Computers and Education Open 3 (2022) 100100

Contents lists available at ScienceDirect

Computers and Education Open

journal homepage: www.sciencedirect.com/journal/computers-and-education-open

The digital divide in online education: Inequality in digital readiness of students and schools

Herman G. van de Werfhorst *, Emma Kessenich, Sara Geven

Department of Sociology, University of Amsterdam, P.O. Box 16608, Amsterdam 1001 NA, the Netherlands

A B S T R A C T

The COVID-19 pandemic has disordered the educational process across the globe, as schools suddenly had to provide their teaching in an online environment. One question that raised immediate concern is the potential impact of this forced and rapid digitalization on inequalities in the learning process by social class, migration background and gender. Elaborating on the literature on the digital divide, we study inequalities in multi-level digital readiness of students and schools before the pandemic took place. Using data from the International Computer and Information Literacy Study (ICILS) on seven countries, and the Teaching and Learning International Survey (TALIS) on 45 countries, both from 2018, we demonstrate that schools and students vary in their readiness for digital education. However, school variation in digital readiness is not systematically related to student composition by SES and migration background. We thus find little evidence for a hypothesized 'multi-level' digital divide, which would result from systematic gradients in the readiness of school environments for digital education by student composition. More important drivers for a digital divide during the COVID-19 pandemic are the ICT skills students have, which are strongly related to students' socioeconomic background. For digital education to be effective for every student, it is important that schools focus on improving students' digital skills.

Introduction

The COVID-19 pandemic distorted the educational process of millions of children, as distance education through online communication channels has become the practice in many societies since March 2020 (UNESCO, 2020[1]). In many societies, schools and teachers made great efforts to deal with this rapid change of life, and schools have now slowly reopened again, at least partially. Nevertheless, it is likely that the pandemic keeps affecting the educational process for some time to come.

One question that swiftly received attention from scholars and policy makers is whether school closures would enlarge sociodemographic inequalities in educational progress [2,7,8]. For distance education to be effective, it takes a good study environment with digital equipment, sufficient digital skills, involved parents, and a well-prepared school; and these circumstances are likely to be socially stratified. While the long-term impact of the COVID-19 pandemic on inequalities in educational progression can only be studied later, it is important to examine whether children were well-prepared for the immediate change to digital education. We define this readiness both in terms of students' own skills and facilities, as well as the resources and facilities of the schools they attend; and study how both these dimensions vary by student socioeconomic status, migration background and gender. Such an analysis will enable us to interpret the baseline situation from which schools suddenly had to work.

In this paper, we examine the extent to which digital gaps were already present before the pandemic enforced a rapid digitalization onto the education sector. While this will not inform us about the question how possible inequalities in digital provisions help to explain the rising inequalities in education that happened during the school closures [8], the results will inform us about the extent to which the basic digital infrastructure was unequally distributed across children from different demographic groups from the start. This is relevant as we can assume that the rapid digitalization during the pandemic went more smoothly in schools where the digital infrastructure and usage of technology were well-developed, and where students had better digital skills and infrastructure at home. The purpose of our study is to understand digital divides by students' socio-economic status (SES), migration background, and gender in multiple countries, both from an individual and contextual perspective. Research finds notable differences along these sociodemographic lines both in terms of ICT access as well as use and skills [27]. Moreover, digital access, use, and skills, as well as the divides herein seem to vary across countries.

Importantly, we consider both student and school readiness for dealing with digital education. Efforts of (local) governments and school boards during the COVID-19 crisis focus on increasing digital provisions

* Corresponding author.
E-mail address: h.g.vandewerfhorst@uva.nl (H.G. van de Werfhorst).

[1] https://en.unesco.org/covid19/educationresponse, accessed 15 April 2021.

https://doi.org/10.1016/j.caeo.2022.100100
Received 10 August 2021; Received in revised form 20 July 2022; Accepted 20 July 2022
Available online 21 July 2022

Table 1
Descriptive statistics of the data for Study I.

	mean	sd	min	max
Student ICT use	0	1	-2.044	3.391
Student ICT skills	0	1	-4.994	3.337
School ICT infrastructure	0	1	-3.023	3.330
School ICT competencies	0	1	-4.138	2.043
Overall digital readiness	0	1	-3.674	3.819
SES	0	1	-3.720	2.567
Immigration status	0.1	0.3	0	1
Gender	0.5	0.5	0	1
Observations	18882			

Table 2
Descriptive statistics of the data for Study II.

	mean	sd	min	max
ICT in teacher education	0	1	-1.624	1.712
ICT in professional development	0.7	0.5	0	1
ICT for classwork	0	1	-1.698	1.563
ICT for student support	0	1	-2.187	1.183
% low-SES students in school (perceived)				
None	12.0 %			
1-10 %	44.6 %			
11-30 %	27.7 %			
31-60 %	10.7 %			
> 60 %	5.1%			
% migration background students in school (perceived)				
None	45.4 %			
1-10 %	39.1 %			
11-30 %	10.2 %			
31-60 %	3.3 %			
> 60 %	1.9%			
Teaching experience in years	16.6	10.8	0	58
STEM teacher	0.4	0.5	0	1
Master degree	0.4	0.5	0	1
Teacher gender	0.7	0.5	0	1
Observations	135169			

for families, for instance by lending computers to children who need one [20]. But as research on the 'digital divide' shows, access to computers and internet are not the main drivers of digital inequalities these days. A second, and currently more important source of digital divisions are the skills to use technology [6,16]. In the context of education, the distinction between access and skills is even more relevant as the two requirements are plausibly applicable to both the student and the school. Not only the student, but also the school needs the necessary equipment and skills to work with online education technology. Such a combination of student skills, equipment and school readiness is likely much harder for students to attain and more difficult for policy-makers to address.

The research question we address is: to what extent is there a digital divide between students by socioeconomic status, migration background, and gender, with regard to their own skills and digital equipment use, as well as with respect to the quality of the digital infrastructure of the schools they attend? We study the digital divide using two different datasets. First, we use the International Computer and Information Literacy Study (ICILS) of 2018, for seven countries (Chile, Denmark, Finland, France, Germany, Italy, and South Korea). This comparative assessment includes data on 8th grade students, school principals, ICT coordinators, and teachers. Thereby, we build upon another study that looks at digital inequalities among students and schools, but lacks information on student digital skills [12]. Second, we use the Teaching and Learning International Survey (TALIS) of 2018, a teacher and school principal survey, covering a much larger set of countries and enabling us to include more direct measures of teachers' digital readiness.

Our results indicate that there are strong inequalities by gender, socioeconomic and migration background in who is well-prepared for digital education. However, most of the inequalities are resulting from the skills that students have, and much less from the infrastructure and digital readiness of the schools that different students attend.

Theorizing the digital divide

Since the early days of the internet, the 'digital divide' has been of concern to social scientists. The literature has proposed three levels of the digital divide [6,16,24,27]. A first layer is *access* to computers and the internet. While access may be less stratified than it used to be when the internet just came up, even today access varies across socio demographic groups [34]. For instance, the family's socioeconomic status is related to the access to ICT resources among 15-year old students in many countries [12]. Especially in less developed economies, access is still limited and highly unequal [21,24,26].

A second level of the digital divide concerns the *skills and usage* of technology [3]. Skills are crucial determinants of the use of technology and the internet, especially for more creative use [18]. Determinants of skills and usage are usually similar to those of access, including socioeconomic status (SES), age, gender, location, and migration background. The literature distinguishes between various forms of internet usage and skills. Predominantly information seeking and engaging in commercial transactions are stratified by educational attainment [3]. Focusing on 15-year old students using the PISA data, González-Betancor et al. [12] find that ICT use in the home was not so strongly stratified by a student's social background. That study was not able, however, to assess students' ICT skills as another important driver of the second dimension of the digital divide. Using the internet for social interaction and entertainment is also hardly stratified by education or other SES indicators [3,31]. However, a Chinese study shows that access to online education during the pandemic was larger among students at higher family incomes and non-agricultural residence rights (hukou) [14]. Also a Nigerian study shows social stratification in access to online education, partly because low-educated families do not have the skills to help their children [1].

The third level of digital divide is concerned with inequality in the *effects* of technology access and of technology skills and usage for various outcomes, such as employment, education, social and political connectedness, and health [30,37]. It refers to differences in the extent to which people are capable of reaping (offline) benefits from their ICT access and use. Hence, even when people have comparable levels of skills and usage, they may still differ in the extent to which they profit from these resources. In the context of education, research shows that digital skills enhance educational performance, particularly among students from less advantaged backgrounds [23].

These three perspectives of the digital divide all focus on the users of technology, students in the context of our study. However, the extent to which digital inequalities emerge in and through education is also dependent on the *context* in which students are educated: their schools. Existing studies have sometimes placed the digital infrastructure available to individuals under the access mechanism [37], and schools could similarly vary in their digital infrastructure (e.g., by the availability of computers in the school). However, the contextual environment may not only vary with regard to the infrastructure that is necessary to have access to digital learning, but also with regard to the skills that teachers have to offer the education necessary in an online environment [28]. Related to this, Hohlfeld et al. [19] argue for the need to adapt the theoretical model to the specific context, and accordingly, suggest a new model specifically designed to understand digital divides in the school context. In this model, the first level refers to the ICT infrastructure of the school, including the school's access to hardware and software, as well as ICT support. The second level refers to the classroom level and considers the extent to which teachers and students use ICT during classroom instruction. The third level pertains to the extent to which

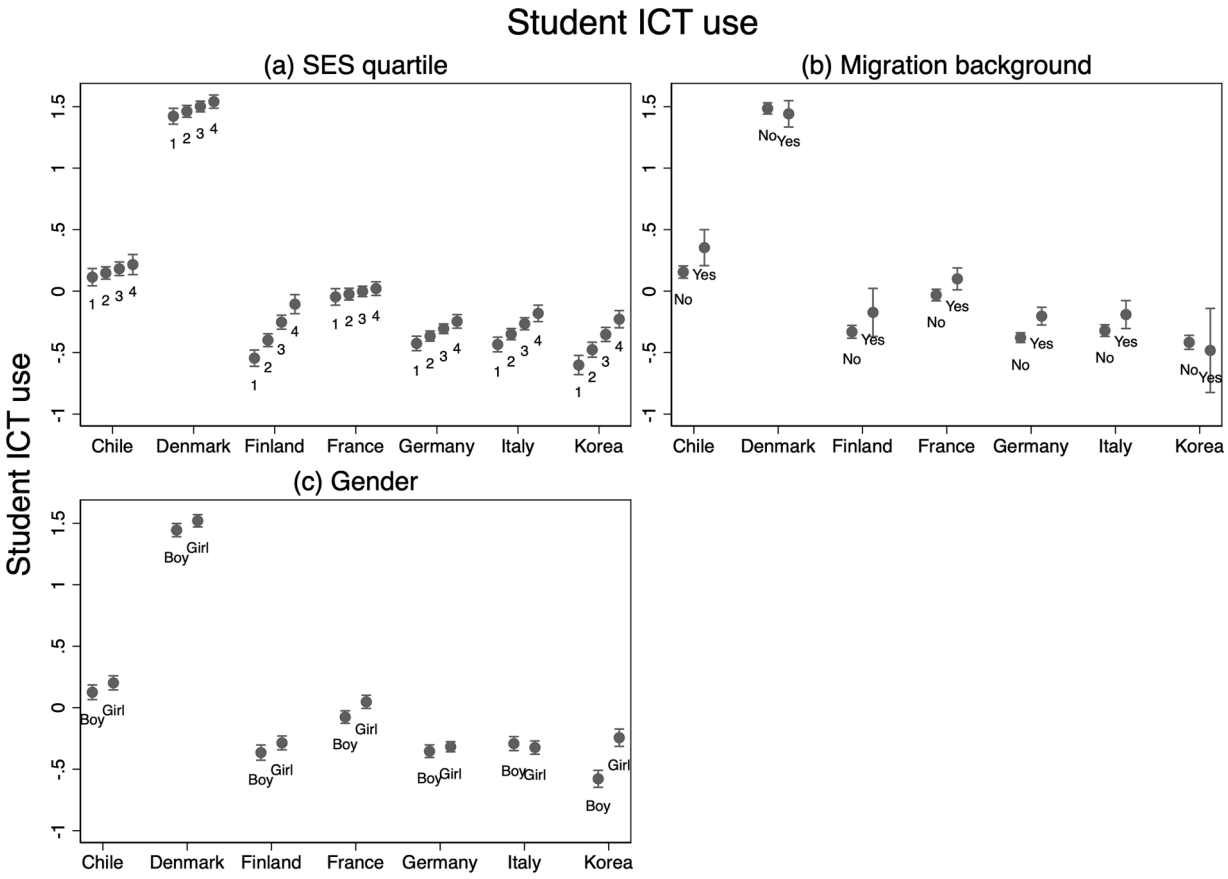

Fig. 1. Student ICT use by country and subgroup
Note: see Table A1 in Supplementary materials for the detailed regression coefficients on which this figure is based.

students can reap individual benefits from their ICT skills and knowledge, such as improvements in their academic achievement.

