Article

IJCS

International Journal of Comparative Sociology
2021, Vol. 62(2) 115–140

DOI: 10.1177/00207152211023540
journals.sagepub.com/home/cos
SAGE

The digital divide at school and at home: A comparison between schools by socioeconomic level across 47 countries

Josef Kuo-Hsun Ma
National Taipei University

Abstract

Despite efforts to improve digital access in schools, a persistent digital divide is identified worldwide. Drawing on data from the 2018 Organisation for Economic Co-operation and Development (OECD) Programme for International Student Assessment (PISA) for 15-year-olds, I examine how students' digital use for educational purposes (at school and at home) and their perceived digital competence differ between schools by socioeconomic status (SES) and vary across 47 countries. Using multilevel modeling, I find that the second-level digital divide between schools exists even among more developed societies. Students attending high-SES schools are more likely to use computers for schoolwork within and outside of schools, and have more digital competence than those attending low-SES schools. These differences remain substantial and statistically significant even when controlling for school-level resources. Moreover, the between-school digital divide in students' digital competence is negatively associated with economic development and educational expenditures, and positively associated with income inequality. In conclusion, I discuss implications of the findings and highlight the importance of examining how schools with varying socioeconomic profiles provide different e-learning experiences for individual students, explained by the different institutional settings and cultural features of schools.

Keywords

Cross-national, digital divide, home, multilevel analysis, PISA, school

Introduction

A large body of research now addresses social exclusion from information and communication technology (ICT) in educational settings (e.g. Dolan, 2016; Robinson et al., 2015). Early research focuses on the first-level digital divide, between those who have access to ICT and those who do not (for a review, see van Deursen and van Dijk, 2019). To reduce this divide, there have been

Corresponding author:
Josef Kuo-Hsun Ma, Department of Sociology, National Taipei University, 151 University Rd., Sanshia, New Taipei City 23741.
Email: jma@ntpu.edu.tw

considerable efforts to expand Internet coverage in the learning environment and provide laptops to schoolchildren in both developed and developing countries (Erichsen and Salajan, 2014; Mo et al., 2013; Warschauer and Newhart, 2016).

Despite significant improvement in both the student–computer ratio and online networked infrastructure in schools, researchers find persistent and worldwide digital inequality in school and at home (Graves, 2019; Scherer and Siddiq, 2019; UNESCO, 2015; Warschauer, 2016). This is often referred to as the second-level digital divide (Hargittai, 2002; Ragnedda and Muschert, 2013; van Deursen and van Dijk, 2014), which suggests marked differences with respect to how students engage in digital learning, how they use ICT, and what digital skills they possess (Robinson, 2014). Moreover, scholars turn their recent focus on the third-level digital divide by examining inequality in the tangible outcomes achieved from ICT use (i.e. for variations in how people benefit from Internet use, see Scheerder et al., 2017; van Deursen and van Dijk, 2019).

A bulk of research identifies socioeconomic background as a crucial source of the gap in ICT engagement and digital skills for learning (Rafalow, 2014; Scheerder et al., 2019). Most literature attributes this gap to deficiencies in school resources and teacher quality (Areepattamannil and Khine, 2017; Erdogdu and Erdogdu, 2015), which explain why resource-poor or underperforming schools fail to promote underprivileged students' digital skills and their e-learning opportunities. Despite these findings, however, little research explores how the cultural processes and institutional features of schools (Agirdag et al., 2012) shape students' understanding of the potential benefits of digital use and also influence their quantity and quality of ICT use for learning within and outside of schools (Graves, 2019; Webster, 2017). These may generate "between-school inequalities in students' engagement with ICT."

Given the fact that recent scholarship on the digital divide in schools focuses exclusively on the experiences of affluent countries (e.g. Dolan, 2016; Hughes and Read, 2018; Leu et al., 2015), we know little about how the pattern of digital inequality differs between countries with disparate income levels. To help fill the gaps in the literature, this article addresses the digital divide in students' engagement with ICT. Specifically, I focus on comparing 15-year-old pupils attending schools with varying socioeconomic status (SES) profiles across 47 high- and middle-income countries. By *inequalities in engagement with ICT*, I mean the second-level digital divides in (1) digital use for educational purposes at school, (2) digital use for academic subjects at home, and (3) perceived ICT competence. The theoretical background of this article is based on a large body of literature documenting the role of the socioeconomic composition of schools in the formation of the school environment, reflecting on how schoolteachers and principals implement different pedagogies and expectations for students across socioeconomic groups (Agirdag et al., 2012; Bowles and Gintis, 2002; Jack, 2016).

Research questions

The article centers on two consecutive research questions: First, how do schools generate inequalities in students' engagement with ICT? More specifically, how does the second-level digital divide differ between schools with varying socioeconomic compositions? I argue that the relationship between in-school digital use and in-home digital learning is largely constrained by the nature of schools; therefore, it is important to examine this issue in its own right. Second, how does the degree of *between-school* inequalities in students' engagement with ICT vary systematically across countries, especially between high- and middle-income countries? Using cross-national data, I seek to move beyond previous research that focuses on individual countries and is conducted primarily in affluent countries (e.g. Leu et al., 2015).

Disparities in engagement with ICT among students from different schools

The rates of computer access and Internet use in schools have greatly improved recently (e.g. see UNESCO, 2015), but the digital divide persists along the line of schools' socioeconomic composition (Hughes and Read, 2018; Leu et al., 2015; Warschauer, 2016; Warschauer and Newhart, 2016). Compared to teachers in high-SES schools, teachers in low-SES schools are less knowledgeable about how to use technology in the classroom (Warschauer, 2016). Low-income and disadvantaged students tend to attend schools with lower educational quality and severe budget deficits. These schools typically have no provision for courses with clear guidance in e-learning or computer labs for practice (Dolan, 2016; Robinson, 2014).

Research on comparative education suggests that schools with a concentration of socioeconomically disadvantaged students have less available resources for learning and lower teaching quality. Comparing across 33 countries, for instance, Schmidt et al. (2015) find that the proportion of the academic achievement gap explained by school SES is appreciable worldwide due to variations in the degree of opportunity to learn (OTL), such as instructional content coverage or content exposure. Similarly, studies by Chiu (2015) and Santibañez and Fagioli (2016) suggest that the socioeconomic achievement gap is mediated by educational materials, student exposure to advanced math courses, and teacher quality at the school level. Based on this group of literature, low-SES schools fail to promote digital learning opportunities due to their lack of basic educational resources. Therefore, targeting school resources toward disadvantaged pupils, as well as improving school conditions for them, would reduce educational inequality (Downey and Condron, 2016; Raudenbush and Eschmann, 2015).

Despite the importance of school resources and teacher quality, it is equally important to examine the effects of schools' cultural processes and institutional settings on educational inequalities (Agirdag et al., 2012; Bowles and Gintis, 2002; Jack, 2016). Building on Bowles and Gintis' (2002) correspondence principle, schools socialize working-class students to accept a set of rules and beliefs that conform to working-class jobs (e.g. punctuality and obedience), whereas middle-class peers are instructed by teachers to learn skills that prepare them to attain upper-class job positions (e.g. critical judgment and creativity). Related research explains that students in low-SES schools feel a lack of control over their academic success and believe the school is working against them (Agirdag et al., 2012). Compared to financially distressed and resource-poor schools, the teacher–student relationship is more positive and constructive in resource-rich, elite schools, regardless of students' family backgrounds (Jack, 2016).

The cultural and institutional settings of schools may also shape individual students' experiences in e-learning and their understanding of the benefits of ICT use, which generate the second-level digital divide. For example, Warschauer (2016) finds that students in low-SES schools use computers more frequently, but mainly for developing the most basic computer skills. Comparatively, students in high-SES schools use computers for more constructivist and innovative purposes (e.g. achievement of deeper knowledge and analysis through critical inquiry). Research also suggests that teachers in low-SES schools tend to discourage students from using ICT, whereas teachers in mid- or high-SES schools encourage students to interact with electronic whiteboards (Graves, 2019; Rafalow, 2014). When schools have a high proportion of low-SES students, tensions arise between the school's pressure to keep up with technology and teachers' resistance to integration with technology (Webster, 2017). This is in part because teachers tend to believe economically underserved students are less technically savvy (Hughes et al., 2015). Based on this rationale, I propose that there is a substantial second-level digital gap along the line of schools' socioeconomic composition. This not only affects students' use of ICT in class, but also influences how they engage with ICT outside of the classroom:

> *Hypothesis 1*: Students attending high-SES schools are more likely to engage in ICT for educational purposes at school and also at home; similarly, they have greater levels of ICT competence compared to their peers from low-SES schools. These gaps remain even when controlling for individual-level family SES and school-level educational resources.

Sources of cross-national variation in the between-school digital divide

Economic development

Going beyond the above school-level explanations for the second-level digital divide, this article addresses whether economic development moderates the digital gap between high-SES schools and low-SES schools, given that scholars find national income to be a strong predictor of the digital divide (Cruz-Jesus et al., 2017; Lechman, 2015). Economic development predicts a country's overall level of digital development by elevating the rates of computer ownership and Internet access in a household (Chinn and Fairlie, 2010; Hu et al., 2018). National wealth is "a prerequisite for ICT diffusion and the main determinant of the global digital divide" (Cruz-Jesus et al., 2017: 835). It also generates pressure on countries to expand their supply of digitally networked technology (Robison and Crenshaw, 2010), such as the promotion of Internet infrastructure and the provision of community e-services (Lechman, 2015).

Zhang (2013) finds that the higher the economic standing of a country, the steeper its curve of Internet diffusion, with more of its citizens able to adopt new technologies. Cruz-Jesus et al. (2017) suggest that economic standing produces diminishing returns for digital development. This indicates that the positive effect of economic development appears to be stronger among less affluent societies. Because of ICT diffusion, access to online networked technology is no longer exclusive to the wealthy. In more affluent countries, socioeconomically disadvantaged people have greater opportunities to use ICT at home as well as in public spaces like schools, community centers, and libraries (van Deursen and van Dijk, 2014; Warschauer and Newhart, 2016). Comparatively, less affluent countries have insufficient financial resources to promote investments in ICT infrastructure (e.g. high-speed Internet landlines) or increase the level of digitalization (Cruz-Jesus et al., 2017), thereby reducing digital engagement opportunities for the socioeconomically underprivileged.

