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KEYWORDS

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Discussion Paper Series

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Discussion paper n. 38/2025

Luca Bungaro (a), Mariagiulia Matteucci (a), Stefania Mignani (a): (a) University of Bologna

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Assessing inequalities in students' digital skills before and after the pandemic: A multilevel quantile regression approach

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Abstract

Using data from the 2018 and 2023 International Computer and Information Literacy Study, this study investigates inequalities in digital skills among eighth-grade students in Italy through an innovative integration of multilevel modeling and quantile regression, which provides deeper insights into the distributional dynamics of digital competencies. The study examines the influence of socio-demographic factors, ICT usage habits, self-efficacy and school environment on digital literacy. A multilevel quantile regression is used to a) examine the gaps in the whole distribution of digital literacy, not just at the mean, and b) take into account the hierarchical structure of the data, where students are nested within schools. The results show significant territorial disparities, with Northern and Central regions outperforming the South. Gender differences favour females at average levels of digital literacy but diminish at the extremes of the distribution. Socio-economic background and educational aspirations emerge as key predictors of digital literacy. Classroom use of general digital applications has a positive effect on low-achieving students, while specific applications show a negative association that warrants further investigation. The school effects are more pronounced for students with low to moderate levels of competence. Between 2018 and 2023, average performance improved; however, underlying inequalities, particularly territorial disparities, persisted and in some cases even worsened. The pandemic-induced digitalization of education did not lead to uniform gains in digital competence but rather exacerbated existing gap. These findings highlight the urgent need for tailored policies to address regional disparities, promote digital inclusion and optimise ICT education.

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1. Introduction

The digital transformation and widespread adoption of information and communication technologies (ICTs) are revolutionizing society, making digital skills essential for social participation and personal development. There is considerable optimism surrounding children and young adults, who are often seen as a generation ready to embrace digital knowledge and equipped with the necessary digital skills to succeed in future employment opportunities (European Commission, 2021).

With the pervasive integration of digital tools and platforms into both formal and informal learning environments, the ability to navigate and use technology has become a fundamental requirement for students to succeed academically and professionally. The ability to effectively use digital resources not only enhances students' access to information and knowledge, but also fosters essential competencies such as critical thinking, problem solving and collaboration. The COVID-19 pandemic has further highlighted this necessity, emphasizing the importance of digital literacy in managing distance learning and adapting to changes in the digital world. The need to respond to the emergency has led to innovative educational practices that would have been unlikely to materialise in such a short time. At the same time, it has highlighted significant challenges in terms of usability and quality of experience.

To promote training projects and appropriate policies, it is necessary to assess the level of competence achieved at a given level of education. This process first requires a definition of digital skills and a standardised tool to measure them at a given point in time. It is important to bear in mind that technological development changes very rapidly, and it is therefore essential to adopt an approach that allows the level of skills to be monitored over time, even when referring to the same age group. The Digital Competence Framework for Citizens, also known as *DigComp* (Vuorikari et al., 2022; Wild & Schulze Heuling, 2021), provides a common language to identify and describe what it means to be digitally literate in an increasingly globalised and digital world (Van den Brande, 2016). Digital literacy consists of the following dimensions: technical, information and data literacy, communication and collaboration, digital content creation, safety, critical thinking and problem solving (Scheerder et al., 2017; Scherer et al., 2017; Van Deursen et al., 2016). Each area involves a specific position with regard to what requirements and efforts the school system should include in order to qualify students for digital societal conditions (Svendsen & Svendsen, 2021; Tamborg et al., 2018; Livingstone et al., 2023).

This paper focuses on the results of the International Computer and Information Literacy Study (ICILS), a large-scale international survey conducted by the IEA (International Association for the Evaluation of Educational Achievement) on digital skills at the end of the first cycle of compulsory education in grade 8 (Fraillon et al., 2019). Based on the idea that it is now essential to participate in everyday life to know how to use information and communication technologies responsibly, the survey aims to investigate the extent to which children exposed to the use of computers, tablets and smartphones from an early age are actually experts in their use. The first edition of the study was conducted in 2013, although Italy did not participate. However, Italy took part in the two subsequent editions, in 2018 and 2023. The structure of the test in terms of content, mode of administration, and sampling design remained consistent across both surveys. Therefore, the shared methodological characteristics are presented here, with any differences highlighted where relevant.

In this study, the digital skills of students measured by the ICILS standardised test are analysed in depth to highlight the main inequalities in the learning process. In particular, we examine contextual factors classified as either antecedents or processes. At the student level, antecedents include gender, socioeconomic status, and geographical area. Processes factors, which directly influence digital learning and may be shaped by antecedents, include students' engagement in digital learning activities, both at school and at home.

The analysis focuses on three main research questions: (i) to verify the existence of gender and territorial differences in digital skills; (ii) to identify aspects of students engagement and school characteristics that significantly influence the measured digital competence; (iii) to compare data from the ICILS 2018 survey, conducted before the COVD-19 pandemic, with those from ICILS 2023, to analyse changes in students' digital competence levels following the global health crisis.

A comparative analysis of data from before and after the pandemic is of particular relevance in order to understand how the health crisis has influenced digital education for students and whether it has exacerbated or reduced existing inequalities. The imposition of a lockdown, coupled with the extensive usage of remote learning modalities, caused a sudden and forced acceleration in the adoption of digital technologies within the educational sector. However, it remains to be seen whether this experience resulted in uniform improvements or further widened pre-existing gaps. The findings of this research could provide valuable insights for the development of future educational policies, contributing to the development of a more equitable and inclusive school system in the digital era.

It was also considered important to examine the impact of these individual and contextual characteristics not only at the average level but across the entire distribution of digital skill achievement, in order to identify potential disparities at low and high levels. To address this research objective, a quantile regression approach was employed. Moreover, to take advantage of the hierarchical structure of the data (students nested within schools), the quantile approach was combined with a multilevel model, resulting in a multilevel quantile model. This approach constitutes an innovative advancement over the traditional multilevel model employed in the IEA report and related literature, which typically presents only the main aggregate results for each participating country.

This work thus confirms existing general findings in the literature, while also offering innovative insights by showing how the effects of certain factors, both individual and related to the technology use, have a different impact on the level of skills attained. Consequently, this analysis suggests the need for more targeted digital inclusion policies and high-quality teaching practices to address persistent inequalities.

2. Background: inequalities in digital literacy

A considerable amount of literature has been published on gender differences in cognitive skills using national and international large-scale assessment data such as INVALSI and OECD-PISA surveys (Caponera et al., 2022). The main findings show that girls outperform boys in reading, while the opposite is true for mathematics (see, e.g. Contini et al., 2017; Costanzo & Desimoni 2017; Di Tommaso et al., 2024). Moreover, some countries, such as Italy, show marked differences between different territorial areas, namely the northern and southern parts of the country (Caponera & Palmerio, 2018; Costanzo & Desimoni, 2017).

A growing body of literature has investigated how gender, socio-economic status, and cultural factors affect the acquisition of ICT skills (see., e.g., Aesaert & van Braak, 2015; Punter et al., 2017). Recent analyses highlight how gender and regional factors shape digital competencies, influencing both access to and engagement with technology across diverse contexts. Several studies, including those in the ICILS assessments, examine how these differences emerge and persist across varied geographic and socio-cultural landscapes (Campos & Scherer, 2024; Gebhardt et al., 2019).

With regard to gender differences, most studies indicate that girls generally perform better than boys in computer literacy and digital skills assessments. For example, the study by Aesaert and van Braak (2015) on sixth-grade students found that girls excel in technical tasks and advanced competencies, such as retrieving files from specific locations or sending emails with attachments. An important aspect of this gender disparity may lie in the different ways boys and girls approach technology use. While boys tend to adopt an exploratory attitude, often using computers for games and entertainment, girls focus more on communication and learning activities. Overall, boys tend to feel more confident in their technical abilities, although girls often outperform them in performance-based assessments, especially in “information literacy” (the ability to search, evaluate, and use information).

Specific studies on ICILS 2013 and 2018 data (Punter et al., 2017; Campos & Scherer, 2024; Gebhardt et al., 2019) indicate that female students often outperform male peers in specific digital skills, particularly those related to information management and communication. These skills correspond to applications more commonly associated with structured academic or organisational settings, where females are reported to excel due to both greater familiarity with information processing and a stronger focus on task-oriented activities. Boys, on the other hand, tend to perform better in technical functionalities such as complex operations or advanced software manipulation, especially when technology is used for gaming or recreational purposes. Also, findings in Campos and Scherer (2024) suggest that gender gaps in digital knowledge and skills may be partially due to gender differences in attitudes toward technology. These findings are also confirmed by Cai et al. (2017), who conducted a meta-analysis on gender difference in the attitude toward technology.