Instead of using a separate theoretical model in order to understand digital divides in a particular context, we suggest to explicitly integrate the larger context in the existing three-level framework. More specifically, we argue that the realization of personal goals and outcomes are determined by a *combination* of both the ICT access, skills and usage of individuals, as well as the ICT resources and skills available in the larger environment in which individuals are embedded. Accordingly, we refer to this latter aspect as the fourth level of the digital divide. When applied to the school-context, this level encompasses both the ICT infrastructure of schools (the first level of Hohlfeld et al.'s [19] model), as well as the extent to which ICT is, or can be, (adequately) used in classroom instruction (the second level of Hohlfeld et al.'s [19] model). However, note that our fourth level does not necessarily pertains to the school context, as it can also be extended and applied to contexts related to other research questions, such as work environments.

Scholarship has also widened the theoretical scope of digital inequalities by proposing a *resources and appropriation theory* of inequality in the diffusion, acceptance, and adoption of advanced technologies [35, 36]. According to this relational theory, it is not sufficient to describe inequalities in new technologies by examining correlations with individual predictors. Instead, we should understand digital inequalities from the appropriation of technology use by elites. "The dominant category is the first to adopt the new technology. It uses this advantage to increase power in its relationship with the subordinate category" [35, 11]. In light of this, schools can be seen as environments where the provision of computers and the importance attached to digital learning function as strategies to advance students over students in other schools. Attending advantaged schools thus not only offers the opportunity to learn to study in a digital environment, but also creates an advantage over schools and students who are less able to learn in a digital way. It follows that a coincidental, but nevertheless highly influential byproduct of the COVID-19 pandemic is that inequalities in digital skills and usage, as well as inequalities in the effects thereof on students' educational outcomes, may be enlarged. Such effects of the pandemic (beyond the scope of this paper) may even be more likely knowing that teachers who did not use technology in pre-pandemic times, have not caught up during the pandemic [29].

Building on this, we consider digital divides to be of a multilevel nature. To the extent that the fourth level of the digital divide exists, policies to reduce digital inequalities should not only consider access, skills and usage at the individual (student) level, but also at the contextual (school) level. On the other hand, if the contexts are not unequally equipped with digital readiness, policies to reduce digital inequalities can primarily focus on the individuals in question (i.e., the students). In such a situation, schools have the potential to act as "compensatory agents" that can mitigate inequalities between individual students [12]. It is possible that the digital divide at the student level is related to their SES, migration background, and gender, but that the between-school variation in digital readiness is unrelated to the student composition on such demographic characteristics.

Research design

We study students' and schools' degree of readiness for digital education using two different datasets and studies, employing secondary data analysis. Study 1 focuses on students and schools in seven countries, study II takes a closer look at digital readiness of teachers in 45 countries.

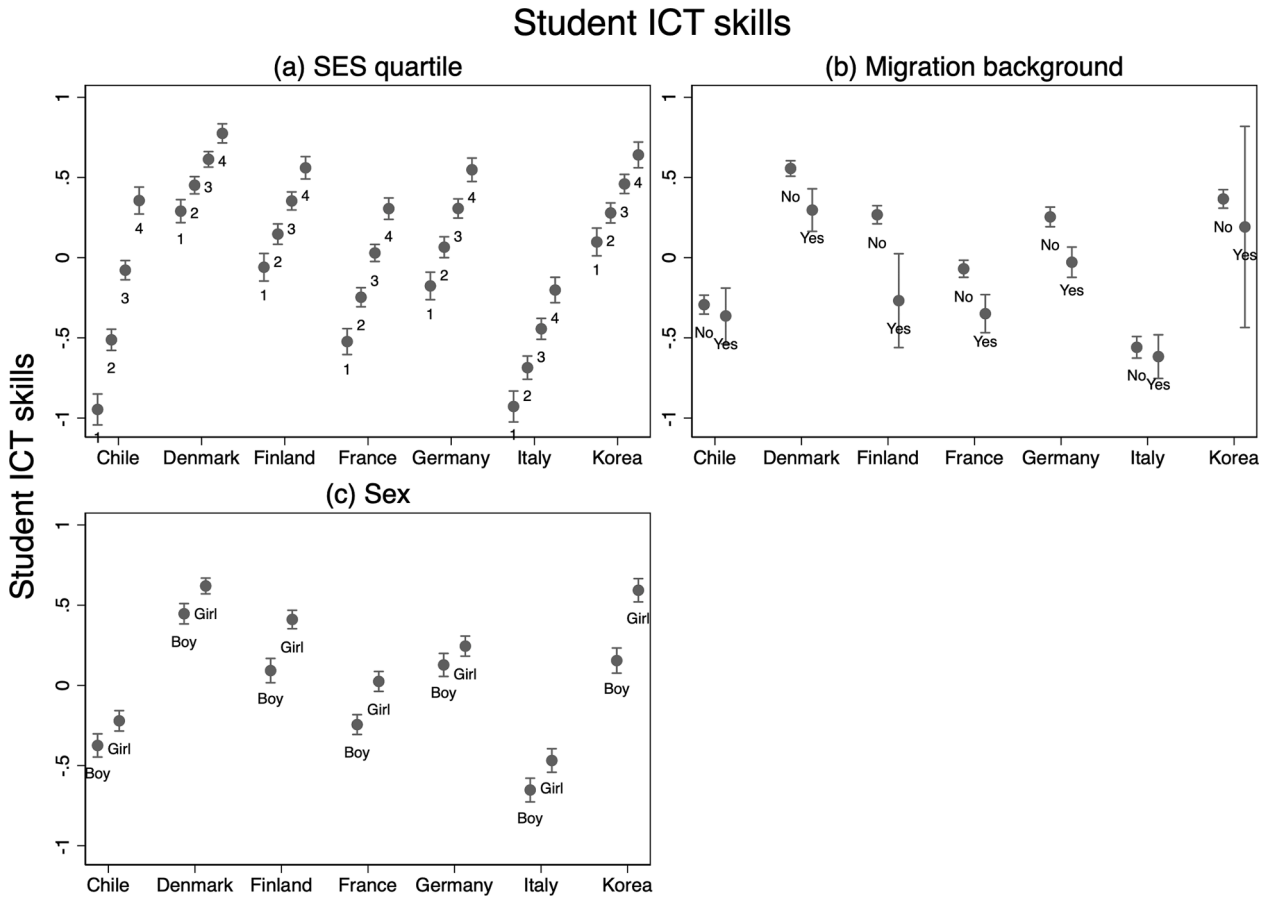

Fig. 2. Student ICT skills by country and subgroup
Note: see Table A2 in Supplementary materials for the detailed regression coefficients on which this figure is based.

Study I: students and schools in seven countries

Survey. For Study I, we use data from the International Computer and Information Literacy Study (ICILS) from 2018. The ICILS is collected by the International Association for the Evaluation of Educational Achievement (IEA), that is also responsible for other well-known recurrent international student assessments such as the Trends in Mathematics and Science Study in fourth and eighth grade (TIMSS) and the Progress in International Reading Literacy Study in fourth grade (PIRLS). The IEA has strong requirements about the representativeness of the data to the national student and school populations.

The ICILS data include information on how well eighth-grade students are prepared for the digital age, and combines this with data on their schools' and teachers' ICT-related resources. Specifically, we focus on students in seven countries across three continents for which high-quality student- as well as school-level data is available[2], i.e., Chile, Denmark, Finland, France, Germany, Italy and South Korea. We argue that readiness for digital education is a function of both a student's individual ICT resources as well as the student's school ICT resources.

Participants. The analytical sample of study I comprises of N=18,882 students, all in eighth grade, in 213 schools in seven countries.

Variables. To measure students' individual readiness, we look at their experience in ICT use and digital skills. To measure ICT use, we calculate a factor score based on 12 manifest variables that pertain to the frequency of *school-related ICT use*, such as how often they use ICT to write a document or prepare a presentation.[3] We exclude survey items on the frequency of students' ICT use for non-educational activities. The items included in our factor all have relatively few missing values and reasonably strong loadings on the emerging factor (≥0.35; [9]). The scale is internally consistent (Cronbach's alpha is 0.86).

We measure *students' digital skills* using a factor score of the five plausible values of a student's score on a Computer and Information Literacy Achievement scale, one of the core concepts of the ICILS data. These measures are derived from students' results on a test that was specifically designed to assess a person'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" [11,17]. Test modules consisted of comprehensive, real-world tasks such as creating a webpage about a school band competition or designing an infographic to raise awareness about waste reduction. Hence, test results combine information about students' level of proficiency across various ICT-related competence areas, ranging from information-gathering to digital communication [4,10,32], and tap both into basic 'operational' and 'evaluative' digital skills [15].

We measure schools' readiness for digital education by two constructs: *the school's digital infrastructure* (availability of internet, software, devices), and the *ICT competencies (usage, skills, encouragement) prevalent in the school*. These two dimensions emerge from a factor analysis of 40 manifest variables that pertain to principals' and ICT

[2] By high-quality we mean that the selected countries meet the ICILS participation rate target of a weighted overall participation rate of schools and students of 75% and that school-level data was available for at least 100 schools per country.

[3] Missing values for all the factor scores are imputed by using the row-mean of the non-missing manifest variables as a predictor.