Based on a report by ITU (2018), economically greater developed countries have greater proportions of population equipped with diverse ICT skills compared to less-developed countries. While the literature described above mainly focuses on the relationship between national income level and ICT diffusion, this article examines another important issue that has received little attention in research on comparative education: Does economic development moderate the degree of between-school inequality in students' engagement with ICT? I predict that increases in national income not only increase the level of digital engagement among disadvantaged students (Ma et al., 2019) but also promote digital learning opportunities and digital competencies among students attending low-SES schools, leading to a smaller second-level digital divide along the line of school SES. The rationale behind this argument is in part because affluent countries that are able to devote considerable resources to their schools may find diminishing marginal returns from these added resources. In contrast, less wealthy countries may not have enough basic resources for each school sector, thereby aggravating the unequal distribution of resources among schools (Hanushek and Luque, 2003).

Hypothesis 2: Economic development will have a negative association with the second-level digital divide. More specifically, increased national income is associated with a reduction in the relationship between schools' socioeconomic status and individual students' digital use at school and at home. Similarly, it reduces the level of between-school digital inequality in students' ICT competence.

Income inequality

After accounting for national economic development, the article further examines how income inequality (i.e. a nation's distribution of family income) affects the between-school digital divide. Countries with greater income inequality have lower social mobility, more tensions among different status groups, and greater proportions of people in poverty (Wilkinson and Pickett, 2009). Moreover, income inequality favors socioeconomically privileged students, as they have more educational resources from school and home, leading to lower performance among the underprivileged students who are confined to economically depressed school districts (Chiu, 2015; Chudgar and Luschei, 2009). Cross-country educational research finds that income inequality is negatively associated with cognitive traits (Freeman et al., 2011); it also leads to a widening dispersion of students' academic performance (Hanushek, 2009; Hanushek and Woessmann, 2008).

According to diffusion theory, privileged social groups have a head start in accessing the newest digital appliances, while the adoption of new technological inventions takes a longer period for their less-privileged counterparts (Rogers, 1995). This suggests that the inequality of ICT use may reflect pre-existing economic inequalities (Ono and Zavodny, 2007). Recent studies show that countries with greater inequality of income distribution have lower ICT adoption rates (Hilbert, 2016; Zhang, 2013).

Based on the above rationale, I contend that the second-level digital divide between students attending high-SES schools versus those attending low-SES schools is more pronounced in countries with higher levels of income inequality. This is largely because income distribution affects the allocation of wealthy students among schools, which also shapes how educational resources are distributed (Chiu, 2015). In countries with relatively unequal income levels, for example, there is fierce competition between schools for government funding. Schools with a concentration of middle- or high-class students are able to divert more educational resources to their pupils, including resources that relate to digital learning. Also, income and wealth inequalities may preclude governments from providing universal access to educational resources, yielding educational underinvestment among low-SES schools.

Hypothesis 3: Income inequality will have a positive association with the second-level digital divide, that is, increased income inequality leads to an increase in the relationship between school SES and individual students' digital use (both at school and at home). It also reduces the level of between-school digital divide in students' ICT competence.

Educational expenditures

Section "Disparities in engagement with ICT among students from different schools" documents the relationship between schools' educational resources and digital learning opportunities. It is commonly believed that greater expenditure on public education increases a country's overall educational opportunities (for a review, see Chmielewski and Reardon, 2016). Therefore, it should be equally important to consider the role of public spending on education and its relationship with digital inequality. Increased educational expenditures may be associated with a narrowing digital gap among students from socioeconomically diverse schools, in part because education plays a fundamental role in a nation's post-industrial progress, which hinges on mass diffusion of ICT (Pick and Sarkar, 2015). Related research finds that countries with more highly educated populations are more digitally literate (ITU, 2018). Therefore, I argue that public investment in education may help promote opportunities for socioeconomically disadvantaged students to develop their digital competency, as long as these investments are used for the promotion of e-learning resources in schools.

Högberg et al. (2019) suggest that policies that aim to increase educational opportunities are likely to promote the psychological well-being of individuals through spillover effects. Such effects are expected to benefit those from vulnerable backgrounds. They contend that

> [increased] educational opportunities can be seen as potentials that need not be realized in order to increase well-being. The mere opportunity to access education offers prospective students peace of mind because it provides the knowledge that they can get a second chance if necessary. (Högberg et al., 2019: 272)

Based on this literature, I expect that increased educational expenditures will promote educational opportunities, which will have spillover effects on students from vulnerable socioeconomic backgrounds.

Based on the concept of diminishing marginal returns, public educational resources should benefit poorer students—who are in greater need of support from schools—more than they benefit richer students (Vegas and Coffin, 2015). Agasisti and Longobardi (2017) focus on the disadvantaged low achievers across 15 European countries, finding that more public spending on education increases the likelihood of schoolchildren becoming "resilient students" (i.e. succeeding in school). This result is different from another group of literature that suggests that whether educational resources enhance students' learning experiences depends largely on the institutional features of schools as well as how money is spent (for instance, see Schütz et al., 2008).

To the best of my knowledge, how national investment in education shapes digital learning opportunities at the school level has received little attention in previous literature. Even among countries with similar economic standing, variation in educational expenditures may influence how ICT resources are distributed (Ma et al., 2019). Given that underprivileged students are more likely to attend schools with inferior teaching and learning resources, and that they are particularly less likely to take advanced computer courses or receive proper e-learning instruction at school (Graves, 2019; Warschauer, 2016), I propose that increases in public spending could promote students' engagement with ICT within and outside of schools. This is particularly true for those attending resource-poor schools:

> *Hypothesis 4*: Educational expenditures will have a negative association with the second-level digital divide, that is, increased expenditures will reduce the effect of school SES on individual students' digital use within and outside of schools. Similarly, it will reduce the level of between-school digital divide in students' ICT competence.

Data, measures, and methods

This study uses the Organisation for Economic Co-operation and Development (OECD) Programme for International Student Assessment (PISA) 2018 data, which examined the digital learning opportunities of students from a wide range of countries. PISA is uniquely suited to this article, as it includes various questions related to behaviors of digital use both at school and at home. In each participating country, the student population is representative of 15-year-olds attending secondary schools. Utilizing the World Bank (2020a) categorization, there are 13 lower-middle-income or upper-middle-income countries and 34 high-income countries.[1] The original sample contains 51 countries participating in the Information and Communication Technology Familiarity Survey. Due to missing data on country-level variables, I restrict the analysis to 47 countries.[2] To address missing data for the individual-level control variables, I generate $m=10$ datasets with multiple imputations by chained equations, using the *ice* option in Stata software (Royston et al., 2009).[3] The imputations are done individually for each country (Appendix 1 presents the percentage of imputed cases for each country). Since there are 10 different sets of imputed values, I average the coefficients and standard errors from statistical analyses across the imputed datasets using HLM software. Schools with fewer than five respondents are removed from the analysis. Dropping missing cases in the dependent variables leads to a final sample size of 246,994 students in 10,531 schools. Appendix 1 presents the descriptive statistics for key individual-level variables and the percentage of imputed cases, and Appendix 2 reports the values of country-level variables in each country.

Dependent variables

The main purpose of this article is to examine the inequalities of ICT use at the school level. I use three dependent variables to measure digital inequalities. The first dependent variable, *digital use for schoolwork at school*, is a composite score containing 10 activities ($\alpha=.93$): browsing the Internet for schoolwork, using material from the school's website, posting work on the school's website, playing simulations, practicing and drilling, doing homework, using school computers for group work and communication, using learning apps or learning websites, chatting online, and using email at school. A combination of these items represents the level of student involvement in ICT-related tasks at school.

The second dependent variable, *digital use for academic subjects at home*, is a composite variable in relation to how often students use ICT for the following subjects ($\alpha=.87$): language, mathematics, science, foreign languages, and social sciences. A combination of these items represents the level of ICT involvement that directly relates to school-related tasks at home.

The third dependent variable is *perceived ICT competence*, which is another composite scale measuring whether students agree with the five statements ($\alpha=.86$): "I feel comfortable using digital devices that I am less familiar with"; "If my friends and relatives want to buy new digital devices or applications, I can give them advice"; "I feel comfortable using my digital devices at home"; "When I come across problems with digital devices, I think I can solve them"; and "If my friends and relatives have a problem with digital devices, I can help them." I use the combination of these items as a proxy for digital skills. To facilitate interpretation of the results, all dependent variables are standardized with a mean of 0 and a standard deviation of 1.

Student-level independent variables

While the article focuses on the influence of several school- and country-level variables, I include four individual-level control variables. *Family SES* is a PISA-created index of economic, social, and cultural status (OECD, 2020), which contains three components: parental occupation status,[4] parental education in years, and an index of household possessions (e.g. having a room for the child, owning classical literature, and owning a number of books). This variable is also standardized with a mean of 0 and a standard deviation of 1. *Gender* controls for the potential digital gap between male and female students (male $=1$). To control for the influence of immigration status, I include two dummy variables—*first-generation immigrant* and *second-generation immigrant*—with *non-immigrant student* as the reference category. To control for differences in language used by immigrant students, I include a dummy variable—*foreign language use at home*—with *use the same language at home as in school* as the reference category. A reason to include these controls is because they may influence both the dependent variables and the key independent variable (i.e. school SES mean), thereby inducing common-cause confounding bias if omitting them from analyses (Elwert and Winship, 2014).

School-level independent variables

The key independent variable is *school SES mean*, which averages the values of the student-reported family SES for each school. I use this variable to examine the level of digital divide along the line of schools' socioeconomic composition (i.e. the effect of *school SES mean* on the two dependent variables).

