The Relation Between Students' Socioeconomic Status and ICT Literacy: Findings from a Meta-Analysis

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Abstract

This meta-analysis synthesized the relation between measures of socioeconomic status (SES) and students' information and communication technology (ICT) literacy—a skillset that has found its way in educational curricula. Using three-level random-effects modeling across 32 independent K-12 student samples that provided 75 correlation coefficients, we identified a positive, significant, and small correlation, $\bar{r}$ = .214, 95 % CI [.184, .244]. This correlation varied between studies and was moderated by the type of SES measure, the type of ICT literacy assessment, the broad categories of ICT skills assessed, the assessment of test fairness, and the sampling procedure employed. The findings of this meta-analysis suggest that students' ICT literacy differs between socioeconomic status groups, thus pointing to a gap in the domain of ICT. However, the relation between SES and ICT literacy was weaker than those reported in other educational domains, such as mathematics and reading. Carefully designed studies and measures for which a validity argument has been crafted are needed when studying achievement gaps in the domain of ICT in future studies.

Keywords: Cultural capital; ICT literacy; meta-analysis; parents' education and occupation; socioeconomic status

The Relation Between Students' Socioeconomic Status and ICT Literacy:

Findings from a Meta-Analysis

1 Introduction

Examining the link between students' socioeconomic status (SES)—a concept that is commonly indicated by parents' education, occupation, and income—and their academic achievement has become one of the core research approaches to describing educational gaps (OECD, 2018; Sirin, 2005; Thomson, 2018). While a large body of research exists that quantifies such achievement gaps in the traditional academic domains of mathematics, reading, and science (e.g., Berkowitz et al., 2017; Bradley & Corwyn, 2002; Bruckauf & Chzhen, 2016; Ferreira & Gignoux, 2013; White, 1982), these gaps have received less attention in cross-disciplinary domains of K-12 education (Siddiq, Hatlevik, Olsen, Throndsen, & Scherer, 2016). Such domains include the so-called "twenty-first century skills"—skills such as problem solving, critical thinking, collaboration, and information and communication technology (ICT) literacy that are not bound to a specific, academic domain but rather operate across domains (Binkley et al., 2012). Among these skills, ICT literacy—a concept often associated with an individual's ability to use computers to investigate, create, and communicate (e.g., Fraillon et al., 2014)—has found its way into educational curricula around the world (Ferrari, 2013; UNESCO, 2017) and is considered a "new literacy" students should acquire in order to collect, manage, produce, and exchange digital information as reflective citizens (Fraillon et al., 2014). Given the relatively recent introduction of ICT literacy, educational gaps—as measured by the relation between students' SES and their performance on ICT literacy tasks—have been reported less often than in the traditional academic domains of mathematics and reading, primarily because the development and validation of measures is still in progress (Siddiq et al., 2016). Nevertheless, several studies reported gaps in ICT literacy based on performance assessments. These studies, however, provided mixed results, as they identified mainly positive and significant relations (e.g., Hatlevik & Christophersen, 2013; Senkbeil et al., 2013) but also insignificant correlations (e.g., Fraillon et al., 2014; Hohlfeld et al., 2013). In other words, the existing body of literature reporting the relation between students' SES and ICT literacy measures abounds in diverse findings. To quantify and explain this diversity, the present meta-analysis synthesized the SES-ICT literacy correlation for primary studies that included K-12 students and performance-based assessments of ICT literacy. The knowledge gained from this synthesis provides insights into the mapping of ICT literacy on the landscape of other, traditional domains (i.e., mathematics, reading, and science). To our best knowledge, this meta-analysis is the first to synthesize an overall SES-ICT literacy relation for K-12 students across studies and to systematize the diverse findings reported in the existing body of literature.

Despite quantifying an overall SES-ICT literacy relation that is based on performance-based assessments of ICT literacy, this meta-analysis quantifies the variation between studies and, more importantly, explores possible variables that may explain this variation. Herein lies one of the key contributions of this work: The primary studies reporting SES-ICT literacy relations for K-12 students, including large-scale studies with representative samples of students across several countries, do not provide insights into the extent to which study, sample, and measurement characteristics may show moderation effects. Linking such characteristics to the variation of the SES-ICT literacy relations contributes to understanding the nature of these relations and thus provides researchers and policy-makers with insights about the contextual effects of these relations.

2 Theoretical Perspectives

In this section, we review the theoretical perspectives underlying this meta-analysis. These perspectives include the conceptualization and standing of ICT literacy as a twenty-first century skill, the conceptualization and measurement of students' socioeconomic status, its relation to academic achievement across several domains, and the existing evidence surrounding the relation between measures of ICT literacy and SES.

2.1 Information and Communication Technology Literacy—A Cross-Disciplinary Skill

Technology and information are everywhere. As a consequence, the knowledge, skills, and attitudes toward them have been brought to attention and summarized under the term "Information and Communication Technology Literacy" (i.e., ICT literacy). Lennon et al. (2003) defined ICT literacy as "the interest, attitude, and ability of individuals to appropriately use digital technology and communication tools to access, manage, integrate, and evaluate information; construct new knowledge; and communicate with others in order to participate effectively in society" (p. 8), and combined skillsets related to the use of technology with skillsets related to the handling of digital information. These two components of ICT literacy have become an integral part of its definition (e.g., ETS, 2007; Ferrari, 2013; Markauskaite, 2006). For instance, the IEA International Computer and Information Literacy Study (ICILS)—an international large-scale assessment of eight-grade students' computer and information literacy in more than 20 countries—referred to ICT literacy as "an individual's ability to use computers to investigate, create, and communicate in order to participate effectively at home, at school, in the workplace, and in society" (Fraillon, Schulz, & Ainley, 2013, p. 17). Again, this is a definition that does not only include the mere use of technology but also skills relevant to the dealing with digital information in today's information societies. Extending on these two aspects, the Digital Competence Framework for Citizens (DIGCOMP)—a framework that defines key skills within ICT literacy from the perspective of digital citizenship—defines digital competence as a skillset comprised of five so-called competence areas (Ferrari, 2013; Carretero, Vuorikari, & Punie, 2017): (1) *Information and data literacy* (e.g., Evaluating data, information, and digital content); (2) *Communication and collaboration* (e.g., interacting and sharing through digital technologies); (3) *Digital content* *creation* (e.g., developing digital content and programming); (4) *Safety* (e.g., protecting devices, personal data, privacy, health, well-being, and the environment); (5) *Problem solving* (e.g., solving technical problems, creatively using digital technologies). In contrast to the ICILS definition, the DIGCOMP framework explicitly mentions problem solving and creative thinking skills as part of ICT literacy; furthermore, DIGCOMP brings to attention ethical and security perspectives next to the skills to retrieve, evaluate, and communicate digital information. In their review of the extant literature on the conceptualization and measurement of ICT literacy, Siddiq et al. (2016) observed that, despite the differences between the definitions and conceptualizations of the construct, the DIGCOMP framework seems a suitable categorization scheme of the skillsets captured by ICT literacy tests.

In the context of the so-called "twenty-first century skills", ICT literacy is considered to be a domain-general rather than a domain-specific construct (Binkley et al., 2012). Specifically, the skills subsumed under the umbrella of ICT literacy can be acquired and applied in multiple domains (P21, 2018), such as mathematics (e.g., using computer algebra systems to solve mathematical problems), reading (e.g., extracting information from multiple digital resources), or science (e.g., modeling scientific processes using computer simulations or programming). At the same time, ICT literacy relates to its own domain, that of computer and information science. As a consequence, several researchers attempted to map the construct onto the landscape of academic skills and concluded that it was similar to other, domain-general skills such as problem solving (Engelhardt, Naumann, et al., 2019; Greiff, Kretzschmar, Müller, Spinath, & Martin, 2014) and, yet, a specific skillset beyond the academic core domains, such as mathematics, reading, and science (Hu, Gong, Lai, & Leung, 2018; OECD, 2012). One may therefore hypothesize that students' performance on ICT literacy tasks may be less lean on knowledge in specific domains and thus more focused on the generation and acquisition of knowledge while solving certain problems. This hypothesis is in line with the hopes on the relevance and added value of twenty-first century skills (Greiff, Wüstenberg, et al., 2014).

To assess students' ICT literacy, several performance-based assessments have been developed. These assessments comprise not only tasks in which students have to retrieve, generate, and evaluate information through digital devices but also tasks that concern more socio-scientific aspects, such as evaluating the safety of digital information or reflecting on information sharing—these types of tasks are, for instance, well-represented in the ICILS 2013 assessment of Computer and Information Literacy (see Fraillon et al., 2014). Similarly, Claro et al. (2015) administered a computer-based assessment of ICT literacy which simulated virtual environments, such as chats, desktops, and other computer tools, to assess "students' ability to solve information and communication problems, as well as ethical dilemmas in a digital context" (p. 4). Focusing on the knowledge dimensions of ICT literacy, Hatlevik et al. (2015) assessed ICT literacy by static multiple-choice tasks, in which students had to show their knowledge about digital communication, responsibility, information handling and retrieval. These studies exemplify the diversity of ICT literacy assessments—an observation Siddiq et al. (2016) supported in their systematic review. Given this diversity, standard tests of ICT literacy which are commonly used in several studies may not exist.

2.2 Socioeconomic Status and Academic Achievement

The concept of socioeconomic status (SES) has received much attention in education—this attention resulted in a large body of research that examined the effects of SES on academic achievement (White, 1982). The Task Force on Socioeconomic Status of the American Psychological Association considered SES to represent the social standing or class of an individual or group and categorized the existing measures of SES into measures of education, income, and occupation (APA, 2006). Sirin (2005) considered SES to be "an individual's or a family's ranking on a hierarchy according to access to or control over some combination of valued commodities such as wealth, power, and social status" (p. 418). These broad conceptualizations synthesize the diversity of SES definitions and measures as they bring together different perspectives on SES. Indeed, taking multiple perspectives on SES is critical to its measurement, and multiple types of measures have been used in the literature (Sirin, 2005). These measures typically tap the areas of health, education, and human welfare, and comprise indicators of family income, parents' education, and occupational status (APA, 2006; Bradley & Corwyn, 2002). In the context of international large-scale assessments, such as the Programme for International Student Assessment (PISA) and the International Computer and Information Literacy Study (ICILS), several SES measures have been taken—the most popular measures refer to the material, social, and cultural resources students have access to (Marks, Creswell, & Ainley, 2006). This variety of SES measures is in fact one of the sources for the variation of the SES-achievement relation across studies (e.g., Harwell et al., 2017, Sirin, 2005; White, 1982).