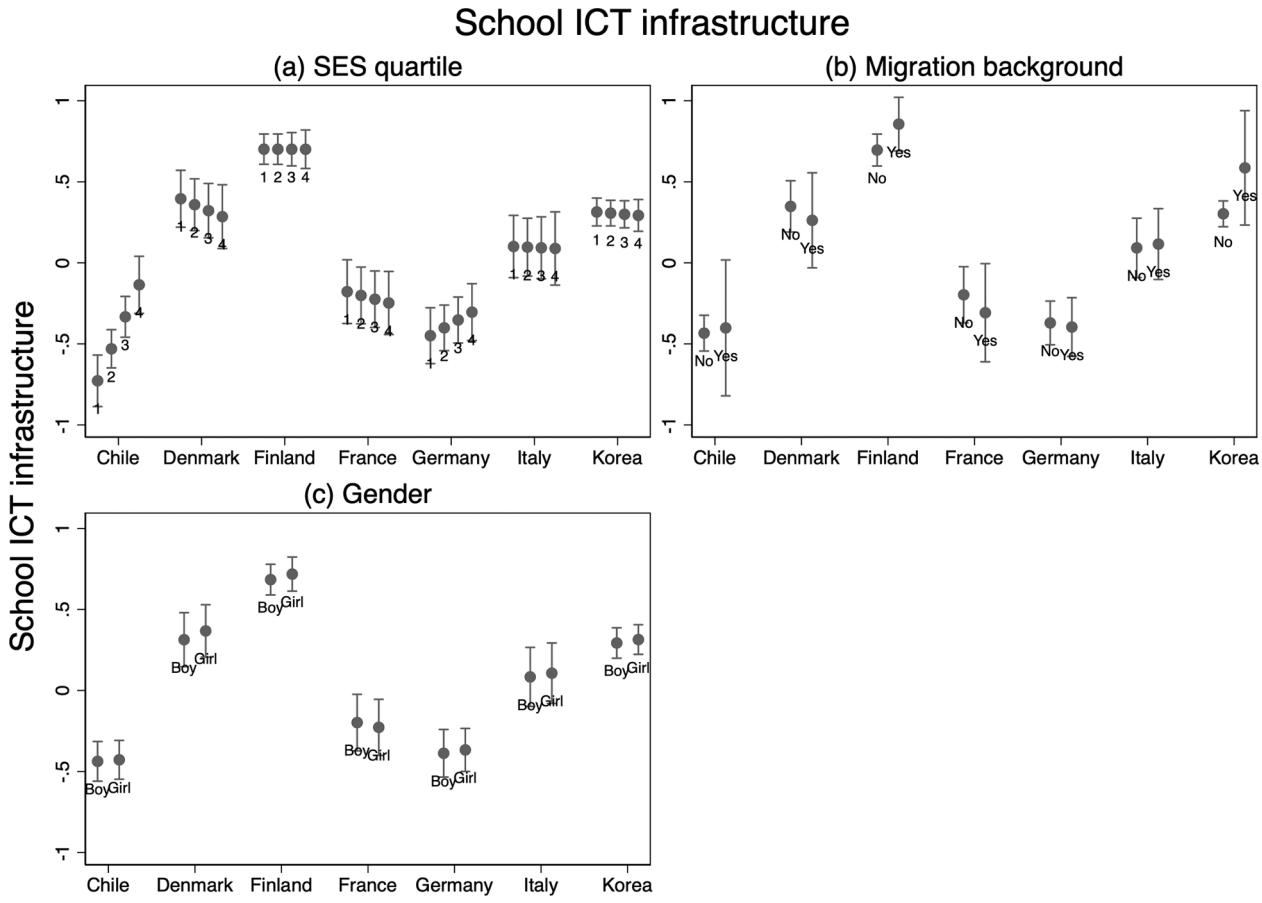

Fig. 3. School ICT infrastructure by country and subgroup
Note: see Table A3 in Supplementary materials for the detailed regression coefficients on which this figure is based.

coordinators' evaluation of their school's ICT provision. Again, we only include manifest variables that clearly and strongly load on one, and only one, of the emerging factors (≥0.35) [9]. The first latent variable includes indicators about the school's technology and software infrastructure, for example internet access or the availability of digital learning resources, a learning management system or email accounts. This first latent construct taps into *access* to digital learning. The second latent construct includes indicators about the importance the school attaches to the digital learning outcomes of students (e.g., the development of students' proficiency in processing information with ICT) and the digital teaching competences of instructors (e.g., the extent to which teachers are expected to integrate ICT into their lessons, or are provided with resources to prepare lessons in which ICT is used).[4] Both school-level measures are internally consistent (Cronbach's alpha is 0.85 for infrastructure and 0.89 for competencies).

In order to study the overall digital divide, we also explore a combined scale of these four constructed variables. For this, we take the average of the four separate standardized indicators discussed above.

To analyze the extent to which digital readiness differs between groups of students, we look at three dimensions of stratification: students' socio-economic status (SES), migration background, and gender. We measure student SES using the National Index of Socio-economic Background (NISB) that is based on parental occupational status, parental education and the number of books at home. We use this measure to construct within-country quartiles of SES. We measure student migration background with a dichotomous variable that classifies a student as a migrant if both parents were born abroad. Finally, with respect to gender, we distinguish between boys and girls.

Table 1 shows the descriptive statistics of the variables used in Study I. The first five variables are the indicators of digital readiness; the latter three variables are the dimensions of stratification. All latent variables are z-standardized, with a mean of 0 and a standard deviation (s.d.) of 1. The standardization enables comparisons across models.

Analytical approach. We employ linear regression models to assess the digital divide in the ICILS data. In all models, we use clustered standard errors at the school level to account for the nested structure in the data. Using clustered standard errors is more appropriate for study I than multilevel modelling as some dependent variables are assessed at the student level, and some at the school level.

Study II: teachers in 45 countries

Survey. In Study II, we examine students' degree of readiness for digital education by focusing specifically on school-level digitalization, and use more direct measures of teachers' ICT skills and a larger sample of countries. For this, we use data from the Teaching and Learning International Survey (TALIS) of 2018. This international survey is organized by the OECD and held among teachers and school principals to study teachers' working conditions and school learning environments. The OECD has strong requirements for the representativeness of the data to the national populations of schools and teachers. We select data of teachers in lower-secondary schools in 45 countries and subnational

[4] Reliance on school principals and ICT coordinators speaks to the importance of school-level self-reflection for assessing school-level digital capacity [5].

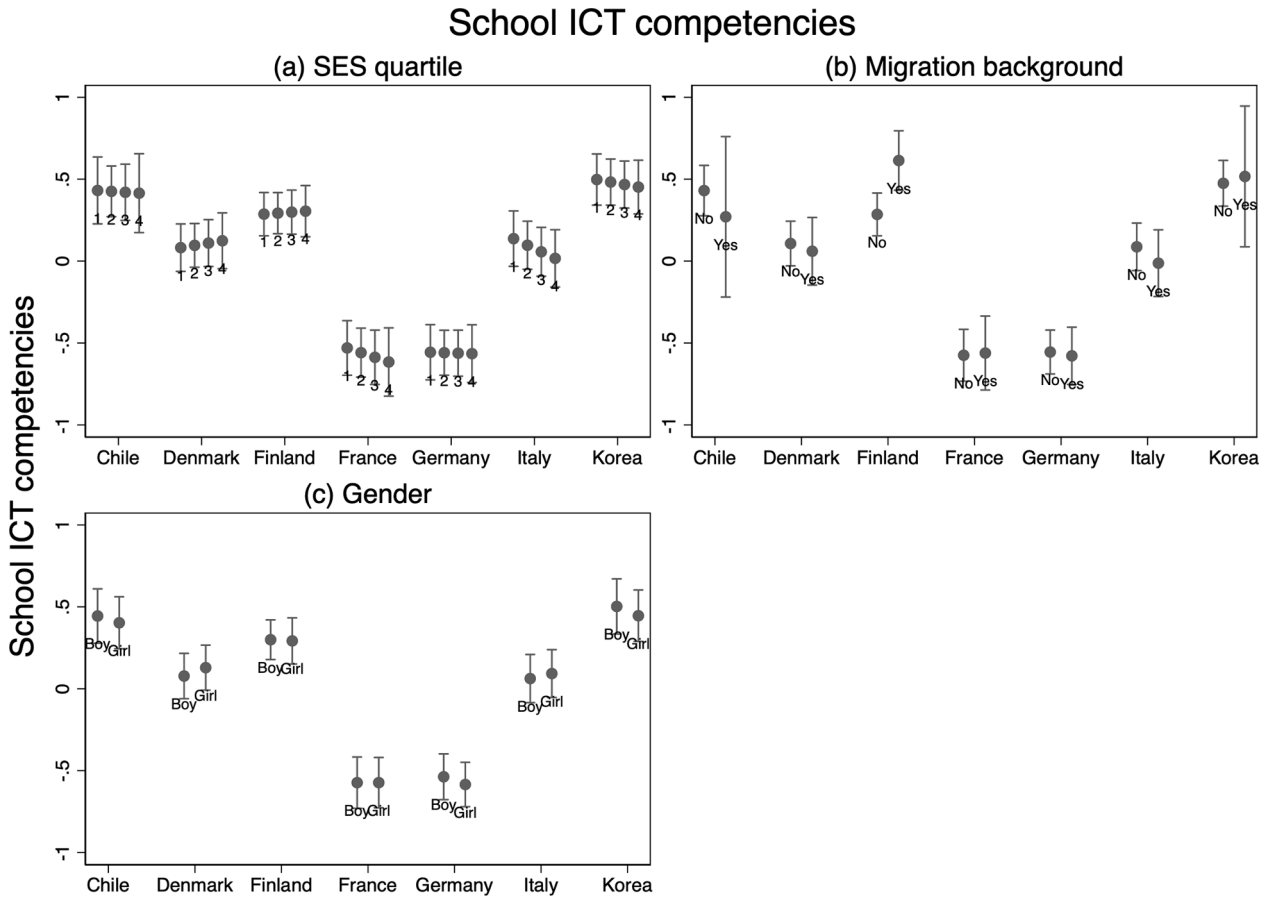

Fig. 4. School ICT competencies by country and subgroup
Note: see Table A4 in Supplementary materials for the detailed regression coefficients on which this figure is based.

regions, thereby covering a similar time frame as well as student age group as in Study I.[5] The countries under study are spread across all continents, and they are economically, politically and socially diverse, including among others Sweden, Saudi Arabia, Colombia and Vietnam. Moreover, the teacher data allow us to zoom in on our proposed fourth level of the digital divide. That is, we study the differential ICT resources of schools by examining teachers' ICT-related behaviour.

Participants. The analytical sample of the TALIS data is N=135,169 teachers, working in 8,064 schools in 45 countries.[6]

Variables. The TALIS data include questions on the use of ICT in teaching and professional development. We distinguish four indicators of the digital readiness of teachers: attention to ICT use in teacher education and training, attention to ICT use as part of teachers' professional development, students' use of ICT during the teacher's classes, and the teacher's use of ICT to support student learning. The first indicator, *ICT in teacher education*, is a standardized continuous scale that both incorporates whether ICT use was addressed as well as how well the teacher was trained in ICT use. The second indicator, *ICT during professional development*, is a dummy variable, measuring whether ICT skills for teaching were part of the teacher's professional development activities during the last 12 months. The third, *ICT for classwork*, and fourth, *ICT for student support*, indicators are standardized categorical variables that indicate respectively (a) how often the teacher lets students use ICT for classwork, and (b) the extent to which the teacher supports student learning through the use of ICT. These four variables tap both into teachers' ICT *skills*, as acquired during teacher training and professionalization activities, as well as into teachers' ICT *usage*, as evidenced by their use of digital technology in class. Hence, these four indicators are complementary, together providing a valid measure of teacher ICT competencies. These items more directly measure ICT competencies relevant for teaching purposes in comparison to Study I. Previous research shows that self-rated digital proficiency is a reliably measure of digital skills (Hargittai and Hsieh 2014).

