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IS STUDENT DIGITAL COMPETENCE SHAPED BY SCHOOLS OR INDIVIDUAL FACTORS?

Insights from SELFIE using multilevel models

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CEDEFOP

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CHAPTER 1.
Introduction

Europe exhibits large economic inequalities within and between countries, which have been further exacerbated by the COVID-19 crisis. Human capital is an important factor in countering these economic disparities: it has been singled out as the most important factor for economic development (Gennaioli et al., 2013; Diebolt and Hippe, 2019). While many studies continue to work with educational attainment rates, in recent focus the literature has shifted from considering the quantity of education towards its quality, considered to be the key factor for growth (Hanushek and Wößmann, 2015). Competences, as a measure of education quality, have moved into the focus of both researchers and policy-makers.

Digital competences have become ever more important as almost all jobs nowadays need them in Europe (European Commission, 2020d). For this reason, new generations of students need to get the best teaching and learning to make the most of their future. SELFIE (Self-reflection on effective learning by fostering the use of innovative educational technologies) supports schools preparing for the digital age. It is an online self-reflection tool that has been developed by the European Commission together with the education community, including ministries of education, education experts and the schools themselves. It measures schools' digital capacity (European Commission, 2021). SELFIE provides questionnaires on the use of digital technologies at schools that are filled out by school leaders, teachers and students. The questionnaires comprise eight areas that include all relevant topics on digital technology use, such as leadership, continuous professional development, pedagogy or students' digital skills. They can be adapted to the needs of each school, with schools adding their own questions. Based on the responses of all groups, SELFIE generates a school report which provides averages for all items and areas. This report can be used by the school for discussion across the school community and creating an action plan for improvement.

The SELFIE tool is provided by the European Commission, safeguards anonymity of respondents and can be used by any school for free. The tool is available for primary, lower-secondary, upper secondary general, upper secondary vocational and post-secondary non-tertiary education. Between the launch of SELFIE in October 2018 and December 2020, more than 800 000 users from more than 50 countries have already participated.

This large database offers new possibilities to investigate the relative importance of individual, school, regional and national levels in the development of school digital readiness in general, and student digital competences in particular. This paper uses SELFIE data that allow disentangling of these various dimensions to analyse the reasons for differences in students' digital competences. More specifically, it develops a multilevel model aiming to estimate factors that are related to competence differences in the data. For this reason, we consider a range of relevant factors that may be associated with differences in students' digital competences.

The paper is structured as follows. First, we present more details on SELFIE, its questionnaires and database. Subsequently, we provide information on the methods used and our specific research approach. Then, we show our findings. A conclusion sums up the results of the paper.

CHAPTER 2.
Background on competence inequalities

The renewed (2020) European Skills Agenda for sustainable competitiveness, social fairness and resilience emphasises that the COVID-19 'pandemic has accentuated the digital skills gap that already existed and new inequalities are emerging as many people do not have the required level of digital skills or are in workplaces or schools lagging behind in digitalisation' (European Commission, 2020d, p. 3). Closing this gap will be crucial, particularly as almost all European jobs require, at the very least, basic digital skills. However, less than half (44%) of EU-27 citizens still do not have basic digital skills according to the latest data available for 2019 (Eurostat, 2021). There are also important differences among EU populations. The Netherlands has the highest level of basic and above basic digital competence (79%), while around three out of 10 citizens of Romania and Bulgaria do not yet have at least basic digital skills.

Digital skills gaps are caused by more widespread skills gaps that have existed for a long time in Europe. Tackling them is crucial, as inequalities in human capital can be seen as a key factor driving economic differences within countries. Rodríguez-Pose and Tselios (2011) analyse the regional distribution of educational attainment in western Europe countries between 1995 and 2010; their results show that attainment rates are strongly correlated with inequality. However, looking at educational attainment rates is useful: what really matters is what competences are acquired at school. As Hanushek and Wößmann (2015, p. 28) put it, '[…] direct measures of cognitive skills offer a superior approach to understanding how human capital affects the economic fortunes of nations' than education attainment or similar variables (e.g. years of schooling) that measure the quantity of education.

Measuring the quality of education has been made possible by international large-scale student assessments, of which OECD's PISA is the most famous. PISA research shows that there are different factors that influence this quality, as measured by test scores, such as socioeconomic background, school resources and institutional features (OECD, 2016; Hanushek and Wößmann, 2014). At the same time, when the focus is on explaining the inequalities in skills, factors including differences in policies at the system level, expenditure and student and school characteristics appear (Agasisti and Cordero-Ferrera, 2013). For example, when different rounds of PISA are considered together, '[…] countries with greater segregation along socioeconomic lines tend to have lower overall levels of performance and greater between-school differentiation' (Willms, 2006, p. 69).

Factors related to students' background characteristics, social, economic and cultural environment of schools, organisation of the school system, and the quality of teaching and learning may be associated with skills and competence inequalities, particularly at the regional level (Hippe, Jakubowski and Araújo, 2018).