I also include further school-level control variables. To control for the difference between rural schools and schools in urban areas, I include two dummy variables—*rural* and *town*—with *city* as the reference category. To control for the time and attention that teachers give to individual students, I include *class size*, which is the average class size of the language of instruction calculated from students' self-reports. In the questionnaire, students were asked, "on average, about how many students attend your language class?" To account for the effect of teacher attributes, I include *shortage of educational staff*, a PISA-created index indicating school principals' perception of four issues hindering the quality of instruction at school ($\alpha = .78$): a lack of teaching staff, inadequate or poorly qualified teaching staff, a lack of assisting staff, and inadequate or poorly qualified assisting staff. Original response categories, from lower to higher values, are "not at all," "very little," "to some extent," "and "a lot." To control for schools' overall educational resource quality, I use another PISA-created index, *shortage of educational material*, which includes the following four problems ($\alpha = .86$): a lack of educational material, inadequate or poor-quality educational material, a lack of physical infrastructure, and inadequate or poor-quality physical infrastructure.

Country-level independent variables

I compile several country-level factors from different publicly available sources. To measure a country's economic standing, I use *gross domestic product (GDP) per capita*, in thousands of 2017 purchasing power parity (PPP) dollars, obtained from the World Bank's Databank (2020b). To represent the level of income inequality, I use the *Gini index*, compiled by the UNU-WIDER (2020) World Income Inequality Database. It ranges from 0 to 100, with 0 representing perfect equality and 100 indicating perfect inequality. To represent a country's investment in secondary education, I include *secondary educational expenditures as a percentage of GDP* from the World Bank's Databank (2020b). All of the country-level data were collected from 2017—a year before the individual-level PISA data were collected.[5] Natural log values are used for GDP per capita to account for the skewness of the distributions (Lee and Lee, 2018) and to address potential curvilinear relationships (Ruiter and van Tubergen, 2009).

Finally, I include *the percentage of students in ability grouping in any subject* as a control variable, calculated based on the PISA 2018 school assessment data. It is taken as a proxy for a country's level of educational differentiation or tracking. I include this variable in part because the way in which educational systems are stratified—indicated by the level of students in ability grouping or in academic tracking—influences the (in)equality of educational opportunity among students within and between schools (Chmielewski and Reardon, 2016; Schütz et al., 2008). This may further determine how e-learning resources are distributed across schools. Table 1 presents the descriptive statistics and coding for the variables.

Analytical strategy and statistical methods

The nature of nested data implies that students attending the same schools in the same countries are not independent of each other, as they share the same educational and social conditions. As a result, conventional ordinary least squares (OLS) analysis may underestimate both the standard errors of regression coefficients and the unexplained variance (i.e. residuals) at the cluster levels. To address this problem, I use multilevel models to account for interdependent variations generated by the clustering of students nested in schools and within countries (Raudenbush and Bryk, 2002), employing both HLM6 and Stata12 software. In this multilevel data structure, each level of analysis is represented by its own subequation, with each subequation allowing capture of the unexplained variance at that level, as well as cross-level interactions between predictors at different levels.

I proceed with the analyses in three stages. The first stage begins with using two-level linear modeling for (1) *digital use for schoolwork at school*, (2) *digital use for academic subjects at home*, and (3) *perceived ICT competence* and estimates the models separately for each of the 47 countries. Each model includes variables at the individual and school levels. Based on these models, I use graphs to visualize how the effect of school SES on the three outcome variables varies cross-nationally. In the second stage, I use three-level linear models (equations (1)–(3)) to access more formally individual-, school-, and country-level variation in digital inequalities. The general form of the model for a student *i* at school *s* in country *j* can be written as

$$Y_{isj} = \pi_{0sj} + \sum_{1}^{k} \pi_{ksj} a_{isj} + e_{isj} \tag{1}$$

$$\pi_{0sj} = \beta_{00j} + \beta_{01j} \left(School\ SES \right)_{sj} + \sum_{2}^{k} \beta_{0kj} X_{sj} + r_{0sj} \tag{2}$$

$$\beta_{00j} = \gamma_{000} + \sum_{1}^{k} \gamma_{00k} W_j + \mu_{00j} \tag{3}$$

$$\beta_{01j} = \gamma_{010} + \sum_{1}^{k} \gamma_{01k} W_j + \mu_{01j} \tag{4}$$

At the individual level (equation (1)), Y is the dependent variable. π_{0sj} is the intercept, adjusted for individual-level independent variables (a_{1sj} to a_{ksj}). e_{isj} is the unexplained variance for individual *i* at school *s* in country *j*. The intercept (π_{0sj}), also adjusted for school SES and other school-level control variables (X_{2j} to X_{kj}), is assumed to vary randomly across schools (r_{0sj} , equation (2)) and countries ($\mu_{00j,}$ equation (3)). In this stage, I focus on whether the unexplained variance at the school level (r_{0sj}) can be substantially explained by school SES.

The third stage focuses on the effects of national contextual factors on the level of the second digital divide at the school level, measured as the slope of school SES. In the multilevel framework, the school SES slope estimated in the school-level equation (equation (2)) becomes a dependent variable in the country-level equation (equation (4)). W_{1j} to W_{kj} indicate a set of country-level variables. Both the intercept (β_{00j}) and the coefficient for school SES (β_{01j}) are assumed to randomly vary across nations (μ_{00j} and μ_{01j}).

Table 1. Descriptive statistics and variable descriptions in the analysis.

Variable	Mean	SD	Description/coding
Dependent variables			
Digital use for schoolwork at school	0.00	1.00	Standardized variable based on 10 ICT activities (Cronbach's $\alpha = .93$): browsing the Internet for schoolwork, using material from the school's website, posting work on the school's website, playing simulations, practicing and drilling, doing homework, using school computers for group work and communication, using learning apps or learning websites, chatting online, and using email at school. Response categories from lower to higher values are "never or hardly ever," "once or twice a month," "once or twice a week," "almost every day," and "every day"
Digital use for academic subjects at home	0.00	1.00	Standardized variable based on five academic subjects (Cronbach's $\alpha = .87$): test language, mathematics, science, foreign languages, and social sciences. Response categories from lower to higher values are "no time," "1–30 minutes a week," "31–60 minutes a week," and "more than 60 minutes a week"
Perceived ICT competence	0.00	1.00	Standardized variable based on five statements (Cronbach's $\alpha = .86$): "I feel comfortable using digital devices that I am less familiar with"; "if my friends and relatives want to buy new digital devices or applications, I can give them advice"; "I feel comfortable using my digital devices at home"; "when I come across problems with digital devices, I think I can solve them"; and "if my friends and relatives have a problem with digital devices, I can help them." Response categories from lower to higher values are "strongly disagree," "disagree," "agree," and "strongly agree"
Individual-level variables			
Family SES	0.00	1.00	Standardized and PISA-created index of economic, social, and cultural status (OECD 2018), including: parental occupation status expressed as the index of ISEI, parental education in years, and an index of household possessions (e.g. a quiet place to study, classic literature, books of poetry, and books to help with school work)
Male	0.49	0.50	1 = male, 0 = female.
First-generation immigrant	0.05	0.21	1 = yes, 0 = no Reference group = non-immigrant
Second-generation immigrant	0.06	0.24	1 = yes, 0 = no Reference group = non-immigrant
Foreign language use at home	0.13	0.33	1 = yes, 0 = no
School-level variables			
School SES	−0.19	0.70	Mean of family SES
Rural	0.08	0.27	1 = yes, 0 = no Reference group = City
Town	0.48	0.50	1 = yes, 0 = no Reference group = City
Class size	27.67	9.08	Average size of a language class

(Continued)

Table 1. (Continued)

Variable	Mean	SD	Description/coding
Shortage of educational staff	0.00	1.00	Standardized variable based on four issues (Cronbach's α = .78): a lack of teaching staff, inadequate or poorly qualified teaching staff, a lack of assisting staff, and inadequate or poorly qualified assisting staff. Response categories from lower to higher values are "not at all," "very little," "to some extent," and "a lot"
Shortage of educational material	0.00	1.00	Standardized variable based on four issues (Cronbach's α = .86): a lack of educational material, inadequate or poor quality educational material, a lack of physical infrastructure, and inadequate or poor quality physical infrastructure. Response categories from lower to higher values are "not at all," "very little," "to some extent," and "a lot"
Country-level variables			
Log GDP per capita	3.53	0.52	GDP in thousands of 2017 PPP dollars. The unlogged value ranges from 7.31 to 126.92
Gini index	34.44	7.05	The distribution of income or consumption expenditure among individuals or households within a country deviating from a perfectly equal distribution. 0 is perfect equality and 100 perfect inequality
Secondary educational expenditures as % of GDP per capita	20.51	5.01	Current public spending on secondary education divided by the total number of students in this level, which includes government spending on educational institutions (both public and private), education administration, and subsidies for private entities (students/households and other privates entities)
Ability grouping (%)	0.69	0.19	Percentage of students attending classes which have ability grouping

Data source: All individual-level variables are from the Programme for International Student Assessment (PISA) 2018. Both GDP per capita and secondary educational expenditures are compiled from the World Bank's Databank (2020b). Gini index is from the UNU-WIDER (2020) World Income Inequality Database. Ability grouping is compiled from the PISA School Assessment 2018.
SD: standard deviation; SES: socioeconomic status; GDP: gross domestic product; PPP: purchasing power parity; ICT: information and communication technology; ISEI: international socio-economic index of occupation status.
To preserve cases, multiple imputations (m = 10) for missing cases are used for individual-level control variables.