Moreover, another factor that could explain this difference is ICT self-efficacy, which refers to confidence in one’s ICT skills. As discussed by Hatlevik et al. (2018), there is generally a positive relationship between ICT self-efficacy and ICT skills. The same study highlights that, although earlier evidence suggested that females tended to be less confident in their ICT abilities, especially among students in grades 5 and 6, this trend appears to have changed in subsequent years. The findings indicate that girls now have ICT self-efficacy levels equal to, if not higher than, their male peers. On the same topic, Rohatgi et al. (2016) also highlighted how the relationship between ICT self-efficacy and ICT achievement is mediated by ICT use. In fact, those with higher ICT use developed greater self-efficacy, which later translated into higher ICT achievement. The study also emphasized that this relationship remains on average unchanged regardless of gender.

The difference also seems to depend, to some extent, on age. In fact, as shown in the work of Gnambs (2021), which examines a period of three years among a sample of German 15-year-olds, males tend to have slightly higher average scores than females as age increases. In fact, the maximum gap, although not particularly large, is reached when the sample considered had turned 18 years old.

What has been presented so far shows how these gender differences depend on many factors, and thus on the specific studies considered. This concept is well expressed in systematic review studies, such as those by Qazi et al. (2021) and Siddiq and Scherer (2019), which highlight that the gender gap in ICT subjects tends to exist but varies depending on the country in which the study was conducted, the grade level examined, and other factors that may differ according to the study considered.

Generally, territorial differences in ICT skills are influenced by factors such as access to technology, educational policies, and cultural context. The ICILS 2013, 2018 and 2023 results show that, in some European countries, gender differences in digital skills are more pronounced. These studies highlight that in certain countries, digital skills are treated as a key component of basic education, whereas in other contexts they may be less emphasized. Disparities in household digital resources also influence the acquisition of advanced skills: children from wealthier families or with highly educated parents tend to show higher ICT competence levels than their peers from lower socioeconomic backgrounds. Regional differences in ICT access are compounded by gender disparities within these regions. Boys often have greater access to personal devices, either through household resources or due to societal norms that encourage boys more than girls to engage with technology from an early age. As a result, boys in these settings may develop better familiarity with ICT hardware and software, which is reflected in their confidence and proficiency with technology.

With regard to the Italian scenario, Caponera et al. (2022) focused on the gender differences of students participating in ICILS 2018. In particular, they used a structural equation model to test the relationship between student characteristics and computer and information literacy performance. The results show that the relationship between performance and self-efficacy and expectations for using ICT for work and study differs between boys and girls. More interestingly, self-efficacy mediates the effect for girls, as higher self-efficacy strengthens the relationship between ICT learning and performance.

Furthermore, as already mentioned, the Italian case is peculiar, as disparities between the northern and southern parts of the country are often quite evident, as highlighted by INVALSI assessments in their areas of competence (Italian, Mathematics, and English) and are also highlighted for the digital literacy scores as reported in the INVALSI national report for the ICILS 2018 (Caponera & Palmerio, 2018). However, there is no further literature specifically investigating this difference in the Italian context. For this reason, this work aims to fill this gap by exploring whether such disparities exist in digital skills as well.

3. Overview of ICILS

The IEA-ICILS is a large-scale survey designed to measure digital skills of grade 8 students over several educational systems, namely countries and benchmarking entities. It is a sample survey involving several countries all around the world (34 countries in the last 2023 edition). It has been conceived to understand how well students are prepared for study, work and life in a digital world (Fraillon et al., 2019). The digital skills deal with two different dimensions: computer and information literacy (CIL) and computational thinking (CT). The CIL scale is conceptualized as “an individual’ s ability to use computers to investigate, create, and communicate in order to participate effectively at home, at school, in the workplace and in society” while the CT scale refers to “an individual’s ability to recognize aspects of real-world problems which are appropriate for computational formulation and to evaluate and develop algorithmic solutions to those problems so that the solutions could be operationalized with a computer” (Fraillon et al., 2019).

Besides the student item responses on the CIL scale and the CT (optional) scale, a student questionnaire is administered to collect individual background information, and separate questionnaires is administered to teachers, school information and communication technology (ICT) coordinators, school principals, and staff in national research centers. The survey places emphasis on the family and school context in which students develop digital competencies and skills.

To evaluate CIL a computer-based test is administered consisting of a sequence of tasks contextualized by a real-world theme and driven by a plausible narrative (Fraillon et al., 2020b). CIL encompasses four strands: understanding computer use, gathering information, producing information, and digital communication (Fraillon et al., 2019). By using a balanced randomized design, each student is required to complete several modules (five in 2018 and seven in 2023) lasting 30 minutes each. Each module is structured into a set of smaller tasks and a single large task that takes 15 to 20 minutes to be completed. The large task involves the development of an information product, such as a website, a presentation, an information sheet, and so on. Each CIL module comprises a sequence of tasks that mimic real world scenarios and are guided by a realistic narrative. Four CIL modules (two used for the first time in 2013 and two used for the first time in 2018) were kept confidential between cycles. Three new CIL modules have been developed for use in ICILS 2023 to address contemporary issues and software environments.

The scaling models used to analyse and scale the test items are the Rasch model (Rasch, 1960) for binary items (correct/incorrect responses) and the partial credit model (Masters and Wrigth, 1997) for polytomous items with more than two response categories. These models belong to the item response theory (IRT) models and are used both to calibrate the items (estimate the item parameters, namely the item characteristics, such as difficulty) and for the student scoring phase. The reporting scale for CIL has a mean of 500 and a standard deviation of 100. This scale has been established in the ICILS 2013 edition, where the mean is the average CIL score across the countries in 2013. A number of 5 plausible values for each student are drawn from the marginal posterior distribution of the latent variable (for details, see Fraillon et al., 2020a; Adams et al., 1997). The plausible values are used to derive summary achievement statistics on the CIL scale. Also, proficiency levels are established by analysing item maps and student achievement data. Proficiency level boundaries are set at 407, 492, 576, and 662 scale points (each level has a width of 85 scale points) to create a classification into 5 proficiency levels (below level 1, level 1, level 2, level 3, level, 4).

The CT test is also computer-based, and this time the tasks students are required to perform involve two strands: conceptualizing problems and operationalizing solutions. However, in Italy, the CT test was administered only in 2023. For this reason, it will not be addressed in the following sections of this work, which will instead exclusively refer to the CIL test.

Also, a student questionnaire is administered to collect information on socio-demographic characteristics, on behavioural engagement with digital devices, on cognitive and emotional engagements (Fraillon et al., 2020b). Among all the available information collected during the ICILS surveys, this paper focuses only the variables that, upon preliminary analysis, showed a relationship with the CIL score and were collected in a similar manner in both the 2018 and 2023 editions. The chosen student variables are: gender, geographical area, index of socio-economic background, experience with ICT (desktop computer, notebook, laptop, smartphone, etc..), engagement with particular tasks using ICT at school and out of school, ICT self-efficacy, and level of education that the student intends to achieve. Some of these variables are built within ICILS combining more items or more scales. For each scale, a Rasch model is estimated with scores standardized to have an average of 50 and a standard deviation of 10 within the international pooled datasets, using data from countries that met the participation requirements.

The survey includes also the teacher and school questionnaires. In particular, the items in the school questionnaire are designed to collect information about factors relating to the school context included school characteristics, such as school size (in terms of student within the school), management, and resources, the availability of ICT resources, and so on. In this paper, only a few questions about schools, focusing on the availability of ICT resources, are integrated into the analysis as second-level variables in the multilevel model.

A stratified two-stage probability cluster sampling design was used for the selection of the school sample for all ICILS countries for both years (2018 and 2023). During the first stage, schools were selected systematically with probabilities proportional to their size as measured by the total number of enrolled target grade students. During the second stage, within participating schools, students enrolled in the target grade were selected using a systematic simple random sample approach. For further details on the sample design and the sampling weights see Fraillon et al. (2020a, 2024).

Before continuing, it is important to note that ICILS is typically administered toward the end of the school year for grade 8 students. However, in 2018, only in Italy, it was administered at the beginning of the school year, making Italy the country with the lowest average student age at the international level. This has two key implications: a) as also reported in the official international report (Fraillon, J. et al., 2019, 2020a), Italy's 2018 results cannot be directly compared with those of other countries participating in the same edition; b) it is not possible to make a statistical comparison between Italy's 2018 and 2023 editions, although a descriptive comparison of the results from the two editions can still be made.