Recent evidence on the COVID-19 pandemic shows that it has led to increases in education inequalities both within and among schools (Maldonado and Witte, 2020). School closures at this scale have been unprecedented in history, and have led to major disturbances in competence provision and acquisition. Particularly vulnerable students were affected, as they did not have the same standards of home equipment and their parents were not able to support them to the same level as other students (Azevedo et al., 2020; Di Pietro et al. 2020; Jaeger and Blaabaek, 2020). Their school's infrastructure related to digital resources may also be less advanced, further contributing to these effects (e.g. Di Pietro et al., 2020). Given the difficulties, parents needed more support and guidance from schools (Vuorikari et al., 2020).

Home schooling lowered students' competence acquisition (Wößmann and Hanushek, 2020; Engzell et al., 2021; Kuhfeld et al., 2020; Kaffenberger, 2020), and thus also their future expected earnings (Azevedo et al., 2020; Psacharopoulos et al., 2020; Di Pietro et al., 2020). Given the expectation that digital education 'is here to stay' after COVID-19, acquiring digital competences will be more important than ever. Understanding what shapes students' digital competences is a key question analysed in this paper.

CHAPTER 3.
The SELFIE tool, questionnaires and database

SELFIE was included as an action in the Digital Education Action Plan (DEAP), 2018-20 (European Commission, 2018) and its success is also mentioned in the new DEAP 2021-27 (European Commission, 2020a). The tool is also part of the Council Recommendation on vocational education and training (VET) for sustainable competitiveness, social fairness and resilience, which supports 'qualitative and effective digitalisation of VET provision in both school-based and work-based learning through promoting the use of European competence frameworks and self-assessment tools' (European Commission, 2020b, p. C 417/9). SELFIE is also a recommended tool of the ET2020 Working Group for VET (European Commission, 2020c).

The SELFIE tool includes questionnaires for school leaders, teachers and students on the use of digital technologies in schools. It allows them to conduct a self-reflection exercise which reveals a schools' strength and points for improvement, providing a school report which is a snapshot of the school's state of play in digital education. This report can kick off a process of reflection at the school level by discussing the results and creating an action plan that can also be monitored by conducting SELFIE on a regular basis.

SELFIE's questionnaires have been evolving over time, as new incoming data have allowed to test their properties and conduct changes to enhance them (for general education: Costa et al., 2020; for VET: Hippe, Pokropek and Costa, 2021). This means that not always all items are included in all sessions (1-7), with some being removed or added. Changes are relatively minor, so most core items are available throughout the entire time period: core items are those questions that are mandatory. The SELFIE tool also includes questions that are optional, so that schools can decide whether they would like to add them for their school community.

Optional questions include some that are relevant to the research questions, but observation numbers (in terms of schools and participants) are lower.

Participating in SELFIE is voluntary for schools and responses are collected anonymously, as data privacy is a core foundation and principle of SELFIE. This means that the sample is not representative at the regional or national level. This always needs to be born in mind when interpreting the data and reaching conclusions.

CHAPTER 4.
Methodology

4.1. Variables

We use those questions in SELFIE that have been answered by students. We focus our analysis on all areas where we have several student questions. These areas are four in SELFIE: infrastructure; pedagogy, implementation in the classroom; assessment practices; and student digital competence (Table 1).

Table 1. **Items used for student indices**

SELFIE area	Short title
Infrastructure	Internet access Technical support Digital devices for learning
Pedagogy: implementation in the classroom	Tailoring to students' needs in school Fostering creativity Engaging students Student collaboration Cross-curricular projects
Assessment practices	Assessing skills in school Timely feedback in school Self-reflection on learning
Student digital competence	Safe behaviour Responsible behaviour Checking quality of information Giving credit to others' work Creating digital content Learning to communicate

Source: Authors, based on European Commission (2021).

We also consider teachers' variables (Table 2.). For teachers we use variables from leadership, collaboration and networking, CPD (continuous professional development) and pedagogy: supports and resources.

Individual variables in all areas have been put together by constructing indices both at the student and at the school level. We have also constructed a teacher experience variable, averaged over schools, which could be related to our outcome variable.

Table 2. **Items used for teacher indices**

SELFIE area	Description
Leadership	Digital strategy Strategy development with teachers New ways of teaching
Collaboration	Progress review Discussion on the use of technology
CPD	CPD needs Participation in CPD Sharing experiences
Pedagogy: supports and resources	Online education resources Creating digital resources Using virtual learning environments Communicating with the school community

Source: Authors, based on European Commission (2021).

4.2. Statistical methods

Our analysis starts with descriptive statistics and linear regression models. These results serve as an introduction to the multilevel analysis. Using linear regression models, we test if the results are robust to different specifications and subsamples. We compare results for all schools that have participated in SELFIE and schools from EU countries only. We also compare results by ISCED level and programme type, to see if the estimated relationships are similar across various types of schools and for students at different ages. Finally, we compare results with and without controlling for SELFIE session number and school closures during the pandemic (using the UNESCO data on school closures). We expect that relationships between student digital competences and explanatory variables should not change depending on the sample taken and regression specification. If there are any important differences between results obtained for school types or samples, these should be taken into account when developing the multilevel model for the whole dataset.

Multilevel regression models are well-suited to the analysis of education data because they recognise the hierarchical structure of the data, with students nested in schools. The associations with student digital competence can be also decomposed into within-school and between-school associations. The model can control for school-level and country-level factors, allowing estimation of average relationships between student-level factors and digital competences, after controlling for differences between schools and countries.