A key issue with statistical tests is that a larger sample size is likely to yield smaller p-values. Statistical significance (or low p-values) might be "an artifact of their large-sample sizes" (Lin et al., 2013: 908), regardless of the size of effect. Researchers increasingly advocate using p-values with caution since they are commonly misinterpreted and misused (e.g. Greenland et al., 2016; Wasserstein and Lazar, 2016). To address this problem, I report average effect sizes (i.e. a standard deviation above or below the mean, see Fiorini, 2010; Lantz, 2013) in the text and present confidence intervals in tables (Lin et al., 2013; Wasserstein and Lazar, 2016). The intent is to improve understanding of the meaning of the predictors within the study context.[6]

Results

Disparities in ICT engagement among students from different schools

To visualize how school SES affects student' engagement with ICT at school and at home, Figure 1 illustrates cross-national variation in the gaps in digital use for schoolwork at school (top panel) and

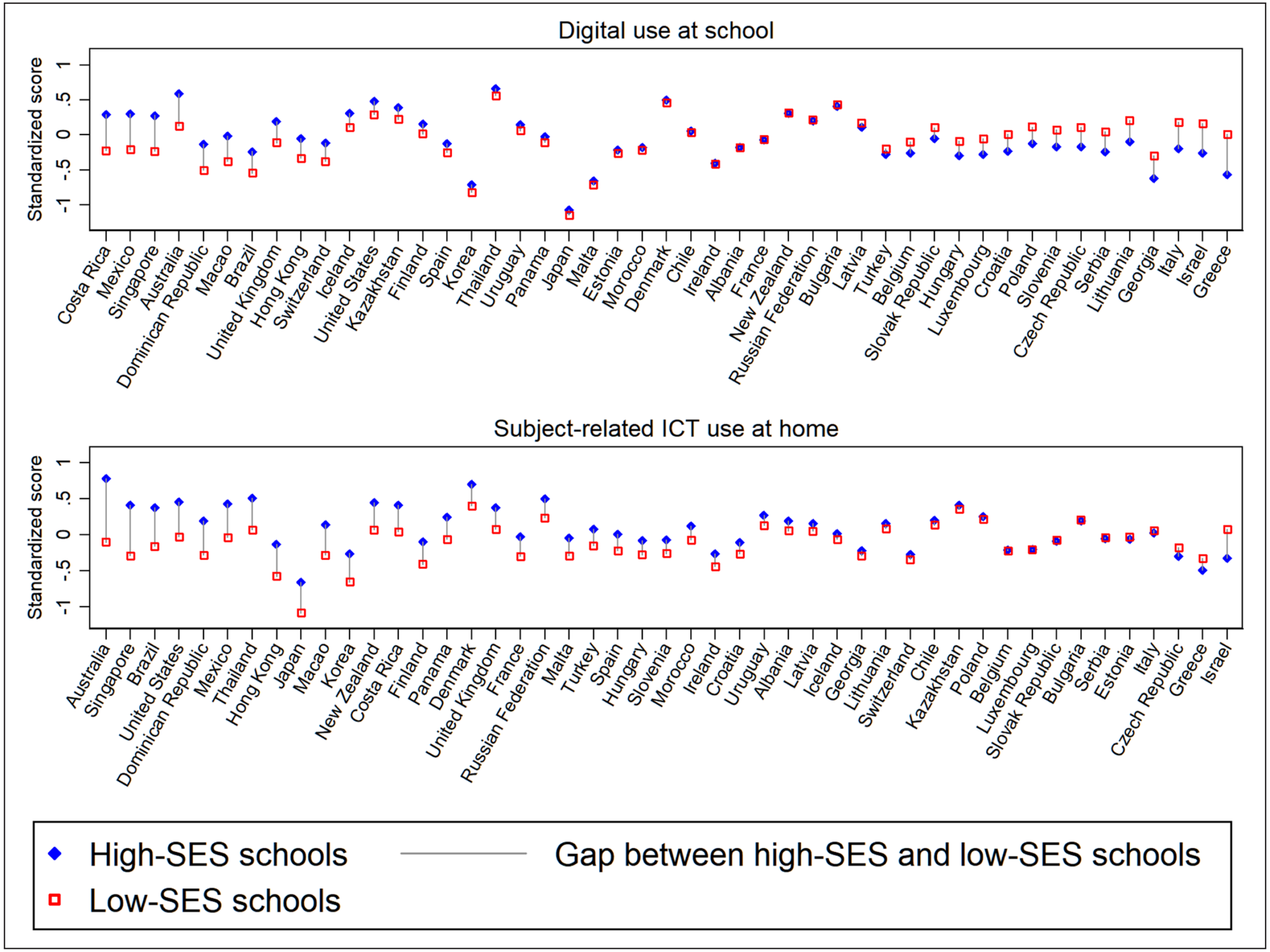

Figure 1. Second-level digital divides in digital use for schoolwork at school and subject-related ICT use at home by school SES.

Note: The size of the second digital divide is calculated based on two-level HLM for each of the 47 countries, where students are considered Level 1 and schools are considered Level 2. Each model includes Level 1 control variables (family SES, gender, immigration status, and foreign language use at home). The line attached to each country represents the size of the gap between the average of high-SES schools (i.e., the top decile of schools' average SES) and the average of low-SES schools (i.e., the bottom decile). Countries are ranked in descending order of the size of the gap between high-SES and low-SES schools.

subject-related ICT use at home (bottom panel), using the results of separate HLM for each country. The vertical lines represent the size of the gap between high-SES schools (defined as schools in the top decile of school SES mean) and low-SES schools (schools in the bottom decile).

In most countries, there is no apparent disadvantage in schools' ICT use for students attending schools with lower socioeconomic profiles. Among countries like Greece, Israel, and Italy, students attending low-SES schools use ICT even more often than those attending high-SES schools (see the top right part of the figure). The exceptions are countries like Costa Rica, Mexico, Singapore, and Australia, listed at the top left, where the average level of ICT use at school is greater among higher SES schools. In general, the pattern remains the same when we turn to focus on subject-related ICT use at home. But again, in several countries like Australia, Singapore, Brazil, and the United States (see the bottom left part of the figure), students are more involved in ICT for schoolwork at home when they attend schools with higher socioeconomic status. Together, we do not find that affluent countries have lower levels of second digital divides at the school level compared to less affluent countries.

Figure 2 shows the cross-national variation in the second digital divide in perceived ICT competence. Overall, the gaps by school SES are substantial in most nations: students attending low-SES schools have lower levels of ICT competence than those attending high-SES schools. These findings are in stark contrast to the results from Figure 1, which suggest that students attending low-SES schools have equal or more opportunities to use ICT—both within and outside of school—than those attending high-SES schools. It is noteworthy that the between-school digital divide in ICT competence is greater in magnitude among less affluent countries (e.g. Mexico, Panama, and the Dominican Republic) than their more affluent counterparts (e.g. Belgium and Japan), which indicates that national income predicts the level of the second digital divide in ICT skills at the school level.

Table 2 shows results of three-level random-intercept modeling testing individual and school-level determinants of digital use for schoolwork at school (Models 1 and 2), digital use for academic subjects at home (Models 3 and 4), and ICT competence (Models 5 and 6). At the individual level, a 1-standard-deviation increase in relative family SES moderately increases digital use at school, by 0.074 standard deviations (Model 1). The same positive relationships are revealed when predicting subject-related ICT use at home (Model 3) and ICT competence (Model 5). In addition, boys are less likely to engage in ICT for learning at home, but their level of ICT competence is higher than girls'. This is consistent with previous literature suggesting a greater tendency for boys to use ICT for non-educational activities (Imhof et al., 2007), and that girls tend to report lower self-assessment of online skills (Hargittai and Shafer, 2006). Compared to non-immigrant students, students with immigrant backgrounds are more involved in ICT for schoolwork and have higher levels of digital competence. Interestingly, speaking a foreign language at home has a positive effect on digital use, but a negative effect on digital competence.

Moving to the influence of school-level factors (the main focus of Table 2), a 1-standard-deviation increase in school average SES increases individual students' ICT use at school by 0.030 standard deviations, after controlling for individual-level factors (Model 1).[7] This is equivalent to a 12th (1/.030) of a standard deviation, which is rather modest in size. Looking at the variance components, 2.4 percent ([.085−.083]/.085) of the between-school variation in digital use at school can be explained by school SES. But when including other school-level control variables, the estimated average effect of school SES decreases only slightly, by 20 percent, and remains statistically significant ($\beta = .024$, $p = .001$).

Moreover, school SES also positively predicts both ICT use for academic subjects at home and perceived ICT competence—which corroborates Hypothesis 1—and the effects are more substantial in size. An increase in school SES by 1 standard deviation increases students' subject-related

