were part of a large-scale project³ either on a national or an international level (i.e., Trends in International Mathematics and Science Study [TIMSS; $n = 23$]; Programme for International Student Assessment [PISA; $n = 31$]; National Assessment of Educational Progress [NAEP; $n = 1$]; National Longitudinal Survey of Youth [NLSY; $n = 2$]; National Longitudinal Study [NLS; $n = 2$]; National Education

² As the terms for secondary education level differ across the international context, we thoroughly reviewed the information provided in the articles. We coded the school type (whether the study was performed in elementary, primary, middle, secondary, high school, or any other school type) and the age/grade provided in the article. We excluded the studies when they were performed in elementary or primary school only with a sample in grade six or below. In case a study included both elementary and secondary schools, we included the study (when effect sizes were reported separately, only the effect size from the secondary school was included).

³ Some of the articles examined multiple large-scale databases, numbers in brackets indicate the number of studies from the final sample.

Longitudinal Study [NELS; $n = 8$]; Longitudinal Study of American Youth [LSAY; $n = 5$]; High-school and Beyond Study [HS:B; $n = 2$]; Educational Longitudinal Study [ELS; $n = 1$]; Early Childhood Longitudinal Study [ECLS; $n = 1$]). We used large-scale studies as inclusion criteria in order to have comparable research designs and instruments assessing the variables under investigation.

During an initial screening in which we reviewed titles and abstracts, we categorised the articles as eligible, non-eligible, or indecisive with regard to the inclusion criteria. In this step, 685 articles were directly excluded. For example, excluded articles solely assessed general (not subject-specific) student outcomes (e.g., Dettweiler, Uenlue, Lauterbach, Becker, & Gschrey, 2015), only elementary schools (e.g., Adams, 2014), were not based on a large-scale study (e.g., Bae, 2007), or did not examine school variables (e.g., Gregory & Weinstein, 2004).

Full texts were acquired for the articles in the eligible and indecisive categories. We contacted authors to retrieve those articles for which full text was not accessible. Articles ($n = 19$) for which the full text still could not be retrieved were excluded from the analysis.

The most frequent reasons for exclusion were that the articles did not address the relationship between school variables and students' outcomes in science or math, did not provide sufficient details for effect sizes, or addressed a sample of elementary students. As we decided to include large-scale studies only (e.g., PISA, TIMSS), we checked whether the studies used the same database (i.e., study year, countries, and variables under investigation) to exclude that the same effect size was aggregated twice. The study pairs Alacacı and Erbaş (2010) and Demir, Kilic, and Unal (2010), Akyüz (2014) and Ker (2015), as well as Lam and Lau (2014) and Sun, Bradley, and Akers (2012), used the same database and some of their variables were similar; however, their models were quite different so that we decided not to exclude the studies. The coding of the full texts with respect to the inclusion criteria yielded a

total of 71 articles, 285 reported effect sizes, 3,960,281 students, and 260,390 schools.⁴ The reference list contains all included studies, which are denoted with an asterisk.

Data Coding

We developed a coding scheme to categorise the articles. Besides general report characteristics (e.g., author, publication year, year of data collection) and methodological issues (e.g., level of analysis or data format), we categorised the independent school variables, dependent student outcome variables, and the disciplines. Figure 2 outlines our final coding framework, which resulted from partly deductive (based on the Integrated Multilevel Model of School Effectiveness by Scheerens, 2015, as described in detail below) and partly inductive coding (adding categories from information that we found in the studies, if matching our research focus). To validate the developed coding schema, in a training phase (i.e., before the final coding process) two of the authors tested whether the studies could be coded accordingly and where sources of disagreement were. With the final coding schema, the two independent raters coded a subset of 10 articles (14% of the data basis), after which they determined the interrater reliability. The Cohen's kappa, averaged across 22 codes, was 80% indicating interrater agreement. All variables were dummy-coded (0 = *not investigated*; 1 = *investigated*).

(Please add Figure 2 here)

School Characteristics

As we specified relatively broad search terms for school variables (e.g., school factor, school context, see Table 1), we sought to include studies that investigate multiple school characteristics concurrently. We used the school and classroom levels of Scheerens' (2015) Integrated Multilevel Model of School Effectiveness as a framework to categorise the school characteristics (the original models additionally comprised a system and a student level which

⁴ Number of students/schools was not retrievable in two/five articles

exceed the focus of this meta-analysis). By using this framework as a theoretical base for our coding scheme, we aimed at capturing the following main categories of school characteristics: school ecology; school leadership, policies, and organization; classroom ecology and climate; and teaching. The following section describes the main categories and the indicators for the main category (see also Figure 2).