To describe gaps in the context of education, researchers predominantly report the relation between SES and academic achievement (Gustafsson, Nilsen, & Yang Hansen, 2018; Thomson, 2018). This relation has been reported for several indicators of academic achievement, ranging from measures of general cognitive abilities to domain-specific skills. For general cognitive abilities, for instance, Strenze (2007) found moderate SES-achievement correlations that ranged between $\bar{r} = .29$ and $\bar{r} = .49$ for measures of parents' education. Sirin (2005) reported an overall relation between SES and academic achievement of $\bar{r} = .32$ and a specific relation for mathematics of $\bar{r} = .35$ and $\bar{r} = .32$ for verbal domains—relations that are considered to be substantial. Finally, van Ewijk and Sleegers (2010), who reviewed a large body of research on the peers' SES-achievement relation supported the moderate association between the two concepts, $\bar{r} = .32$. At the same time, for certain measures of SES and for certain achievement measures, these relations can also be weak. In their meta-analysis, Strenze (2007) also identified weak relations between intelligence measures and SES measures that were based on parents' income, $\bar{r}$ = .08–.19. Robbins et al. (2004), who meta-analyzed the prediction of college outcomes by psychosocial and study skills, found that SES and students' grade point average were also weakly correlated, $\bar{r}$ = .16. In his early review, White (1982) reported a weak and significant association between SES and academic achievement, $\bar{r}$ = .22. Harwell et al. (2017) point to the surprisingly modest SES-achievement correlation in their meta-analysis of K-12 study samples in elementary, middle, and high school, $\bar{r}$ = .16–.24. The list of studies exemplifying that the SES-achievement correlation may also be small could be extended further.

Apart from these meta-analytic findings, several studies reported small and insignificant SES effects on students' achievement in cross-disciplinary domains: For instance, in a study of 299 9th-graders, Sonnleitner et al. (2014) reported achievement differences between students with and without an immigration background in a computer-based assessment of complex problem solving. The authors found that, whereas native students outperformed students with an immigration background in the overall problem-solving performance, the opposite was true for the specific performance on knowledge acquisition tasks—tasks that do not rely on prior knowledge but require students to generate knowledge actively. The PISA 2012 study of creative problem solving revealed that the positive relation between SES and performance was not substantial in all participating countries, such as Macao-China, Canada, and Norway (OECD, 2014). Some researchers argue that SES and immigration gaps might be reversed due to the cross-disciplinary nature of skills such as problem solving (Martin et al., 2012). Despite this claim, the majority of SES-achievement correlations were reported for the classical academic disciplines, including mathematics, reading, and science. Whether similar correlations, aggregated across several studies, samples, and measurements, are also present for the relatively young domain of ICT literacy is still unclear.

2.3 The Relation Between SES and ICT Literacy

As noted earlier, given the relative novelty of the domain of ICT literacy in educational research, the existing body of literature reporting SES-achievement correlations is limited. Nevertheless, some findings and possible explanations exist. Coining the term "digital divide", Warschauer et al. (2004) observed substantial disparities in ICT-related knowledge and skills across age, gender, and SES groups in favor of young and well-educated people who may show a larger affinity to technology in general. Scheerder et al. (2017) further argued that this divide does not only concern the knowledge and skills related to ICT but also the access and use of it. Similarly, Ferro et al. (2011) considered SES to be a key determinant of ICT access and use. Since this line of argumentation has mainly referred to disparities in ICT access and use, Desjardins and Ederer (2015) extended it by providing evidence for the direct and significant relation between ICT literacy and several measures of SES. In their re-analysis of the Programme for the International Assessment of Adult Competencies (PIAAC) 2012 data, they found that 16-65-year-olds' performance on technology-based problem-solving tasks was strongly related to age, education, and immigration status, next to ICT use in several contexts. For studies focusing on K-12 ICT literacy measures, the existing findings on the correlation to SES are diverse. Some studies identified weak correlations between SES and ICT literacy (e.g., Fraillon et al., 2014; Hohlfeld et al., 2013), while others found more substantial and positive correlations (e.g., Hatlevik & Christophersen, 2013; Senkbeil et al., 2013). To our best knowledge, this diversity in the SES-ICT literacy has not yet been explained by key sample, study, and measurement characteristics. Knowledge about which characteristics moderate the correlation, however, facilitates a more informed interpretation of the SES gaps in ICT literacy, especially in light of contextual information. Reviewing the wealth of evidence on the SES-achievement relation in domains other than ICT, we identified several characteristics that may explain between-sample variation. The list of characteristics contains, but is not limited to:

- *Type of SES measure:* As noted earlier, socioeconomic status can be measured in several ways, be it by the three traditional groups of indicators (i.e., parents' education, occupation, and income; see Glass, 1976) or indicators at different levels of aggregation (e.g., family SES, school SES, district SES). The categories describing the types of SES measures moderated the SES-achievement relation in several meta-analyses: White (1982), for instance, found the highest correlation for the income-based SES measures; van Ewijk and Sleegers (2010) found the highest correlation between peers' SES and educational achievement for measures based on parents' education. Harwell et al. (2017) further observed that the sources of SES measures explained between-sample variance in the correlation, with the highest correlation for the least accurate source, that is, secondary data on SES. At the same time, Sirin (2005) did not find significant differences between the three traditional indicators, supporting what Glass (1976) found in an early synthesis. Overall, moderation effects of the type of SES measure on the SES-achievement correlation may surface and should therefore be explored.
- *Type of achievement measure, including its psychometric properties:* Similar to the type of SES measure, the characteristics of the achievement measure may moderate the SES-achievement relation. These characteristics include but are not limited to the domain the measure is based on (e.g., general cognitive abilities, verbal, math- or science-related skills; Sirin, 2005), the degree to which a validity argument has been established for the measure (Harwell et al.,

2017; White, 1982), or the sub-skills or sub-domains assessed (e.g., Strenze, 2007). Psychometric properties of the measure may include the reported reliability and the steps taken to craft a validity argument (Siddiq et al., 2016).

- *Educational level of the study sample:* Sirin (2005) observed significant differences in the SES-achievement correlation across educational levels, with the strongest relation for middle-school students ($\bar{r}$ = .31) and the weakest relation for kindergarten children ($\bar{r}$ = .19). Harwell et al. (2017) supported the moderation effects, yet with the strongest relation for kindergarten children ($\bar{r}$ = .33) and the weakest relation for middle and high-school students ($\bar{r}$ = .16). Again, these observations warrant considering students' educational level as a possible moderator.
- *Sampling strategy:* Different sampling strategies may indeed result in different SES-achievement correlations, as Harwell et al. (2017) found. In their meta-analysis, they detected significant moderation effects using randomized, stratified, and convenience sampling as the main categories for differentiating the primary studies. Siddiq et al. (2016), as they review studies of performance-based ICT literacy assessments, point to the sampling strategy as a key feature of the quality of validation studies of ICT literacy measures.
- *Study year:* As researchers' understanding of academic achievement progresses over time, the conceptualizations of the corresponding constructs (e.g., reading literacy, numeracy skills) may change. As a consequence, interpreting the SES-achievement correlation across several decades may be biased by these changes. For instance, White (1982), Strenze (2007), and Harwell et al. (2017) argued for considering the study or publication year as

possible moderators to at least partly account for possible changes in the conceptualization and measurement of achievement.

- *Publication status:* It has been established in many meta-analyses that differences between published and grey literature or between even more fine-grained categorization of the publication status may exist. These moderation effects are sometimes interpreted as evidence for publication bias and should therefore be reported in any meta-analysis (Borenstein et al., 2009). Harwell et al. (2017), for instance, identified such effects in their meta-analysis. The inclusion of grey literature has been discussed controversially in the literature because it may introduce additional bias to the meta-analytic estimates (Higgins & Green, 2008). Part of the reluctance to include this literature refers to the misconception that the studies reported in the grey literature have lower quality than the studies in academic journals after peer review (Schmidt & Hunter, 2014). In our meta-analysis, this reasoning did not apply, because all included studies—independent of their publication status—fulfilled the inclusion and exclusion criteria and consequently had sufficient quality. The investigation of publication bias is therefore independent of the studies' quality and merely a test of the publication status. The inclusion of grey literature is aimed at addressing the possible issue of publication bias and is considered critical to meta-analyses (e.g., as part of the PRISMA statement; see Moher et al., 2015; Shamseer et al., 2015; Paez, 2017).

These sample, study, and measurement characteristics can be transferred to the ICT literacy domain in order to gain insights into their moderating effects. Of course, evidence on the moderation effects of these variables does not provide any ground for causal claims—more in-depth knowledge about the possible mechanisms underlying SES gaps in ICT literacy would be needed to identify possible reasons for the SES-ICT literacy relationship. Models describing these mechanisms may include additional variables, such as ICT access, resources, and use, direct measures of parents' ICT skills and parent-child interactions, as well as school-related variables (e.g., Scheerder et al., 2017).

2.4 The Present Meta-Analysis

Our review of the extant literature suggested that educational gaps, quantified as the correlation between students' socioeconomic status and academic achievement, have received much attention in the core domains of mathematics, reading, and science. At the same time, these gaps have received less attention in cross-disciplinary domains, including ICT literacy. For the domain of ICT literacy, the existing but limited body of research abounds in diverse findings ranging from weak to more substantial correlations between SES and ICT literacy. As a consequence, the present study is aimed at synthesizing this body of literature and quantifying the SES-ICT literacy correlation across studies and independent samples. This synthesis and, ultimately, the resultant, pooled correlation has two main purposes: (a) to map the SES effects on the relatively new skillset of ICT literacy onto the landscape of existing SES effects of academic achievement next to the well-established domains of reading, mathematics, and science; (b) to describe and update the existing knowledge about possible SES gaps in ICT literacy. The latter may serve as a basis for future updates of this research synthesis in order to examine possible changes in these gaps. Our first research question consequently reads:

1. To what extent are measures of students' socioeconomic status related to their performance on ICT literacy tests? (*Overall correlation*)

Although information about an overall correlation contributes to understanding the magnitude of the SES-ICT literacy correlation, its variation between samples or studies and especially the possible factors explaining it provide even further insights. To our best knowledge, the extant literature did not examine the extent to which sample, study, and measurement characteristics may explain variation in the SES-ICT literacy correlation. Information about this variance explanation, however, is critical to the understanding of the context in which inequalities are reported (e.g., van Ewijk & Sleegers, 2010, for academic achievement). For instance, the SES-ICT literacy correlation may differ between independent samples of different nationalities or between studies that employed different sampling designs; it may also differ across the characteristics of both the ICT literacy and the SES measures (e.g., education vs. occupation vs. capital measures; see also Sirin, 2005, for academic achievement). To systematically explore the factors that may explain variation in the SES-ICT literacy correlation, we pose a second research question:

2. Which study, sample, and measurement characteristics explain the possible variation in the relation between SES measures and performance on ICT literacy tests? (*Moderation by study, sample, and measurement characteristics*)

At this point, we notice that our first research question may well be addressed by analyzing the data obtained the large-scale educational assessment ICILS 2013. This study included several representative samples of secondary-school students around the world and administered a performance-based assessment of ICT literacy, next to several measures of SES. Nevertheless, the second research question cannot be answered by relying on the ICILS 2013 data only, mainly because sampling and measurement characteristics have not been varied across the samples in this study—exploring possible moderator effects requires a broader sample of primary studies. As a consequence, we perform meta-analytic modeling techniques to address both research questions.