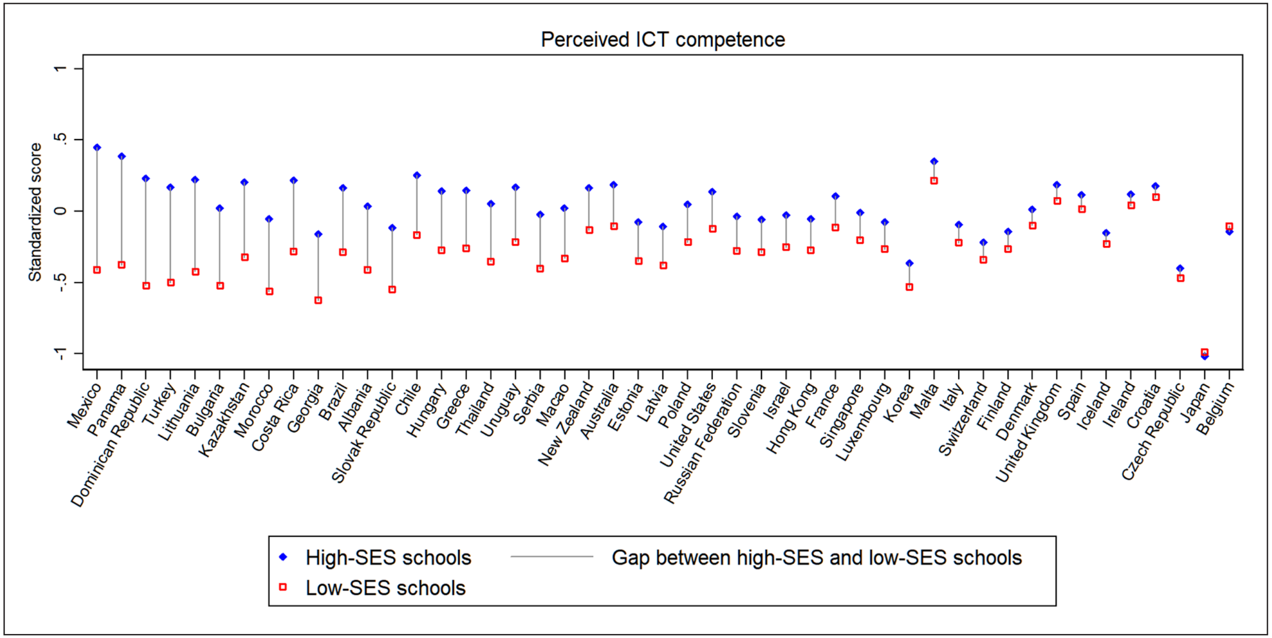

Figure 2. Second-level digital divide in perceived ICT competence by school SES.
Note: The size of the second digital divide is calculated based on two-level HLM for each of the 47 countries, where students are considered Level 1 and schools are considered Level 2. Each model includes Level 1 control variables (family SES, gender, immigration status, and foreign language use at home). The line attached to each country represents the size of the gap between the average of high-SES schools (i.e., the top decile of schools' average SES) and the average of low-SES schools (i.e., the bottom decile). Countries are ranked in descending order of the size of the gap between high-SES and low-SES schools.

Table 2. Multilevel analyses predicting digital use in education and ICT competence.

	Digital use for schoolwork at school[a]		Digital use for academic subjects at home[b]		Perceived ICT competence[c]	
	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6
Intercept	–.078 [–.168, .012]	–.086 [–.176, .003]	–.025 [–.104, .055]	–.012 [–.091, .067]	–.136 [–.190, –.083]	–.127 [–.181, –.073]
Family SES	.074 [.070, .079]	.074 [.070, .079]	.083 [.078, .088]	.083 [.078, .088]	.114 [.108, .119]	.113 [.108, .119]
Male	.101 [.093, .108]	.101 [.093, .108]	–.020 [–.027, –.012]	–.020 [–.027, –.012]	.230 [.222, .237]	.229 [.222, .237]
First-generation immigrant	.057 [.037, .076]	.057 [.038, .077]	.134 [.114, .153]	.132 [.112, .152]	.050 [.030, .070]	.049 [.029, .069]
Second-generation immigrant	.040 [.023, .056]	.040 [.024, .057]	.088 [.071, .105]	.086 [.069, .104]	.061 [.044, .078]	.059 [.041, .076]
Foreign language use at home	.074 [.060, .088]	.073 [.059, .088]	.029 [.014, .043]	.028 [.014, .043]	–.020 [–.034, –.006]	–.021 [–.035, –.006]
School SES	.030 [.018, .043]	.024 [.010, .037]	.121 [.111, .131]	.107 [.096, .119]	.167 [.159, .176]	.158 [.149, .168]
Rural		–.003 [–.029, .024]		–.022 [–.044, .001]		–.073 [–.092, –.054]
Town		.017 [.001, .033]		–.022 [–.036, –.009]		–.005 [–.016, .006]
Class size		–.002 [–.003, –.001]		.001 [.000, .002]		–.000 [–.001, .000]
Shortage of educational staff		–.001 [–.009, .008]		–.006 [–.013, .001]		.001 [–.005, .006]
Shortage of educational material		–.026 [–.035, –.018]		–.013 [–.020, –.006]		–.003 [–.008, .003]
Variance components						
Country-level intercept	.098	.095	.077	.075	.035	.035
School-level intercept	.083	.082	.042	.042	.016	.016
Student-level intercept	.802	.802	.871	.871	.919	.919
Log-likelihood	–329,527	–329,493	–337,279	–337,256	–341,964	–341,932
N (student level)	246,994	246,994	246,994	246,994	246,994	246,994

ICT: information and communication technology; SES: socioeconomic status.

Number of countries = 47. Number of schools = 10,531. The 95 percent confidence intervals are in brackets. All coefficients are adjusted by multiple imputations for missing cases in the control variables ($m = 10$). Log-likelihood is from imputed dataset $m = 1$.

[a]For an intercept-only model: between-country intercept variance is .097; between-school intercept variance is .085; individual-level variance is .808. The intraclass correlation (ICC) is .098 at the country level and .086 at the school level.

[b]For an intercept-only model: between-country intercept variance is .071; between-school intercept variance is .047; individual-level variance is .875. ICC is .072 at the country level and .047 at the school level.

[c]For an intercept-only model: between-country intercept variance is .035; between-school intercept variance is .023; individual-level variance is .940. ICC is .035 at the country-level and .023 at the school level.

ICT use at home and ICT competence by an 8th (.121 in Model 3) and a 6th (.167 in Model 5) of a standard deviation, respectively. Equally important, the inclusion of school SES explains 10.6 percent ([.047−.042]/.047) of the school-level variation in subject-related ICT use at home and 30.4 percent ([.023−.016]/.023) of ICT competence.

Considering other school-level effects, students attending rural schools have lower levels of both ICT use at home and ICT competence than those attending urban schools. Students are less likely to use ICT at school, but more likely to use it at home when attending a larger class. While educational staff do not have an independent effect, the shortage of school-related material is associated with a reduction in digital use for education. Taken together, only about 1 percent of the school-level differences can be explained by a set of school-level controls. By contrast, school socioeconomic composition is a main source of the second digital divide in perceived ICT competence and explains about one-third of variation across schools.

Sources of cross-national variation

Table 3 shows results of three-level random-slope modeling that examines how the effect of school SES varies across countries. Each model includes the same individual- and school-level control variables used in Table 2. The top half of the table shows the effects of country-level measures on the intercept; the bottom half of the table examines the effects of country-level variables on the slope of school SES (or, in other words, the coefficient of school SES when predicting digital use at school in Models 1–2, digital use at home in Models 3–4, and ICT competence in Models 5–6). At the country level, I control for percentage of students in ability grouping as a proxy of educational stratification. It is notable that the influence of school SES is more pronounced among countries with higher levels of ability grouping, especially when predicting digital use at school ($b = .242$; see Model 1).

Beginning with digital use for schoolwork at school, I find that both GDP per capita and educational expenditures do not moderate the effect of school SES. But the relationship between schools' socioeconomic composition and ICT use at school is stronger among countries with higher levels of income inequality. Moving to digital use for academic subjects at home, I find similar results for the effect of the Gini index. Surprisingly, increased GDP per capita is associated with a slight increase (but not a decrease) in the size of the school SES effect.

Finally, there is a negative association between GDP per capita and the school SES slope when predicting students' ICT competence. Also, the link between school SES and ICT competence is stronger among countries with higher levels of income inequality and weaker among countries with higher levels of educational expenditures (Model 6). The size of these cross-national differences is moderate; for instance, a 1-standard-deviation increase in educational expenditures (i.e. 5.01; see Table 1) leads to a decrease in the effect of family SES by 0.025 standard deviations. This is approximately the difference between the Slovak Republic (educational expenditures = 20.08% of GDP) and Finland (educational expenditures = 24.75% of GDP).

To summarize, the above results lend support to Hypothesis 3 that the second-level digital divide between high-SES and low-SES schools is more pronounced for countries with higher levels of income inequality. In addition, both Hypotheses 2 and 4 are partially supported, to the extent that economic development and public expenditures on education are negatively associated with the second-level digital divide in ICT-related skills.

Discussion and conclusion

Despite the progressive spread of e-learning opportunities and the increased provision of computers for schoolchildren, there is persistent digital inequality in educational settings (van Deursen and van

Table 3. Multilevel analyses of the between-school digital divide: country-level variables.

	Digital use for schoolwork at school		Digital use for academic subjects at home		Perceived ICT competence	
	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6
Effects on the intercept[a]						
Intercept	–.077 [–.165, .011]	–.077 [–.165, .010]	–.014 [–.083, .056]	–.014 [–.082, .055]	–.116 [–.169, –.062]	–.115 [–.169, –.062]
Ability grouping (%)	.329 [–.163, .822]	.319 [–.168, .806]	.375 [–.012, .763]	.367 [–.016, .749]	.156 [–.142, .453]	.158 [–.140, .456]
Log GDP per capita	–.103 [–.280, .074]	–.105 [–.280, .071]	–.198 [–.337, –.058]	–.199 [–.337, –.061]	–.026 [–.133, .081]	–.025 [–.132, .082]
Gini index	–.002 [–.014, .010]	–.004 [–.016, .009]	.006 [–.003, .016]	.005 [–.005, .015]	.006 [–.001, .013]	.006 [–.001, .014]
Secondary educational expenditures as % of GDP per capita		–.009 [–.025, .007]		–.007 [–.020, .006]		.002 [–.008,.011]
Effects on the school SES slope						
Intercept	–.002 [–.036, .033]	–.002 [–.036, .033]	.102 [.066, .138]	.102 [.067, .138]	.156 [.133, .179]	.156 [.134, .177]
Ability grouping (%)	.242 [.051, .434]	.247 [.056, .437]	.152 [–.047, .351]	.156 [–.042, .354]	.095 [–.031, .220]	.087 [–.033, .206]
Log GDP per capita	.049 [–.020, .119]	.050 [–.019, .119]	.069 [–.003, .141]	.070 [–.002, .141]	–.079 [–.124, –.034]	–.080 [–.123, –.038]
Gini index	.009 [.004, .013]	.009 [.004, .014]	.007 [.002, .012]	.007 [.002, .012]	.003 [–.001, .006]	.002 [–.001, .005]
Secondary educational expenditures as % of GDP per capita		.002 [–.004, .008]		.003 [–.004, .009]		–.005 [–.009, –.001]
Variance components						
Country-level intercept	.092	.090	.057	.056	.034	.034
Country-level school SES slope	.012	.011	.013	.013	.005	.004
School-level intercept	.078	.078	.037	.037	.013	.013
Student-level intercept	.802	.802	.871	.871	.920	.920
Log-likelihood	–329,339	–329,338	–337,016	–337,015	–341,779	–341,777
N (student level)	246,994	246,994	246,994	246,994	246,994	246,994

ICT: information and communication technology; GDP: gross domestic product; SES: socioeconomic status.
Number of countries = 47. Number of schools = 10,531. The 95 percent confidence intervals are in brackets. All coefficients are adjusted by multiple imputations for missing cases in the control variables ($m = 10$). Log-likelihood is from imputed dataset $m = 1$.
[a]All models include individual-level control variables (family SES, gender, immigration status, and foreign language use at home) and school-level control variables (rural/town, class size, shortage of educational staff, and shortage of educational material). All continuous variables at the country and school levels are grand mean centered.