The category school ecology consisted of *schools' composition regarding students' socioeconomic background* and *school climate*. We used several variables as indicators for school SES composition, namely parental educational and occupational background, SES index (e.g., International Socio-Economic Index of Occupational Status [ISEI], Index of Economic, Social and Cultural Status [ESCS]), free or reduced lunch eligibility, and ethnic minority (e.g., Alacacı & Erbaş, 2010). For this code, it was necessary that socioeconomic background was not measured exclusively at the student level, but that a measure at the school level was analysed (e.g., school mean). School climate can be defined as the quality and character of school life (Cohen, McCabe, Michelli, & Pickeral, 2009). Studies examining school climate had to explicitly address the school environment (as opposed to classroom climate). Indicators were problem behaviors (e.g., attendance, crime, violence, suspension; Perry & Morris, 2014), quality of relationships (e.g., student-teacher, teacher-teacher; Shin, Lee, & Kim, 2009), school learning climate (e.g., Grubb, 2008), and safety (e.g., Parcel & Dufur, 2001).

The category school policies and organization is characterised by *curriculum*, *schools' academic press*, *material resources*, and *personnel resources*. Curriculum is defined by differentiation and focus of courses. Specifically, this includes ability grouping (e.g., Park & 이광현, 2005). Schools' academic press refers to the school environment (Bryk & Thum, 1989) and was defined by how strongly the school environment pushes students to academic success and conforms to specific standards of achievement. Indicators were academic

achievement expectations (e.g., Ker, 2015) and emphasis on homework (Matsuoka, 2014).

Material resources refer to a school's material infrastructure at the school—in particular, the availability or shortage of adequate resources (e.g., Akyüz, 2014) and information and communication technology (ICT) resources (e.g., Zhang & Liu, 2016). Personnel resources refer to the characteristics of a school's personnel. Indicators were: the degree to which teachers were certified (e.g., Southworth, 2010), whether they had a teaching degree or a Master's in education (e.g., Parcel & Dufur, 2001), teacher experience (e.g., Mohammadpour, 2012b), the number of teachers (i.e., percentage of female teachers, percentage of science teachers, teacher-student ratio, teacher shortage; e.g., Mohammadpour, 2012b), and teachers' readiness to teach (e.g., Ker, 2015).

As indicators for the category classroom ecology we used *classroom climate* and examined how learning climate in class (e.g., student-teacher or student-student relationships, and disciplinary climate; Shin et al., 2009) or limitations on instruction (e.g., academic abilities, backgrounds, or needs too diverse; disruptive or uninterested students; Mohammadpour, 2012b) were related to student outcomes.

Finally, the category teaching was assessed by teachers' *instructional practices*, *preparation for the future*, and *out-of-school activities*. With regard to instructional practices, we contrasted student-centered techniques (e.g., hands-on activities, investigation, inquiry-based teaching, or application to real-world context; Mere, Reiska, & Smith, 2006) with teacher-centered techniques (e.g., traditional teaching approaches; Papanastasiou, 2008). In addition to teachers' instructional practices, schools may offer supplementary learning opportunities for experiences in science and math, such as preparation for the future and out-of-school activities. The studies defined preparation for the future as the degree to which schools prepare their students for science/academic careers in general or for a STEM career in college (e.g., Basl, 2011). Experiences and learning opportunities in science and math that do not take place in the regular classroom were coded as out-of-school activities. Indicators

included offering school activities (e.g., science clubs, excursions, competitions) or programs in science and math (e.g., Taskinen et al., 2013).

Due to the small number of studies that investigated preparation ($n = 3$) and curriculum ($n = 2$) these variables were excluded from the analyses, as the statistical power for these variables would be rather low (Valentine et al., 2010).

Student Outcome Variables

In the large-scale study set, students' cognitive outcomes were operationalised by using test scores, grades, or GPA. The *motivational-affective outcomes* comprised motivation, enjoyment, interest, attitudes, self-efficacy, or self-concept. All variables were used as equivalent indicators for cognitive or motivational-affective outcomes.

Discipline Variables

Finally, the discipline under investigation was coded. We coded articles according to whether they examined *math or science*.

Effect Sizes

The primary studies included in the meta-analysis reported multiple types of effect sizes (differences in mean, log odds, correlation coefficients, β , etc.). Borenstein, Hedges, Higgins, and Rothstein (2009) point out that 'the fact that they used different metrics should not be an impediment' (p. 45), in case the studies are judged to be comparable. To summarise the effect sizes, it is essential that all effect sizes have the same metric (Morris & DeShon, 2002).