The basic two-level model with random effects at the school level can be described by two equations. The first describes the model for the student-level, where *i* is an index for students and j is an index for schools:

$$Y_{ij} = \beta_{0j} + \beta_1 X_{ij} + e_{ij}.$$

In this equation, Y_{ij} (the outcome variable) is student digital competence. X_{ij} is a vector of student-level predictors of student digital competence and e_{ij} is a student-level error.

The second level equation describes school level intercepts:

$$\beta_{0j} = \gamma_{00} + \gamma_{01} W_j + u_{0j}$$

where W_j is a school-level explanatory variable (or a set of variables) and u_{0j} is a school random error component.

To decompose the associations into within- and between-school effects in the multilevel models, the student-level variables used as predictors in the multilevel model need to be centred at school averages (i.e. the student-level variables are deviations from school means). After centring, variables at the student level explain outcome differences across students within schools, while variables at the school level explain performance differences between schools. This model also allows decomposing variance into within- and between-school variance to see how much of performance difference is explained by the model at both levels. These estimates are also of interest as we want to see how student digital competences vary between schools and between students within the same schools: if digital competences are shaped by individual or school-level factors.

An extension of this model would be to look at the regional and national levels to see if regions or whole countries play an important role in shaping digital competences, improving infrastructure, or spreading teaching practices and innovations that are positively viewed by the students. To test it, we employ a three-level model with regional random effects added similarly to school-level effects. We use this model to decompose variance into individual, school, and regional or national levels, and to see if additional effects at the regional or national level affect estimated relations for student- and school-level variables.

We use data from the SELFIE database (European Commission, 2021) and analyse the SELFIE results stemming from all user groups (school leaders, teachers and students). In this way, we are also able to identify the heterogeneity in responses among the various groups.

For this reason, we use data from all available education levels (five levels from ISCED 1-4). As we have various education levels included in the database, we may see differences in the impact among them and compare them. However, sample size is low in some levels (particularly post-secondary non-tertiary education) which limits our possibilities of analysis. The different levels also serve as a robustness check that findings from one level can be interpreted to be more general results that affect similarly all education levels.

The SELFIE database includes information on the location of schools at the regional and national levels. The regional data is composed of NUTS (Nomenclature of Territorial Units of Statistics) regions, which is the official classification of regions in the European Union. These data allow us to contrast regional and national levels in our analysis.

CHAPTER 5.
Results

5.1. Descriptives

Table 3 provides basic statistics for the variables analysed. Student and teacher indices are standardised, so their means are close to zero and standard deviation is close to 1 for the full sample of individual observations. While for students we use individual observations in the multilevel and regression models, for teachers we first collapsed the data to school-average means to link them with student data. The basic statistics reflect the fact that these variables were often averaged across several teachers from one school and their standard deviation might be lower than 1.

Table 3. **Basic statistics for variables used in regression and multilevel models**

Variables	Mean	Standard deviation	Min	Max	N
Students					
Index of digital competences (outcome variable)	0.00	1.00	-4.56	4.94	654 206
Index of digital infrastructure	0.00	1.00	-4.79	4.58	655 253
Index of pedagogy	0.00	1.00	-4.42	5.09	655 210
Index of assessments	0.00	1.00	-4.02	4.54	497 826
Schools					
Teacher experience (school average)	5.39	0.77	1	7	656 841
Index of leadership	0.01	0.60	-3.02	2.46	657 002
Index of professional collaboration	0.03	0.63	-2.90	2.13	657 005
Index of professional development	0.02	0.61	-3.56	2.24	657 001
Index of pedagogy - supports and resources	0.04	0.55	-3.68	2.97	657 020
Combined index of leadership and professional collaboration and development	0.02	0.59	-2.97	1.92	656 968
School type					
ISCED1	0.24	0.43	0	1	657 020
ISCED2	0.37	0.48	0	1	657 020
ISCED3 general	0.20	0.40	0	1	657 020
ISCED3 VET	0.18	0.38	0	1	657 020
ISCED4	0.02	0.12	0	1	657 020

Source: Authors.

5.2. Results from the multilevel analysis

Table 4 shows results of linear regression analysis explaining student self-reported digital competences with student-level and school-level variables. Regression (1) differs from (2) and (3) by inclusion of student digital assessment index. As data for this index were not collected for primary schools, regressions (2) and (3) include this index among explanatory variables, but that means that data for primary school are automatically excluded from the analysis. There is a similar difference between regression (4) and regressions (4) and (6), which, in addition, are estimated with country fixed effects. Regressions (2) and (3), and regressions (5) and (6), differ in the way teacher-provided data are included. In regressions (2) and (5) all four indices based on teacher responses are included. However, indices of leadership, professional development and professional collaboration are collinear (Pearson correlation around 0.8), which do not allow to disentangle their effects in regression analysis. In regressions (3) and (6) these three indices were replaced by the average index of leadership, professional development and collaboration, to capture its overall association with student digital competences.