3 Methods

3.1 Literature Search

The present meta-analysis was based on a recent systematic review of existing, performance-based assessments of ICT literacy (Siddiq et al., 2016). This review identified 66 publications that presented 38 measures of ICT literacy in K-12 education, each of which assessed certain dimensions of these skills (i.e., competence areas such as information, communication, content-creation, safety, and problem solving). On the basis of the search protocol and screening criteria reported by Siddiq et al. (2016), we updated the body of literature and added three more studies which were published between November 2014 and August 2017 (Claro et al., 2015; Hatlevik et al., 2017; Siddiq et al., 2017), using the original search terms. These terms contained three categories, Measurement AND ICT literacy AND Education, and were extended by synonymous terms through OR operators (see Siddiq et al., 2016). The resultant publications were then screened once again to sort out whether they reported a correlation between a measure of SES and students' performance on the ICT literacy tests. In these publications, authors had to make explicit the measures of SES, either by labelling them as SES measures or by referencing them as capital or educational indicators of students' background. This final screening resulted in a total sample of m = 32 independent samples that reported k = 75 correlations with an overall sample size of N = 86405 K-12 students in n = 11 studies. Only one of the three studies added to Siddiq et al.'s (2016) review was included (Claro et al., 2015; one sample, two correlations). To summarize, all publications contained the reports on (a) a performance-based measure of ICT literacy, (b) a K-12 student sample, (c) the constructs measured in the assessments (e.g., subdimensions of ICT literacy), (d) the relation between at least one measure of SES and ICT literacy, (e) the types of SES measures administered to the students (i.e., educational, occupational, or cultural capital measures). The details of the search and screening processes are shown in Figure 1.

Using and updating the existing data set provided by Siddiq et al. (2016) were key elements in our strive for replicating existing findings and using open-access data for follow-up analyses (Gewin, 2016; Open Science Collaboration, 2015). Siddiq et al.'s data set is unique in a sense that it was based on a systematic review of performance-based rather than self-report-based and thus direct rather than indirect tests of ICT literacy. Moreover, these data provided a detailed classification of these tests according to key measurement characteristics.

3.2 Coding

We extracted all relevant study, sample, and measurement information from the primary studies and recoded the initial studies according to the variables described below. We provide the details of the coding here and refer the reader to the Supplementary Material S1, which contains the details of the coding for each primary study. As our coding scheme was based on that developed and validated by Siddiq et al. (2016), we also refer readers to this source for more examples and explanations.

3.2.1 SES Measures

Socioeconomic status was measured differently across studies. Some studies used measures that represented the cultural capital students had access to in their homes, including the number of books at home (see also Sirin, 2005). Other studies used measures that represented the education or occupation of parents, including the highest level of education each parent achieved. Overall, we used the three main categories of SES measures, as they were established in the extant literature (e.g., APA, 2007; Bradley & Corwyn, 2002; Glass, 1976): Parents' education, parents' occupation, and income. In the body of primary studies, the latter was mainly indicated by the cultural capital at home, namely the number of books at home, one of the most prominent SES indicators in educational large-scale studies (Gustafsson, Nilsen, & Yang Hansen, 2018). These three types of SES measures were coded as 'educational SES measures', 'occupational SES measures', or 'capital SES measures' in the present meta-analysis. Table 1 provides more examples, and the Supplementary Material S1 contains more detailed information about these measures. Unlike the meta-analysis presented by van Ewijk and Sleegers (2010), we considered measures of SES to be an individual-level rather than peer-, school-, country-, or system-level indicator, given that students reported on the above-mentioned SES categories in most primary studies.

3.2.2 ICT Literacy Measures

To describe the ICT literacy measures, we coded several aspects describing the skills assessed by the measures, the design of tasks, and aspects of their psychometric quality.

Types of outcome measures. ICT literacy assessments that mainly administered interactive tasks (i.e., both the item stimulus and the response options contained some degree of interactivity, such as options to retrieve information by searching for it in place other than the task environment) or authentic tasks (i.e., tasks with a fully authentic digital environment, such as simulations) were considered 'interactive', while ICT literacy assessment that mainly administered multiple-choice tasks with a constrained (static) response format were considered 'static' (more detailed examples are provided by Siddiq et al., 2016).

Types of skills assessed by the ICT literacy assessments. The ICT literacy assessments administered in the primary studies covered several sub-skills. We used the DIGCOMP framework—a generic framework that classifies ICT literacy into several subskills (i.e., problem solving, communication, technical skills, information, and safety)—to categorize these skills. Of course, alternative frameworks may result in different classifications of the sub-skills, as Siddiq et al. (2016) noticed when they observed the commonalities and discrepancies between the existing frameworks at the time of their review. We coded the *skills* the ICT literacy tests mainly assessed as either 'applied' or 'theoretical', depending on the anchoring in the revised DIGCOMP framework. This simplified, dichotomous categorization was chosen because (a) the authors mainly provided the correlations for the overall scores of ICT literacy, not allowing for any further differentiation; and (b) the sample sizes within these categories were too small to conduct further analysis or draw any valid inference for each sub-skill. It also resonates with the categorization of sub-skills under the umbrella of technical skills and information skills van Laar et al. (2017) presented in their systematic review. *Applied skills* required the generation and application of knowledge and included the competence areas of problem solving, communication, and technological skills—the latter being subsumed as “developing content”, “integrating and re-elaborating”, and “programming” under the label “content creation”. *Theoretical skills* focused more on the actual knowledge students have and included the competence areas of information, safety, and the aspect of “copyright and safety” under the label “content creation”. The detailed codes for each study are shown in the Supplementary Material S1.

Assessment of test fairness. We coded dichotomously (*1 = Test fairness assessed*, *0 = Test fairness not assessed*) whether or not the authors of the primary studies examined and reported the *fairness* of the ICT literacy test, for instance, via differential item functioning or measurement invariance testing across educationally relevant groups, such as gender and SES groups. Investigating the fairness of a test and accounting for possible deviations is considered an important step in the crafting of a validity argument (Pellegrino et al., 2016).

Test reliability. Finally, we extracted the reliability coefficients from the primary studies and used them to correct the reported correlations in subsequent sensitivity analyses. These reliability measures were obtained as measures of scale reliability based on item response theory models or reported as Cronbach’s α.

3.2.3 Study Samples

To describe the study sample, we coded students’ *educational level* as either ‘primary level’ or ‘secondary level’; the studies selected for this meta-analysis did not include kindergarten children. We further extracted the average age of students in years to supplement the information about their educational level. Next to these variables, the *sampling procedure* was coded as either ‘convenience sample’ or ‘randomized and/or stratified sample’. We decided to collapse the three sub-categories ‘randomized’, ‘stratified’, and ‘randomized and stratified’ to ‘randomized and/or stratified sample’, because too few studies would have fallen into each of the more fine-grained categories. Specifically, the authors of two studies reported that they had stratified their samples (Aesaert & van Braak, 2015; Hohlfeld et al., 2013), one reported randomization only (Hatlevik et al., 2015), and two indicated both randomization and stratification (ACARA, 2012; Claro et al., 2015). In the first two cases, however, authors presented and discussed their results as if they had randomized or stratified their samples in addition. Given this limited number of studies, we decided to compare convenience sampling with randomized/stratified sampling. Finally, we coded the country in which the study was conducted according to world regions (i.e., continents) as ‘Europe’, ‘Australia’, ‘Asia’, ‘America’, and ‘Africa’.

3.2.4 Publication Status

Besides the year in which the study was conducted, we extracted information about the type of publication and coded each primary study as either ‘published’ or ‘grey literature’. While the former contained peer-reviewed journal articles or book chapters, the latter contained research reports, conference proceedings, and presentations. This classification was based on the recommendations made by Adams, Smart, and Huff (2017).

3.3 Statistical Analyses

3.3.1 Effect Sizes

We extracted Pearson’s correlations *r* as measures of associations between students’ SES and ICT literacy from the primary studies, along with the sample sizes *N*. The corresponding variances were approximated by $v_r = (1 - r^2)^2/(N - 1)$ (Borenstein et al., 2009). If the authors of the primary studies established SES as a categorical variable (e.g., low- vs. high-SES), we first estimated Cohen's d as the standardized mean difference and converted it into r, applying the conversion formulas proposed by Borenstein et al. (2009). For instance, we applied this procedure to the data provided by the International Computer and Information Literacy Study (ICILS)—the international reports exhibited the mean performance differences between SES groups, along with their standard errors (see Fraillon et al., 2014, Tables 4.3-4.5), and allowed us to convert these differences into standardized mean differences and, ultimately, into correlations. To further correct the correlations r for the unreliability of the ICT literacy measure Rel_X, we used the attenuation formula, $\varrho_r = r/\sqrt{Rel_X}$ (Schmidt & Hunter, 2014; *Note:* Reliability coefficients of the SES measures were not reported).

3.3.2 Publication Bias

To examine the extent to which the selection of studies and ultimately correlations was subject to publication bias, we conducted several analyses. First, we inspected the funnel plot of correlations for asymmetry and performed additional trim-and-fill analyses (see Duval & Tweedie, 2000). The latter provided a correlation between SES and ICT literacy that was adjusted for studies we may have missed due to publication bias. To supplement these analyses of the symmetry of the funnel plot, we performed Egger's linear regression test (Egger et al., 1997). Second, we tested for moderation effects of publication status to identify possible differences in correlations between published and grey literature. Third, Rosenberg's fail-safe *N*s provided information about the number of additional, negative studies that would be needed to turn the overall correlation insignificant ($p > .05$; Borenstein et al., 2009). Fourth, we plotted the *p*-curve using the 'P-curve Online App' (Simonsohn, Nelson, & Simmons, 2017) and inspected its skewness. In the case of a right-skewed *p*-curve, the primary studies selected for our meta-analysis exhibited evidential value, testifying against *p*-hacking (Simonsohn, Nelson, & Simmons, 2014).

3.3.3 Influential Correlations and Sensitivity Analyses

In addition to the analyses of publication bias, we identified influential correlations in the data set using the distance measures Viechtbauer and Cheung (2010) suggested (e.g., Cook's distance). We performed the corresponding diagnostics in the R package 'metafor'. We further tested the sensitivity of our findings to several factors: (1) the correction of correlations for the unreliability of the ICT literacy measures, (2) the treatment of the large-scale data set obtained from ICILS 2013, and (3) the inclusion of an additional level of analysis, that is, the study level.

3.3.4 Meta-Analytic Models

To synthesize the extracted correlations, we specified a series of meta-analytic models each of which was based on different assumptions on the variation within and between study samples (Card, 2012). At this point, we note that the 32 samples were independent in a sense that they represented diverse samples of different schools, districts, regions, or countries—study samples were not assessed at multiple measurement occasions. More specifically, given the nested structure of our meta-analytic data set (i.e., multiple correlations nested in independent samples), we tested which variance components (i.e., sampling variability, between-sample variation, within-sample variation) were statistically significant. To achieve this, we specified a series of models with different variance constraints and compared them using likelihood-ratio tests (LRTs)—this procedure circumvents some issues of direct significant testing of variances and allows researchers to identify a baseline model that represents their data best (Cheung, 2015). The first model in this series was a three-level random-effects model which quantified the variation of correlations between independent samples (level 3), their variation within the samples (level 2), and the sampling variability (level 1; Cheung, 2014). This model accounts directly for the existence of multiple correlations for the same samples (Moeyaert et al., 2017). The second and the third model constrained either the level-2 or the level-3 variances to zero, representing the data by (two-level) random-effects models. Finally, the fourth model constraints all variance components to zero, assuming only fixed effects without any variation of the SES-ICT literacy correlations. Once we established a baseline model, we further introduced possible moderators to the model. To circumvent possible multicollinearity issues, we performed a “divide-and-conquer” approach and introduced the moderator variables one at a time. Furthermore, as a part of our sensitivity analyses, we added the study level in order to check whether moderators may not only explain between-sample but also between-study variation. All models were based on restricted maximum-likelihood estimation and were specified in the R package ‘metafor’ (Viechtbauer, 2017). The Supplementary Material S3 contains the corresponding R code.