Therefore, we first transformed all effect sizes to correlation coefficients and their standard errors using the Comprehensive Meta-Analyses software (Borenstein, Hedges, Higgins, & Rothstein, 2014). We used Peterson and Brown's (2005) formula to convert standardised *regression coefficients* into correlation coefficients. The articles reported regression coefficients as standardised or unstandardised effect sizes. To avoid an immense loss of information by excluding these articles, we converted the unstandardised regression

coefficients into standardised coefficients by using the (pooled) standard deviations of the dependent and independent variables (Becker & Wu, 2007; Slagt, Dubas, Dekovic, & van Aken, 2016).⁵ In cases where no standard deviation for the independent and/or dependent variables was reported, or where the manually standardised values were invalid (e.g., values larger than 1), the effect sizes were excluded from the analysis.

Finally, we recoded negatively directed variables (e.g., percentage of students eligible for free lunch) and their corresponding effect sizes so that all effects were positively directed. If several regression or multilevel models were reported in the article, we used the coefficients from the most comprehensive model in this study, except when a mediator or moderator was added to the final model.

Data Analysis

On average, 4.01 effect sizes were reported per study. Studies investigated (a) multiple outcomes (e.g., science and math achievement), (b) multiple indicators for one outcome variable (e.g., math grade and standardised math achievement test), (c) multiple independent variables (e.g., SES composition and climate variables), (d) multiple indicators for one independent variable (e.g., percentage of free lunch, or Economic Social Cultural Status [ESCS], as indicators for SES), or (e) independent subsamples/subgroups within the study (e.g., data from PISA 2006 and PISA 2009, different countries, different ages/grades, different projects).

When studies analysed multiple indicators for either the independent or the dependent variable (b and c), we averaged these effect sizes (Donker, de Boer, Kostons, Dignath van

⁵ When no standard deviations were reported in the article, we tried to acquire the standard deviations from external sources to standardise the regression coefficients ($n = 103$ effect sizes). Specifically, for articles using TIMSS and PISA data, standard deviations could partly be retrieved in OECD and IEA documents (e.g., Technical Reports) or studies that investigated the same kind of variable. For instance, Zhang (2016) reported results on PISA data over all countries in the years 2000, 2003, 2006, 2009, and 2012. While they provided standard deviations for the independent variables, the SDs for the achievement outcomes in science and math were set to 100.

Ewijk, & van der Werf, 2014; Hunter & Schmidt, 2004; Malti & Krettenauer, 2013) using the Comprehensive Meta-Analysis software (Borenstein, Hedges, Higgins, & Rothstein, 2013), yielding a combined measure of effect sizes.

With the exception of independent samples/subgroups within studies (e), effect sizes within studies were interdependent. Consequently, we conducted multilevel meta-analyses to address the nested data structure using the metaSEM package (Cheung, 2015) in the R statistical environment (R Development Core Team, 2016). Since 26.76% of the articles examined multiple independent samples, we used the sample instead of the articles/studies as cluster variables. We performed a three-level meta-analysis, with the sampling variance of effect sizes on level one, the effect sizes within each study's specific sample on level two, and the study samples on level three (cf. Gajda, Karwowski, & Beghetto, 2016; Machts, Kaiser, Schmidt, & Möller, 2016; Scammacca, Roberts, & Stuebing, 2014). Finally, we used the metafor package (Viechtbauer, 2010) to examine publication bias via the funnel plot and the Egger's regression test (Egger, Smith, Schneider, & Minder, 1997). The raw data and R scripts are available via the Open Science Framework:

https://osf.io/umbng/?view_only=752250be2bb346908970a908bea64c60

Before answering the research questions, we first examined the within- and between-sample variances of the overall model. In order to examine differences in effect sizes across school characteristics (research question 1a), cognitive and motivational-affective variables (research question 1b) and disciplines (research question 1c), we used two approaches: First, we calculated separate analyses for each variables to gain a descriptive overview over the data. Second, we calculated moderator analyses in a multilevel meta-analysis model. These moderator analyses enabled us to account for dependencies among effect sizes, examine statistical significance of the differences, and explain the variance of the baseline model.

Sensitivity Analysis and Publication Bias

To identify whether outliers might bias the analyses, we first examined the distribution of effect sizes in a forest plot, and then identified effect sizes that were larger than three standard deviations above or below the overall effect. Further, to test whether the results were influenced by a publication bias, we used funnel plots and Egger's regression test (Egger et al., 1997) which are both available in the metafor package (Viechtbauer, 2010) using trim and fill (Duval & Tweedie, 2000). Finally, we included a robustness check with regard to whether the findings depending on their research designs and measurement (i.e., original metric as correlation or regression coefficient, originally unstandardised or standardised regression coefficient, prior achievement controlled or not, and individual student characteristics controlled or not). The results of these performed moderator analyses are presented in the Appendix (Table A.1).