4. Methods

ICILS data have specific characteristics that must be considered during the analysis, as also specified by the user guide for the survey (Mikheeva & Meyer, 2020).

The first of these characteristics concerns the plausible values, which are values of the CIL score drawn from the marginal posterior distribution of the latent variable. The ICILS response data consist of 5 plausible values for each student. This means that each analysis must be repeated 5 times, one for each plausible value. Only then can summary values for each parameter estimate and the associated standard errors be obtained. For the summary parameter values, these can be obtained as a simple average of the values obtained from the 5 analyses:

$$\hat{\beta}_k = \frac{1}{P}\sum_{p=1}^{P}\hat{\beta}_{pk}, \qquad p = 1, \dots, P = 5, \quad k = 1, \dots, K, \ \#(1)$$

where $\hat{\beta}_{pk}$ is the estimated parameter of the variable k for the plausible value p, and $\hat{\beta}_k$ is the summary value of the parameter for the variable k.

Instead, the calculation of the standard errors cannot be based on a simple average, which would lead to an underestimation of the errors. Instead, the multiple imputation formula (Rubin, 2004) is used:

$$\hat{\sigma}_{\beta_k} = \sqrt{\frac{1}{P}\sum_{p=1}^{P}\sigma^2_{\hat{\beta}_{pk}} + \left(1 + \frac{1}{P}\right)\frac{1}{P-1}\sum_{p=1}^{P}\left(\hat{\beta}_k - \hat{\beta}_{pk}\right)^2}, \#(2)$$

where $\sigma^2_{\hat{\beta}_{pk}}$ is the variance of the estimator of the parameter of the variable k for the plausible value p, $\frac{1}{P}\sum_{p=1}^{P}\sigma^2_{\hat{\beta}_{pk}}$ is the within variance of the estimator for the variable k and $(1+\frac{1}{P})\frac{1}{P-1}\sum_{p=1}^{P}(\hat{\beta}_k-\hat{\beta}_{pk})^2$ is the between variance.

The second characteristic to consider is related to the sampling design. Given the use of a two-stage sampling design, where schools are first sampled based on their size and then students are sampled within those schools, both student-level and school-level sampling weights need to be considered. Moreover, these weights must be adjusted to account for non-responses. The school-level and student-level sampling weights, the respective non-response adjustment weights, and the total weights are provided in the data supplied by the IEA. However, depending on the analysis to be performed, all or only some of these weights were considered in this paper. Additionally, for the quantile multilevel analyses, it was necessary to scale the data by applying an appropriate transformation, as will be explained in Section 4.2. Finally, the two-stage sampling design allows the hierarchical structure of the data to be taken into account, both at school and student level, making the use of multilevel analyses both useful and necessary.

4.1 Quantile regression

Quantile regression linear models (Koenker, 2005), can be seen as a generalization of the traditional least squares method for estimating conditional mean models, extending it to the estimation of conditional quantile functions.

This method is useful for exploring the linear relationship between a dependent variable y and a set of explanatory variables x across various quantiles q of the dependent variable (see, for example, Davino et al., 2013; Koenker, 2005). Quantile regression is an approach that enables a detailed analysis of how the explanatory variables impact the entire conditional distribution of the dependent variable. Specifically, it considers that this impact may vary for individuals with different levels of the response variable.

Traditional linear regression techniques typically describe the average association between explanatory variables and the outcome variable by focusing on the conditional mean function $E(y|x)$, which only gives a limited perspective of the relationship. In contrast, quantile regression allows us to examine the relationship at various points along the conditional distribution of y, offering a more comprehensive view. The quantile regression model is represented by the following equation:

$$Y_i = X_i^T \beta_q + \varepsilon_i, \#(3)$$

where X_i^T is a covariate vector of dimension k with $i = 1, \ldots, n$ refers to the subjects and β_q is the vector of regression coefficients associated with the q-th quantile.

Compared with classical linear regression methods, based on minimizing sums of squares residuals, quantile regression methods are based on minimizing asymmetrically weighted absolute residuals:

$$\sum_{y_i \geq x_i^T \beta_q} q|y_i - x_i^T \beta| + \sum_{y_i < x_i^T \beta_q} (1 - q)\left|y_i - x_i^T \beta\right|, \#(4)$$

The use of any q between 0 and 1 allows to study the dependence structure at any location of the response conditional distribution. For example, by setting $q = 0.5$, can be derived the median solution.

As can be seen from Equation (4), the estimation of coefficients for each quantile regression is based on the weighted data of the whole sample, not just the portion of the sample at that quantile. The minimization of Equation (4) can be achieved with different algorithms (Koenker, 2005). For this type of analysis, we used the R package "EdSurvey," (Bailey et al., 2024) which alternatively employs the Barrodale and Roberts simplex algorithm (Koenker & d'Orey, 1987) or the Frisch-Newton algorithm in its basic form (Portnoy & Koenker, 1997), or with a preprocessing step that can considerably speed things up (Koenker, 2022). The estimated regression coefficients in quantile regression models have the same interpretation as those of classical linear models, namely indicate how much a one-unit change in the independent variable affects a specific quantile q of the dependent variable, holding constant the others regressors.

4.2 Multilevel quantile regression

As previously mentioned, given the two-stage sampling used for the ICILS survey, the data we used are characterized by a hierarchical structure, with students as the first-level units and schools as the second-level units. The desire not to lose the information derived from this hierarchical structure led us to evaluate multilevel models. In particular, the two-level random-intercept model for unit i in cluster j, which can be expressed as follows

$$Y_{ij} = X_{ij}^T \beta + \gamma_j + \varepsilon_{ij}, \qquad i = 1, \ldots, N_j, \quad j = 1, \ldots, M, \#(5)$$

where X_{ij}^{T} is a covariate vector of dimension k, β is a vector of regression coefficients (including the intercept β_o), $\gamma_j \sim N(0,\ \sigma_\gamma^2)$ is the group-specific random effects for cluster j and $\varepsilon_{ij} \sim$ N $(0, \sigma_\varepsilon^2)$ are individual random effects.

However, the classical multilevel regression model provides an incomplete picture of the distribution of the response variable given the auxiliary information, because it just summarizes the behaviour of the mean of the outcome variable, while we are interested in discovering its effect across the entire distribution of the CIL scores. For this reason, we decided to use the weighted multilevel-quantile random-effects (W-MQRE) model, proposed by Schirripa Spagnolo et al. (2020). This model is based on the multilevel-quantile (M-quantile) regression for the linear case,

$$MQ_y\left(X_{ij}; \psi\right) = X_{ij}^{T}\beta_{\psi q}, \#(6)$$

where $\beta_{\psi q}$ is defined as the minimizer of

$$E[|q - I(\mu < 0)|\rho(\mu)] \#(7)$$

and μ is the rescaled residual. Following Tzavidis et al. (2016), Schirripa Spagnolo et al. (2020) extended the linear specification of model (6) to allow for the inclusion of random effects to account for a two-level (2L) hierarchical structure (MQRE-2L) in the data as follows

$$MQ_{y_{ij}}\left(X_{ij}, \gamma_{qj}; \psi\right) = X_{ij}^{T}\beta_{\psi q} + \gamma_{qj}, \#(8)$$

where γ_{qj} is the random effect for cluster j at the q-th M-quantile.

The reason why Schirripa Spagnolo et al. (2020) directly investigated the case with a two-level structure in their work, rather than a more general one, is because they tested the model on the PISA-OECD 2015 mathematics data. These data, just like the ICILS data used in our analysis, present a complex sampling design with a two-step approach (schools and students inside schools), which requires consideration of sampling and adjustments weights. Thus, the main contribution of their work, at the modeling level, was precisely to extend the MQRE-2L to account for these weights, following the works of Grilli and Pratesi (2004), Asparouhov (2006) and Rabe-Hesketh and Skrondal (2006). The resulting estimation procedure follows a pseudo-likelihood approach, where the sampling weights are included before the derivatives of the log-likelihood function are taken. Consequently, a robustification (Tzavidis et al., 2016) of the weighted estimation equations is performed. Then, to obtain the estimate of the regression coefficients and the variance parameters, those equation are solved iteratively using a Newton–Raphson algorithm and the fixed-point iterative method.