4 Results

4.1 Description of Primary Studies

The meta-analytic sample contained m = 32 independent samples from n = 11 primary studies that yielded k = 75 correlations between measures of SES and ICT literacy—the main characteristics of these studies and the student samples they included are shown in Table 2. Supplementary Material S1 contains the full data set. Most correlations were published in reports rather than in peer-reviewed journals between 2008 and 2015. The three types of SES measures were almost balanced (parents’ education: 33.3 %, parents’ occupation: 29.3 %, cultural capital: 37.4 %). Concerning the measures of ICT literacy, most studies included interactive items (e.g., simulations or authentic assessment situations) instead of static items, assessed applied skills within the ICT literacy framework, reported on the test reliability (, and examined the fairness of the assessment. Primarily, the study samples were comprised of secondary-school students, followed by primary-school students. Most studies stratified and/or randomized their student samples. As for the origin of the samples, more than half of the sample of primary studies were conducted in Europe, followed by American studies, Asian studies, and Australian studies. The overall sample sizes ranged between 54 and 5369 with a mean of M = 2642.2, a standard deviation of SD = 1097.4, and a median of 2880. On average, the reliabilities of the ICT literacy assessments were M = 0.88 (SD = 0.04, Mdn = 0.89) and ranged between 0.67 and 0.95. The authors of the primary studies mainly reported Cronbach's α or reliabilities based on models of item response theory.

4.2 Publication Bias and Influential Correlations

To test the extent to which publication bias and influential correlations may exist in the data set, we performed several analyses. First, the inspection of the funnel plot showed some degree of asymmetry (Figure 2a). Second, the supplementary trim-and-fill analysis supported this observation and indicated that some correlations might be missing on the right side of the plot, providing an overall correlation of $\bar{r}$ = .237 (95 % CI [.215, 259], k = 92, z = 20.9, p < .001) based on random effects. Third, we performed Egger's regression test for funnel plot asymmetry using standard errors as predictors in the regression model. This test resulted in a significant t-statistic (t[73] = -4.6, p < .001) and therefore suggested the asymmetry of the funnel plot. Fourth, Rosenberg's fail-safe N was 136929 for the target significance level of .05, 79248 for the significance level of .01, and 48532 for .001 respectively. These many 'zero-correlation' studies would be needed to turn the existing, overall correlation between measures of SES and ICT literacy insignificant, that is, to increase the p-value above the specified level. Overall, these fail-safe Ns are large in comparison to the available number of studies and correlations. Fifth, the p-curve was right-skewed and indicated that the correlations obtained from the primary studies had evidential value (Figure 2b). Finally, we checked whether some correlations in the data set were more influential than others and did not find any correlation to be influential (see Supplementary Material S2). In sum, the results of the analyses presented here suggested some degree of publication bias, yet did neither provide evidence for a possible file-drawer problem nor the existence of influential cases.

4.3 Overall Correlation Between SES and ICT Literacy

To quantify the correlation between SES and ICT literacy measures across all studies, we first established a baseline, meta-analytic model which accounted for the nested structure of the data (i.e., effect sizes nested in studies). To select an appropriate baseline model, we specified four models and compared them using likelihood ratio testing and information criteria (Cheung, 2015). Model 1 represents a random-effects model that allows for both variation within and between studies. Models 2 and 3 restrict either of these variance components and consequently describe only one variance component—these models therefore represent standard random-effects models. Finally, Model 4 restricts all variance components and represents a fixed-effects model without any variance components within or between studies. Table 3 shows the average correlations, their variances, and the information criteria of all four meta-analytic models.

Overall, the average correlation between measures of SES and ICT literacy ranged between $\bar{r}$ = .204 (Model 3) and $\bar{r}$ = .227 (Model 4). All of these correlations exhibited statistical significance and indicated a small relation between the two variables. Comparing the information criteria across the four models, we found that Model 1 is preferred over all other models, due to smaller values of the AIC and BIC. In addition, the likelihood-ratio tests suggested a clear preference of Model 1, and this model showed significant level-2 and level-3 variances. Cheung (2015) argued that researchers must consider whether they want to "generalize the findings to both level 2 and level 3" when testing the null hypothesis of $\sigma_3^2 = 0$ (p. 185). Both the estimation of the variance confidence interval and the likelihood-ratio test are not free from bias, especially because variance components are tested against their boundary of zero while they can only have positive values. Given that we tested the effects of moderators that represented characteristics of both effect sizes (or measures; level 2) and the independent samples (level 3) when addressing research questions 2 and 3, we decided to accept Model 1—the three-level random-effects model—as the baseline. The intraclass correlations resulting from this model were $ICC_2 = .415$ (level 2) and $ICC_3 = .585$ (level 3); the I^2 statistics were $I_2^2 = 39.0$ % and $I_3^2 = 55.1$ %, respectively. These two statistics indicated the variability and heterogeneity of correlations within and between study samples. In sum, our response to research question 1 is as follows: Measures of SES and ICT literacy were significantly and positively correlated, with a small average effect of $\bar{r}$ = .214.

Sensitivity analyses.

Correction for unreliability. After correcting the correlations for the unreliability of the ICT literacy measures, we specified Models 1-4 to the corrected data. The resultant average correlations ranged between $\bar{r}$ = .217 (Model 3) and $\bar{r}$ = .242 (Model 4). Again, Model 1 was preferred over all other models, and the confidence intervals of the level-2 and level-3 variances did not include zero. Although the corrected correlations were slightly higher than the uncorrected correlations, the correction for unreliability did not lead to different conclusions than we had initially drawn from the uncorrected correlations. Supplementary Material S2 contains all relevant details.

Treatment of the ICILS 2013 data. To examine the influence of the ICILS 2013 data on the overall correlation, we performed a two-step procedure: First, we combined the correlations extracted from this study and aggregated them using random-effects models. The resultant, pooled correlations we used as input for the second stage in which we meta-analyzed the pooled ICILS correlations together with the correlations obtained from the other studies. Both the results of the first and the second stage are shown in detail in the Supplementary Material S2. This procedure resulted in an overall SES-ICT literacy correlation of $\bar{r}$ = .29 (95 % CI [.21, .36]), which was slightly higher than that obtained from the data without the pooling of the ICILS 2013 data.

Four-level random-effects modeling. As a part of our sensitivity analyses, we accounted for the nesting of the study samples in studies by adding another level to the three-level random-effects model. The resultant four-level model revealed an overall correlation of $\bar{r}$ = .283 (95 % CI [0.209, 0.356]) and indicated significant heterogeneity in the data, $Q(74)$ = 1617.1, $p < .001$. This model estimated the intraclass correlation for the study level to be ICC_4 = 0.697, the homogeneity index to be I_4^2 = 67.3 %, and the between-study variance to be σ_4^2 = 0.011 (95 % CI [0.003, 0.038]). The likelihood-ratio test suggested the preference of the four-level model (LL = 83.7, *df* = 4, AIC = -159.3, BIC = -150.1) over the three-level model, LRT $\chi^2[1]$ = 14.4, $p < .001$. In sum, the overall correlation did not differ largely from that obtained from the three-level model; the between-study variation was significant but small.

4.4 Moderation by the Type of SES Measures

After establishing the small, positive, and statistically significant correlation between SES and ICT literacy measures, we further examined possible differences in this correlation between educational, occupational, and capital SES measures taking two analytic approaches: First, we tested whether the type of SES measure moderated the SES-ICT literacy relation in a three-level mixed-effects model. More precisely, we extended the baseline Model 1 by the type of SES measure as a predictor. The resultant model showed significant moderation effects ($Q_M[2]$ = 12.5, $p < .01$), with higher correlations for studies using capital SES measures ($\bar{r}$ = .246, 95 % CI [.212, .280], $m = k = 28$) in comparison to those using educational ($\bar{r}$ = .186, 95 % CI [.151, .222], $m = k = 25$) and occupational SES measures ($\bar{r}$ = .199, 95 % CI [.163, .235], $m = k = 22$). Overall, 16.6 % of the level-2 variance (i.e., within-sample variation) and 7.3 % of the level-3 variance (i.e., between-sample variation) could be explained. This finding provides some evidence that the type of SES measure moderates the

SES-ICT literacy correlation. Notice that this analytic approach assumes equal variance components for all types of SES measures and that all moderator analyses are not based on the study level (n = 11) but the sample and effect size levels to circumvent possible power issues associated with the small number of studies.

Given that the assumption of equal variances may not be fulfilled, we performed separate meta-analyses, one for each SES measure. Given that this separation dispersed the nested data structure so that only one effect size was available per study, common (two-level) random-effects modeling was conducted. Figures 3, 4, and 5 show the underlying forest plots. For the studies using *educational SES measures*, the SES-ICT literacy correlation was $\bar{r}$ = .181, 95 % CI [.140, .221]), and showed significant variation between studies (σ^2 = 0.009, 95 % CI [0.005, 0.018]; fixed- versus random-effects model: LRT $\chi^2[1]$ = 456.5, p < .001). For the studies using *occupational SES measures*, the SES-ICT literacy correlation was $\bar{r}$ = .178, 95 % CI [.155, .202]), and showed significant variation between studies (σ^2 = 0.003, 95 % CI [0.001, 0.006]; fixed- versus random-effects model: LRT $\chi^2[1]$ = 63.5, p < .001). For the studies using *capital SES measures*, the SES-ICT literacy correlation was $\bar{r}$ = .245, 95 % CI [.210, .279]), and showed significant variation between studies (σ^2 = 0.008, 95 % CI [0.005, 0.015]; fixed- versus random-effects model: LRT $\chi^2[1]$ = 536.2, p < .001). These correlations are in line with those obtained from the three-level mixed-effects approach. Overall, the SES-ICT literacy correlations differ between the two types of SES measures, with a higher correlation for capital SES measures. To summarize, Table 4 depicts these correlations along with the correlation obtained from the analyses with all SES measures combined.

Sensitivity analyses.

Correction for unreliability. Correcting the SES-ICT literacy correlations for unreliability supported the moderation effects by the type of SES measure, $Q_M(2)$ = 12.8, p < .01 (see Supplementary Material S2. Again, the correlation was significantly higher for capital SES measures ($\bar{r}$ = .262, 95 % CI [.226, .298]) as compared to educational SES measures ($\bar{r}$ = .199, 95 % CI [.161, .237]), and occupational SES measures ($\bar{r}$ = .212, 95 % CI [.173, .251]).