Results

Descriptive Analysis of the within- and between-Sample Variance

First, we calculated the overall model. Table 2 presents the overall effect of the relationship between school characteristics and students' outcomes. Correlation coefficients ranged between -.33 and .82. The distribution of all effect sizes included in the meta-analysis are displayed in the forest plots (Figure 3-9; separated by the school variables).

(Please add Table 2 here)

(Please add Figure 3-9 about here)

The Q statistic indicates that the effect sizes are heterogeneous ($Q(df = 283) = 489,321.9, p < .01$). While the within-sample variance (between particular effects) was significant, the between-sample variance was not. Consequently, most of the variance was within ($I^2 = .89$) rather than between samples ($I^2 = .11$). Due to the heterogeneity of effect sizes, we chose the random-effects model as the model of analysis. Also, we conducted a moderator analysis to explain between-sample variance (see below). Before we examined the

research questions, we examined whether the obtained effect may be influenced by outliers or publication bias.

Sensitivity Analysis and Publication Bias

In the present analyses, two effect sizes were above or below three standard deviations of the overall mean and can thus be regarded as outliers (i.e., Horn, Balazsi, Takacs, and Zhang, 2006, SES composition; Papanastasiou, 2008, instruction). We eliminated the effect sizes and re-ran the overall meta-analysis. The results did not meaningfully differ ($r = .14$; 95% CI [.12, .17]). Thus, we decided to use the full study sample as the data basis.

We created a funnel plot (see Figure 11; standard error on the y-axis, effect sizes on the x-axis) and used Duval and Tweedie's trim and fill method to assess how the point estimates are affected. The imputed effect sizes (white dots) indicate that rather positive effect sizes necessary for a symmetric plot are missing in the study set. Similarly, the Egger's regression test revealed indication of publication bias on the effect size level ($z = -2.58, p < .01$). On the study level, the Egger's regression did not indicate publication bias ($z = 0.08, p < .93$). In sum, it seems that significant positive effects are missing in our sample.

(Please add Figure 11 here)

Identification of most effective School Variables

To identify which school characteristics showed the most strong effect sizes for student science and math outcomes (research question 1a), we analyzed the estimated effect sizes from a descriptive perspective using *separate multi-level meta-analysis models*. Table 3 presents the estimated effect sizes for all school variables. The number of included effect sizes for each school variable ranged from eleven effect sizes (out-of-school activities) to 69 (for SES composition). The results indicate that the relationship between school variables and student outcomes varies, depending on the specific school variable. The strongest relationships (all with $p < .05$) were found for SES composition ($r = .30$), out-of-school activities ($r = .18$), school's academic press ($r = .14$), instructional practices ($r = .13$), and

classroom climate ($r = .13$). The weakest relationships were found for personnel resources ($r = .03, p = .12$). While most of the proportion of variation in effect sizes was on the within level $I^2(2)$ for school's academic press (.68), classroom climate (.96), and instructional practices (1.00); the heterogeneity of the effect sizes for SES composition (.98), school climate (.95), material resources (.96), personnel resources (.84), and out-of-school activities (.99) was between samples $I^2(3)$. This indicates that the source variation in effect sizes for the latter one was due to sample characteristics.

(Please add Table 3 here)

Next, we calculated multilevel meta-analysis models for the *moderator analysis*. We used personnel resources as reference category because no significant relationship was found in the separate analysis for this variable. The results indicate significant positive relationships for schools with high SES composition ($B = .29$), high academic press in school ($B = .13$), out-of-school activities ($B = .13$), classroom climate ($B = .11$), and positive instructional practices ($B = .10$), as compared to the relationship for personnel resources. Climate and material resources do not differ significantly from the relationship for personnel resources. The model demonstrated a better fit to the data than did the overall model ($\Delta-2LL = 116.33, \Delta df = 7, p < .00$). The school variables explained 54% of the within-sample variance, indicating that the school variables should be included as moderator variables rather than simply assess the overall model. As in the overall model a close-to-zero variation between samples was found, no between-sample variance was explained by the school characteristics.

Differences across cognitive and motivational-affective Variables

The descriptive analysis of differences in relationships across outcome variables (research question 1b, see Table 4) indicated that most of the articles included cognitive outcome variables. The separate meta-analysis showed that the relationships did not differ between school variables and students' cognitive ($B = .15$) and motivational-affective outcomes ($B = .15$). Likewise, the moderator analyses (cognitive outcome as reference category) showed no

significant difference between cognitive and motivational-affective outcomes. Thus, the model fit did not change ($\Delta-2LL = 0.01$, $\Delta df = 1$, $p = .93$) and no within-sample nor between-sample variance was explained by the outcome variables.