Lastly, in the multilevel model framework, all the weights have to be scaled. To achieve that, we decide to use the same scaling method of Schirripa Spagnolo et al., (2020) and also used in Grilli and Pratesi (2004), i.e.

$$w^{*}_{i|j} = \frac{n_j w_{i|j}}{\sum_{i=1}^{n_j} w_{i|j}}, \#(13)$$

where n_j is the number of sample units in the jth cluster, and $w_{i|j}$ are the first-level weights. An R-script (R Core Team, 2018) provided by the Authors (Schirripa Spagnolo et al., 2020) was used to implement this approach for each of the 5 plausible values.

5. Results

5.1 The sample

In this work, for the 2018 we use a sample of 2,713 students grouped into 144 schools, representing 96% of the original 2,810 (150 schools) Italian ICILS 2018 sample. The units not considered in our analysis are part of 6 schools that lacked data at school level (because neither the ICT coordinator nor the principal had responded to the questionnaire). In 2023 only one school did not respond to the questionnaire. For this reason, those units were removed, resulting in a final sample of 3,350 units grouped into 151 schools, which corresponds to 99% of the original 3,376 (152 schools) Italian ICILS 2023 sample. The test administration was conducted during the second half of the school year, as for the other countries.

5.2 The exploratory analysis

In Appendix A, Table A1, a list and a description of the covariates used in this study is provided. Descriptive statistics of the socio-demographic characteristics and the other covariates at student and school level are presented in Appendix A (Tables A2, A3 and A4) for both 2018 and 2023 samples.

Concerning the target variable, the CIL score, in 2018 the average score is 461 (s.e. = 2.6), significantly below the international average of that year, equal to 538. The median of 467 corresponds to Level 1, indicating that half of the students are at or below the lowest level of proficiency. Focusing on the distribution of the proficiency levels (Table 1), most students either lack digital skills (scores below Level 1) or have basic skills that do not go beyond using the computer for basic communication or research. However, some demonstrate the ability to use the computer for data collection and management tasks (Level 2), but very few show high-level skills that translate into independence and autonomy when performing more complex computer-based tasks.

Table 1. Students' percentage distribution by proficiency levels (s.e. in brackets).

Level	2018	2023
Below Level 1	23.73 (1.22)	13.67 (1.27)
At Level 1	38.90 (1.24)	32.03 (1.10)
At Level 2	30.50 (1.22)	43.64 (1.48)
At Level 3	6.610 (0.68)	10.37 (0.83)
At Level 4	0.26 (0.15)	0.29 (0.11)

Note. The standard errors are calculated considering the five plausible values of the CIL score.

In 2023 the average CIL score is approximately 490 (s.e. = 2.563), significantly higher than the international average for that year (equal to 476) and the median is equal to 499, corresponding to Level 2. Therefore, at the national level, there has been an increase in average performance over the five-year period. Additionally, the percentage of students at Level 2 and Level 3 is higher by approximately 16 and 4 percentage points, respectively. However, the percentage of students at the highest proficiency level has remained unchanged between the two editions.

The analysis of gender gaps and territorial inequalities shows interesting results. In both years considered, females outperform males, with a significant difference of 16 points in 2018, when males had a mean score of 451 (s.e. = 2.981) and females 467 (s.e. = 3.464), and 18 points in 2023, with males scoring 478 (s.e. = 3.075) and females 496 (s.e. = 2.700). This pattern is consistent across countries (Campos & Scherer, 2024).

Regarding geographical areas, students from Northern and Central Italy achieve significantly higher average scores than those from the South. In 2018, students from the North scored on average 43 points more than their Southern peers, with an average score of 476 (s.e. = 3.687) compared to 433 (s.e. = 4.510). In 2023, this gap increased to 47 points, with Northern students scoring 505 (s.e. = 3.159) and Southern students 458 (s.e. = 5.262). This result could be due to the pandemic, which increased the differences between geographical areas, especially compared to the North, where the situation is generally more favourable in terms of student services.

Students from the Centre scored 36 points higher than those from the South in 2018, 469 (s.e. = 6.188) versus 433 (s.e. = 4.510), and 40 points higher in 2023, with scores of 498 (s.e. = 4.669) and 458 (s.e. = 5.262). The difference between the North and the Centre, however, is not statistically significant in either year.

The results of a joint analysis of gender and geographical area is illustrated in Table 2. In 2018, the difference between females and males is not significant for students in Centre, while in 2023 this difference is significant for all the three areas of the country.

Table 2. Gender difference in mean CIL scores by geographical areas (*p*-value in brackets).

Geographical area	**Difference Female-Male 2018**	**Difference Female-Male 2023**
North	14.695 (0.007)	13.547 (0.000)
Centre	12.528 (0.138)	18.844 (0.015)
South	18.158 (0.008)	21.843 (0.000)

5.3 The quantile regression results

Classical regression analysis allows for a general assessment of the effect of a given characteristic, but in the case of skills, it can be very useful to examine whether it has a greater impact on lower or higher levels. In fact, those who already have high skills often manage to improve even in less favourable contexts, but may find fewer stimuli or advanced opportunities for growth (e.g. workshops, mentors, extracurricular activities). Those with low skills, on the other hand, are hit harder by the lack of infrastructure, support and positive role models: this may lead to a stall, or even a deterioration, over time.

The use of quantile analysis (instead of just focusing on the average) can bring out these effects more clearly. Having this information makes it possible to implement more targeted learning interventions. Moreover, when considering the pre- and post-pandemic comparison, quantile analysis can offer valuable insights into where digital skills and usage behaviours may play an even more crucial role.

To investigate inequalities in CIL scores by gender and geographical area, we estimated three separate quantile regression models: one including only gender, one including only geographical area, and a third including all the covariates. Tables 3 and 4 present the results for the quantile regression model with gender as the only covariate for the 2018 and the 2023, respectively.

As already reported in Section 5.2, females show a significantly higher average score than males; however, the quantile analysis reveals that this difference is more pronounced for lower quantiles (0.05, 0.10, 0.25) compared to the middle ones (0.5, 0.75) both for 2018 and 2023. Additionally, at highest quantile (0.95), the differences between the two groups tend to be non-significant. However, in 2018 this difference was no longer significant even at the 90th and 5th quantiles (at a 5% significance level). This means that while in 2018 the difference between males and females was significant in the lower-middle and upper-middle parts of the distribution, in 2023 the difference appears to have become more pronounced across almost the entire distribution.

Table 3. Estimated model parameters for seven quantiles, with Male as reference category, 2018 data (*p*-value in brackets).

	Quantile						
	0.05	**0.10**	**0.25**	**0.50**	**0.75**	**0.90**	**0.95**
Intercept	306.931	344.544	401.903	459.536	510.257	553.395	581.713
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Female	19.877	20.899	20.447	15.039	15.404	12.732	9.150
	(0.068)	(0.040)	(0.005)	(0.030)	(0.012)	(0.100)	(0.270)

Table 4. Estimated model parameters for seven quantiles, with Male as reference category, 2023 data (*p*-value in brackets).

	Quantile						
	0.05	**0.10**	**0.25**	**0.50**	**0.75**	**0.90**	**0.95**
Intercept	341.756	375.841	434.491	491.806	537.135	572.569	593.219
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Female	26.638	27.800	24.877	14.594	11.058	10.750	10.334
	(0.031)	(0.002)	(0.000)	(0.004)	(0.013)	(0.041)	(0.172)

Tables 5 and 6 show the results for the model with geographical area as the only covariate for 2018 and 2023, respectively.

Table 5. Estimated model parameters for seven quantiles, with North as reference category, 2018 data (*p*-value in brackets).

	Quantile

	0.05	0.10	0.25	0.50	0.75	0.90	0.95
Intercept	343.225	379.094	431.140	481.214	530.144	570.338	595.716
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Centre	0.103	-5.337	-6.648	-7.199	-10.526	-7.675	-7.195
	(0.996)	(0.732)	(0.559)	(0.391)	(0.212)	(0.478)	(0.426)
South	-58.467	-59.128	-49.152	-40.216	-34.698	-27.746	-27.025
	(0.004)	(0.000)	(0.000)	(0.000)	(0.000)	(0.006)	(0.006)

Table 6. Estimated model parameters for seven quantiles, with North as reference category, 2023 data (*p*-value in brackets).

	Quantile						
	0.05	0.10	0.25	0.50	0.75	0.90	0.95
Intercept	384.398	417.793	467.937	514.803	554.936	587.351	607.358
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Centre	-12.183	-9.196	-7.193	-6.048	-5.563	-3.207	-3.335
	(0.436)	(0.548)	(0.469)	(0.337)	(0.292)	(0.600)	(0.686)
South	-61.445	-60.608	-53.645	-43.877	-38.167	-34.433	-33.043
	(0.001)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)

Unlike gender, the inequality between the South and the other two areas of the country remains significant throughout the entire distribution of scores, although this value tends to decrease as higher quantiles are considered for both 2018 and 2023. This means that the difference is more pronounced when considering students with very low competencies, while it becomes less pronounced, though still significant, for students with high digital competencies. The difference between the North and the Centre remains non-significant throughout the entire distribution. This time there are not differences between 2023 and 2018, suggesting that over the five-year period, there have been no changes in how the gap between the areas is distributed.