Table 4. Summary of main results based on key hypotheses.

Hypothesis	Explanatory variable	Association with:		
		Digital use for schoolwork at school	Digital use for academic subjects at home	Perceived ICT competence
(1)	School SES	+	+	+
		Strength of the relationship between school SES and:		
Hypothesis	Explanatory variable	Digital use for schoolwork at school	Digital use for academic subjects at home	Perceived ICT competence
(2)	Economic development			−
(3)	Income inequality	+	+	
(4)	Educational expenditures			−

ICT: information and communication technology; SES: socioeconomic status.

Dijk, 2014; Warschauer, 2016). Prior quantitative studies attribute this form of inequality to deficiencies in educational resources and e-learning opportunities in schools (e.g. Erdogdu and Erdogdu, 2015). While this body of literature is insightful, little is known about how the cultural processes and institutional features of schools (Agirdag et al., 2012) shape students' experiences with ICT engagement within and outside of school contexts ((Warschauer, 2016; Webster, 2017), and the extent to which students' use of ICT technology in classrooms enhances their digital skills. Equally important, how the *pattern* of digital inequality at the school level varies cross-nationally has received surprisingly little attention. Motivated by this gap in the literature and given that a large body of research on school-related digital inequality is based on qualitative fieldwork (for instance, see Leu et al., 2015; Warschauer, 2016), this article uses the PISA 2018 data and examines how the ICT engagement of 15-year-olds differs between schools and across 47 countries, with a focus on the second-level digital divide between schools with varying socioeconomic compositions.

The article is limited by analyses that only include middle- and high-income countries, which is a common issue with large-scale international datasets (Chiu, 2010). Despite this shortcoming, the article has several key findings (see Table 4 for a summary of main results based on the research hypotheses): First, there is a second-level digital divide along the line of schools' socioeconomic composition. That is, students in higher SES schools are more likely to engage in ICT for learning within and outside of the school environment, and they also have higher levels of ICT competence compared to their peers attending lower SES schools (with the exception of a few countries; see Figure 1). The effect of school SES on individual students' in-school digital engagement is modest in size. But the influence of school SES on students' perceived ICT competence is substantial, to the extent that the inclusion of schools' socioeconomic composition in statistical models accounts for about one-third of unexplained variation that occurs at the school level. The findings are in line with previous research (e.g. Warschauer, 2016) which suggests that students attending resource-poor or low-SES schools are likely to use computers for basic tasks or remedial purposes. By contrast, teachers in high-SES schools tend to encourage students to use ICT for constructivist and creative purposes, which can stimulate their learning experiences and enhance their competence with digital technology. Policymakers should therefore keep in mind that schools with varying student socioeconomic profiles provide different digital learning experiences for individual students, partly due to the school's particular institutional and cultural atmosphere.

Second, income distribution determines the second-level digital divide. In more unequal societies, students attending high-SES schools have higher levels of digital engagement—both within and outside of schools—than those attending low-SES schools. While the size of the determinant is modest, it remains substantial and statistically significant even after controlling for several country-level contextual factors. This implies that income and wealth inequalities may affect the allocation of educational funding (Chiu, 2010) and preclude governments from providing universal access to e-learning resources.

Third, a country's economic development and public expenditures on education moderate the relationship between schools' socioeconomic profile and students' ICT skills. This suggests that increased national income level and greater expenditures on secondary education are associated with increasing the average digital competence among schools with a concentration of socioeconomically disadvantaged students.

Fourth, it is noteworthy—and perhaps surprising—that increased national economic standing and nationwide efforts to promote educational expenditures *fail* to bridge the second digital divide in ICT engagement for schoolwork. These findings contradict research that finds economic development to be a prerequisite for the diffusion of digital technology (Cruz-Jesus et al., 2017; Robison and Crenshaw, 2010). A possible explanation is widely available high-speed Internet access in schools, libraries, and individual households among more developed countries. Therefore, further investment in digital technology in schools offers few solutions for bridging this form of the digital divide. On the contrary, it is also likely that the rapid development of digital technology further widens the e-learning gap in affluent countries. In Australia, Singapore, and the United States (see Figure 1), for example, students attending resource-rich or high-SES schools are more engaged with e-learning as opposed to those in low-SES schools.

Supplementary analyses (results not reported here but available upon request) find that the increasing use of ICT in the classroom does not diminish, but rather enhances, the relative advantage of attending socioeconomically favored schools among high-income nations. Even when these schools provide comparable ICT instruction and have similar profiles of online-connected computers, attending an economically privileged school is more likely to positively affect the development of digital capabilities than going to an economically challenged school. This supports findings from recent research that demonstrate the pronounced third-level digital divide (Scheerder et al., 2017) and the growing importance of intangible resources in the learning environment (Chiu, 2010; Notten and Becker, 2017). These resources tend to favor middle-class students, despite the high levels of educational expansion and human capital investment in more developed countries. Sociologist James Coleman (1987) notes that schools "are more effective for children from strong family backgrounds than for children from weak ones. The resources devoted by the family to the child's education interact with the resources provided by the school" (p. 35). It is likely that high-SES schools have more intangible school resources, thereby enhancing students' e-learning experiences and their motivations to learn advanced computer skills. This suggests that policy focusing on bridging the digital learning divide is in itself not sufficient to address the problem. Educators and policymakers should think about how to allocate both tangible and intangible resources to low-SES schools, creating an inviting atmosphere for students and teachers to become involved in different e-learning activities that go beyond basic tasks or remedial computer-based drills.

While not the focus of this article, I also find that the impact of school SES on individual students' digital engagement at school is more pronounced among countries with higher levels of academic tracking. To my knowledge, this article is the first one that accounts for the influence of tracking on the digital divide. Future research should examine whether allocating students into different classrooms affects their behavior and attitudes toward ICT use.

Finally, this article offers contributions to education and stratification research. First, it delineates different patterns between high-income versus middle-income countries regarding how ICT generates inequality in educational settings, which provides insights into developing new theories that account for digital learning inequalities in different regions of the world. Second, much of the research on the global educational achievement gap focuses almost exclusively on academic performance. I argue that the ways in which students incorporate digital technology into learning affect pre-existing educational inequalities, and thus should be examined in its own right. This article provides insight into explaining what school- and country-level factors determine students' experiences with digital technology and their engagement with e-learning. There remain substantial digital inequalities between schools with varying socio-economic composition, even among affluent nations. Future scholars and educators should continue to seek out ways to improve the e-learning atmosphere among schools serving a great majority of low-income students.

Acknowledgements

I would like to thank the editor, guest editors, and five anonymous reviewers for providing valuable and insightful comments on previous versions of this paper.

Funding

The author received no financial support for the research, authorship, and/or publication of this article.

ORCID iD

Josef Kuo-Hsun Ma https://orcid.org/0000-0002-4977-1231

Notes

1. In the 2017 data year, lower-middle-income or upper-middle-income countries are defined as countries where the gross national income (GNI) per capita is below US$12,055. The GNI per capita of high-income countries is above US$12,055.
2. The three countries or economies excluded from the study are Brunei Darussalam, Taiwan, and two regions of Russia (Moscow and Tatarstan).
3. I include missing cases in dependent variables in imputation equations, but they are excluded in descriptive and regression analyses.
4. This component is expressed as the index of the international socio-economic index of occupation status (ISEI).
5. For countries that are missing data on certain country-level variables in 2017, I utilize data from the closest adjacent year in which data are available.
6. In supplementary analyses, I rerun the models by randomly drawing a sample of 20 percent from each analyzing country, where the total sample size becomes 49,398. Results from these random data subsets show similar effect patterns to the results reported here. These models are available upon request.
7. The intraclass correlation (ICC) coefficients for empty models are .086, at the school level, when predicting digital use at school. This suggests that about 9 percent of the variation in the intercept is due to the school which students attend.

References

Agasisti T and Longobardi S (2017) Equality of educational opportunities, schools' characteristics and resilient students: An empirical study of EU-15 countries using OECD-PISA 2009 data. *Social Indicators Research* 134: 917–953.

Agirdag O, Van Houtte M and Van Avermaet P (2012) Why does the ethnic and socio-economic composition of schools influence math achievement? The role of sense of futility and futility culture. *European Sociological Review* 28: 366–378.

Areepattamannil S and Khine MS (2017) Early adolescents' use of information and communication technologies (ICTs) for social communication in 20 countries: Examining the roles of ICT-related behavioral and motivational characteristics. *Computers in Human Behavior* 73: 263–272.

Bowles S and Gintis H (2002) Schooling in capitalist America revisited. *Sociology of Education* 75: 1–18.

Chinn MD and Fairlie RW (2010) ICT use in the developing world: An analysis of differences in computer and Internet penetration. *Review of International Economics* 18: 153–167.

Chiu MM (2010) Effects of inequality, family and school on mathematics achievement: Country and student differences. *Social Forces* 88: 1645–1676.