As the TALIS data do not contain information on individual students, we use information on school composition to assess digital inequalities. It should be noted that inequalities are thus assessed in a different way than in Study I. School principals estimate the proportion of students in the school that (a) come from a socioeconomically disadvantaged home, and (b) are migrants or have a migration background. In doing so, principals are asked to judge a student as 'disadvantaged' if they "lack the basic necessities or advantages of life" ([22]: 8), and as a migrant if either the student or the parents were born abroad. The data are categorized ((0) none, (1) >0-10%, (2) >10-30%, (3) >30-60%, (4) >60%).

We control for several teacher characteristics that could influence both the digital aptness of the teacher as well as the type of school the teacher works for. These encompass teaching experience in years, teaching experience squared, whether a teacher is a STEM-teacher (mathematics, science or technology), whether the teacher has a Master degree, and the teacher's gender. With the exception of the experience measures, all control variables are dichotomously coded.

Table 2 shows the descriptive statistics of the variables included in Study II. Seventy percent of teachers have recently participated in ICT-related professional development activities; the other three indicators of

[5] TALIS matches with the PISA student assessments of 15-year-old students, while ICILS studies grade-8 studies with a modal age of 14.

[6] Two countries of the total of 47 dropped out due to missing data on teachers' degree level (Spain) and the percentage of migrant students (United States).

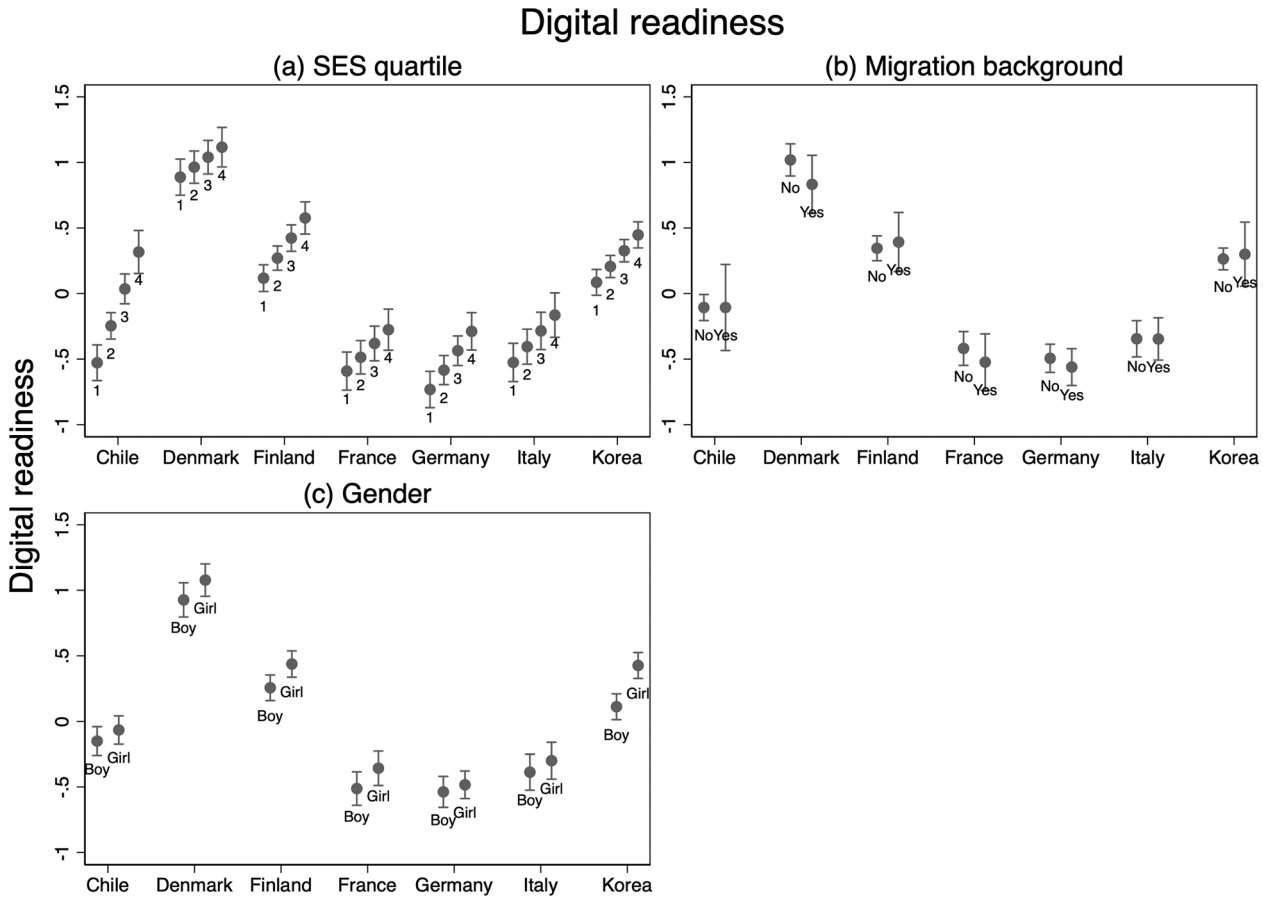

Fig. 5. Digital readiness by country and subgroup
Note: see Table A5 in Supplementary materials for the detailed regression coefficients on which this figure is based.

teachers' digital readiness are standardized and have their mean set at zero and s.d. at 1. ICT attention in teacher education and ICT use for classwork are approximately equally dispersed, whereas the dispersion in ICT use for student support is comparatively higher. The overwhelming majority of schools in the sample have no (45.4%) or less than 10% (39.1%) of students who are migrants or have a migration background. The largest group of schools have some but at most 10% of students from socioeconomically disadvantaged backgrounds (44.6%), with schools estimated to have 11–30% of disadvantaged students scoring second (27.7%). The teachers in the sample have widely varying degrees of experience, averaging 16.6 years. 40% of them are STEM teachers, 40% have a Master degree and 70% of them are female.

Analytical approach. We fit linear multi-level regression models, separately for each country, whereby teachers are nested in schools. The four indicators of teachers' digital readiness serve as the respective dependent variables, while the student composition measures function as the main independent variables.

Data analysis and results

Study I

To study the extent to which students are ready for digital education and how this readiness varies by students' sociodemographic background, we conduct linear regression analyses and compare different student groups' predicted outcomes on the four indicators of digital readiness.[7] Fig. 1 depicts the predicted outcomes of students' usage of ICT of these regression models. A first notable finding is that students' predicted level of ICT usage for school-related activities varies by country, with especially high values in Denmark. Inequality in ICT use across the SES quartile distribution is smaller in Chile, Denmark and France, not exceeding 0.12 standard deviations, but larger in Finland, Germany, Italy and Korea where it amounts to up to 0.44 standard deviations. In all countries, the differences point in the expected direction, meaning the higher a student's SES, the more they use ICT for educational purposes.

Inequality in ICT usage by migration background is small in most countries. In fact, controlling for student SES and gender, students with and without migration background do not differ statistically significantly in terms of their ICT usage in Denmark, Finland and Korea. In Chile, France, Germany and Italy, there are statistical differences but again of modest magnitude, not exceeding 0.2 standard deviations. Interestingly, if there are differences, they indicate that students with a migration background use ICT more frequently for educational purposes, meaning they are *better* prepared for digital education than students without a migration background (and similar SES).

Gender differences in school-related ICT usage are similarly small but statistically significant in all countries except for Germany and Italy. Where there are differences, girls tend to use ICT for educational purposes more frequently than boys, most distinctly in Korea where girls' score 0.33 standard deviations higher than boys. Overall, we thus find variations along sociodemographic lines in the extent to which students

[7] The tables with the detailed regression coefficients can be found in the online Supplementary File, with reference to the figures they pertain to.

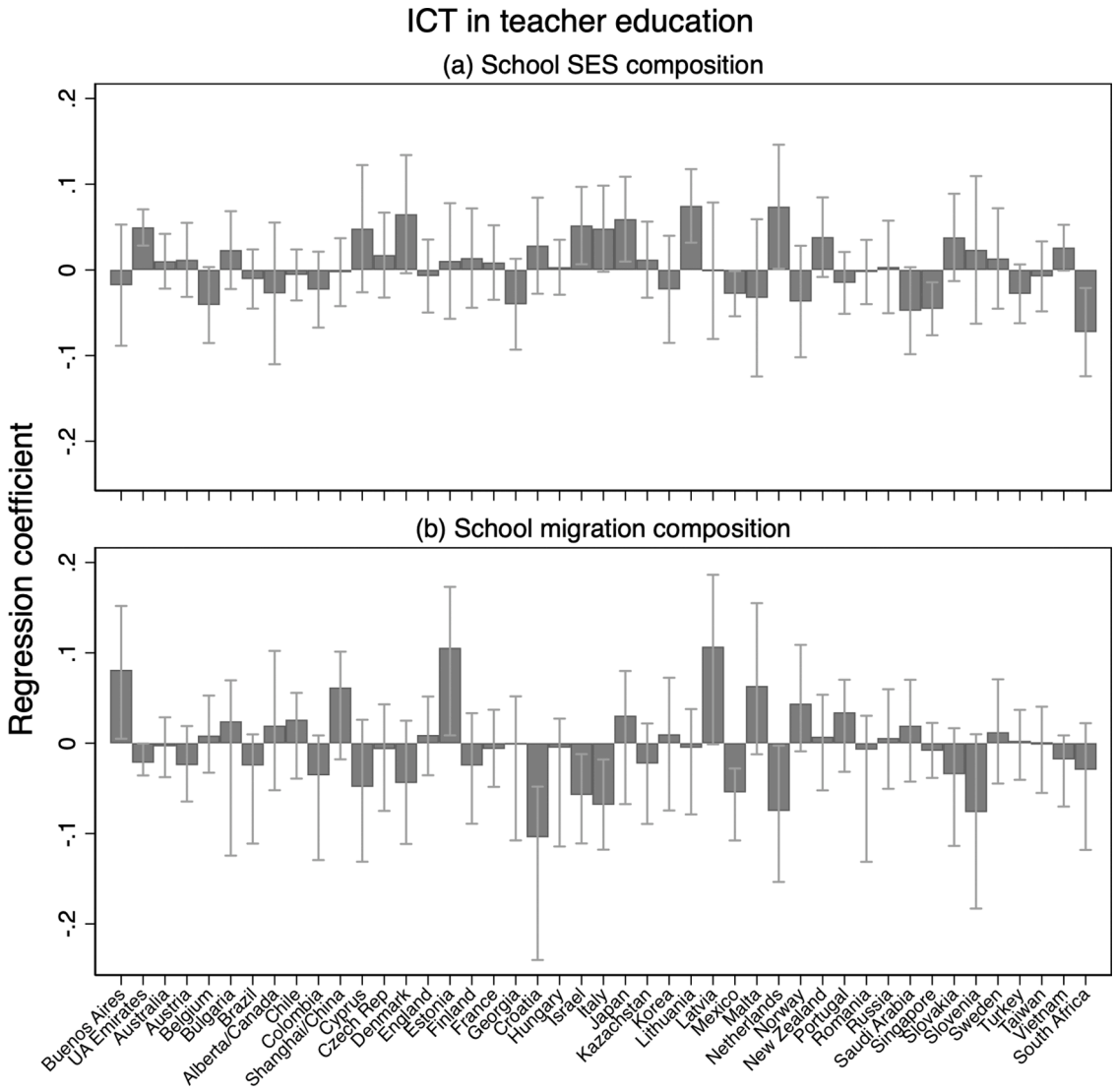

Fig. 6. Regression coefficients of school composition variables on ICT in teacher education
Note: see Table A6 in Supplementary materials for the detailed regression coefficients on which this figure is based.

use ICT for school-related tasks, yet differences are relatively modest.