Finally, a quantile regression analysis was conducted in which, in addition to gender and geographic area, the full set of students' covariates are considered (see Table A1 in Appendix 1). The results on the quantile model parameters are reported in Appendix B (Table B1 for 2018 and Table B2 for 2023). To gain a clear and intuitive overview of the results, Figure 1 and Figure 2 show graphically the regression coefficients for the 2023 data.

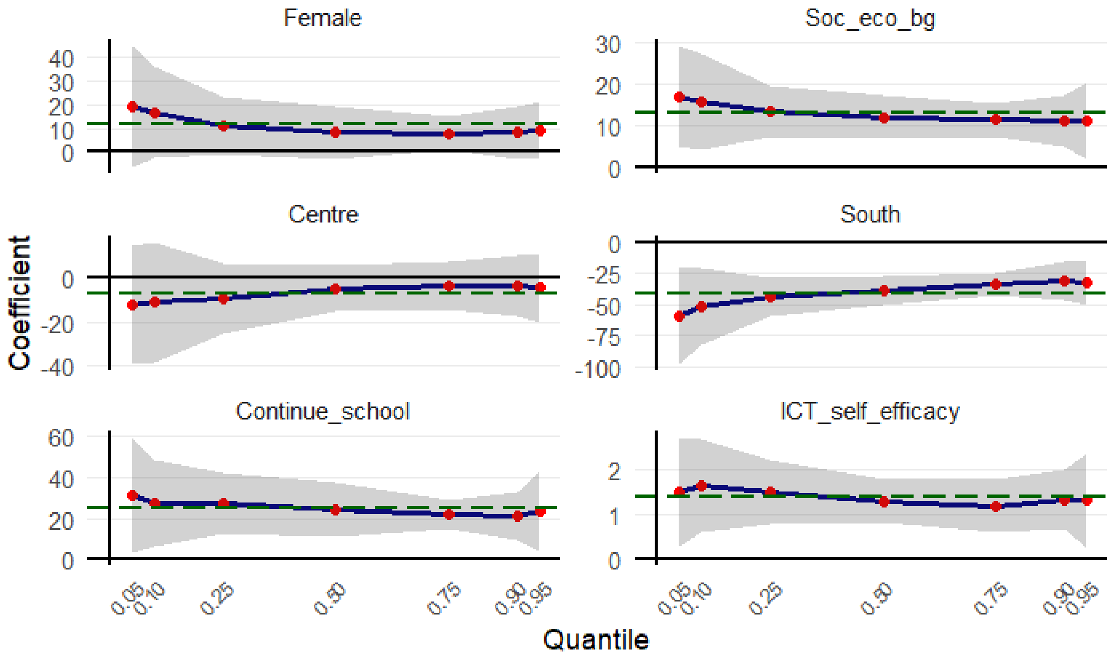

Figure 1. Quantile regression coefficients for personal characteristics, 2023 data.

Note. The green dashed line represents the average of the coefficients over the seven quantiles, and the grey area is the 95% confidence band.

First, it can be noted that the gender difference is non-significant for almost all the quantiles in 2023. The coefficient estimates for the territorial areas exhibit a similar pattern to those reported in Table 6. This means that, when other students' covariates are considered, the territorial differences between the South and the other two areas persist throughout the distribution, while part of the gender difference is absorbed by the other covariates. This result was already evident in 2018, and the pandemic period does not appear to have altered the influence of these two characteristics on digital skills.

The socio-economic background (*Soc_eco_bg*) has a significant positive impact on the CIL score along the whole distribution, but more pronounced for the lower proficiency levels. Similar results but at average level have been documented by Van Deursen and Helsper (2024) confirming that the student background has become an even more determining factor since the expansion of distance learning. Their research shows that inequalities in digital literacy linked to socio-economic background have become more pronounced, especially in contexts characterised by large territorial divisions, such as Southern Italy.

Similar behaviours are present also with respect to the intention to continue studying or not after high school (*Continue_school*). Moreover, the degree of how student is confident about her/his ability to use ICT (*ICT_self_efficacy*) appears to have a positive and significant effect at all levels of the distribution. The regression coefficients are also very similar, indicating that what impacts is having good self-confidence. All those behaviours are quite the same between the two editions (2018 and 2023).

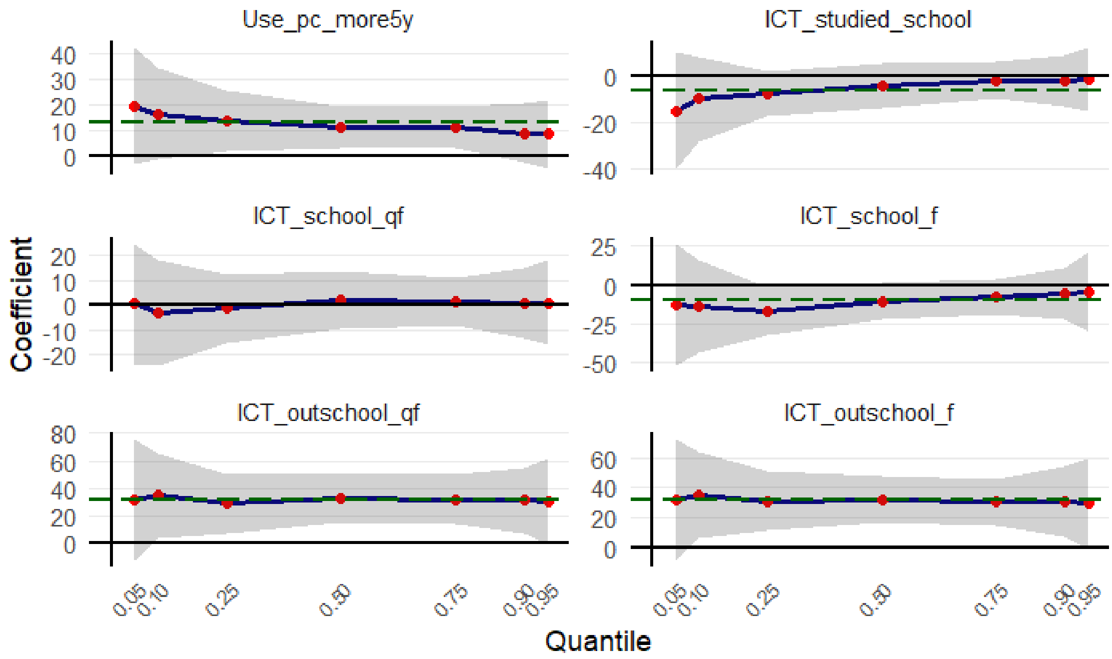

Figure 2. Quantile regression coefficients for behaviour of digital engagement in ICT, 2023 data.

Figure 2 presents the regression coefficients for the covariates related to students' ICT engagement behaviors, based on the 2023 data. Using a PC for more than 5 years (*Use_pc_more5y*) has a positive and significant impact only at intermediate levels, suggesting that more established usage is less relevant for students with either high digital performances or significant difficulties. In 2018, this covariate showed significantly positive coefficients for all the quantiles except the last.

The relationship between having studied Computer Science during the current school year (*ICT_studied_school*) and students' digital competencies lacks statistical significance across all quantiles for both 2018 and 2023. The same happens for the use of ICT at school (*ICT_school*), with non-use as the reference category. In contrast, the use of ICT outside school (*ICT_outschool*), appears to have a consistently positive effect, with similar coefficients for both occasional and frequent use, and relatively stable across all quantiles. The effect is statistically significant in most parts of the distribution (especially in 2023), except for the lowest and highest quantiles. This may indicate that independent, self-directed use of digital technologies, such as for communication, information seeking, problem-solving, or informal learning, contributes more directly to the development of digital skills, likely because it meets real-life needs and encourages more active engagement.

In summary, these results may suggest that it is not the amount of technology use that matters most, but rather the context and quality of the experience. The school environment, if not supported by effective teaching methods, may fail to fully harness the educational potential of ICT. Conversely, out-of-school ICT use, being more spontaneous and interest-driven, appears to be more effective in fostering practical and transversal digital competencies.