Treatment of the ICILS 2013 data. After pooling the ICILS 2013 data, we found the following correlations for each type of SES measure: For the educational SES measures, the correlation was $\bar{r}$ = .29 (95 % CI [.18, .40]); for the occupational SES measures, the correlation was $\bar{r}$ = .16 (95 % CI [.14, .19]); for the capital SES measures, the correlation was $\bar{r}$ = .30 (95 % CI [.21, .40]). Overall, these sensitivity analyses showed a weak effect on the overall correlations; yet, given that this procedure was based on a substantially smaller sample of primary studies (*n* = 11), some deviations, for instance, the higher correlation for educational SES measures, occurred.

Four-level mixed-effects modeling. Adding the study-level to the analytic model supported the moderation effect by the type of SES measure (see Supplementary Material S2), $Q_M(2)$ = 10.6, $p < .01$ (see Supplementary Material S2). Again, the correlation was significantly higher for capital SES measures ($\bar{r}$ = .303, 95 % CI [.230, .375]) as compared to educational SES measures ($\bar{r}$ = .248, 95 % CI [.173, .323]), and occupational SES measures ($\bar{r}$ = .266, 95 % CI [.190, .342]).

4.5 Moderation by Study, Sample, and Measurement Characteristics

To address our third research question, which was concerned with the moderation effects by study, sample, and measurement characteristics, we extended the three-level baseline model (Model 1), as identified under research question 1, to mixed-effects models. In these models, the study, sample, and measurement characteristics served as predictors, explaining either within- or between-sample variation. Table 5 contains the resultant moderation effects, significance tests, and variance explanations for the categorical moderators.

All study characteristics that were related to the ICT literacy measure showed significant moderation effects, thus explaining variance in the SES-ICT literacy correlation. More specifically, we could identify a significantly smaller average correlation for samples that worked on interactive ICT tasks ($\bar{r}$ = .190) than for those working primarily on static tasks ($\bar{r}$ = .290). Similarly, for ICT literacy tests that mainly assessed the application of certain skills, the SES-ICT literacy correlation was significantly smaller ($\bar{r}$ = .196) than for test focusing on more theoretical skills ($\bar{r}$ = .307). Finally, samples for which the authors tested the fairness of their ICT literacy assessment, be it across gender or SES groups, showed significantly lower correlations ($\bar{r}$ = .187) than those without any test of fairness ($\bar{r}$ = .353). Overall, the between-sample variance explanations for these three moderators ranged between 26.6 % and 59.6 %.

Concerning the sample characteristics, we found significant moderation effects of the sampling strategy employed in the primary studies. More precisely, randomized and/or stratified student samples showed a significantly smaller average correlation ($\bar{r}$ = .190) than convenience samples ($\bar{r}$ = .389). This difference accounted for 62.0 % of between-sample variation in the data. Besides, neither the educational level of students (primary vs. secondary school; $Q_M[3]$ = 7.8, p = .05) nor the publication year ($Q_M[1]$ = 1.9, p = .17) or study year ($Q_M[1]$ = 0.3, p = .61) moderated the SES-ICT literacy correlation, and the differences between continents were marginal.

We further investigated whether the correlations differed significantly between world regions; yet, we did not find support for significant differences. To explore possible differences at a more fine-grained level, we explored the extent to which the correlations differed between countries, in addition to the between-samples variance. Adding the country-level to the three-level random-effects model resulted in a four-level model (LL = 49.8, *df* = 4, AIC = -91.5, BIC = -83.4) with a between-country variance of σ_4^2 = 0.002 (95 % CI [0.000, 0.007]), a heterogeneity coefficient of I_4^2 = 14.9 %, and an intraclass correlation of ICC_4 = 15.8 %. Comparing this model to the three-level model indicated that the three-level model was preferred, LRT $\chi^2[1]$ = 1.2, *p* = .26. Overall, we did not find evidence for significant between-country variation in the SES-ICT literacy correlations.

Sensitivity analyses.

Correction for unreliability. The correction for unreliability did not change the moderation effects identified for the uncorrected data (see Supplementary Material S2). Some of the effects became more pronounced, for instance, the differences between continents, and showed slightly higher variance explanations. Overall, the results of the moderation analyses were only marginally sensitive to the correction for unreliability.

Treatment of the ICILS 2013 data. Given the reduced sample size after pooling the ICILS 2013 data, some of the moderation effects disappeared, for instance, the previously identified difference between tests that were comprised of mainly interactive tasks and those with mainly static tasks (see Supplementary Material S2). At the same time, some effects remained, such as the difference between tests for which fairness was assessed and those for which fairness was not assessed, $Q_M(1)$ = 5.9, *p* < .05. Similarly, the moderation effect of the sampling design remained, $Q_M(1)$ = 8.6, *p* < .01. Overall, the moderation effects are sensitive to the treatment of the ICILS 2013 data.

Four-level mixed-effects modeling. Similar to the treatment of the ICILS 2013 data, adding the study-level as another level of analysis changed some of the moderation effect due to the small number of studies that were available (*n* = 11). Once again, the effects of test fairness and sampling remained; yet, all other effects disappeared (see Supplementary Material S2). Hence, the moderation effects are indeed sensitive to the number of levels specified in the mixed-effects models.

5 Discussion

5.1 Summary of Results

This meta-analysis was aimed at describing the relation between measures of students' socioeconomic status and their performance on ICT literacy tests. This relation quantified possible educational gaps in the cross-disciplinary domain of ICT which has gained considerable importance in K-12 education over the last two decades. Using three-level random-effects modeling, we found a significant, positive, and weak correlation ($\bar{r}$ = 0.214) which was subjected to within- and between-samples differences. The overall correlation was only marginally sensitive to corrections for the unreliability of the ICT literacy measures; however, it was moderated by the type of SES measure, so that slightly higher correlations were reported in studies using capital-based measures. Moreover, the SES-ICT literacy correlation was moderated by several study, sample, and measurement characteristics, including the type of ICT literacy tasks, the ICT skills assessed, the assessment of test fairness, and the sampling procedure. Overall, the moderation analyses pointed to lower correlations if the authors strived for better quality of their primary studies.

5.2 The Relation Between SES and ICT Literacy

Our meta-analysis examined the relation between K-12 students' performance on ICT literacy measures and measures of their SES—a relation that has become a key element in the set of evidence for educational inequalities (APA, 2007; Berkowitz et al., 2017). The positive relation identified in our study has several implications and interpretations: First, despite our conceptual argumentation that ICT literacy may be less prone to SES differences, the SES-ICT literacy was positive and statistically significant. At the outset of this meta-analysis, we hypothesized that ICT literacy, among other, cross-disciplinary skills (Binkley et al., 2012), represents a skillset that may not rely heavily on students' prior knowledge. This reasoning was based on the observation that the existing ICT literacy assessments emphasize the processes of knowledge acquisition and subsequent application, mostly while students interact with the ICT environment (Siddiq et al., 2016). Despite the hope that ICT, as a relatively young domain in education, may compensate for SES differences, our study found that this hope has not been fulfilled so far. The significance of the SES-ICT literacy relation, indeed, testifies that educational inequalities also exist in the domain of ICT skills: Students of higher socioeconomic status performed better on the ICT tasks administered in the primary studies than students of lower socioeconomic status, independent of the way SES was measured. Differences in the access to digital resources and devices, for instance, may lead to differences in ICT literacy, simply because students with little access may have less opportunities to engage in ICT activities and the related skills (Harris, Straker, & Pollock, 2017; OECD, 2018). In light of these findings, we conclude that the domain of ICT literacy is sensitive to differences in K-12 students' socioeconomic status.

Second, the association between SES and ICT literacy measures was weak, suggesting that the socioeconomic gap in the domain of ICT may not be as severe as in other domains. For general cognitive abilities, for instance, Strenze (2007) found moderate SES-achievement correlations as high as $\bar{r}$ = .49, and Sirin (2005) reported an overall relation between SES and academic achievement of $\bar{r}$ = .32. At the same time, Strenze (2007) identified weak relations for intelligence measures and parental income measures, $\bar{r}$ = .08–.19. White (1982) reported a similar overall correlation for broad measures of academic achievement, $\bar{r}$ = .22. The range of SES-achievement relations across domains complicate the mapping of ICT literacy: Although ICT literacy may comprise elements that map this skill as being close to general cognitive abilities (Greiff, Kretzschmar, et al., 2014; Moehring et al., 2016), it may also comprise elements that are close to specific academic domains, such as mathematics and reading (OECD, 2012). We therefore argue that a construct-related perspective on ICT literacy may not provide sufficient ground for explaining the magnitude of the overall SES-ICT literacy correlation. Moreover, the relative novelty of ICT literacy, as a skill and domain that has made its way in educational curricula, necessitates more investigations of mapping its SES differences onto the landscape of academic domains.

Third, the relation between SES measures and measures of ICT literacy varied across study samples. This variation suggests that the correlations are not uniform and may depend on the specific context the primary study was conducted in as well as the characteristics of the sample. As noted earlier, some primary studies reported weak or slightly negative correlations whereas others reported positive and up to moderate correlations. This diversity surfaced in the preference of random instead of fixed effects. Possible sources of variation may refer to the characteristics of the sample, the study, or the measures (Sirin, 2005; Strenze, 2007; White, 1982). Together with van Ewijk and Sleegers (2010), we interpret the between-sample variation as evidence for the context-specificity of the SES-ICT literacy correlation. This context-specificity may further be examined across academic domains for the same student cohorts and over time.

5.3 Explaining Variation in the Relation Between SES and ICT Literacy

As noted in the previous section, our meta-analysis identified a significant variation of the SES-ICT literacy correlation within and between the independent samples. This variation was partly explained by study, sample, and measurement characteristics. From our point of view, several moderation effects are worthwhile discussing: First, the degree to which measures of SES and ICT literacy were related was dependent on the type of SES measure. More specifically, larger gaps were reported in primary studies using capital SES measures than in studies using educational SES measures. Similar moderation effects were found in previous meta-analyses in other domains. For instance, van Ewijk and Sleegers (2010) reported that different peer-SES measures showed different relations to students' academic achievement and found that the strongest relations occurred for measures of parents' education rather than the home resources. In his early meta-analysis, White (1982) found moderating effects as well, yet with the strongest SES-achievement link for measures of parents' income. In contrast, Sirin (2005) did not find any moderation effects of the type of SES measure (i.e., across the education, occupation, and income dimensions of SES). The finding that different SES measures may show different relations to ICT literacy does not only indicate that different dimensions of SES are differentially important to gaps in the ICT domain, it also shows that the different SES measures may capture students' socioeconomic background to different degrees (APA, 2007; OECD, 2018). The latter explanation taps into the validity discussion of the existing SES measures (Rutkowski & Rutkowski, 2013). Besides, some studies assessed SES at different levels of analysis (e.g., Hohlfeld et al., 2013), thus complicating the alignment between sample, study, and measurement characteristics and the individual ICT literacy measures. Against this background, we argue that research in the field of equity and ICT should always clarify the type of SES measure used in primary studies and the reasoning behind the choice for certain measures. Given that the reporting of educational gaps in ICT may have policy implications, policy-makers should be informed about the possible variation of these gaps across SES measures.