Fig. 2 displays predicted gaps in the ICT skills as assessed in the ICILS student assessment. We find the lowest levels of ICT skills in Chile and Italy, and the highest in Denmark and Korea. Chilean students coming from the highest SES quartile have ICT skills at a similar level as Danish students at the lower half of the SES distribution. The gaps in ICT skills by SES groups are sizeable and statistically significant in all countries, with students from higher SES backgrounds possessing considerably better ICT skills. The strongest gaps are in Chile, where the digital skills of students from the highest SES quartile are 1.3 standard deviations higher than those of students from the lowest SES quartile. By contrast, in Denmark, the difference in skills between students from the highest and lowest SES quartiles 'only' amounts to 0.48 standard deviations.

Gaps in ICT skills by migration background vary across countries: while there are no statistically significant differences in Chile, Italy and Korea, students with a migration background are significantly disadvantaged in their ICT skills in all other countries, scoring up to 0.54 standard deviations lower than students without a migration background. In contrast to the first indicator, ICT usage, migrants thus appear to be *less* prepared for digital education than non-migrants in terms of ICT skills.

Considering students' gender, the patterns found for ICT usage are confirmed for ICT skills: again, girls tend to be better prepared for digital education; their skills are statistically significantly better than those of boys, by up to 0.44 standard deviations. Students' ICT skills, therefore, vary to a considerable extent, especially by SES but also by migration background and gender.

Fig. 3 presents the predicted outcomes of the ICT infrastructure in schools, by student SES, migration background and gender. There are large differences across countries in students' school infrastructure to promote access to digital education. In Denmark, Finland and Korea, schools are generally well-equipped, while the ICT infrastructure is less generous in France, Germany, and Chile, and intermediate in Italy. An important finding is, however, that statistically and substantively significant inequality by SES is only found in Chile, where high-SES students score 0.59 standard deviations above low-SES students. Inequality by migration background only occurs, to a small extent, in Finland where migrants go to schools whose ICT infrastructure is 0.16 standard deviations higher than non-migrants. Inequality by gender occurs in none of the countries, meaning that boys and girls go to schools that are equally equipped in terms of their ICT infrastructure. All in all, students' schools' ICT infrastructure hardly varies along sociodemographic lines.

Fig. 4 shows the predicted differences between schools' ICT competencies for students of different SES quartiles, migration background

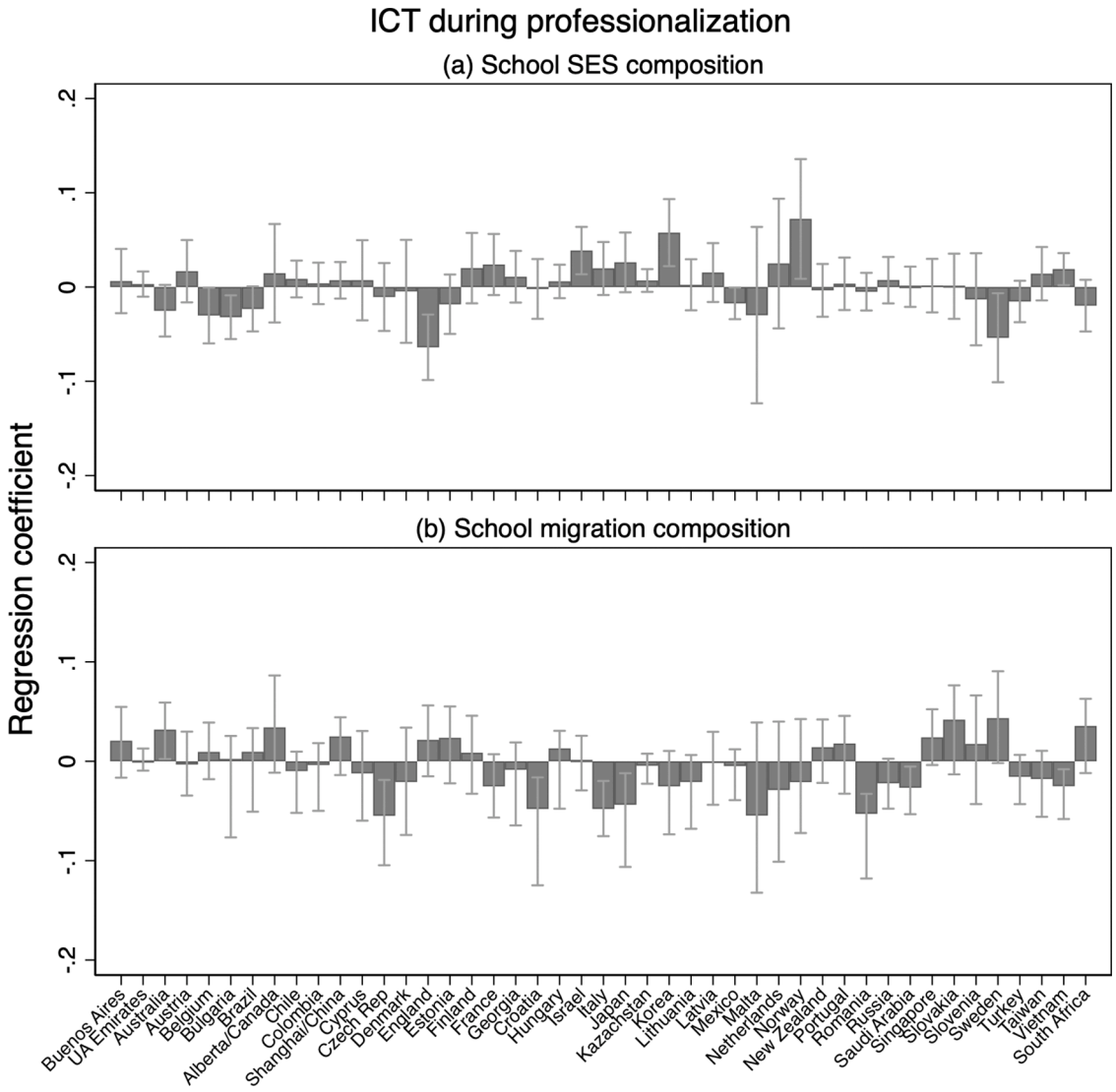

Fig. 7. Regression coefficients of school composition variables on ICT during professionalization
Note: see Table A7 in Supplementary materials for the detailed regression coefficients on which this figure is based.

and gender. Countries differ in the importance schools attach to digital learning and teaching: ICT competencies of schools are relatively low in Germany and France, countries that also scored relatively low on infrastructural provisions. Comparatively well-resourced are schools in Chile, Finland and Korea, whereas Denmark and Italy take intermediate positions when it comes to schools' skills and usage of digital learning. In none of the countries, there is an SES or gender gap in the ICT competencies available in students' schools. A migration gap in school-level ICT competencies only occurs in Finland, where migrants' schools are 0.33 standard deviations better skilled than non-migrants' schools. This confirms the results with regard to schools' infrastructure, where a migration gap also only occurs in Finland. Overall, the ICT competencies of the schools that students attend thus hardly vary according to students' sociodemographic characteristics.

Interestingly, the school-level indicators of students' readiness for digital education differ considerably from the individual-level indicators. While students' individual ICT usage and especially their digital skills are characterized by significant sociodemographic gaps in all countries, ICT resources of schools hardly vary by their student composition in terms of sociodemographic background in the countries under study. Moreover, the indicators also differ in their absolute level: while Danish students seem to be best prepared for digital education on the basis of the individual-level indicators, they are no longer in the lead when considering the school-level ICT resources. Hence, the question emerges which students in which countries 'have it all' or, at least, 'most of it'? Arguing that readiness for digital education hinges on all four indicators, that is, on students' individual ICT experience and skills as well as their schools' ICT access and usage, we analyze which students are digitally prepared multidimensionally, using the combined indicator of readiness.

Fig. 5 visualizes predicted gaps in students' overall digital readiness, by SES, migration background and gender. Students are overall best prepared in Denmark, followed by Finland and Korea. Students are least prepared in Germany and France, and slightly better off in Italy and Chile. We also find inequality in digital readiness by student SES, and this SES inequality is most pronounced in Chile (0.84 standard deviations) and least pronounced in Denmark (0.23 standard deviations). In all countries under study, high-SES students are statistically significantly and substantively better prepared for digital education than low-SES students.

Inequalities by migration background and gender are less pronounced. With regard to students' migration background, the four separate indicators do not indicate a clear pattern, with migrants appearing sometimes better and sometimes worse prepared.

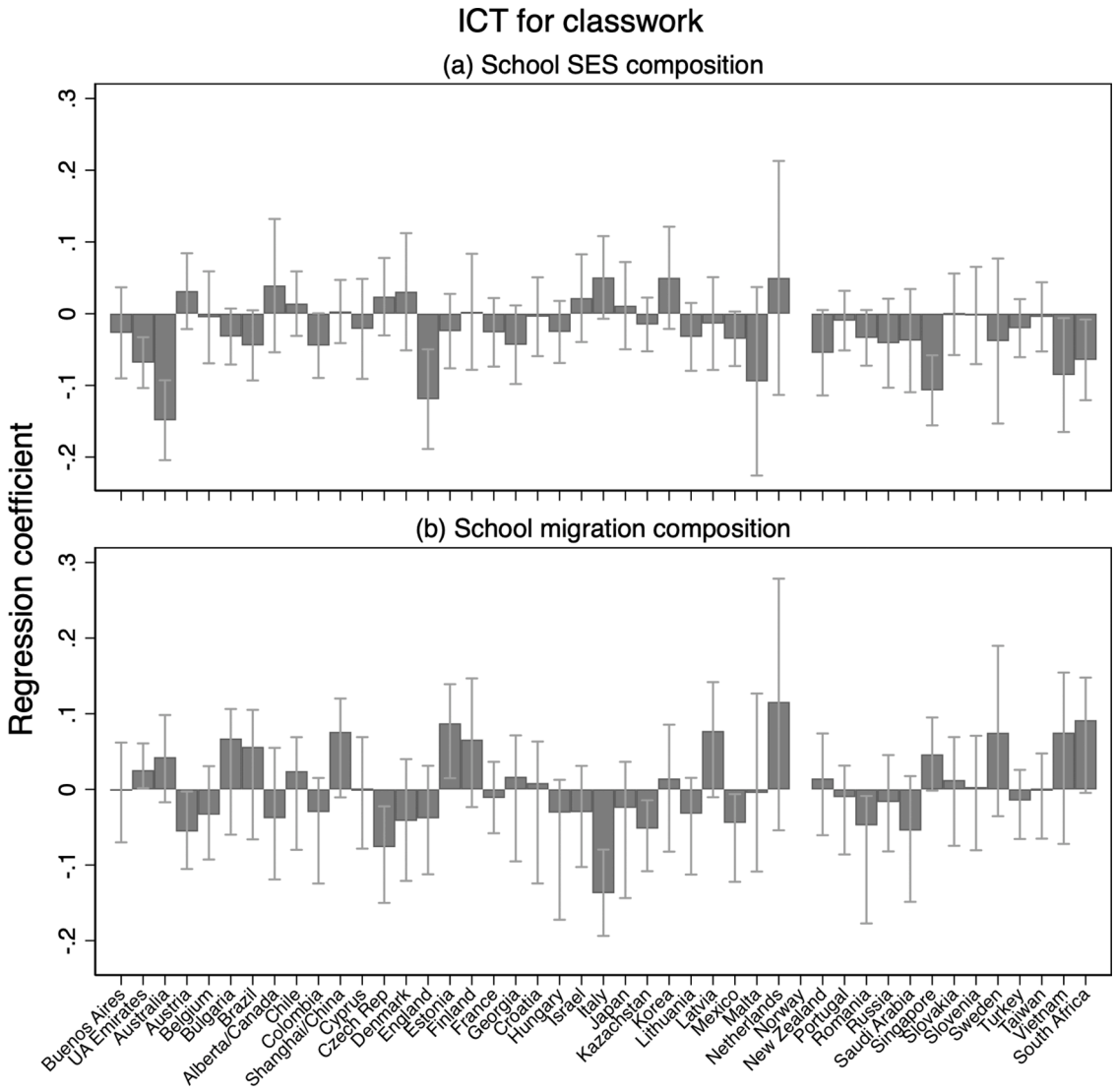

Fig. 8. Regression coefficients of school composition variables on ICT for classwork
Note: see Table A8 in Supplementary materials for the detailed regression coefficients on which this figure is based.