(Please add Table 4 here)

Differences between Science and Math

With regard to research question 1c, the descriptive analysis of differences between science and math (see Table 5) showed no difference for the relationship for math ($B = .15$) than for science ($B = .14$). The moderator analyses (math as reference category) showed no significant difference across disciplines. Similarly, the model fit did not improve as compared to the overall model ($\Delta-2LL = 0.19$, $\Delta df = 1$, $p = .67$) and no within-sample nor between-sample variance was explained by the discipline variables.

(Please add Table 5 here)

Summary of Findings

The present meta-analyses of studies revealed that the relationship does indeed differ between different school variables (research question 1a). We found the strongest positive relationship for the schools' SES composition, followed by school's academic press, out-of-school activities, instructional practices, and classroom climate. Accounting for dependency across variables, the moderator analyses showed that material and personnel resources, as well as climate, did not differ each from other (for which a close to zero-correlation was found). Furthermore, the results showed no differences for cognitive and motivational-affective variables (research question 1b) and for studies in math and science (research question 1c).

Discussion

In the present paper, we attempted to investigate how school variables differ in their relationship with student outcomes in science and math (research question 1a). Contrary to meta-analyses and reviews that examine single variables only, the present meta-analysis provided insights into the most promising school-related variables by investigating multiple

school variables concurrently in a multi-level moderator analysis. The findings revealed that the effect sizes differ significantly across school variables and that including the school variables in the model (instead of having an overall model only) enabled us to explain 54% of the within-sample variation in the effect sizes. In particular, we gained knowledge about the specific relevance of the most relevant school characteristics (Wood, Lawrenz, Huffman, & Schultz, 2006).

We found the largest relationship for schools' SES composition. While the individual socioeconomic status of students is often related to students' cognitive achievement (e.g., Berkowitz, Moore, Astor, & Benbenishty, 2017), in the present analyses we focused on the schools' SES composition (Willms, 2010). The effect size ($r = .30$) is in line with previous meta-analyses on SES (Harwell, Maeda, Bishop, & Xie, 2017; Sirin, 2005; van Ewijk & Sleegers, 2010). The higher the schools' SES, the better students' science and math outcomes were. The question is how school differences in SES are reflected in student outcomes. Previous research has considered possible underlying mechanisms from schools' SES composition to students' learning. Lupton (2005), for example, pointed out that schools located in poor neighborhoods also seem to provide lower quality education, and thus the relationship between socioeconomic status and students' outcomes may be confounded by education quality. Inadequate distribution of resources may be one of the reasons (Thrupp & Lupton, 2006). Other mediating effects may be through school policies and organization (e.g., school's academic press), classroom ecology (e.g., classroom disciplinary climate), and teaching (e.g., teaching style; Sirin, 2005; van Ewijk & Sleegers, 2010). These variables are of particular interest as they may be more easily affected by schools (instead of changes on the national and community level) and might thus be more relevant to identify (e.g., Wood et al., 2006). Contrary to previous meta-analyses, the present study included these variables that promote student outcomes over and above schools' SES composition and that can be influenced by education. In particular, high academic press, classroom climate, instructional

practices, and out-of-school activities were most notable in providing learning opportunities for students' science and math outcomes (with an effect over and above schools' SES composition). Classroom climate, instructional practices, and out-of-school activities can be conceptualised as proximal learning opportunities for students' outcomes. It is interesting that schools' general learning expectations (i.e., schools' academic press) were also predictive. Common Core Standards in Mathematics and Next Generation Science Standards, for example, set nationwide standards for teaching math and science in the U.S. and, through this unified framework, are designed to develop greater interest and understanding among students (e.g., National Research Council, 2013). Our findings revealed that initiatives on these proximal learning opportunities may, in turn, promote students' engagement in science and math. Finally, with the exception of SES composition, our results showed that structural conditions are not as relevant as learning opportunities.

In addition to school variables as independent variable, we used multiple outcomes to identify relevant school variables as criteria of success (National Research Council, 2011a). Our results, however, showed no difference between cognitive and motivational-affective outcomes (research question 1b). Finally, we focused on empirical research in science and math. Grossman and Stodolsky (1995) detected different subcultures for teachers between science and math. Similarly, while schools' academic press may be regarded as a generic factor, instructional practices and out-of-school activities seem to be subject-specific school characteristics. Hence, we followed Scheerens and Blömeke's (2016) claim to examine subject-specific relationships. However, our overall relationship for school variables and students' outcomes did not differ between science and math (research question 1c). Therefore, the revealed relevance of the school variables seems to be generalizable across science and math, as they are interrelated (National Research Council, 2011b). This is in line with van Ewijk and Sleegers (2010) who also did not find significant differences between science and math for the effect of SES on students' achievement.