Chiu MM (2015) Family inequality, school inequalities, and mathematics achievement in 65 countries: Microeconomic mechanisms of rent seeking and diminishing marginal returns. *Teachers College Record* 117: 1–32.

Chmielewski AK and Reardon SF (2016) Patterns of cross-national variation in the association between income and academic achievement. *AERA Open* 2: 1–27.

Chudgar A and Luschei TF (2009) National income, income inequality, and the importance of schools: A hierarchical cross-national comparison. *American Educational Research Journal* 46: 626–658.

Coleman JS (1987) Families and schools. *Educational Researcher* 16: 32–38.

Cruz-Jesus F, Oliveira T, Bacao F, et al. (2017) Assessing the pattern between economic and digital development of countries. *Information Systems Frontiers* 19: 835–854.

Dolan JE (2016) Splicing the divide: A review of research on the evolving digital divide among K-12 students. *Journal of Research on Technology in Education* 48: 16–37.

Downey DB and Condron DJ (2016) Fifty years since the Coleman Report: Rethinking the relationship between schools and inequality. *Sociology of Education* 89: 207–220.

Elwert F and Winship C (2014) Endogenous selection bias: The problem of conditioning on a collider variable. *Annual Review of Sociology* 40: 31–53.

Erdogdu F and Erdogdu E (2015) The impact of access to ICT, student background and school/home environment on academic success of students in Turkey: An international comparative analysis. *Computers & Education* 82: 26–49.

Erichsen EA and Salajan FD (2014) A comparative analysis of e-learning policy formulation in the European Union and the United States: Discursive convergence and divergence. *Comparative Education Review* 58: 135–165.

Fiorini M (2010) The effect of home computer use on children's cognitive and non-cognitive skills. *Economics of Education Review* 29: 55–72.

Freeman RB, Machin SJ and Viarengo MG (2011) Inequality of educational outcomes: International evidence from PISA. *Regional and Sectoral Economic Studies* 11: 5–20.

Graves KE (2019) *Disrupting the Digital Norm in the New Digital Divide: Toward a Conceptual and Empirical Framework of Technology Leadership for Social Justice through Multilevel Latent Class Analysis*. Doctoral Dissertation. Columbia University, New York.

Greenland S, Senn SJ, Rothman KJ, et al. (2016) Statistical tests, P values, confidence intervals, and power: A guide to misinterpretations. *European Journal of Epidemiology* 31: 337–350.

Hanushek EA (2009) School policy: Implications of recent research for human capital investments in South Asia and other developing countries. *Education Economics* 17: 291–313.

Hanushek EA and Luque JA (2003) Efficiency and equity in schools around the world. *Economics of Education Review* 22: 481–502.

Hanushek EA and Woessmann L (2008) The role of cognitive skills in economic development. *Journal of Economic Literature* 46: 607–668.

Hargittai E (2002) Second-level digital divide: Differences in people's online skills. *First Monday* 7(4): 942.

Hargittai E and Shafer S (2006) Differences in actual and perceived online skills: The role of gender. *Social Science Quarterly* 87: 432–448.

Hilbert M (2016) The bad news is that the digital access divide is here to stay: Domestically installed bandwidths among 172 countries for 1986–2014. *Telecommunications Policy* 40: 567–581.

Högberg B, Voßemer J, Gebel M, et al. (2019) Unemployment, well-being, and the moderating role of education policies: A multilevel study. *International Journal of Comparative Sociology* 60: 269–291.

Hu X, Gong Y, Lai C, et al. (2018) The relationship between ICT and student literacy in mathematics, reading, and science across 44 countries: A multilevel analysis. *Computers & Education* 125: 1–13.

Hughes JE and Read MF (2018) Student experiences of technology integration in school subjects: A comparison across four middle schools. *Middle Grades Review* 4: Article6.

Hughes JE, Read MF, Jones S, et al. (2015) Predicting middle school students' use of web 2.0 technologies out of school using home and school technological variables. *Journal of Research on Technology in Education* 47: 211–228.

Imhof M, Vollmeyer R and Beierlein C (2007) Computer use and the gender gap: The issue of access, use, motivation, and performance. *Computers in Human Behavior* 23: 2823–2837.

ITU (2018) *Measuring the Information Society Report*. Geneva: ITU.

Jack AA (2016) (No) harm in asking class, acquired cultural capital, and academic engagement at an elite university. *Sociology of Education* 89: 1–19.

Lantz B (2013) The large sample size fallacy. *Scandinavian Journal of Caring Sciences* 27: 487–492.

Lechman E (2015) *ICT Diffusion in Developing Countries: Towards a New Concept of Technological Takeoff*. Cham: Springer.

Lee CC and Lee CC (2018) The impact of country risk on income inequality: A multilevel analysis. *Social Indicators Research* 136: 139–162.

Leu DJ, Forzani E, Rhoads C, et al. (2015) The new literacies of online research and comprehension: Rethinking the reading achievement gap. *Reading Research Quarterly* 50: 37–59.

Lin M, Lucas HC, Jr and Shmueli G (2013) Too big to fail: Large samples and the p-value problem. *Information Systems Research* 24: 906–917.

Ma JK-H, Vachon TE and Cheng S (2019) National income, political freedom, and investments in R&D and education: A comparative analysis of the second digital divide among 15-year-old students. *Social Indicators Research* 144: 133–166.

Mo D, Swinnen J, Zhang L, et al. (2013) Can one-to-one computing narrow the digital divide and the educational gap in China? The case of Beijing migrant schools. *World Development* 46: 14–29.

Notten N and Becker B (2017) Early home literacy and adolescents' online reading behavior in comparative perspective. *International Journal of Comparative Sociology* 58: 475–493.

OECD (2020) *PISA 2018 Technical Report*. Available at: https://www.oecd.org/pisa/data/pisa2018technicalreport/

Ono H and Zavodny M (2007) Digital inequality: A five country comparison using microdata. *Social Science Research* 36: 1135–1155.

Pick JB and Sarkar A (2015) *The Global Digital Divides: Explaining Change*. Berlin: Springer.

Rafalow MH (2014) The digital divide in classroom technology use: A comparison of three schools. *International Journal of Sociology of Education* 3: 67–100.

Ragnedda M and Muschert GW (eds) (2013) *The Digital Divide: The Internet and Social Inequality in International Perspective*. Abingdon: Routledge.

Raudenbush SW and Bryk AS (2002) *Hierarchical Linear Models: Applications and Data Analysis Methods*. 2nd ed. Thousand Oaks, CA: SAGE.

Raudenbush SW and Eschmann RD (2015) Does schooling increase or reduce social inequality? *Annual Review of Sociology* 41: 443–470.

Robinson L (2014) Freeways, detours, and dead ends: Search journeys among disadvantaged youth. *new media & society* 16: 234–251.

Robinson L, Cotten SR, Ono H, et al. (2015) Digital inequalities and why they matter. *Information, Communication & Society* 18: 569–582.

Robison KK and Crenshaw EM (2010) Reevaluating the global digital divide: Socio-demographic and conflict barriers to the Internet revolution. *Sociological Inquiry* 80: 34–62.

Rogers EM (1995) *Diffusion of Innovations*. New York: Free Press.

Royston P, Carlin JB and White IR (2009) Multiple imputation of missing values: New features for MIM. *Stata Journal* 9: 252–264.

Ruiter S and van Tubergen F (2009) Religious attendance in cross-national perspective: A multilevel analysis of 60 countries. *American Journal of Sociology* 115: 863–895.

Santibañez L and Fagioli L (2016) Nothing succeeds like success? Equity, student outcomes, and opportunity to learn in high- and middle-income countries. *International Journal of Behavioral Development* 40: 517–525.
Scheerder AJ, van Deursen AJ and van Dijk JA (2017) Determinants of Internet skills, use and outcomes: A systematic review of the second- and third-level digital divide. *Telematics and Informatics* 34: 1607–1624.
Scheerder AJ, van Deursen AJ and van Dijk JA (2019) Internet use in the home: Digital inequality from a domestication perspective. *new media & society* 21: 2099–2118.
Scherer R and Siddiq F (2019) The relation between students' socioeconomic status and ICT literacy: Findings from a meta-analysis. *Computers & Education* 138: 13–32.
Schmidt WH, Burroughs NA, Zoido P, et al. (2015) The role of schooling in perpetuating educational inequality: An international perspective. *Educational Researcher* 44: 371–386.
Schütz G, Ursprung HW and Wößmann L (2008) Education policy and equality of opportunity. *Kyklos* 61: 279–308.
UNESCO (2015) *Education for All 2000-2015: Achievements and Challenges*. Paris: UNESCO.
UNU-WIDER (2020) *World income inequality database*. Version 4, May 2020. Available at: https://www.wider.unu.edu/project/world-income-inequality-database-wiid
van Deursen AJ and van Dijk JA (2014) *Digital Skills: Unlocking the Information Society*. New York: Palgrave Macmillan.
van Deursen AJ and van Dijk JA (2019) The first-level digital divide shifts from inequalities in physical access to inequalities in material access. *new media & society* 21: 354–375.
Vegas E and Coffin C (2015) When education expenditure matters: An empirical analysis of recent international data. *Comparative Education Review* 59: 289–304.
Warschauer M (2016) Addressing the social envelope: Education and the digital divide. In: Greenhow C, Sonnevend J and Agur C (eds) *Education and Social Media: Toward a Digital Future*. Cambridge, MA: MIT Press, pp. 29–48.
Warschauer M and Newhart VA (2016) Broadening our concepts of universal access. *Universal Access in the Information Society* 15: 183–188.
Wasserstein RL and Lazar NA (2016) The ASA statement on p-values: Context, process, and purpose. *The American Statistician* 70: 129–133.
Webster MD (2017) Philosophy of technology assumptions in educational technology leadership. *Educational Technology & Society* 20: 25–36.
Wilkinson R and Pickett K (2009) *The Spirit Level: Why Greater Equality Makes Societies Stronger*. New York: Bloomsbury.
World Bank (2020a) *World Bank Country and Lending Groups*. Available at: https://datahelpdesk.worldbank.org/knowledgebase/articles/906519-world-bank-country-and-lending-groups
World Bank (2020b) *World Bank's Databank*. Available at: https://databank.worldbank.org/home.aspx
Zhang X (2013) Income disparity and digital divide: The internet consumption model and cross-country empirical research. *Telecommunications Policy* 37: 515–529.