Consequentially, when controlling for SES and gender, in most countries migrants and non-migrants are approximately equally prepared for digital education, with the only exception being Denmark where migrants are disadvantaged by 0.19 standard deviations. While this is a notable gap, Danish students with a migration background are still much better prepared than students in all other countries. Finally, with respect to student gender, girls are overall significantly better prepared for digital education than boys in all countries except for Germany. The magnitude of girls' premium varies, however, from 0.31 standard deviations in Korea to less than 0.1 standard deviations in Chile and Italy. Considering the multidimensional measure of digital readiness, we thus conclude that a student's country, SES, and gender matter. The students that 'have it all' - i.e., that are multidimensionally prepared for digital teaching - tend to live in Denmark, are from higher SES backgrounds, and girls.

Study II

To examine the inequalities in school-level readiness for digital education, we conduct multi-level regression analyses, and compare the coefficients of the school composition variables across the 45 countries under study. Regarding the attention to ICT in teacher education (Fig. 6), a significant negative relationship with the percentages of students from low-SES and migration backgrounds occurs in only one case: Mexico. Here, in schools where more than 60% of students come from socioeconomically disadvantaged or migration backgrounds, teachers are, respectively, 0.2 and 0.12 standard deviations less well trained in ICT in their teacher education than teachers in schools with no students from these backgrounds. In most other cases, these effects are weaker and not statistically different from zero, or even point in the opposite direction. In Lithuania, for instance, teachers working in schools where more than 60% of the students are socioeconomically disadvantaged are 0.28 standard deviations significantly better trained in ICT use than teachers in schools with no disadvantaged students.

Regarding the attention to ICT during professional development activities (Fig. 7), a similar picture emerges. That is, there tends to be no statistically significant relationship between the proportion of students from low-SES or migration background in school and the ICT competencies of teachers. In the overwhelming majority of countries, the improvement of ICT skills as part of teacher professionalization activities are not related to a school's student body. There are a few noteworthy exceptions in both the positive and the negative direction. In England, for example, teachers at schools with more than 60% of low-SES students are 24 percentage points less likely to have attended an

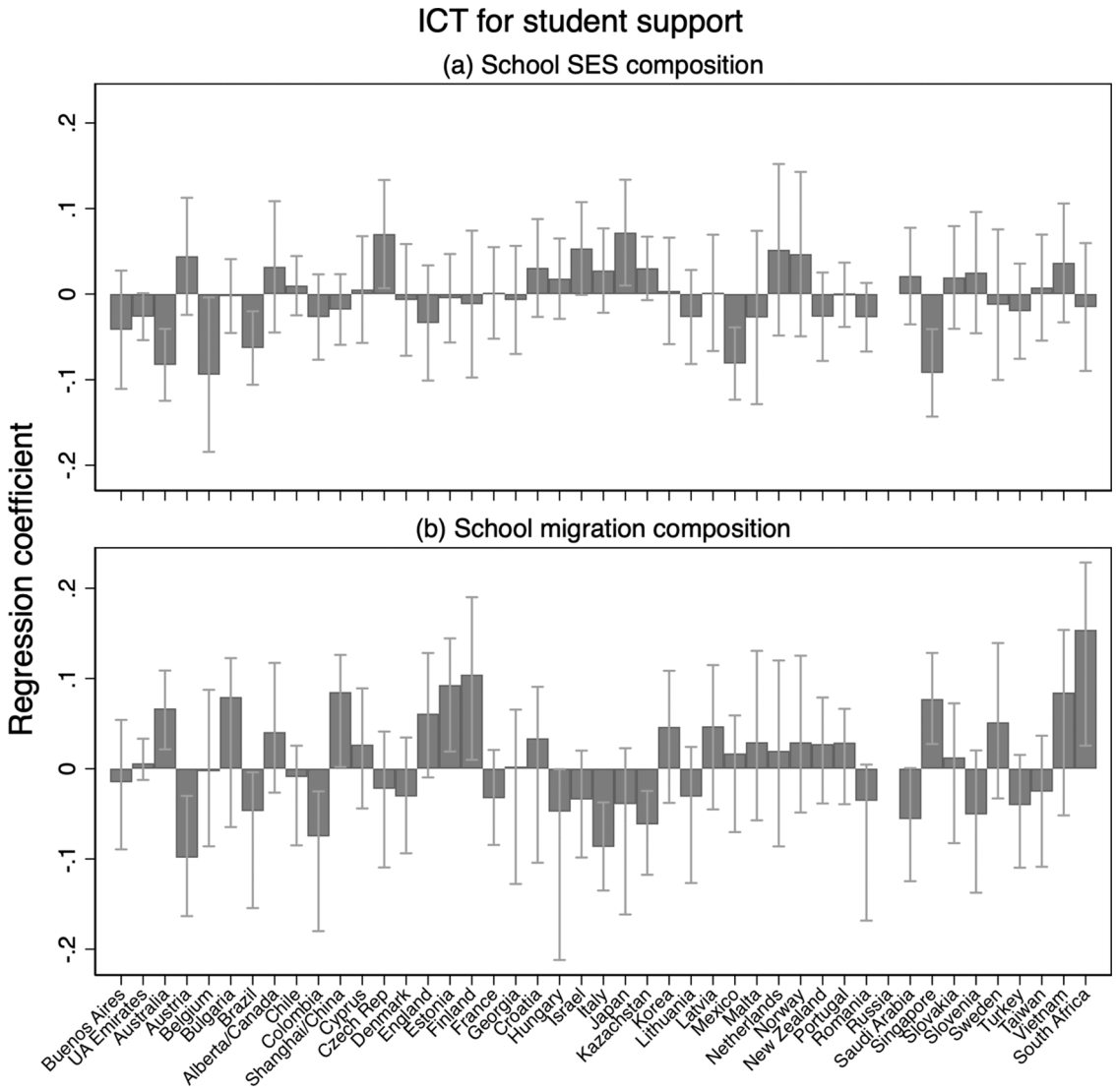

Fig. 9. Regression coefficients of school composition variables on ICT for student support
Note: see Table A9 in Supplementary materials for the detailed regression coefficients on which this figure is based.

ICT-related professionalization activity than teachers at schools with no low-SES students. By contrast, in Norway, teachers working in schools with a high percentage (>60%) of disadvantaged students are 28 percentage points more likely to have upgraded their ICT skills as part of their professional development than teachers working in schools without disadvantaged students.

Moving from teachers' theoretically acquired ICT skills to their practical ICT usage in class, the relationship with the school's student composition does not substantially change. In most countries, students' use of ICT during a teacher's class does not significantly vary with the perceived proportion of students from socioeconomically disadvantaged or migration backgrounds in school (Fig. 8). In countries where we do find a significant relationship, however, we find a more consistent and larger negative relationship than we found for the first two indicators of teachers' ICT competencies. In Australia, for instance, we find that teachers working in schools with more than 60% of low-SES students let their students use ICT for classwork 0.6 standard deviations less frequently than teachers working in schools without low-SES students. Likewise, in Italy, in schools with more than 60% of students with a migration background, students use ICT during class 0.56 standard deviations less often than in schools without migrants. There is no country where the SES composition of a school is significantly positively related to teachers' ICT use in class and for students' migration background, we only find a positive association between the share of migrants in school and teachers' ICT use in class in the United Arab Emirates and Estonia.

Regarding teachers' use of ICT to support student learning (Fig. 9), the relationship with the perceived sociodemographic student composition is less consistent than for the ICT-for-classwork indicator, and it continues to be insignificant in most cases. That is, in most countries, teachers in schools with many disadvantaged or migrant students are neither more nor less able to support their students via the use of ICT than teachers in schools with fewer students from such backgrounds. However, there are exceptions in both directions: in Singapore, for example, teachers in schools with more than 60% of socioeconomically disadvantaged students are 0.36 standard deviations less able to support their students by using ICT than teachers in schools with no low-SES students. At the same time, teachers in schools with a comparably high proportion of students with a migration background are 0.28 standard deviations better able to support their students via ICT than teachers in schools without migrant students. Hence, while students with a low SES tend to be disadvantaged in their school-level digital readiness, students with a migration background tend to be advantaged in Singapore (net of SES composition).

Overall, the associations between sociodemographic school

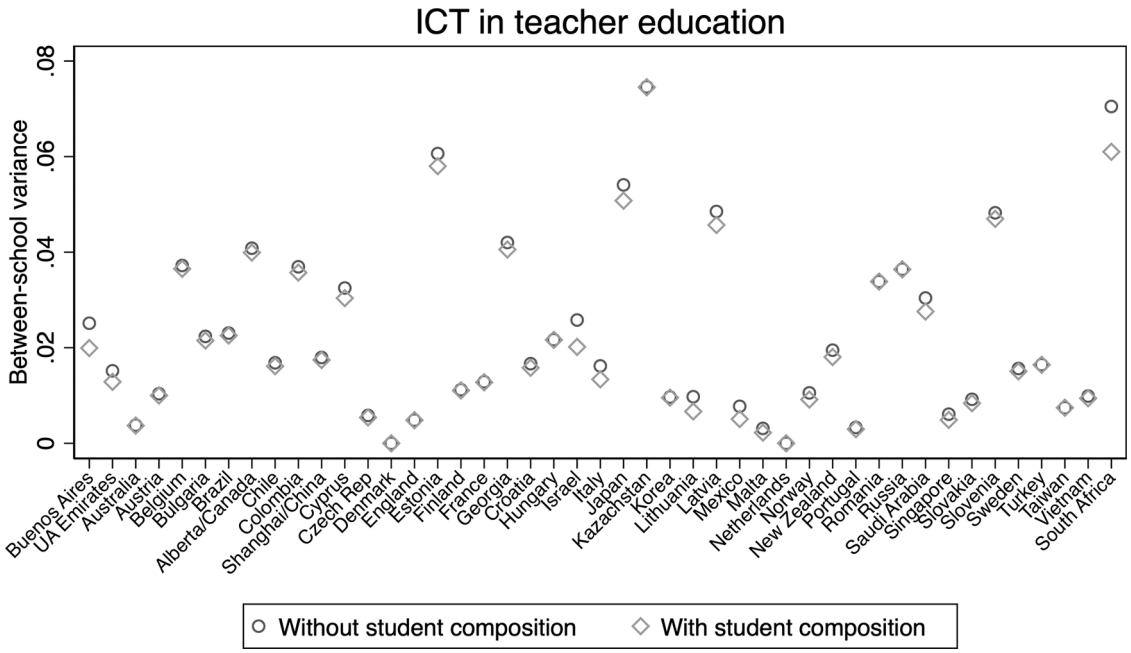

Fig. 10. Between-school variance in ICT in teacher education
Note: see Table A6 in Supplementary materials for the detailed regression coefficients on which this figure is based.