Second, for interactive assessments of ICT literacy and assessments focusing on the application of skills, the SES-achievement relation was lower than for static assessments and assessments focusing on students' knowledge. This finding may suggest that the type of assessment could compensate for possible SES gaps in ICT literacy. Studying students' performance on complex problem-solving tasks in technology-rich environments, Sonnleitner et al. (2014) found that students with an immigration background outperformed those without in exploring tasks to generate knowledge about the problem-solving situation. As immigration background is often considered another proxy of SES (OECD, 2018), it may well be that less knowledge-focused assessments, in which students have to acquire and generate knowledge, are less prone to SES gaps. However, this hypothesis was only partly tested in the present meta-analysis and requires more systematic investigations across several performance domains.

Third, the SES-ICT literacy correlation was moderated by whether or not the researchers conducted and reported test of fairness. Fairness, in this context, represents a feature of an assessment that assigns the same probability of answering an item correctly to students of different groups (Millsap, 2011). This study characteristic impacts the reporting of educational gaps in ICT to a moderate, yet significant degree. We therefore suggest making the examination and testing for possible deviations from fairness or, in psychometric terms, measurement invariance, a key element in the repertoire of crafting a validity argument of the ICT literacy measures. Information about possible differential item or task functioning across SES groups will help researchers and test users to interpret the resultant scores and relations to SES more meaningfully (Hatlevik et al., 2017; Siddiq et al., 2016).

The fact that features of the study design and the quality of the ICT literacy measures moderated the SES-achievement relation points to the necessity of carefully designed studies and measures in the domain of ICT. In his review of the body of research on ICT-based gaming education, Mayer (2015) concluded that using appropriate designs and measures for which a validity argument can be crafted is needed when addressing key research questions in the field. Siddiq et al. (2016) observed that, especially the latter, the crafting of a validity argument, has been largely missing in the existing studies of K-12 students' performance on ICT literacy tasks. Existing attempts, however, seem to be promising (e.g., Huggins, Ritzhaupt, & Dawson, 2014; Siddiq et al., 2017). In fact, the quality of measures influences the reporting of the educational gaps in ICT, due to possible bias in the resultant SES-achievement correlation.

Finally, we point to the fact that other moderators of the relation between SES and ICT literacy may exist, which could provide stronger educational implications. For instance, there is ample evidence that a positive school climate and sufficient teacher support have the potential to decrease the impact SES has on academic achievement across several domains (e.g., Berkowitz et al., 2017; Gustafsson, Nilsen, & Yang Hansen, 2018; Morgan et al., 2016). Moreover, the degree to which parents support their children and get involved in their learning process, be it by setting certain expectations or overseeing learning activities, may also determine the degree to which SES differences may translate into achievement differences (e.g., Castro et al., 2015; Fan & Chen, 2001). We believe that exploring the space of possible moderators that represent certain aspects of school climate, instruction, parental involvement, and the socioeconomic environment (e.g., neighborhood SES, rural vs. urban areas) in the domain of ICT could shed light on opportunities to reduce the existing SES gaps.

Our sensitivity analyses suggested that the presented findings are not sensitive to the correction for the unreliability of the ICT literacy measures, yet marginally sensitive to the handling of the large-scale ICILS 2013 data and the level of analysis. The latter mainly resulted from the reduction of the number of primary studies and independent samples either in the reduced data set or the added level (i.e., study level). We therefore recommend updating our meta-analysis in several years to gain a larger sample of primary studies.

5.4 Limitations and Future Directions

The present meta-analysis has some limitations worthwhile mentioning: First, the meta-analytic sample of primary studies was only limited to m = 32 independent study samples which were retrieved from n = 11 studies and yielded k = 75 correlations, primarily due to the novelty of the ICT literacy domain (see Siddiq et al., 2016). Despite the seemingly small number of studies, the number of independent samples and correlations resulted in an overall power of $1-\beta$ = 0.999 (calculations according to Valentine, Pigott, & Rothstein,

2010) to detect the small overall correlation between SES and ICT literacy, even when estimating random effects (Jackson & Turner, 2017)—of course, had the correlation been smaller, the power to detect it on the basis of our sample would have decreased. As a consequence, the subgroup analyses (i.e., moderator analyses) were not based on the study but the sample and effect size levels to circumvent possible power issues with detecting group differences. Moreover, the moderator analyses were based on models with only one categorical moderator, yet not multiple at the same time (Valentine, Pigott, & Rothstein, 2010). Nevertheless, we encourage updating and replicating the findings presented in this paper to constantly monitor and evaluate possible changes in the SES-ICT literacy relation over time. Knowledge about these changes can inform policy-makers about the possible long-term effects of technology in education and researchers about the nature of ICT literacy as a cross-disciplinary domain next to the more traditional domains in K-12 education. Second, the types of SES measures varied across studies and explained between-study variation significantly. This observation brings to attention issues of comparability: As Rutkowski and Rutkowski (2013) argued, even “simple” measures of SES, such as the number of books at home, may not be comparable—or, in measurement terms, invariant—across countries, cultures, and subgroups of students. This lack of comparability concerns the validity of the SES measures and necessitates their thorough psychometric evaluation in future studies. Third, this meta-analysis focused on performance-based assessments of ICT literacy, discarding self-reports and observational ratings. Our findings may not hold for the latter two types of measures, given that they rely on different sources of information and are thus prone to different kinds of bias (Siddiq et al., 2016). We therefore caution readers to interpret our findings only in light of K-12 students’ performance measures of ICT literacy and the evidence on validity the primary studies provided. Fourth, concerning the classification of skills assessed by the ICT literacy tests, this meta-analysis was limited by the number of independent study samples and test domains. A more fine-grained view of the ICT literacy skills with larger sample sizes within these categories would have provided more insights into possible, differential relations between SES and ICT literacy. Our current classification only allowed for examining differences in correlations between tests that focused on applied or theoretical skills—alternative classifications may, of course, result in different moderator effects. We therefore encourage researchers in the field of educational technology to gather more detailed evidence on these effects. Fifth, although our sensitivity analyses suggested that the dominance of ICILS 2013 in the data did not impact our overall findings, it is generally uncertain to what extent the inclusion of international large-scale studies in education may introduce publication bias. Overall, we believe that this data-related issue deserves some attention in meta-analytic research (e.g., Cheung & Jak, 2016). Sixth, our analyses indicated some degree of publication bias, as indicated, for instance, by the high proportion of grey literature and the significant differences in the SES-ICT literacy correlation between grey literature and journal articles. Considering the additional analyses (e.g., trim-and-fill), the overall correlation, if a substantial number of studies would have been added to achieve funnel-plot symmetry, was only marginally higher than that without these studies. Overall, the degree of publication bias and the practical consequences for the interpretation of the results should be reiterated in subsequent updates of our meta-analysis in the future.

Finally, given the limitations of the existing data sets, possible mechanisms and causes that may underlie the relation between SES and ICT literacy could not be examined. We believe that future research should consider possible causal pathways between SES and ICT literacy via ICT access, use, resources, and beliefs, next to the three traditional types of SES measures. Besides, additional moderators, including the school and teacher characteristics (e.g., interactions with technology in classrooms and teachers' instructional practices of using

ICT for teaching and learning), could shed further light on these mechanisms from a multilevel perspective.

5.5 Implications

The findings presented in the article may have several implications for several audiences: From the perspective of policy-making, the significant and positive correlation between SES and ICT literacy points to the existence of inequalities in the relatively novel academic domain. The hopes to possibly reduce such inequalities for the cross-disciplinary skillset underlying ICT literacy may not have been completely fulfilled. At the same time, our meta-analysis provided some evidence that several factors may indeed reduce these inequalities (as measured by the SES-ICT literacy correlation), such as the testing of applied skills rather than skills that heavily rely on knowledge. Moreover, the fact that several study and measurement characteristics showed significant moderator effects implies that any SES-ICT literacy correlation should be interpreted always with this contextual information in mind—in other words, context matters for the interpretation of the inequalities.

From the perspective of research, our meta-analysis indicated several factors that require attention in the design of future studies and assessments of ICT literacy gaps. These factors include but are not limited to the sampling design, the skillsets covered by the performance assessments, and the interactivity of ICT literacy tasks. Carefully designed studies with thorough sampling designs and a focus on applied skills in interactive test designs tend to reduce the effects of SES. The latter may also have implications for education: Interactive tasks and tasks that require what we labelled applied skills could provide learning opportunities that compensate for differences in students' socioeconomic status—at least to some extent.

6 Conclusion

The present meta-analysis examined the relation between measures of students' socioeconomic status and their ICT literacy—a cross-disciplinary skill that has found its way into K-12 school curricula and skills frameworks. Focusing on performance-based assessments of ICT literacy, we identified a positive and significant correlation to SES that suggested the existence of educational gaps in this new domain. Despite the existence of these gaps, their extent to which they were displayed in the present meta-analysis was less than for other, more traditional domains, such as reading, mathematics, and science. This finding seems promising as skills assessed by technology with options to actively generate and retrieve information may be less lean on prior knowledge but the active generation of knowledge and its application in problem-solving situations (Siddiq et al., 2016). At the same time, the magnitude of the SES-ICT literacy correlation varied between studies, and this variation could be partly explained by study design and measurement features. These observations bring to attention the importance of well-designed studies with thorough sampling procedures for examining educational gaps in the ICT literacy domain. Moreover, the quality and variety of measures of both SES and ICT literacy are relevant factors that may influence their correlation—we therefore encourage researchers to examine and report the psychometric quality of ICT literacy performance measures and consider using multiple indicators of students' SES to test for possible measurement bias in the SES-ICT literacy correlation.

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Tables

Table 1

Examples of SES measures in the primary studies

Type of SES measures	*SES indicators*	*Sample references*
Educational SES measures	▪ Highest educational level of the student's mother (e.g., primary, secondary, or tertiary education degree) ▪ Highest educational level of parents	Aesaert & van Braak (2005); Claro et al. (2015); Fraillon et al. (2014); Senkbeil et al. (2013)
Occupational SES measures	▪ Highest occupational status of parents	ACARA (2012); Fraillon et al. (2014)
Capital SES measures	▪ Home educational resources ▪ Cultural possessions (e.g., number of books at home) ▪ Free lunch at school	Claro et al. (2015); Fraillon et al. (2014); Hatlevik & Tømte (2014); Hohlfeld et al. (2013)

Table 2

Description of study samples and correlations

Characteristics	*m*	*k*	*Proportion of samples*	*Proportion of correlations*
Measurement characteristics				
Type of SES measure				
Educational SES measure	25	25	78.1 %	33.3 %
Occupational SES measure	22	22	68.8 %	29.3 %
Capital SES measure	28	28	87.5 %	37.4 %
Type of outcome measure				
Interactive	23	64	71.9 %	85.3 %
Static	9	11	28.1 %	14.7 %
Skills assessed				
Applied skills	25	68	78.1 %	90.7 %
Theoretical skills	7	7	21.9 %	9.3 %
Score reliability				
Reliability reported	28	70	87.5 %	93.3 %
Reliability not reported	4	5	12.5 %	6.7 %
Test fairness				
Fairness examined	25	67	78.1 %	89.3 %
Fairness not examined	7	8	21.9 %	10.7 %
Study characteristics				
Publication status				
Published literature	8	10	25.0 %	13.3 %
Grey literature	24	65	75.0 %	86.7 %
Sampling				
Convenience sample	5	6	15.6 %	8.0 %
Randomized and/or stratified sample	27	69	84.4 %	92.0 %
Publication year				
2008	2	2	6.3 %	2.7 %
2013	6	7	18.8 %	9.3 %
2014	21	62	65.6 %	82.7 %
2015	3	4	9.4 %	5.3 %
Sample characteristics				
Educational level				
Primary school	2	2	6.3 %	2.7 %
Secondary school	30	73	93.7 %	97.3 %
Regions				
America	6	15	18.8 %	20.0 %
Asia	4	12	12.5 %	16.0 %
Australia	3	5	9.4 %	6.7 %
Europe	19	43	59.3 %	57.3 %

Note. m = Number of independent samples, *k* = Number of correlations.