Appendix 1. Sample size and descriptive statistics for key individual and school-level variables.

	Sample size		Digital use for schoolwork at school		Digital use for acad. subjects at home		Perceived ICT competence		School SES		% Imputed at Lv1
	Lv1	Lv2	Mean	SD	Mean	SD	Mean	SD	Mean	SD	
Albania	5410	236	–0.06	1.12	0.13	1.00	–0.13	0.98	–0.91	0.58	0.9
Australia	8651	578	0.45	0.76	0.44	0.99	0.19	0.96	0.29	.48	2.3
Belgium	5817	236	–0.17	0.88	–0.23	0.86	0.05	0.92	0.10	0.47	1.2
Brazil	4936	376	–0.32	1.13	0.06	1.17	0.00	0.96	–1.01	0.77	2.7
Bulgaria	2913	160	0.44	1.12	0.19	1.06	–0.12	1.07	–0.25	0.64	2.8
Chile	4360	184	0.07	0.88	0.15	1.03	0.14	0.99	–0.26	0.83	1.8
Costa Rica	5864	199	0.08	0.99	0.21	1.10	0.07	1.02	–0.96	0.83	1.5
Croatia	5461	176	–0.09	1.02	–0.23	0.93	0.24	1.04	–0.25	0.36	1.2
Czech Republic	5241	287	0.04	0.96	–0.23	1.03	–0.19	0.92	–0.13	0.51	0.3
Denmark	4173	238	0.58	0.65	0.70	0.98	0.22	0.92	0.39	0.39	0.9
Dominican Republic	2908	149	–0.29	1.12	–0.07	1.15	–0.08	1.09	–1.04	0.63	3.7
Estonia	4615	200	–0.13	0.90	–0.05	0.84	–0.03	0.94	0.03	0.41	0.7
Finland	4271	187	0.15	0.70	–0.24	0.82	–0.02	0.97	0.27	0.30	0.8
France	4105	195	–0.07	0.81	–0.14	0.92	0.21	1.09	–0.10	0.55	0.4
Georgia	3010	207	–0.36	1.18	–0.18	1.03	–0.36	1.05	–0.40	0.47	3.3
Greece	4893	196	–0.19	1.15	–0.36	0.91	0.07	0.95	–0.12	0.47	1.3
Hong Kong	3941	111	–0.12	1.02	–0.39	1.06	–0.08	0.81	–0.54	0.60	0.7
Hungary	4237	175	–0.13	0.94	–0.16	0.88	0.08	1.00	–0.10	0.60	0.6
Iceland	2277	94	0.23	0.76	–0.03	0.93	–0.08	1.00	0.44	0.33	0.7
Ireland	4446	153	–0.39	0.90	–0.32	0.83	0.19	0.91	0.11	0.39	2.3
Israel	4140	131	–0.08	0.94	–0.16	0.93	–0.03	1.07	0.26	0.48	1.8
Italy	8115	438	0.03	0.89	0.03	0.95	–0.07	0.94	–0.23	0.43	1.2
Japan	5802	182	–1.09	0.75	–0.88	.64	–0.84	1.01	–0.11	0.37	0.0
Kazakhstan	15,797	542	0.39	1.00	0.37	0.99	0.02	1.04	–0.46	0.42	1.6
Korea	6169	182	–0.71	0.96	–0.47	0.94	–0.33	0.99	0.07	0.37	0.7
Latvia	4052	254	0.26	0.87	0.07	0.91	–0.12	0.91	–0.08	0.42	0.6
Lithuania	5176	274	0.11	1.04	0.14	0.96	0.03	1.11	–0.04	0.46	1.1
Luxembourg	3835	39	–0.07	0.92	–0.15	0.95	–0.01	1.03	0.14	0.62	1.2
Macao	3650	44	–0.20	0.87	–0.09	0.92	–0.10	0.79	–0.48	0.57	0.8
Malta	2528	47	–0.52	1.13	–0.17	1.02	0.25	0.97	0.15	0.45	1.5
Mexico	4542	229	0.08	0.96	0.20	1.01	0.07	1.03	–1.01	0.79	2.3
Morocco	3343	154	–0.38	1.05	–0.08	1.05	–0.20	1.00	–1.83	0.84	3.0
New Zealand	4670	179	0.34	0.68	0.29	0.92	0.18	0.94	0.12	0.47	2.7
Panama	2000	123	–0.05	0.96	0.11	1.05	0.05	1.06	–1.00	0.84	6.2
Poland	4749	222	0.12	1.05	0.21	0.92	0.02	0.95	–0.16	0.43	0.5
Russian Federation	5741	224	0.27	1.16	0.37	1.02	–0.03	0.95	0.10	0.36	0.7
Serbia	4062	165	–0.05	1.10	–0.06	1.05	–0.12	1.07	–0.23	0.42	1.2
Singapore	6044	160	0.07	0.89	0.05	1.00	0.06	0.93	0.14	0.48	1.0
Slovak Republic	4091	259	0.14	0.99	–0.07	0.90	–0.18	0.93	–0.16	0.47	0.6
Slovenia	4558	236	0.00	0.97	–0.17	0.90	–0.01	1.00	0.00	0.42	0.4

(Continued)

Appendix 1. (Continued)

	Sample size		Digital use for schoolwork at school		Digital use for acad. subjects at home		Perceived ICT competence		School SES		% Imputed at Lv1
	Lv1	Lv2	Mean	SD	Mean	SD	Mean	SD	Mean	SD	
Spain	23,835	993	–0.15	0.89	–0.11	0.91	0.16	0.98	–0.08	0.53	1.5
Switzerland	4529	206	–0.15	0.84	–0.30	0.84	0.00	1.04	–0.01	0.45	1.7
Thailand	7863	256	0.68	0.89	0.28	1.05	–0.10	0.84	–1.18	0.90	1.3
Turkey	6193	178	–0.18	1.03	–0.07	0.97	–0.12	1.06	–1.16	0.71	1.9
United Kingdom	4460	202	0.06	0.77	0.24	0.91	0.32	0.96	0.25	0.45	1.9
United States	3588	137	0.41	0.80	0.26	0.97	0.13	0.94	0.11	0.51	1.8
Uruguay	2603	138	0.12	0.94	0.15	0.96	0.04	0.99	–0.92	0.72	3.6

ICT: information and communication technology; SES: socioeconomic status; SD: standard deviation.

Appendix 2. Country-level variables: 47 countries.

	GDP per capita	Gini index	Secondary educational expenditures as % of GDP per capita	Ability grouping (%)
Middle-income countries[a]				
Morocco (MA)	7.31	.40	36.36	49
Albania (AL)	13.04	.29	7.98	82
Georgia (GE)	13.59	.38	13.60	30
Brazil (BR)	14.52	.53	21.53	26
Serbia (RS)	16.53	.38	11.12	61
Dominican Republic (DO)	16.74	.44	18.72	64
Thailand (TH)	17.42	.34	18.00	85
Costa Rica (CR)	19.11	.48	24.68	83
Mexico (MX)	19.80	.48	14.43	71
Bulgaria (BG)	21.36	.40	22.18	61
Kazakhstan (KZ)	24.86	.27	21.21	84
Russian Federation (RU)	26.01	.36	14.60	59
Turkey (TR)	27.93	.43	13.51	65
Mean	18.33	.40	18.30	63
High-income countries[a]				
Uruguay (UY)	21.32	.39	16.16	28
Chile (CL)	23.66	.46	18.68	52
Croatia (HR)	26.60	.30	25.90	51
Latvia (LV)	28.49	.35	26.43	52
Greece (GR)	29.09	.33	23.02	21
Hungary (HU)	29.53	.28	23.06	83
Poland (PL)	30.15	.29	22.56	86
Panama (PA)	30.45	.50	9.19	52
Slovak Republic (SK)	30.91	.23	20.08	70
Estonia (EE)	33.82	.32	21.17	71

(Continued)

Appendix 2. (Continued)

	GDP per capita	Gini index	Secondary educational expenditures as % of GDP per capita	Ability grouping (%)
Lithuania (LT)	33.82	.38	17.90	74
Slovenia (SI)	36.65	.24	23.04	65
Czech Republic (CZ)	38.49	.25	22.30	66
Israel (IL)	38.97	.34	18.66	99
Spain (ES)	39.58	.34	18.88	52
Japan (JP)	40.86	.34	24.05	70
Korea (KR)	41.00	.36	28.18	65
New Zealand (NZ)	41.49	.34	21.11	95
Malta (MT)	41.55	.28	29.55	95
Italy (IT)	41.78	.33	22.90	51
France (FR)	44.83	.29	26.28	49
United Kingdom (GB)	45.97	.33	21.19	99
Finland (FI)	47.48	.25	24.75	65
Australia (AU)	48.91	.33	14.98	92
Belgium (BE)	50.73	.26	24.53	63
Denmark (DK)	55.06	.28	31.14	76
Iceland (IS)	55.56	.24	19.40	56
Hong Kong (HK)	59.85	.42	22.20	95
United States (US)	59.96	.46	22.13	90
Switzerland (CH)	67.14	.30	24.46	77
Ireland (IE)	78.13	.31	15.94	98
Singapore (SG)	94.94	.47	21.64	94
Luxembourg (LU)	112.82	.31	19.41	79
Macao (MO)	126.92	.36	10.09	75
Mean	47.84	.33	21.86	77

Note: [a]The classification of income groups is based on the World Bank (2020a). GDP per capita is in thousands of 2017 purchasing power parity dollars.