Limitations

The findings from this meta-analysis need to be interpreted in light of the focus of the study and the inclusion criteria imposed for study selection. In the present study, we aimed at synthesizing international research on general school characteristics in science and math. Therefore, we used broad search terms with synonyms of school characteristics as one relevant keyword and, in a second step, we coded the variables under investigation more specifically (i.e., generic as well as subject-specific variables). We deliberately applied this approach in order to gain knowledge about the specific relevance of various school variables. However, studies that investigated a specific variable not labeled as school characteristics, for example, the relationship between school climate and students' outcome in science, may not have been included in the present meta-analysis. Therefore, the estimated effect sizes are limited to those studies who embed their analyses in the context of general school characteristics.

Moreover, as this study constitutes a first step towards demonstrating schools' potential to promote student outcomes in science and math, we restricted our analysis to school characteristics as an independent variable even though internal factors such as students' personal backgrounds are highly relevant for predicting student outcomes in science and math. Nevertheless, a large number of the included studies analysed both individual and school characteristics in their regression models. Consequently, the summarised overall effect can be interpreted as the relationship between school variables and student outcomes in science and math over and above individual student differences.

As the primary studies included in the meta-analysis possessed a multitude of indicators for school characteristics, we limited our search to large-scale studies. Through this restriction as well as through careful coding and analysis of studies we included only comparable effect sizes in the aggregation (Cooper, Hedges, & Valentine, 2009). Otherwise, measurements and research designs would have been too diverse and the requirement for a

meta-analysis to include comparable studies only would not have been met. Without the restriction to large-scale studies, 115 effect sizes stemmed from non-large-scale studies as compared to 307 effect sizes from large-scale studies. With the focus on large-scale studies, the present study takes up nicely Middleton, Cai, and Hwang's (2015) work on large-scales studies in mathematics education. While they present exemplary studies on the topics of curriculum, teaching, and learning, with a focus on intervention studies in mathematics education, the present meta-analysis adopted a more comprehensive approach on school-level predictors of learning, included science as well, and aggregated the existing findings statistically. Nevertheless, the restriction to large-scale studies also inheres some limitations. Depicting the fact that large-scale studies are dominated by correlational designs, we transformed all effect sizes to correlation coefficients in order to be able to compare and synthesise effect sizes. Thus, we are unable to draw causal inferences from the results. Experimental studies, applying controlled designs, have a higher potential regarding causal conclusions; however, with the broad focus on school characteristics, these operationalization would have not been comparable anymore.

Finally, the study selection was limited to studies from secondary education as well as English and peer-reviewed journals. As DeWitt and Archer (2015) revealed that differences in science career orientations already exist in elementary school, the question remains whether our findings on the potential of school characteristics for student outcomes can be transferred to elementary education as well. The restriction to publications in the English language might not reflect the international state of research. However, 73 % of the studies have included countries other than the US, covering countries such as Singapore (11%) or Turkey (7%), so we can conclude that international data has been synthesised in the present meta-analysis. Country-specific effects cannot be excluded, however, due to the high degree of standardisation and high quality standards in large-scale studies, between-country differences should not result from differences in the methodological procedure. The restriction to peer-

reviewed journals may have caused publication bias in favour of significant results (Matt & Cook, 2009). The analysis of publication bias revealed that significant positive effects are missing in the present study. This pattern is rather uncommon for publication bias as a consequence of focusing on peer-reviewed journals, for which missing non-significant effects must be expected. Therefore, we suggest that with our focus on large-scale studies, the restriction on peer-reviewed journals was the method of choice.

Implications for future Research

The present study yields implications for future research and practice. First, in addition to the aggregation of effect sizes, this meta-analysis also provides a literature overview of studies focused on school characteristics and student outcomes in science and math. The review and the coding of the included studies demonstrate that the majority examines cognitive student outcomes (256 effect sizes as opposed to 29 from motivational-affective). To increase our knowledge about how school variables are related to students' motivational-affective variables, more research is needed. In particular, future research should rely on theoretical considerations of differential effects between school characteristics and students' cognitive and motivational-affective variables, respectively. While it may be assumed that out-of-school activities, for example, may rather be related to motivational-affective variables, research has not yet compared cognitive and motivational-affective outcome variables systematically. Second, Scheerens and Blömeke (2016) claimed to examine subject-specific relationships. In the future, it will be interesting to contrast disciplines that conceptually may be more different from science and math. Although some of the included studies in the present meta-analysis also examined outcomes in other fields, such as reading, history, or life sciences, with our search terms we did not intend to compare these disciplines systematically. Third, focusing on science and math, one additional outcome variable may be derived, namely students' career orientations (Means et al., 2016; National Research Council, 2011a; Osborne et al., 2003; Reinhold et al., 2018). In an overview of 28 studies investigating school effects