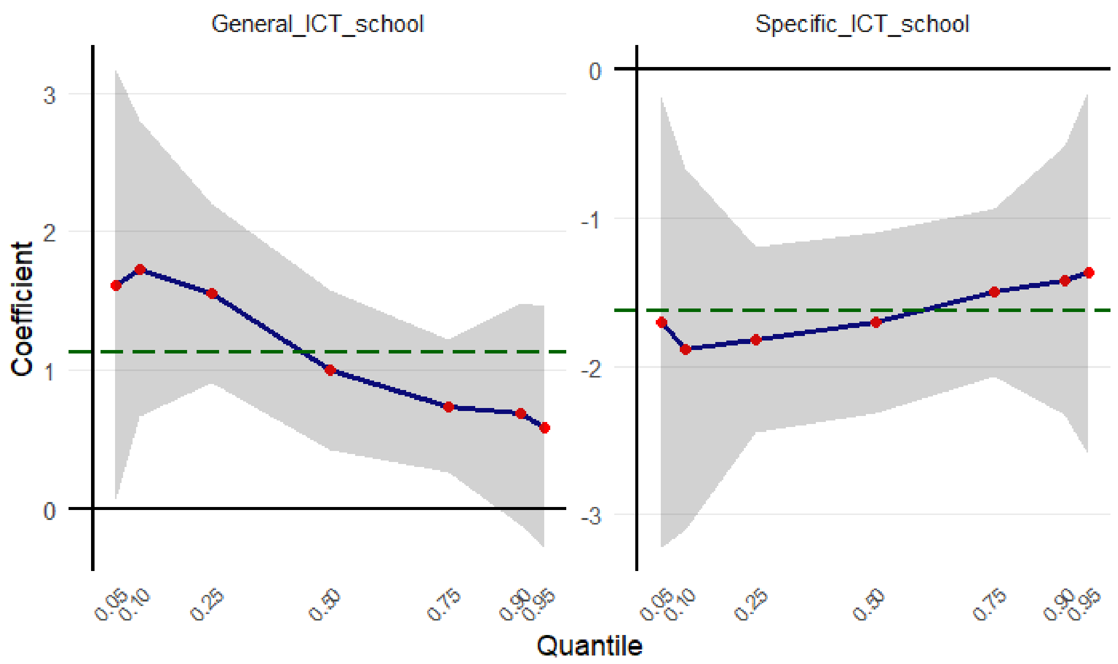

Figure 3. Quantile regression coefficients for digital tool use, 2023 data.

Concerning the impact of digital tools use, the quantile regression coefficients for 2023 are illustrated in Figure 3. The analysis of the impact of digital tool use at school on students' digital competencies in 2023, reveals distinct patterns depending on the type of tools employed. In particular, the use of general-purpose digital tools (*General_ICT_school*), such as collaboration platforms, word processing applications, web search engines, or communication tools, shows a positive and statistically significant effect on digital skills, across almost the entire distribution, except for the two highest quantiles. This suggests that these more transversal and accessible tools, which are often closer to students' everyday practices, contribute effectively to the development of operational and functional digital skills, especially among those with medium to low competence levels. In this sense, general tools appear to play an important role in narrowing skill gaps and reinforcing foundational digital literacy.

In contrast, the use of specific digital tools (*Specific_ICT_school*), such as technical software, programming environments, or specialized platforms, shows a consistently negative and statistically significant effect across the entire distribution of competencies. This outcome can be interpreted in several ways. On one hand, it may reflect the difficulty students encounter when using more complex and less intuitive tools that require prior knowledge or greater autonomy (especially for those with lower digital skills). On the other hand, it might point to an ineffective or poorly supported use of such tools in the school context, which may disadvantage students who lack adequate instructional guidance or scaffolding.

From a practical standpoint, these findings highlight the importance of adopting a thoughtful and gradual approach to the pedagogical integration of digital technologies. It is crucial to select and adapt digital tools according to students' starting skill levels and the learning objectives to be pursued. While general-purpose tools seem to offer an inclusive pathway for strengthening basic and transversal digital skills, more specific tools should be carefully embedded within a well-designed teaching strategy to avoid becoming an obstacle to learning, particularly for the least experienced students.

In 2018 the pattern was the same. Once again, the pandemic period does not seem to have changed the impact of certain behaviors on digital skills.

5.3 The multilevel quantile regression results

The hierarchical structure of the data (students nested into schools) is taken into account through a multilevel quantile regression based on the W-MQRE model, introduced in Section 4.2, in order to highlight the presence of a school effect, the direction and intensity, and whether the effect is similar across all levels of competence. The results included in this section refer exclusively to the 2023 data. However, the analysis is conducted with a comparative perspective, taking into account the 2018 results, which can be found in Appendix B (Tables B3-B6).

The first step in the analysis is to verify, by estimating the parameters of the empty model without covariates, if there is a school impact on the variability of the CIL score. Table 7 reports the results on the variance components for the empty model, while Table 8 presents the fixed effects estimates. The average interclass correlation coefficient (ICC) is 0.238 (0.208 in 2018), meaning that around 24% (21%) of the variability in the CIL score is at the school level. While the value is quite high, to warrant further analysis of the outcomes. The variance values at the school level and the student level, as well as the ICC value, are distributed across the 7 considered quantiles. As highlighted in Schirripa Spagnolo et al. (2020), both variances follow an inverted U-curve that is higher at the centre of the outcome distribution (also in 2018). However, the ICC seems to follow a decreasing trend, with the highest value at the initial quantile dropping only slightly in the first half of the distribution, and then decreasing more sharply in the second half, reaching very low values in the final two quantiles considered. This indicates that the school effect is stronger when considering subjects with low or medium CIL competence values, becoming almost negligible for students with very high scores. The situation in 2018 is similar (Table B3), although both the average value and the values at each of the seven quantiles are higher in 2023 compared to 2018, suggesting a general, albeit slight, increase in the school effect. Furthermore, while the trend in the second half of the distribution closely mirrors that described for 2023, in the first part of the distribution the highest value is found at the 25th quantile, rather than at the 5th.

Table 7. Variance terms (random part) for the null W-MQRE model, 2023 data (s.e. in brackets).

Level		Quantile						
		0.05	**0.10**	**0.25**	**0.50**	**0.75**	**0.90**	**0.95**
2	School variance	344.919 (232.666)	578.466 (317.299)	1087.369 (330.297)	1157.669 (167.149)	462.712 (85.178)	123.208 (32.204)	47.948 (15.495)
1	Residual variance	1043.923 (208.204)	1822.951 (270.543)	3496.169 (377.040)	4068.176 (186.614)	2304.309 (146.124)	987.153 (93.943)	531.926 (63.555)
	ICC	0.248	0.241	0.237	0.221	0.167	0.111	0.082

Table 8. Fixed effects for the null W-MQRE model, 2023 data (*p*-value in brackets).

	Quantile						
	0.05	**0.10**	**0.25**	**0.50**	**0.75**	**0.90**	**0.95**
Intercept	390.065 (0.000)	416.303 (0.000)	454.495 (0.000)	492.168 (0.000)	524.770 (0.000)	551.171 (0.000)	567.000 (0.000)

The conditional W-MQRE model includes, besides the student covariates already used for the quantile regression analysis, also a few covariates at school level obtained from the school questionnaire or derived from the student variables. In particular, we chose to include three variables. The first (*School_over_devices*) is the ratio of school size (number of students) to the number of devices available to students only, so that higher values indicate a lower number of devices per student. The second one reflects the availability of ICT resources at school (*ICT_availability_school*). As for the student covariates, this scale is estimated using a Rasch model. The third covariate is calculated as the school mean of the student socio-economic background index (*Soc_eco_bg_school*). The selection of school-level variables was also guided by data availability, in order to avoid variables with substantial missing data that could either reduce the sample size or further complicate an already complex model through the need for imputation. Some summary descriptive statistics on the school variables are presented in Appendix A, Table A4.

Table 9. Variance terms (random part) for the conditional W-MQRE model, 2023 data (s.e. in brackets).