Table 3

Selection of a Baseline Model Describing the Overall Correlation between SES and ICT Literacy Measures

Model	$\bar{r}$	95 % CI	*z*	σ_2^2 [95 % CI]	σ_3^2 [95 % CI]	LL (*df*)	AIC	BIC	Model comparison	LRT
Full sample (*m* = 32, *k* = 75)										
1	.214	[.184, .244]	14.0*	0.004 [0.002, 0.007]	0.005 [0.002, 0.011]	76.4 (3)	-146.9	-140.0	-	-
2	.219	[.186, .252]	12.8*	0	0.009 [0.005, 0.016]	-27.5 (2)	58.9	63.5	1 vs. 2	$\chi^2(1) = 207.8$*
3	.204	[.183, .225]	19.1*	0.008 [0.006, 0.011]	0	71.5 (2)	-139.1	-138.9	1 vs. 3	$\chi^2(1) = 9.8$*
4	.227	[.222, .232]	83.8*	0	0	-604.8 (1)	1211.7	1214.0	1 vs. 4	$\chi^2(2) = 1362.5$*

Note. 95 % CI = 95 % Wald confidence interval, σ_2^2 = Level-2 variance, σ_3^2 = Level-3 variance, LL = Loglikelihood value, AIC = Akaike's Information Criterion, BIC = Bayesian Information Criterion, LRT = Likelihood-Ratio Test, *df* = degrees of freedom, *m* = Number of independent samples, *k* = Number of correlations.

* $p < .01$

Table 4

Overview of the correlations between measures of SES and ICT Literacy

SES measure	*n*	*m*	*k*	$\bar{r}$	95 % CI
Parents' education	5	25	25	.181	[.140, .221]
Parents' occupation	2	22	22	.178	[.155, .202]
Cultural capital	8	28	28	.245	[.210, .279]
All measures combined	11	32	75	.214	[.184, .244]

Note. n = Number of studies, *m* = Number of independent samples, *k* = Number of correlations. The correlations were based on random-effects models.

Table 5

Moderation effects of categorical study, sample, and measurement characteristics (m = 32, k = 75)

Moderator variables	*m*	*k*	$\bar{r}$	95 % CI	Q_M (*df*)	*p*	Q_E (*df*)	*p*	R_2^2	R_3^2
Measurement characteristics										
Type of outcome measure										
Interactive	23	64	.190	[.162, .218]	10.5 (1)	< .01	910.4 (73)	< .001	0.0 %	43.7 %
Static	9	11	.290	[.236, .343]						
Skills assessed										
Applied skills	25	68	.196	[.167, .225]	8.5 (1)	< .01	1089.3 (73)	< .001	8.6 %	26.6 %
Theoretical skills	7	7	.307	[.238, .376]						
Test fairness										
Fairness examined	25	67	.187	[.163, .211]	26.5 (1)	< .01	761.4 (73)	< .001	6.5 %	59.6 %
Fairness not examined	7	8	.353	[.295, .412]						
Sample characteristics										
Educational level										
Primary school	2	2	.205	[.063, .347]	0.1 (1)	.90	1613.4 (73)	< .001	0.0 %	0.0 %
Secondary school	30	73	.214	[.183, .245]						
Regions										
America	6	15	.201	[.137, .265]	7.8 (3)	.05	1386.6 (71)	< .001	2.3 %	14.7 %
Asia	4	12	.130	[.055, .205]						
Australia	3	5	.178	[.080, .276]						
Europe	19	43	.243	[.206, .280]						
Study characteristics										
Publication status										
Published literature	8	10	.315	[.258, .372]	15.3 (1)	< .01	926.7 (73)	< .001	0.0 %	51.7 %
Grey literature	24	65	.189	[.163, .215]						
Sampling										
Convenience sample	5	6	.389	[.321, .457]	29.8 (1)	< .01	864.4 (73)	< .001	8.4 %	62.0 %

Randomized and/or stratified sample	27	69	.190	[.167, .213]

Note. *m* = Number of independent samples, *k* = Number of correlations, 95 % CI = 95 % Wald confidence interval, Q_M = *Q*-statistic underlying the test of moderators, Q_E = *Q*-statistic underlying the test for residual heterogeneity, *df* = degrees of freedom, R_2^2 = Level-2 variance explanation, R_3^2 = Level-3 variance explanation. Values of variance explanations are based on the reduction of level-2 or level-3 variance after introducing moderators (Snijders & Bosker, 2012).

Figures

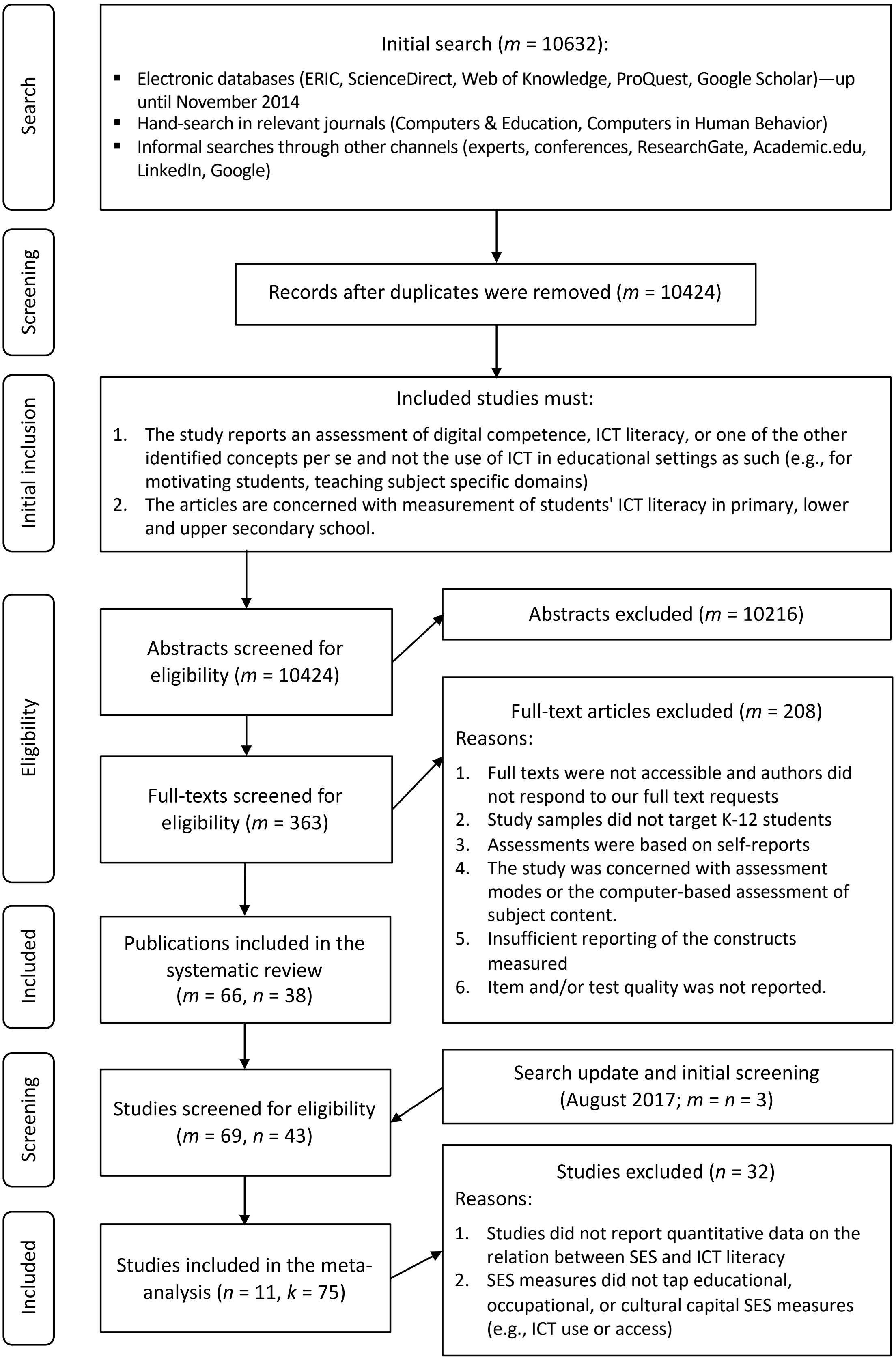
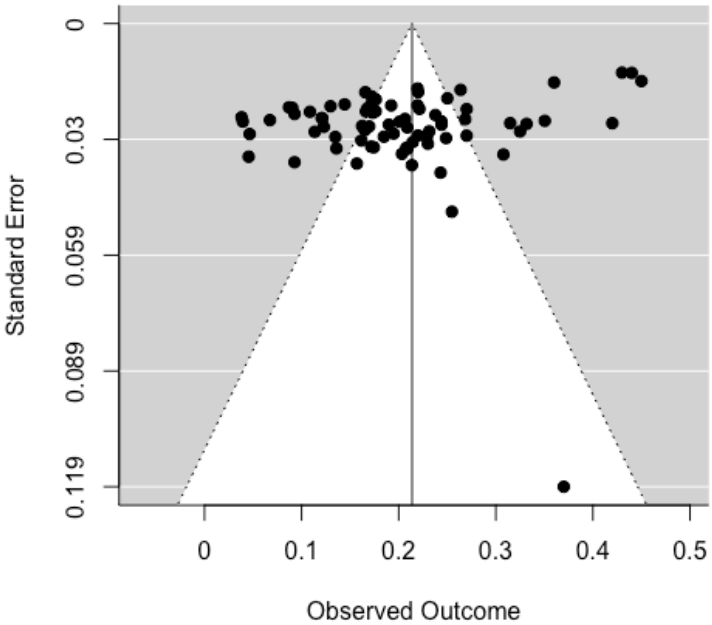


Figure 1. Flow diagram describing the literature search and the selection of eligible studies.

Note. m = Number of publications, *n* = Number of studies, *k* = Number of correlations.