All three student-level indices are significantly and positively related to student digital competences. In regression (1) and (4) without the index of digital assessments, the coefficient for the index of pedagogy is larger than for the index of infrastructure. However, that effect disappears after inclusion of the index of digital assessments in regression (2), (3), (5) and (6) where the highest coefficient is estimated for the index of assessments, and pedagogy and infrastructure both have similar and lower coefficients. Note that the addition of country fixed effects does not change the results for indices reflecting student perception of infrastructure, pedagogy and assessment. The results are almost the same, suggesting that between-country differences do not play a significant role here. Also, additional regressions performed with fixed effects for SELFIE session and controlling for school status during the pandemic (open, partially open, or fully closed) yielded very similar results and are not presented here for brevity.

The estimated coefficients suggest that higher digital competences are reported by students who also have a positive opinion about school digital infrastructure and adaptation of pedagogy to digital teaching, and even more by those who often use digital assessments. While we cannot claim any causal relationship, the results show that digital competences are higher among students who also have positive opinions or experiences in these three areas, especially in digital assessment.

The results show that teacher-level indicators are, in most cases, not associated with student digital competences or that they have only weak relationship. In all regressions, coefficient for teacher experience is close to zero.

Index of leadership is negatively associated in model (1), but the coefficient is small and it is insignificant after inclusion of digital assessments index or in the models with country fixed effects. Index of professional collaboration has significant and positive relationship to digital competences, but is close to zero after inclusion of country fixed effects. Index of professional development is significantly but negatively related to competences, but the coefficient is relatively small, and it is indistinguishable from zero after inclusion of country fixed effects. In regressions (3) and (6) with these three indices combined into one measure, the results show insignificant relationship with student digital competences. For the teachers index of pedagogy coefficients are very close to zero. In general, in regressions with country fixed effects all the school-level coefficients are insignificant or very close to zero when statistically significant.

These results suggest that only student-level variables show significant relationship with student digital competences. The regression results also provide estimates for differences between various school levels and types. Interestingly, primary and lower secondary school students report higher digital competences in all regressions. In models (1) and (4), dummy indicators for all ISCED levels and types are negative as they are compared to the baseline category of primary school students. In models (2), (3), (5) and (6) the baseline category is lower secondary school students as primary school students are excluded. The negative coefficients for higher levels of schooling are smaller, but significant. These results suggest that older students are less positive about their digital competences.

In all regression the percentage of explained variance (r-squared) is relatively high and ranges from 57 to 66%. Adding digital assessments to the set of explanatory variables increases share of explained variance, while the results with country fixed effects show similar explanatory power as those without controlling for between-country differences.

Table 4. **Results for linear regression analysis explaining student digital competences**

Variables	(1)	(2)	(3)	(4)	(5)	(6)
Students						
Students: digital infrastructure	0.33***	0.25***	0.25***	0.35***	0.26***	0.26***
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
Students: pedagogy	0.44***	0.23***	0.23***	0.43***	0.23***	0.23***
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
Students: assessments		0.41***	0.41***		0.40***	0.40***
		(0.00)	(0.00)		(0.00)	(0.00)

	(1)	(2)	(3)	(4)	(5)	(6)
Teachers						
Teacher experience: (school average)	0.01*	0.00	0.00	0.01**	0.01***	0.01***
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
Teachers: leadership	-0.08***	0.01		-0.02	-0.01	
	(0.01)	(0.01)		(0.01)	(0.01)	
Teachers: professional collaboration	0.16***	0.06***		0.02	-0.01	
	(0.01)	(0.01)		(0.01)	(0.01)	
Teachers: professional development	-0.04**	-0.06***		0.00	0.00	
	(0.01)	(0.01)		(0.01)	(0.01)	
Teachers: combined index of leadership and professional collaboration and development			0.00			-0.02*
			(0.01)			(0.01)
Teachers: pedagogy - supports and resources	0.01	0.00	0.01	-0.01	-0.02*	-0.02*
	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)
ISCED 1 (based category for regressions (1) and (4)						
ISCED 2 (based category for regressions (2) (3) (5) and (6)	-0.08***			-0.11***		
	(0.01)			(0.01)		
ISCED 3 general	-0.20***	-0.09***	-0.09***	-0.21***	-0.08***	-0.08***
	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)
ISCED 3 VET	-0.18***	-0.12***	-0.13***	-0.20***	-0.12***	-0.12***
	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)
ISCED 4	-0.18***	-0.15***	-0.15***	-0.23***	-0.15***	-0.15***
	(0.01)	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)
Constant	0.05*	0.00	0.00	0.08***	-0.08**	-0.08**
	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)
Country fixed effects				Yes	Yes	Yes
N	652 738	496 696	496 696	652 738	496 696	496 696
R2	0.572	0.656	0.656	0.580	0.661	0.661

NB: Robust cluster standard errors in parentheses; * p<0.05, ** p<0.01, *** p<0.001
Source: Authors.

Table 5 provides results of similar regression analysis but limited to data from EU countries. Results are similar. For student-level indices, the estimated coefficients are identical. For teachers, the estimated coefficients are only slightly different but, in general, the relationships are qualitatively the same, showing lack of relationship between teacher-level indices and student digital competences. Also, the predictive power of the models is almost the same. That robustness check shows that we can proceed with all SELFIE data and benefit from a larger sample size as the relationships between variables are highly similar in the sub-sample of EU countries. That could be expected, noticing that regressions with country fixed effects yield similar results, so the differences between countries are less important that differences between students and schools. This is a finding on its own, showing that SELFIE data describe student- and school-level relationships that can be generalised to various groups of countries.