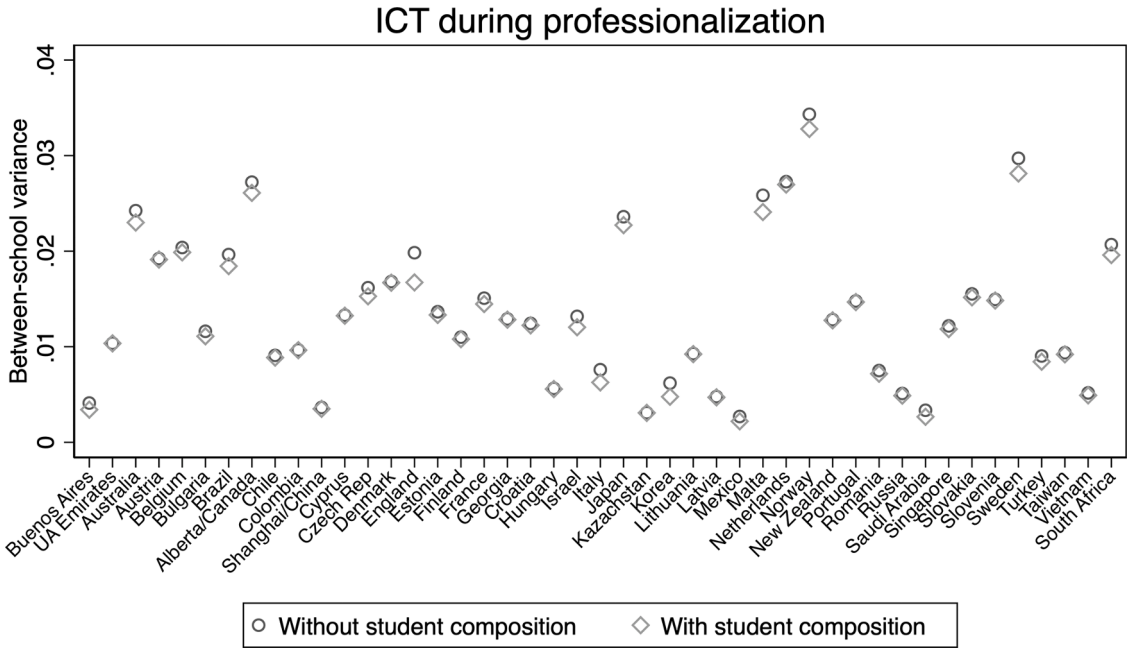

Fig. 11. Between-school variance in ICT during professionalization
Note: see Table A7 in Supplementary materials for the detailed regression coefficients on which this figure is based.

composition and school-level digital readiness are very weak, and hardly significantly different from 0. Moreover, we cannot detect any systematic patterns: in some cases, teachers are less digitally prepared in schools with relatively many students from socioeconomically disadvantaged or migration backgrounds; in other cases, teachers at comparable schools are more digitally prepared. In the overwhelming majority of countries, the school' sociodemographic composition is not at all statistically related with the digital readiness of its teachers and, consequentially, with the school-level digital readiness of its students. No matter their sociodemographic background, students are approximately equally prepared for digital education at the school level, and their teachers are approximately equally digitally apt.

To further corroborate our conclusion that there is hardly a digital divide by the SES composition of the school, we analyze the between-school variance in teachers' digital readiness. If there is a school-level digital divide, we expect that the between-school variance in teachers' digital readiness can be (partially) explained by schools' student composition. Figs. 10–13 visualize how the between-school variances in the respective indicators of teachers' ICT competencies change when additionally controlling for schools' student composition, whilst also accounting for teacher characteristics. Regarding the attention paid to ICT during teachers' initial training (Fig. 10), the unexplained between-

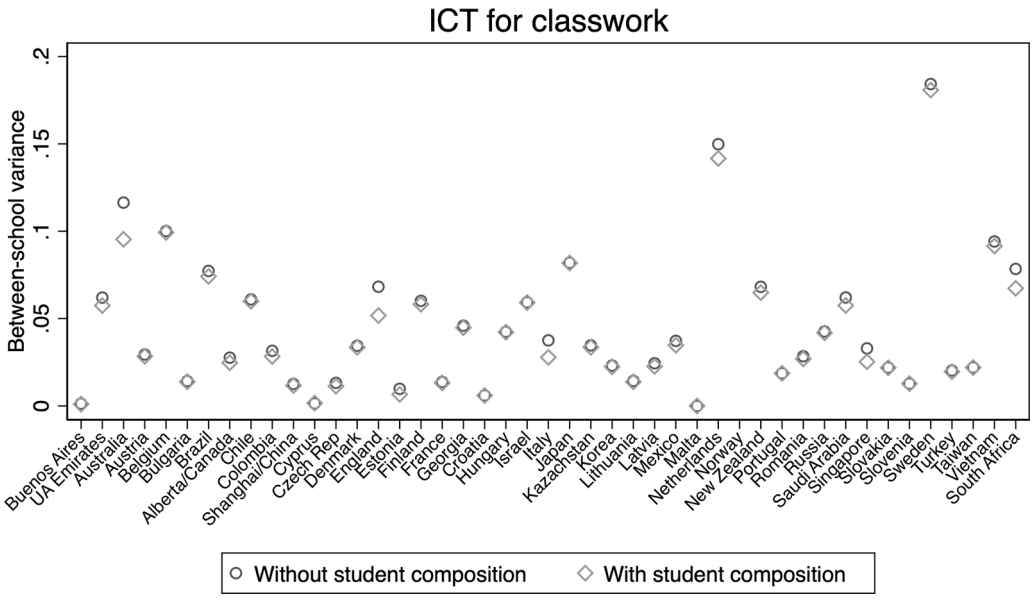

Fig. 12. Between-school variance in ICT for classwork
Note: see Table A8 in Supplementary materials for the detailed regression coefficients on which this figure is based.

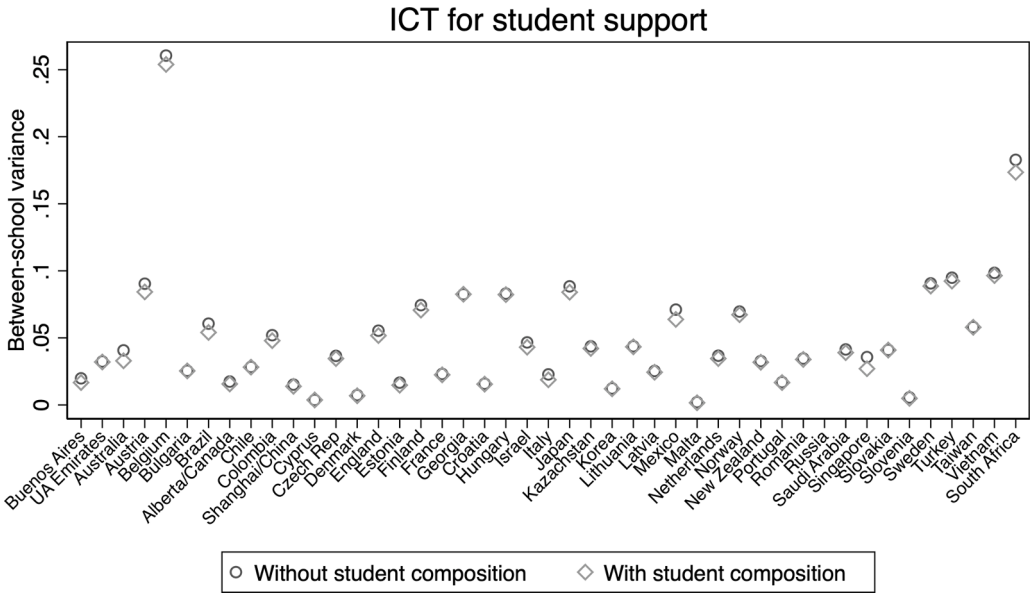

Fig. 13. Between-school variance in ICT for student support
Note: see Table A9 in Supplementary materials for the detailed regression coefficients on which this figure is based.

school variance generally tends to be low (less than 0.08 in all cases), and is hardly reduced when accounting for schools' student composition. Without accounting for student composition, the school-level variance is highest in Kazakhstan (0.07) but cannot be explained by the school composition variables. In fact, the only cases where the between-school variance in teachers' attention to ICT during their teacher education can be non-negligibly explained by a school's student composition are Buenos Aires/ Argentina, Israel and South Africa, but even here the variance reduction amounts to less than 0.01.

Regarding the attention paid to ICT during teachers' professional development activities (Fig. 11), the likelihood of ICT-related professionalization also hardly varies between schools and is mostly independent of schools' sociodemographic student composition. Without accounting for school composition, the between-school variance is relatively high in Norway (0.034) but schools' student composition can only explain a small part of it (4.5%). School composition can explain the largest proportion of the between-school variance in teachers' ICT attention during their professionalization in Korea (23.0%) but in absolute levels the unexplained variance is reduced by only 0.001. In absolute terms, students' sociodemographic background can best explain this between-school variance in England, but even here the reduction only amounts to 0.003.

When considering teachers' digital readiness in terms of their ICT usage instead of their ICT skills, the between-school variances tend to be higher in absolute terms but the explanatory power of schools' student composition remains similarly limited. Regarding students' ICT use during classes (Fig. 12), the total between-school variance amounts up to 0.1 in most of the countries under study. It is highest in the Netherlands (0.15) and Sweden (0.18) but the student composition of schools can hardly explain these between-school variances. This is not

surprising given that neither the proportion of low-SES, nor the proportion of migrant-background students, significantly correlate with teachers' digital readiness in these two countries. Instead, in absolute terms, the largest reduction in unexplained between-school variance in teachers' digital readiness when accounting for student composition is achieved in Australia (by 0.02) where the proportion of low-SES students at a school is highly significantly related to the frequency of teachers' ICT-for-classwork use.

Regarding teachers' use of ICT to support student learning (Fig. 13), the picture is again similar. In most countries under study, the total between-school variance in teachers' ICT usage for student support is low (below 0.1). There are two notable exceptions: South Africa (0.18) and Belgium (0.26). Students' background characteristics, however, cannot explain more than 0.01 of the between-school variance in any of the countries studied.

To conclude, we generally find that there is little between-school variance in school-level digital readiness. The between-school variance that does exist can hardly be explained by schools' student composition. This finding confirms the previous conclusions that the fourth level of the digital divide tends to be minor, at least in relation to the student body in terms of SES and migration background.

Conclusion and discussion

The COVID-19 pandemic has forced schools to rapidly digitalize their educational process, and demanded from children to be educated in an online environment [25]. Given the expected inequalities that may come with this, the current study assessed whether there were pre-existing inequalities in digital readiness of students and schools, before the pandemic started. We examined the digital divide in a multilayered framework, by examining students' individual ICT skills and use, and the ICT infrastructure and competencies in the schools that students attend. More precisely, we examined whether SES, migration background and gender were associated with gaps in these different facets of digital readiness.