on students' career orientations, Reinhold et al. (2018) found various conceptualizations of the construct of career orientation in STEM (science, technology, engineering, and math) (e.g., interest in engineering or science-related careers, intention to declare a STEM major in college, career aspirations in science, completion of a STEM major). Due to this conceptual heterogeneity and the small number of studies they have identified (only eight were large-scale studies), we decided to focus, as a first step, on the comparison of cognitive and motivational-affective outcomes. Fourth, the literature review revealed further gaps in the literature with regard to curriculum ($n = 2$) and preparation programs ($n = 3$). We have excluded these variables from our analyses due to reasons of statistical power. Hence, this points to the need for future research to learn more about their relevance. Finally, although theoretically assumed, hardly any study included in the present meta-analysis examined mediating or moderating effects. For instance, it could be reasonable that effect sizes for instructional practices might differ depending on the availability of material resources and thus do not show a linear, but rather a nonlinear effect. Therefore, future research should not only focus on underlying mechanisms to promote students' engagement in science and math but also address various conditions for a potential influence (i.e., moderator analyses).

Practical Implications

By including studies that investigate school characteristics in general and by including multiple school variables concurrently, the present meta-analysis analysed the relative importance of different school variables and identified which school variables matter the most for student cognitive and motivational-affective outcomes in science and math. Previous meta-analyses have focused on single school variables and thus prevent comparing effect sizes across studies and across school variables. In the present study, the largest effect sizes were found for schools' SES composition. However, our findings also underline the importance of those learning opportunities that can be shaped and modified by schools (e.g., school's academic press, classroom climate, instructional practices, and out-of-school activities). Certainly, these

learning opportunities take place within a particular context of a school (i.e., school's SES composition or material or personnel resources), which cannot easily be altered. Likewise, student outcomes in science and math are—in a large part—determined by internal factors, such as the student's educational background. The fact that significant effects were found over and above the contextual variables reveals that secondary schools do have the potential to promote students' engagement in science and math. Thus, our findings support that individual schools are not only accountable for but also capable of promoting students' STEM outcomes. Based on the results of the present meta-analysis, initiatives on the promotion of science and math (from administrators or stakeholders) should focus on how proximal learning opportunities such as the classroom climate, instructional practice, and out-of-school activities could be modified.

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Tables

Table 1

Search Terms

Category	Search terms ^a
(1) School variables	School* NEAR/0 level* OR characteristic* OR organ?ation* OR effect* OR environment* OR context* OR factor* OR program* OR profil*
(2) Student outcomes	<i>Cognitive</i> (a) skill* OR competen* OR abilit* OR achiev* OR attain* OR aptitude* OR perform* OR learn* OR know* OR understand* OR expertise OR comprehen* OR assess* OR concept* OR literacy OR proficien* OR success <i>Motivational-affective</i> (b) Interest* OR motivat* OR attitud* OR emotion* OR enjoy* OR affective OR anxiety* OR avoid* OR value* OR belief* OR self-efficac* OR self-concept*
(3) STEM Disciplines	Math* OR Scien*

Note. ^a Terms were used in different grammatical forms, such as plural and singular (e.g., characteristic/characteristics), nouns and verbs (to aspire/aspiration), British English and American English spelling; or short forms (math/mathematics) by using the respective operators in the ERIC and Web of Science advanced search engines. Please contact the authors for the database specific search syntax.

Table 2

Overall Effect Size obtained by the Three-Level Meta-Analysis

	No. of samples	No. of effects	Estimate	SE	95% CI			<i>p</i>
					<i>LL</i>	<i>UL</i>		
Overall effect	111	285	.15*	.01	.12	.17		<.01
Model summary	Within-sample variance $\tau^2(2)$		.03*	.00	.02	.03		<.01
	Between-sample variance $\tau^2(3)$		.00	.00	.00	.01		.15

Note. CI = confidence interval; *LL* = lower limit; *UL* = upper limit.

An asterisk denotes significance at the 5% level.

Table 3

*Multi-level Meta-Analyses for School variables (Cluster = Sample)**Separate Meta-Analyses*

	Estimate	SE	p	I^2 (2)	I^2 (3)	Q(df)	N (samples)	N (effects)
SES composition	.30*	.03	<.01	.01	.98	175,402.6 (68)	54	69
Academic press	.14*	.02	<.01	.68	.11	95.38 (27)	25	28
School Climate	.08*	.02	<.01	.03	.95	910.76 (45)	37	46
Material resources	.08*	.02	<.01	.03	.96	6124.13 (51)	37	52
Personnel resources	.03	.02	.12	.08	.84	329.70 (35)	29	37
Classroom Climate	.13*	.03	<.01	.96	.00	249.48 (22)	18	23
Instructional practices	.13*	.06	<.05	1.00	.00	2,368.77 (18)	15	19
Out-of-school activities	.18*	.04	<.01	.00	.99	264.12 (10)	9	11