Table 5. **Results for linear regression analysis explaining student digital competences for EU countries only**

Variables	(1)	(2)	(3)	(4)	(5)	(6)
Students						
Students: digital infrastructure	0.33***	0.25***	0.25***	0.34***	0.26***	0.26***
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
Students: pedagogy	0.44***	0.23***	0.23***	0.42***	0.23***	0.23***
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
Students: assessments		0.40***	0.40***		0.40***	0.40***
		(0.00)	(0.00)		(0.00)	(0.00)
Teachers						
Teacher experience (school average)	0.03*	0.01**	0.01*	0.01**	0.01**	0.01**
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
Teachers: leadership	-0.04***	0.03*		-0.01	-0.01	
	(0.01)	(0.01)		(0.01)	(0.01)	
Teachers: professional collaboration	0.12***	0.04**		-0.01	0.01	
	(0.01)	(0.02)		(0.01)	(0.01)	
Teachers: professional development	-0.04**	-0.07***		0.00	-0.02	
	(0.01)	(0.01)		(0.01)	(0.01)	
Teachers: combined index of leadership and professional collaboration and development			0.00			-0.02
			(0.01)			(0.01)
Teachers: pedagogy - supports and resources	0.01	-0.01	-0.01	0.00	-0.02**	-0.03**
	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)
ISCED 1 (based category for regressions (1) and (4)						
ISCED 2 (based category for regressions (2) (3) (5) and (6)	-0.11***			-0.13***		
	(0.01)			(0.01)		
ISCED 3 general	-0.22***	-0.09***	-0.09***	-0.23***	-0.08***	-0.08***
	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)
ISCED 3 VET	-0.20***	-0.13***	-0.13***	-0.21***	-0.12***	-0.12***
	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)
ISCED 4	-0.24***	-0.15***	-0.14***	-0.25***	-0.15***	-0.15***
	(0.01)	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)
Constant	-0.05*	-0.09***	-0.07**	0.05*	-0.09***	-0.09***

Variables	(1)	(2)	(3)	(4)	(5)	(6)
	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)
Country fixed effects				Yes	Yes	Yes
N	465 316	342 773	342 773	465 316	342 773	342 773
R2	0.555	0.641	0.641	0.562	0.646	0.646

NB: Robust cluster standard errors in parentheses; * p<0.05, ** p<0.01, *** p<0.001
Source: Authors.

Table 6 and Table 7 show separate regression analysis for different school types. We did not include the index of digital assessment in these regressions to allow comparisons with primary school students. The results show much stronger association between explanatory variables in our model for older students. In primary school, our model is able to explain 42% of differences in student digital competences, while in ISCED 4 schools and ISCED 3 VET schools it explains 65-67% of variance. In ISCED 2 and ISCED 3 general schools it explains 57-58% of variance.

In all school types, digital competences are positively associated with indices of digital infrastructure and pedagogy. The estimated coefficient for the index of pedagogy is higher, suggesting that this aspect of digital teaching is more strongly associated with competences. Both indices show weaker association in primary schools.

For teacher-level indices the results are mixed, but in all cases the estimated coefficients are much lower and are less consistent across different school types than for the student-level indices. Only the index of professional collaboration shows consistent and larger positive effects, especially for ISCED 3 and 4 schools. However, all coefficients for teacher-level indices become significant after inclusion of country fixed effects. This, again, suggests that while student-level relationships are not related to between-country differences, it is the opposite for teacher-level indices, which seem to be mostly driven by variation across countries. However, the inclusion of country fixed effects does not change the explanatory power of our models, which suggests that student digital competences are mostly related to individual differences and to school- or country-related factors.

Table 6. **Regression results for different school types**

Variables	ISCED 1	ISCED 2	ISCED 3 general	ISCED 3 VET	ISCED 4
Students: digital infrastructure	0.27***	0.35***	0.35***	0.37***	0.37***
Students: pedagogy	0.34***	0.44***	0.46***	0.49***	0.52***
Teacher experience (school average)	0.01	0.05***	0.06***	0.04**	0.02

Variables	ISCED 1	ISCED 2	ISCED 3 general	ISCED 3 VET	ISCED 4
Teachers: combined index of leadership and professional collaboration and development	0.01	0.06***	0.05**	0.04	-0.02
Teachers: pedagogy - supports and resources	0.12***	-0.01	-0.02	-0.03	-0.02
Constant	0.04	-0.08*	0.02	-0.08	-0.11
r2	0.42	0.57	0.58	0.64	0.67
N	154 111	242 446	128 453	118 044	9 684

NB: Robust cluster standard errors in parentheses; * p<0.05, ** p<0.01, *** p<0.001
Source: authors.