With respect to students' individual ICT skills and use, we found evidence for a digital divide by migration background, gender, and especially SES. Children from higher SES backgrounds, without a migration background, and girls had higher-level ICT skills than their male peers from disadvantaged SES, and migration backgrounds. These findings are in line with results from previous studies on gender and SES divides in digital skills [15,33]. Moreover, they suggest the importance of also taking migration background into consideration when studying (divides in) ICT skills. While these results provide support for the second level of the digital divide ([6]; the first one being access to technology), inequalities in the usage of ICT for educational purposes were less pronounced. However, in line with previous work [16], we found that students from advantaged SES backgrounds used ICT more for school than their peers from disadvantaged SES backgrounds in several of the countries under study.

With respect to school-level ICT resources and usage, we found less stratification by student background. Lower SES and migrant children were not less likely to go to schools with a good digital learning environment. While between-school differences in digital infrastructure and teacher competencies existed in many countries, they were hardly related to the (perceived) share of disadvantaged children or children with a migration background in school. It should be emphasized that the differences across schools within a country were sometimes quite substantial. This is in itself an important digital divide, as some students go to secondary schools with good ICT provisions while other students attend less well-resourced schools. But as this between-school variation is not strongly related to student composition, this is not a fourth level of the digital divide.

Limitations, future directions for research, and implications

Our study also knows some limitations. First, it does not reveal how the rapid digitalization during school closures has affected (inequality in) student outcomes like academic performance. Given the educational situation during the COVID-19 pandemic, it is important to investigate whether the demonstrated digital divides strengthen the third-level digital divide concerned with the (educational) outcomes of access and usage of technology (c.f. [13,27,37]). New research may want to focus on the *consequences* of digital inequalities at both the student and the school level. More causal evidence is also needed on the effects of schools, something our study was unable to consider, as the non-random sorting of students into schools is always an issue in assessing school effects.

The digital divide literature can advance by further theorizing and researching the multilevel nature of gaps between groups of people. The three levels of the digital divide, which relate to the digital skills and usage and their effects on individual-level outcomes such as learning, health, or finding a job [27,35], can be extended to include a fourth level of entering certain contexts that vary in terms of infrastructure and skills of relevant other agents. Given the relational nature of how inequalities emerge, other agents deserve more explicit attention in the digital divide literature [35,36]. In our case, these other agents were teachers and school principals, but a multilevel nature can also refer, for instance, to the digital skills of medical practitioners, or labour market agencies. Important questions can then be asked about the complementary or compensatory character of individual-level and contextual level skills; do the ones with the least individual digital resources also enter contexts with fewer provisions, or can the social context compensate for individual-level digital deprivation?

If we relate our results more deeply to the resources and appropriation theory of Van Dijk [35], we may tentatively conclude that the suggested appropriation by elites of technology has not happened; at least we do not see that individual and school-level advantages accumulate among privileged families. We can speculate on the relevance of this finding for learning inequalities that deepened during the COVID-19 pandemic. It is likely that the COVID-19 pandemic would have had even stronger effects on learning inequalities if the accumulation of (dis) advantage across families and schools would have been found. Recent findings by Strietholt et al. [29] may give some support to this view: using a panel study of teachers in pre-pandemic (2018) and pandemic (2020) times in Denmark, Finland, and Uruguay, it was concluded that school-SES gaps in technology use were stable or slightly reduced.

Our study may help educational practitioners, policy makers, and scientists to deal with the digital educational revolution that we were suddenly confronted with. Since the COVID-19 pandemic, digital education has become more and more commonplace. Even though schools have partly moved back to onsite education, it is highly possible that we may face future situations that will force schools to switch to online teaching again. This, combined with our finding that in many countries important between-school differences exist in schools' readiness for digital education, highlights the importance of policy makers to monitor, invest in, and equalize the (quality of) digital skills and resources of schools. Moreover, our findings suggest that there are important inequalities in the ability of individual students to accommodate to digital education. The more education is digitalized, the more such inequalities may lead to unequal opportunities to academically perform. To level the playing field, governments may want to provide additional funding to schools so they can offer digital trainings for students who are lacking ICT competencies and knowledge.

Declaration of Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Acknowledgment

This research has partially been funded by ZonMW, grant 10430032010003.

Supplementary materials

Supplementary material associated with this article can be found, in the online version, at doi:10.1016/j.caeo.2022.100100.

References

[1] Azubuike OB, Adegboye O, Quadri H. Who gets to learn in a pandemic? Exploring the digital divide in remote learning during the COVID-19 pandemic in Nigeria. Int J Educ Res Open 2021;2:100022.
[2] T. Bol 2020. Inequality in homeschooling during the Corona crisis in the Netherlands. First Results from the LISS Panel. SocArXiv. DOI:10.31235/osf.io/hf32q.
[3] Büchi M, Just N, Latzer M. Modeling the second-level digital divide: a five-country study of social differences in internet use. New Media Soc 2016;18(11):2703–22.
[4] S. Carretero, R. Vuorikari, & Y. Punie (2017). DigComp 2.1: the digital competence framework for citizens with eight proficiency levels and examples of use. Retrieved from https://publications.jrc.ec.europa.eu/repository/handle/JRC106281.
[5] Costa P, Castaño-Muñoz J, Kampylis P. Capturing schools' digital capacity: psychometric analyses of the SELFIE self-reflection tool. Comput Educ 2021;162:104080.
[6] edited by DiMaggio P, Hargittai E, Celeste C, Shafer S. Digital inequality: from unequal access to differentiated use. In: Neckerman K, editor. Social inequality. New York: Russell Sage Foundation; 2004. p. 355–400. edited by.
[7] Donnelly R, Patrinos HA. Learning loss during COVID-19: an early systematic review. Prospects 2021;51:1–9.
[8] Engzell P, Frey A, Verhagen MD. Learning loss due to school closures during the COVID-19 pandemic. In: Proceedings of the national academy of sciences; 2021. forthcoming.
[9] Fabrigar L, Wegener D. Exploratory factor analysis. Oxford: Oxford University Press; 2012.
[10] Fraillon J, Ainley J, Schulz W, Friedman T, Duckworth D. Preparing for life in a digital world: IEA international computer and information literacy study 2018 international report. Amsterdam, The Netherlands: International Association for the Evaluation of Educational Achievement (IEA); 2019. Retrieved from, https://www.iea.nl/publications/study-reports/preparing-life-digital-world.
[11] Fraillon J, Schulz W, Ainley J. International computer and information literacy study: assessment framework. Amsterdam, The Netherlands: International Association for the Evaluation of Educational Achievement (IEA); 2013. Retrieved from, https://www.iea.nl/publications/assessment-framework/international-computer-and-information-literacy-study-2013.
[12] González-Betancor SM, López-Puig AJ, Cardenal ME. Digital inequality at home. The school as compensatory agent. Comput Educ 2021;168:104195.
[13] Goudeau S, Sanrey C, Stanczak A, Manstead A, Darnon C. Why lockdown and distance learning during the COVID-19 pandemic are likely to increase the social class achievement gap. Nat Hum Behav 2021;5(10):1273–81.
[14] Gu J. Family conditions and the accessibility of online education: the digital divide and mediating factors. Sustainability 2021;13(15):8590.
[15] Gui M, Argentin G. Digital skills of internet natives: different forms of digital literacy in a random sample of northern Italian high school students. New Media Soc 2011;13(6):963–80.
[16] Hargittai E, Hinnant A. Digital inequality: differences in young adults' use of the internet. Commun Res 2008;35(5):602–21.
[17] Hargittai E, Hsieh YP. Succinct survey measures of web-use skills. Soc Sci Comput Rev 2012;30(1):95–107.
[18] Hargittai E, Walejko G. The participation divide: content creation and sharing in the digital age. Inf Commun Soc 2008;11(2):239–56.
[19] Hohlfeld TN, Ritzhaupt AD, Barron AE, Kemker K. Examining the digital divide in K-12 public schools: four-year trends for supporting ICT literacy in Florida. Comput Educ 2008;51(4):1648–63.
[20] Iivari N, Sharma S, Ventä-Olkkonen L. Digital transformation of everyday life – how COVID-19 pandemic transformed the basic education of the young generation and why information management research should care? Int J Inf Manag 2020;55:102183.
[21] Lavery MPJ, Abadi MM, Bauer R, Brambilla G, Cheng L, Cox MA, Dudley A, Ellis AD, Fontaine NK, Kelly AE, Marquardt C, Matlhane S, Ndagano B, Petruccione F, Slavík R, Romanato F, Rosales-Guzmán C, Roux FS, Roux K, Wang J, Forbes A. Tackling Africa's digital divide. Nat Photonics 2018;12(5):249–52.
[22] OECD. Teaching and learning international survey (TALIS) 2018: principal questionnaire. Paris, France: Organisation for Economic Co-operation and Development (OECD); 2018. Retrieved from, http://www.oecd.org/education/school/TALIS-2018-MS-Principal-Questionnaire-ENG.pdf.
[23] Pagani L, Argentin G, Gui M, Stanca L. The impact of digital skills on educational outcomes: evidence from performance tests. Educ Stud 2016;42(2):137–62.
[24] Ragnedda M, Muschert GW. The digital divide. The internet and social inequality in international perspective. Abingdon: Routledge; 2013.
[25] Reimers FM. Primary and secondary education during Covid-19: disruptions to educational opportunity during a pandemic. Springer Nature; 2022.
[26] Rotondi V, Kashyap R, Pesando LM, Spinelli S, Billari FC. Leveraging mobile phones to attain sustainable development. Proc Natl Acad Sci 2020;117:13413–20.
[27] Scheerder A, van Deursen A, van Dijk J. Determinants of internet skills, uses and outcomes. A systematic review of the second- and third-level digital divide. Telemat Inform 2017;34(8):1607–24.
[28] Sipilä K. Educational use of information and communications technology: teachers' perspective. Technol Pedagog Educ 2014;23(2):225–41.
[29] Strietholt R, Fraillon J, Liaw YL, Meinck S, Wild J. Changes in digital learning during a pandemic–findings from the ICILS teacher panel. International Association for the Evaluation of Educational Achievement (IEA); 2021.
[30] Van Deursen AJAM, Helsper EJ. The third-level digital divide: who benefits most from being online?". Communication and Information Technologies Annual. Studies in Media and Communications. Emerald Group Publishing Limited; 2015. Pp. 29–52 Vol. 10.
[31] Van Deursen AJAM, Helsper EJ, Eynon R. Development and validation of the internet skills scale (ISS). Inf Commun Soc 2016;19(6):804–23.
[32] A.J. Van Deursen, E.J. Helsper, & R. Eynon (2014). Measuring digital skills. From digital skills to tangible outcomes project report. Retrieved from https://www.lse.ac.uk/media-and-communications/assets/documents/research/projects/disto/Measuring-Digital-Skills.pdf.
[33] Van Deursen AJ, van Dijk JA. Internet skill levels increase, but gaps widen: a longitudinal cross-sectional analysis (2010–2013) among the Dutch population. Inf Commun Soc 2015;18(7):782–97.
[34] Van Deursen AJAM, Dijk JAGM. The first-level digital divide shifts from inequalities in physical access to inequalities in material access. New Media Soc 2019;21(2):354–75.
[35] Van Dijk JAGM. The deepening divide: inequality in the information society. SAGE Publications; 2005.
[36] edited by Van Dijk JAGM. A theory of the digital divide. In: Ragnedda M, Muschert GW, editors. The digital divide. Abingdon: Routledge; 2013. p. 29–51. edited by.
[37] Wei KK, Teo HH, Chan HC, Tan BCY. Conceptualizing and testing a social cognitive model of the digital divide. Inf Syst Res 2011;22(1):170–87.