Moderator analysis (RC = Personnel Resources)

	Estimate	SE	p	τ^2 (2)	τ^2 (3)	Q(df)	N (samples)	N (effects)
Intercept	.03	.03	.21					
SES composition	.29*	.03	<.01					
Academic press	.13*	.04	<.01					
School Climate	.04	.03	.20					
Material resources	.01	.03	.69	.01	.01	489321.9(283)	111	285
Classroom climate	.11*	.04	<.01					
Instructional practices	.09*	.04	<.05					
Out-of-school activities	.13*	.05	<.01					

Note. RC = Reference category. (2) level 2, (3) level 3.

An asterisk denotes significance at the 5% level.

Table 4

*Multi-level Meta-Analyses for Outcome variables (Cluster = Sample)**Separate Meta-Analyses*

	Estimate	SE	p	I^2 (2)	I^2 (3)	Q(df)	N (samples)	N (effects)
Cognitive	.15*	.01	<.01	.92	.08	481,495.2(254)	102	256
Motivational- affective	.15*	.03	<.05	.53	.47	5,719.80(28)	17	29

Moderator analysis (RC = cognitive)

	Estimate	SE	p	τ^2 (2)	τ^2 (3)	Q(df)	N (samples)	N (effects)
Intercept	.15*	.01	<.01	.03	.00	489321.9(283)	111	285
Motivational- affective	-.00	.04	.93					

Note. RC = Reference category. (2) level 2, (3) level 3.

An asterisk denotes significance at the 5% level.

Table 5

Multi-level Meta-Analyses for Discipline variables (Cluster = Sample)

Separate Meta-Analyses

	Estimate	SE	p	I^2 (2)	I^2 (3)	Q(df)	N (samples)	N (effects)
Math	.15*	.02	<.01	1.00	.00	114,385.5(160)	74	162
Science	.14*	.02	<.01	.91	.08	45,644.73 (122)	55	123

Moderator analysis (RC = Personnel Resources)

	Estimate	SE	p	τ^2 (2)	τ^2 (3)	Q(df)	N (samples)	N (effects)
Intercept	.15*	.02	<.01					
science	-.01	.02	.67	.03	.00	489321.9(283)	111	285

Note. RC = Reference category. (2) level 2, (3) level 3.

An asterisk denotes significance at the 5% level.

Figures

Figure 1. Overview of the literature search and coding process according to PRISMA (Moher et al., 2009).

Figure 2. Coding Framework, adapted from Scheerens (2015).

Figure 3. Forest Plot for all Effect Sizes Examining SES Composition.

Figure 3. (continued) Forest Plot for all Effect Sizes Examining SES Composition.

Figure 4. Forest Plot for all Effect Sizes Examining School Climate.

Figure 5. Forest Plot for all Effect Sizes Examining Academic Press.

Figure 6. Forest Plot for all Effect Sizes Examining Material Resources.

Figure 7. Forest Plot for all Effect Sizes Examining Personal Resources.

Figure 8. Forest Plot for all Effect Sizes Examining Classroom Climate.

Figure 9. Forest Plot for all Effect Sizes Examining Instructional Practices.

Figure 10. Forest Plot for all Effect Sizes Examining Out-of-School Activities.

Figure 11. Funnel Plot with Trim-and-Fill method with imputed effect sizes marked as white dots. In the pyramid, white background color indicates $p > .10$, light grey $.05 < p < .10$, and dark grey $.01 < p < .05$. Dots outside the pyramid indicate $p < .01$.

Table A.1

Multi-level Meta-Analysis of Effect Sizes for the Methodological Moderator Variables (Cluster = Study)

	<i>Estimate</i>	<i>SE</i>	<i>p</i>	$\tau^2(2) / (3)$	<i>Q(df)</i>	<i>N(studies)</i>	<i>N(effect sizes)</i>
Model 1				.02 / .01	489,133.5(277)	69	281
Intercept	.11	.04	<.01				
Regression coefficient (1) vs. correlation coefficient (0)	.03	.05	.52				
<i>Moderator variables for regression coefficients only</i>							
Model 2				.02 / .01	481,339.4(251)	63	252
Intercept	.13	.02	<.01				
Standardised coefficient	.07	.04	.10				
Model 3				.02 / .01	481,415.6(253)	64	251
Intercept	.15	.01	<.01				
Prior achievement controlled	-.05	.05	.27				
Model 4				.02 / .01	481,415.6(253)	64	254
Intercept	.12	.05	.01				
Student characteristics controlled	.03	.05	.61				

Note. (2) level 2, (3) level