Level		Quantile						
		0.05	**0.10**	**0.25**	**0.50**	**0.75**	**0.90**	**0.95**
2	School variance	136.447 (102.528)	222.637 (136.229)	397.689 (145.020)	458.14 (101.470)	208.138 (47.435)	59.013 (17.139)	23.017 (7.948)
1	Residual variance	814.947 (161.729)	1346.466 (192.541)	2560.215 (259.677)	3238.679 (168.312)	1861.005 (119.004)	783.227 (72.575)	413.932 (48.403)
	ICC	0.143	0.142	0.134	0.124	0.101	0.070	0.053
2	EV_j	60%	62%	63%	60%	55%	52%	52%
1	EV_{ij}	22%	26%	27%	20%	19%	21%	22%

The results on the variance components are presented in Table 9 for 2023 (Table B5 for 2018). As expected, the inclusion of covariates reduced the ICC values. However, the trend along the distribution did not change. The last two rows of Table 9 show the change in the variance of the conditional model with respect to the null model at student level (EV_{ij}) and at school level (EV_j) for the 7 quantiles considered. For 2023, EV_{ij} shows a reduction of the student-level explained variance that is uniform (around 22%) over the 7 quantiles considered, while at school-level EV_j shows a reduction of about 60% for the lowest quantile that tends to decrease for higher-performing students (52%). In 2018, the pattern of the changes is the same, although the decreases are generally more pronounced, with a value of around 29% for the explained student-level variance and a value ranging from 77% to 61% for the explained school-level variance (Table B5). In the pre-pandemic survey, the changes from the null to the conditional model were more pronounced. This should mean that school-level differences in 2018 were less influential in determining students' digital competence.

Figures 4 to 7 provide a graphical representation of the fixed effects from the conditional W-MQRE model for the 2023 data. The estimates of the coefficients can be found in the Appendix B, Table B7 (Table B6 for the 2018 data).

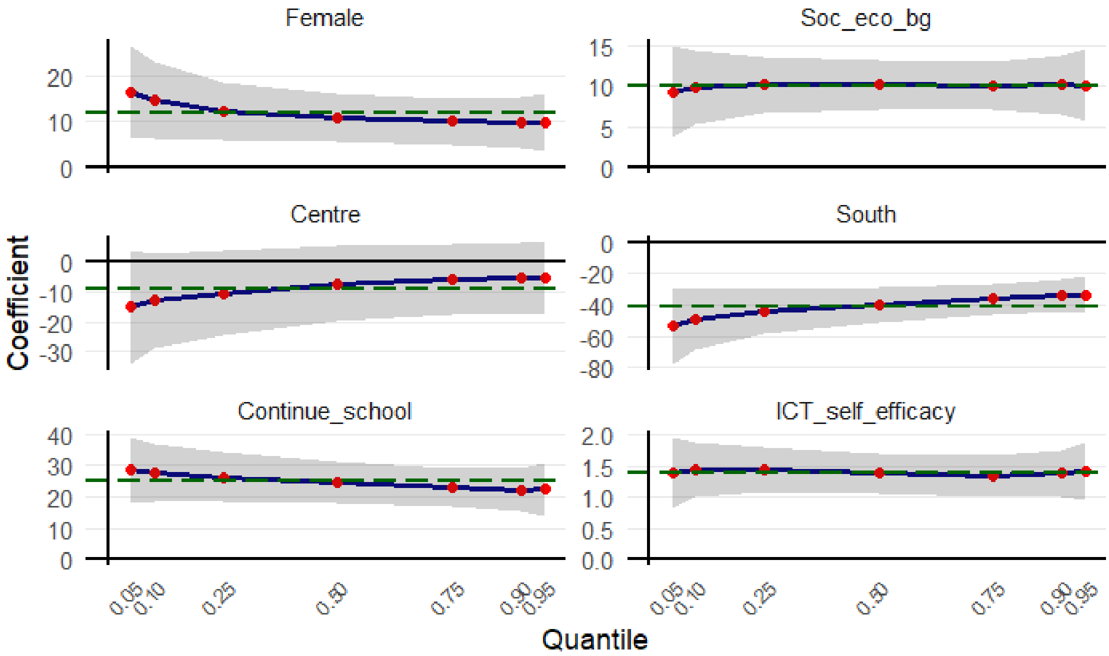

Figure 4. W-MQRE regression coefficients for personal characteristics, 2023 data.

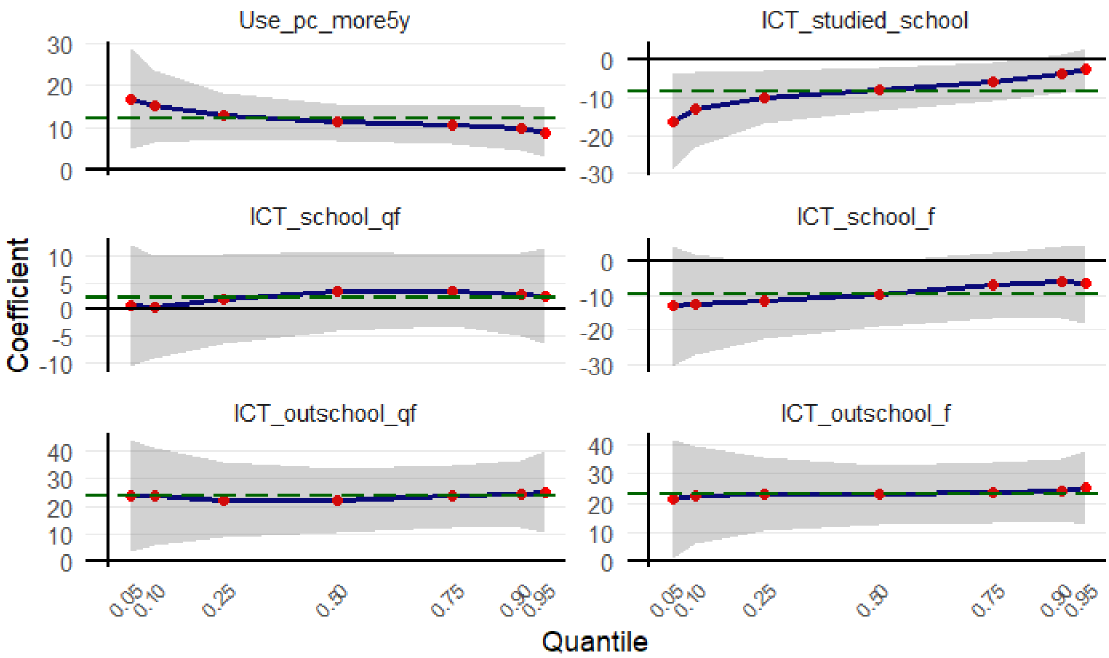

Figure 5. W-MQRE regression coefficients for behaviour of digital engagement in ICT, 2023 data.

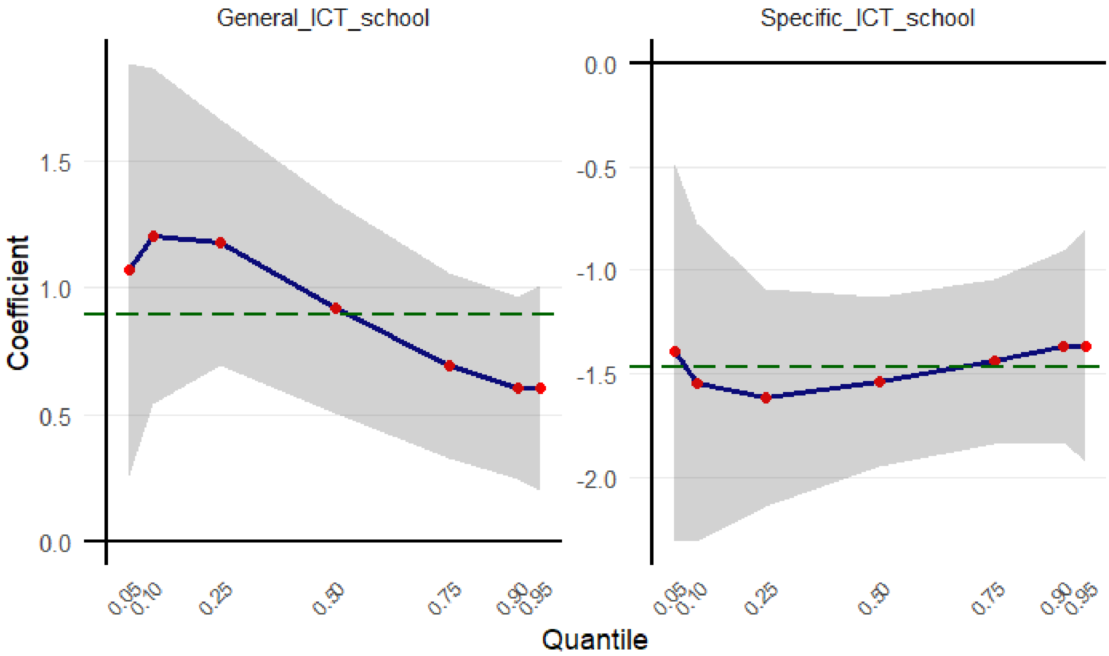

Figure 6. W-MQRE regression coefficients for digital tool use, 2023 data.