Table 7. **Regression with country fixed effects for different school types**

Variables	ISCED 1	ISCED 2	ISCED 3 general	ISCED 3 VET	ISCED 4
Students: digital infrastructure	0.28***	0.35***	0.37***	0.38***	0.37***
Students: pedagogy	0.33***	0.43***	0.45***	0.48***	0.52***
Teacher experience (school average)	0.01*	0.02***	0.02	0.00	0.00
Teachers: combined index of leadership and professional collaboration and development	0.04***	0.01	-0.03	-0.04*	-0.03
Teachers: pedagogy - supports and resources	0.03**	-0.01	-0.03	0.02	0.00
Constant	0.04	-0.08*	0.02	-0.08	-0.11
r2	0.42	0.57	0.58	0.64	0.67
N	154 111	242 446	128 453	118 044	9 684

NB: Robust cluster standard errors in parentheses; * p<0.05, ** p<0.01, *** p<0.001
Source: Authors.

The relationship between student-level and school-level factors can be directly analysed using multilevel models. Table 8 presents results of the model with all students and school types that have participated in SELFIE. The student level variables were re-calculated before the analysis to have mean of 0 for each school. Thus, they were recentred around school mean to reflect within-school differences between students. The results for the three student-level indices and their within-school effects suggest that the positive relationship with student competences holds also within schools. Students with relatively positive perception of digital infrastructure, pedagogy, and the use of assessments also report relatively higher digital competences. The coefficients are again stronger for digital assessments, suggesting that is a critical area in relation to digital competences.

The same student-reported indices can be averaged at the school level to estimate between-school effects. These coefficients represent how average values of these indices are associated with average values of student-reported digital competences across schools. Also, here the estimated coefficients are positive and highly significant, but the coefficients for digital assessments are similar to those estimated for the index of pedagogy, and only slightly higher than those for digital infrastructure. Overall, however, the results show almost equally strong relationship at the student level within schools as between schools. Variables based on teacher reports show much smaller, and mostly insignificant effects.

In regressions (2)-(6) additional information about schools was added to explain differences in school mean level of student digital competences. In all regressions dummy indicators for ISCED level and school type were added, yielding similar results to those obtained with linear regression and suggesting more positive reports of digital competences among primary school students. A dummy denoting school funding sources was also added, with value 0 for schools funded mostly from public sources (government, local government or other authorities) and 1 for schools funded mostly from non-public sources (student fees, charges, donors, etc.). The difference between these school types is insignificant in most regressions except the last, where a small disadvantage for non-public schools was found. However, these results generally show lack of difference in self-reported student digital competences between schools with different sources of funding, even after controlling for all indicators and country fixed effects.

The multilevel models provide estimates of variance at each level of analysis. The so-called empty model (1) provides decomposition of raw variance in student self-reported digital competences into student- and school-level variation. This model, without any explanatory variables, shows that a quarter of the total variance is associated with differences between schools, while the remaining variance is at the individual student level. Model (2), with country fixed effects, shows that inclusion of country fixed effects explains 19.5% of school-level variance; the remaining 80% of school-level variance is not associated with fixed country characteristics. While these results show significant differences between schools, in general they demonstrate that most variation in digital competences is at the individual level.

Comparing model (1) to (3), (4), (5), and (6), we can estimate how well our variables are able to explain variance in digital competences at the two levels of analysis. At the school level, our models explain 85-91% of the variance. Thus, the variables in the model explain almost all variation between schools in self-reported student digital competences. At the individual level the models are also quite powerful, explaining from 48 to 57% of student-level within-school variation in digital competences. The model (6) which has the highest explanatory power, leaves less than 10% of the initial variation among schools unexplained, while at the individual level it leaves 43% of the initial variation unexplained. Using SELFIE data we can explain nearly all differences in student digital competences between schools, and most of student-level differences.

Table 8. **Results for the multilevel model with students nested in schools**

Variables	(1)	(2)	(3)	(4)	(5)	(6)
Within-school student-level effects						
Students: digital infrastructure			0.36***	0.36***	0.27***	0.27***
			(0.00)	(0.00)	(0.00)	(0.00)
Students: pedagogy			0.43***	0.42***	0.22***	0.22***
			(0.00)	(0.00)	(0.00)	(0.00)
Students: assessments					0.41***	0.41***
					(0.00)	(0.00)
Between-school effects						
School-average student opinion about infrastructure			0.18***	0.24***	0.20***	0.22***
			(0.01)	(0.01)	(0.01)	(0.01)
School-average student opinion about pedagogy			0.60***	0.53***	0.33***	0.33***
			(0.01)	(0.01)	(0.01)	(0.02)
School-average student opinion about assessment					0.36***	0.34***
					(0.01)	(0.01)
School-average teacher experience			0.02***	0.02***	0.02***	0.02***
			(0.01)	(0.01)	(0.01)	(0.01)
School-average teacher combined index of leadership and professional collaboration and development			0.05***	0.01*	-0.01	-0.03*
			(0.01)	(0.01)	(0.01)	(0.01)
School-average teacher index of pedagogy - supports and resources			0.00	0.00	-0.02***	-0.03***
			(0.01)	(0.01)	(0.01)	(0.01)
Schools funded from non-public resources (=1; 0 for all other schools)			0.01	-0.01	-0.02	-0.04***
			(0.01)	(0.01)	(0.01)	(0.01)
Constant	0.06***	-0.41***	0.06**	-0.09***	0.01	-0.10***
	(0.01)	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)
Dummies denoting different school type (ISCED level and type)			Yes	Yes	Yes	Yes
Country fixed effects		Yes		Yes		Yes