(a)



(b)

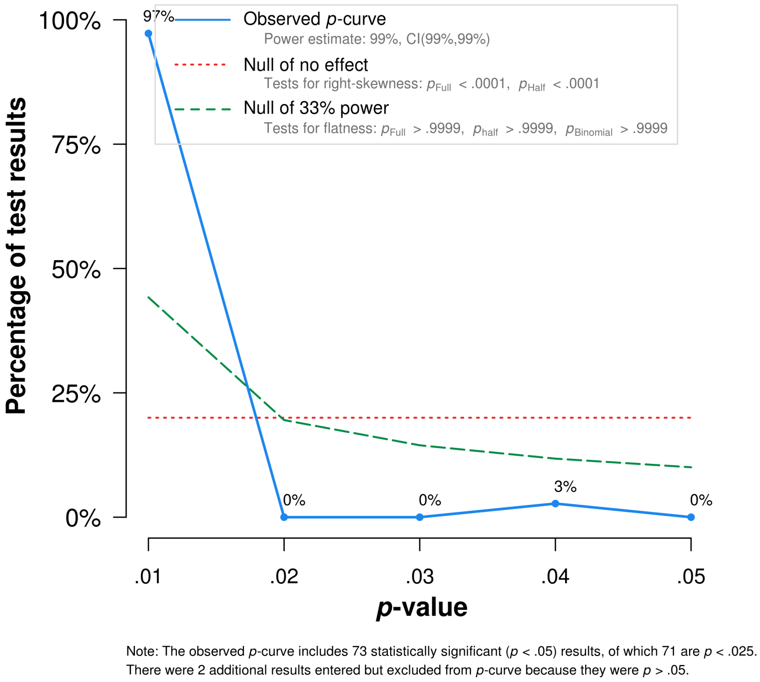


Figure 2. (a) Funnel plot based on the three-level random-effects model and (b) *P*-curve of the correlations between measures of SES and ICT literacy.

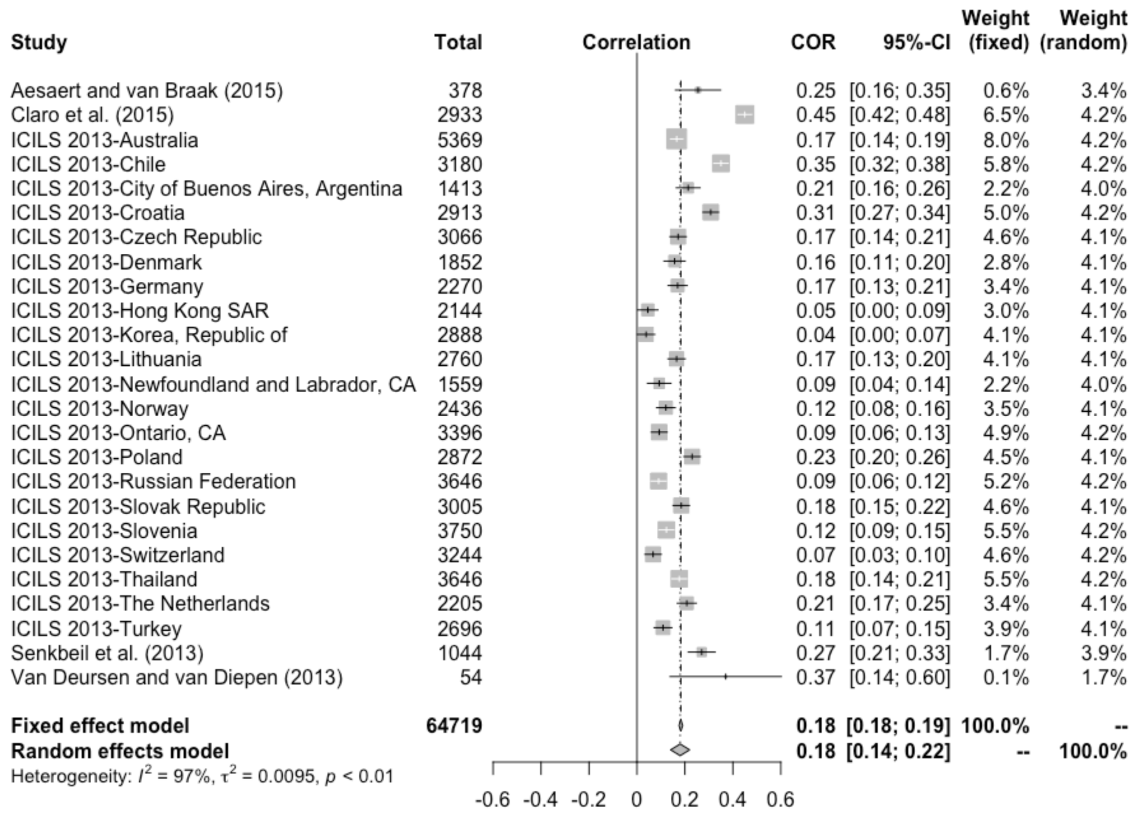


Figure 3. Forest plot of the correlations between educational measures of SES and ICT literacy.

Note. COR = correlation.

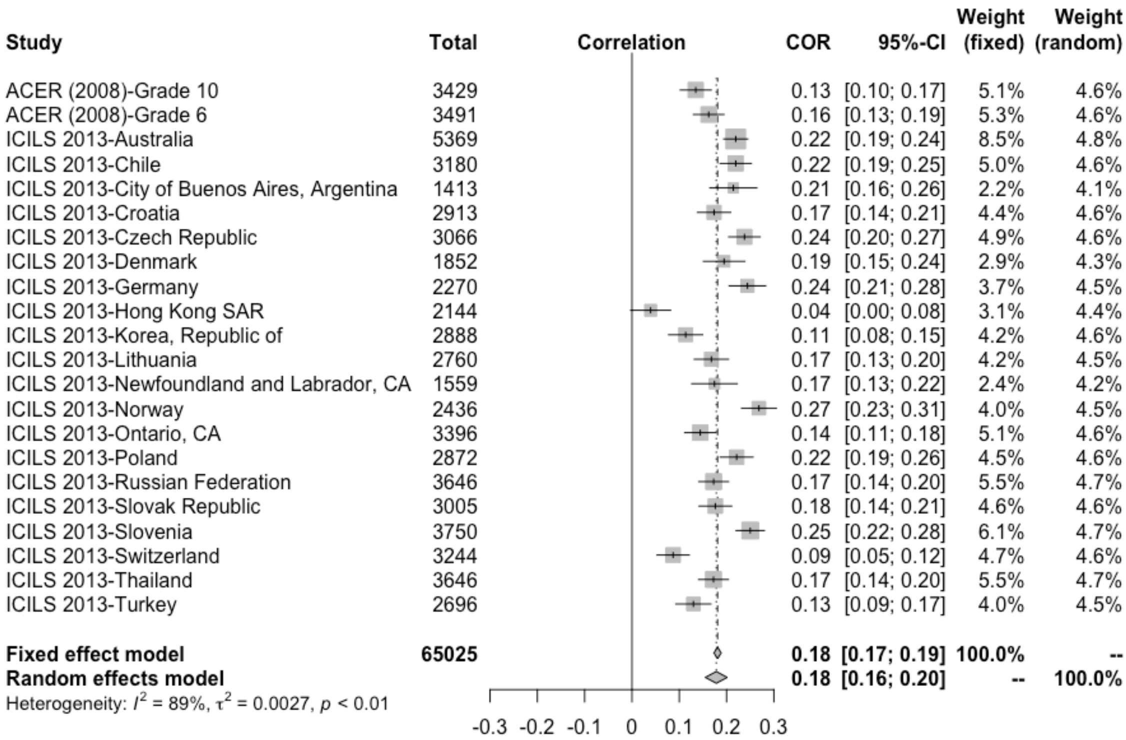


Figure 4. Forest plot of the correlations between occupational measures of SES and ICT literacy.

Note. COR = correlation.

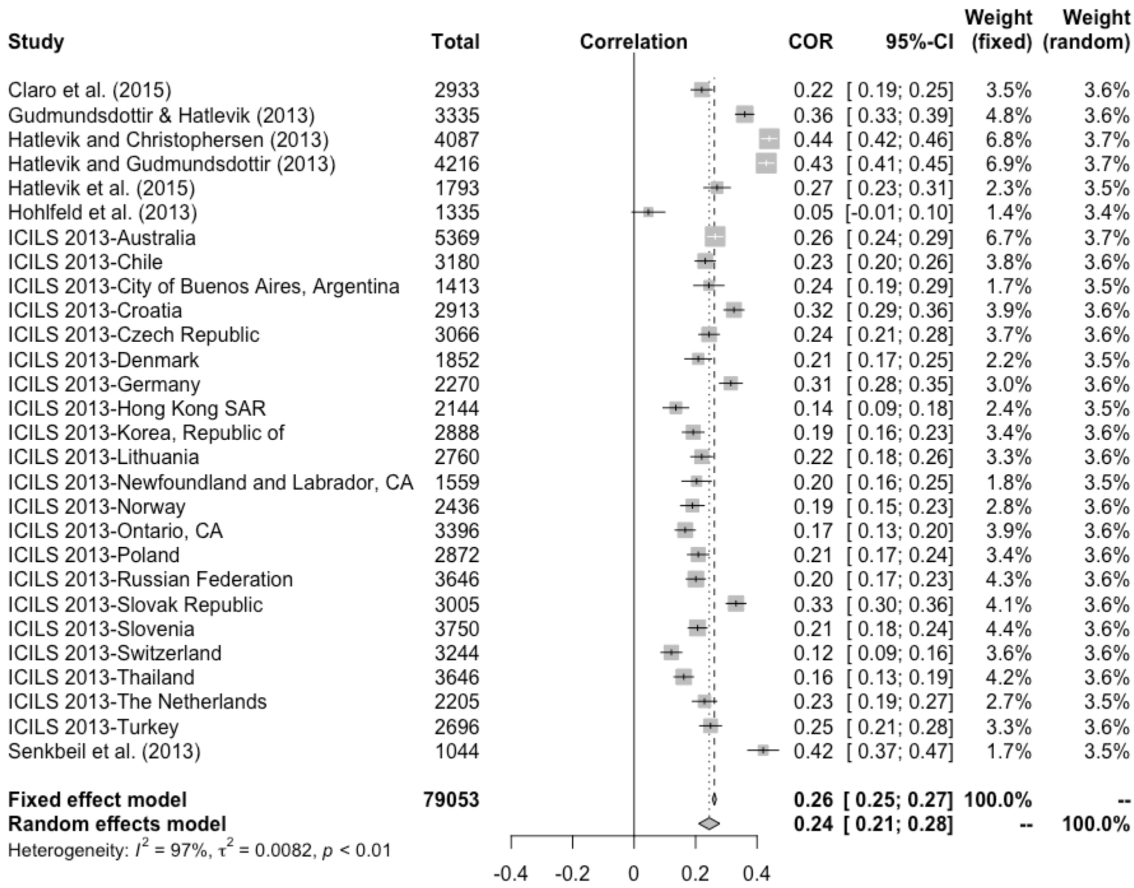


Figure 5. Forest plot of the correlations between capital measures of SES and ICT literacy.

Note. COR = correlation.