	(1)	(2)	(3)	(4)	(5)	(6)
Variance components						
Variance at the school level	0.256	0.206	0.038	0.030	0.026	0.022
Variance at the student level	0.751	0.751	0.392	0.392	0.323	0.323
Share of variance at the school level	25.4%	21.5%	8.8%	7.1%	7.4%	6.4%
Share of variance explained at the school level		19.5%	85.2%	88.3%	89.8%	91.4%
Share of variance explained at the student level		0.0%	47.8%	47.8%	57.0%	57.0%
Number of students	654 206	654 206	652 738	652 738	496 696	496 696
Number of schools	7 137	7 137	7 122	7 122	4 635	4 635

NB: Standard errors in parentheses; * p<0.05, ** p<0.01, *** p<0.001
Source: Authors.

Finally, we estimate the same multilevel model but with regional and country effects added. Results are presented in Table 9. First note the variance decomposition estimates at the bottom of the table. The estimated variance for school effects is highly similar to the model (2) from Table 8, which controls for country fixed effects. The estimated country-level variance is relatively low and explains only 4.6% of the total variance in student-reported digital competences. Estimated regional variance is even lower and explains only 1.7% of the total variance. Around 6.3% of the variation is associated with country or region effects, while 21% is associated with between-school differences within countries and regions, and the rest is individual student-level effect.

The student-level coefficients are highly similar to those presented in column (4) of Table 8, so the inclusion of country and region effects did not change the relationships at the student level. Also, school-average responses of students are similarly associated with digital competences with indicators derived from teacher questionnaires barely related to student outcomes.

Estimates for country and regional average values, which were not included in the previous model, are of interest. None of the region-level effects is statistically significant, which is not surprising considering how little variance is explained by this level of analysis. However, for country-level effects, the indices reflecting teacher experience and teacher pedagogical support are significant. The first is negatively associated with digital competences at country level. This is interesting, as at the school level we estimated a small, but positive effect of teacher experience. One possible explanation for this is that teacher experience correlates with age and at the country level an older teacher workforce might be correlated with lower usage of digital tools, but this is just a hypothesis that would require further investigation.

The strongest association at the country level is between student average digital competences and the average value for the index of teacher pedagogical support and resources. This index is not positively related to student outcomes at the school level but is strongly related to digital competences when variation between countries is compared. A reasonable explanation for this is that, while differences between individual teachers in their opinion about pedagogical support and resources is not related to student learning, for the whole country it makes a difference if teachers are more supported and have sufficient resources. This is an important finding, which also suggests that country policies and support matters for student digital competences.

The model also explains a similar share of variance at the student and school level to the model presented in Table 8, but without regional and country random intercepts. The variance between regions and countries is relatively small, but it is almost entirely explained by the model. The remaining unexplained variance, after inclusion of all explanatory variables, is smaller than 1% at the country level and around 0.2% at the regional level. Thus, the model has a high predictive power considering differences in student self-reported digital competences between countries and regions.

Table 9. **Results for the multilevel model with students nested in countries, regions, and schools**

Variables	(1)	(2)	(3)
Within-school student-level effects			
Students: digital infrastructure		0.36***	0.36***
		(0.00)	(0.00)
Students: pedagogy		0.41***	0.41***
		(0.00)	(0.00)
Between-school effects			
School-average student opinion about infrastructure		0.25***	0.26***
		(0.01)	(0.01)
School-average student opinion about pedagogy		0.54***	0.54***
		(0.01)	(0.01)
School-average teacher experience		0.02***	0.02***
		(0.00)	(0.00)
School-average teacher index of pedagogy - supports and resources		-0.02***	-0.03***
		(0.01)	(0.01)
School-average teacher combined index of leadership and professional collaboration and development		0.01	0.01
		(0.01)	(0.01)

Variables	(1)	(2)	(3)
Schools funded from non-public resources (=1; 0 for all other schools)		-0.00	-0.00
		(0.01)	(0.01)
Between-region effects			
Region-average student opinion about infrastructure			-0.02
			(0.05)
Region-average student opinion about pedagogy			-0.07
			(0.08)
Region-average teacher experience			0.00
			(0.02)
Region-average teacher index of pedagogy - supports and resources			-0.02
			(0.04)
Region-average teacher combined index of leadership and professional collaboration and development			0.06
			(0.04)
Between-country effects			
Country-average student opinion about infrastructure			-0.12
			(0.09)
Country-average student opinion about pedagogy			0.07
			(0.13)
Country-average teacher experience			-0.11**
			(0.04)
Country-average teacher index of pedagogy - supports and resources			0.38***
			(0.09)
Country-average teacher combined index of leadership and professional collaboration and development			-0.11
			(0.07)
Constant	0.03	-0.01	0.59**
	(0.04)	(0.03)	(0.20)
Dummies denoting different school type (ISCED level and type)	Yes	Yes	Yes
Variance components			
Variance at the country level	0.045	0.019	0.008
Variance at the region level	0.017	0.002	0.002
Variance at the school level	0.207	0.034	0.034
Variance at the student level	0.713	0.379	0.379

Variables	(1)	(2)	(3)
Share of variance at the country level	4.6%	4.4%	1.9%
Share of variance at the region level	1.7%	0.5%	0.5%
Share of variance at the school level	21.1%	7.8%	8.0%
Number of students	537 237	535 773	535 773
Number of countries	47	46	46
Number of regions	180	179	179
Number of schools	6 168	6 154	6 154

Source: Authors.

CHAPTER 6.
Discussion and conclusions

Differences in competences have been pointed out by the related literature as being a fundamental factor for economic inequalities. More specifically, differences in digital competences are nowadays seen as one of the major factors shaping future inequalities in labour market prospects, social cohesion, or public participation. Therefore, it is crucial to understand them better to ensure that inequalities in Europe do not growth in the future. For this reason, in this paper we have used data from the European Commission's SELFIE tool and developed a statistical model to explain observed differences in students' digital competences.

The results show that students' self-reported digital competences are associated with student perceptions of digital infrastructure, pedagogy, and assessments. Students who report that infrastructure is sufficiently well-developed, that pedagogy recognises new possibilities opened up by technology, and that assessments are often conducted using digital tools, are more often reporting higher digital competences. That is expected, as a combination of investments into infrastructure, pedagogy, and the use of technology for assessments are seen as major factors supporting development of digital competences in schools. Still, the results indicate, using the largest volume of up-to-date data from students and schools across Europe and beyond, that this understanding of how student competences are developed is correct. The results also show that this combination of support for student learning of digital skills is not equally distributed across students and schools, so it requires further policy considerations.

The individual student-level effects are strengthened through school-level associations of average student responses. In schools where most students provide positive responses about digital infrastructure, pedagogy, and the use of assessments, more students also provide positive self-reports about their digital competences. The associations are even stronger at the school level, suggesting there is a large compositional effect of these factors.

The research also shows a puzzling result: similar factors measured through teacher responses are not associated with school-average student digital competences. Teacher-related variables are mostly insignificant and do not show a clear role towards student digital competence. These results seem to be robust to different model and sample specifications, although some regressions suggested that between-country differences could play a role here as the inclusion of country fixed effects has changed the results visibly.

To investigate these results further, we estimated four-level multilevel models with region and country effects added. This model allows for decomposition of the total variation in student self-reported digital competences into individual, school, region, and country differences. Estimates show that while most of the variation is at the individual level, more than 6% can be related to region or country differences, and around 21% to further differences between schools. Estimates from these models replicate previous results when it comes to individual and school effects. However, they show that pedagogical support and investment in digital resources as perceived by teachers is associated with differences between countries in student digital competences. While differences between schools in teacher perception of the support they received are not associated with student competences, it is different for the differences between countries; this can partly be explained by varying support for teachers, or at least in their perception.

Policies that support teacher pedagogy and access to resources when it comes to digital tools are associated with between-country differences, but cannot explain differences between schools within countries. That suggests that country policies do differ in their impact on teachers and possibly also student learning of digital competences. Within countries, schools receive similar support or, at least, the perceived differences are not associated with student digital competences.

To sum it up, differences between countries, schools, and students are associated with student self-reported competences. Individual perceptions of students of infrastructure, pedagogy and assessments are strongly related to their reports of digital competences. At the school-level, only student aggregates explain variation in student reported digital competences, but teacher-reported indicators are not significant. At the country-level, however, perceived support for teacher pedagogy and digital resources is associated with between-country differences in student competences. With the variables used in our data set, we can explain a large part of the total variance in student self-reported digital competences, and nearly all the differences between schools, regions, and countries.

Policy-makers need to be aware of the repercussions that the COVID-19 pandemic has had and act quickly to remedy the negative effects it has had on inequality in students' digital competences. Providing sufficient digital equipment, improving pedagogy and conducting assessment using digital technologies may be central to ensuring that students have the competences they need for the future. Our results indicate that the individual needs of all students must be addressed, and digital education has long been considered potentially to offer more individualised learning opportunities that allow learning to take place with the methods and the rhythm that each student fits best. Student-centred and more personalised teaching and learning may offer great opportunities for improving students’ digital competence. However, the results also suggest that differences in the support teachers receive between countries is also associated with student outcomes in terms of digital skills.

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IS STUDENT DIGITAL COMPETENCE SHAPED BY SCHOOLS OR INDIVIDUAL FACTORS?

Insights from SELFIE using multilevel models

SELFIE for schools is a free online self-reflection tool which supports schools going digital. Its questionnaires ask school leaders, teachers and students about their opinions on the use of digital technologies for teaching and learning. In this paper, we examine whether digital competences of students vary more at the country, regional, school or individual level and what factors are associated with differences in competences at each level. The results show substantial variance at the school level but student digital competences are associated with other student-related factors, particularly digital infrastructure, pedagogy and assessments, and with school averages of these factors. Teacher-related variables are mostly insignificant and between-country differences are not important for the relationship between digital competences and other factors. Overall, the results show that individual level differences are the most important but composite peer effects also play a role in shaping digital competences.

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