The sign, magnitude, and significance of the covariate coefficients are similar to those observed in the previous quantile regression model (Section 5.2). The only notable differences are for the gender variable and the variable which indicates whether the student studied an ICT subject during the school year (*ICT_studied_school*). The two variables shift from being non-significant to showing significance across most of the score distribution, except at the upper end for the *ICT_studied_school* variable. This pattern may indicate that the effects are context-dependent: in some schools, these differences are meaningful, while in others they are negligible. As a result, when the hierarchical structure is not accounted for, the overall average effect may appear non-significant.

Other variables related to the behaviour engagement (*Use_pc_more5y*, *General_ICT_school*, and *ICT_outschool*) also exhibit a shift in their significance patterns, moving from being significant only around the middle of the score distribution to becoming significant across its entire range. This again points to the influence of school-level effects, suggesting that these variables play a role in shaping digital competence not only for average-performing students but also for those at both the lower and upper ends of the distribution. In 2018 (Table B6), the considerations are largely the same, with the only exception being that the variable indicating whether ICT is frequently used outside of school for homework (*ICT_outschool_f*) remained non-significant.

Finally, at the school level, the two covariates related to the availability of digital tools for students at school (*School_over_devices* and *ICT_availability_school*) do not show a significant effect across the entire score distribution, while the average school socio-economic background index (*Soc_eco_bg_school*) is significant only in the lower part of the distribution (Table B7). For the 2018, this index is not significant even in the first half of the distribution (Table B6), showing that over the five-year period, this effect has become significant at least for students with mid-to-low scores.

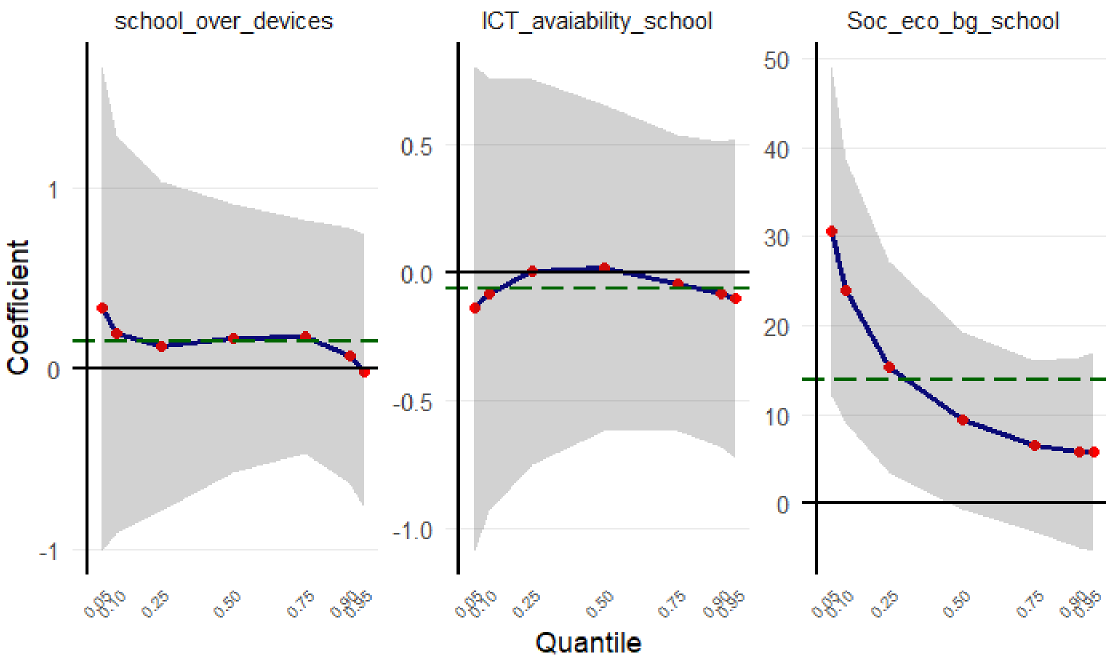

Figure 7. W-MQRE regression coefficients for school covariates, 2023 data.

6. Summary and conclusions

6.1 Main considerations

This study aimed to investigate inequalities in the digital skills of Italian students through a multilevel quantile regression approach using ICILS 2018 and 2023 data. Three key objectives guided the analysis: (i) assessing gender and territorial disparities in digital competence; (ii) identifying student engagement and school-level characteristics that influence digital skill development; and (iii) examining changes over time in digital competence, particularly in light of the COVID-19 pandemic.

The findings highlight persistent gender and territorial inequalities in digital skills. Female students consistently outperformed their male counterparts, particularly in the lower and middle parts of the score distribution. However, when controlling for other covariates, the gender gap becomes less pronounced, suggesting that differences in ICT-related behaviours, self-efficacy, and engagement may mediate the effect of gender on digital skills. In contrast, the gap between

Northern/Central and Southern Italy remains significant across the entire distribution, even after accounting for individual and school-level variables, indicating a deep-rooted territorial divide in digital education. This finding is consistent with findings at the European level, where the digital divide between Northern and Southern Europe has widened since the pandemic (Siddiq, 2024; Perez & Garzia, 2024).

The analysis also shed light on the importance of student engagement and contextual factors. Variables such as ICT use outside school, years of experience with computers, ICT self-efficacy, and students' intention to continue their studies were positively associated with digital competence, particularly at lower quantiles of the distribution. Interestingly, ICT use within schools, did not demonstrate the same significant effect. This suggests that quality and context of digital engagement, rather than frequency alone, are crucial for skill development. These considerations are also supported by a study showing that frequent use of technology in school does not automatically lead to better digital skills but, on the contrary, the effect depends on the pedagogical quality (Hatlevik & Throndsen, 2024).

From a temporal perspective, the comparison between 2018 and 2023 reveals that while average performance has improved, the underlying inequalities have not diminished. In fact, territorial disparities have become even more pronounced. Despite the forced digitalization of education during the pandemic, data suggest that this shift did not lead to a uniform improvement in digital competence, but rather reinforced pre-existing gaps.

Finally, the multilevel quantile regression analysis confirmed the presence of a school-level effect, especially for students with lower to intermediate digital competencies. This underlines the role of schools not only in mitigating inequalities, but also in potentially exacerbating them if resources and strategies are not equitably distributed. However, the effect diminishes at higher levels of student competence, suggesting that more proficient students are less dependent on school context to develop their digital skills.

6.2 Policy implications

The findings of this study suggest several directions for educational policy aimed at reducing digital skill inequalities and fostering inclusive digital education.

First, the persistent territorial disparities call for targeted interventions in the most disadvantaged areas, particularly Southern Italy, through increased investments in infrastructure, teacher professional development, and digital resources. Special attention should be paid to ensuring that schools serving lower-performing student populations are equipped not only with devices, but also with pedagogical support to use them effectively.

Second, the limited impact of ICT use within schools, especially in its more technical forms, highlights the importance of re-thinking how digital tools are integrated into teaching. Policymakers should promote teacher training programs that focus on pedagogical innovation, meaningful use of technology, and strategies that engage students actively and critically with digital media. Emphasis should be placed on transversal digital skills, such as information literacy, collaboration, and communication, rather than purely technical or tool-specific competencies.

Third, the positive effect of out-of-school ICT use and ICT self-efficacy suggests the need for policies that extend beyond the school setting. Supporting informal learning opportunities, digital mentorship programs, and family-oriented digital inclusion initiatives can reinforce students' confidence and autonomy in using technology, especially for those with limited exposure at home.

Finally, given that the most pronounced school-level effects were observed among students with lower competence levels, it is crucial to prioritize equity-focused measures, such as early identification of digital learning gaps, differentiated instructional strategies, and remedial digital skill programs, aimed at preventing long-term disadvantage in digital education.

Taken together, these recommendations underscore the need for a systemic, multi-level approach to digital competence development, one that recognizes the interplay between individual, school, and territorial factors and that promotes inclusion as a guiding principle of digital education policy.

But digital technology transcends boundaries. New developments, such as generative digital intelligence, challenge us to rethink the role of education today and in the future. Only by intensifying efforts and involving everyone in this process of co-designing and co-implementing effective, efficient, and equitable digital education policies and practices can we positively influence the growth of the entire education and training system. In line with the principles set out in DiGComp (Vuorikari et al., 2022; Wild & Schulze Heuling, 2021), each country must therefore ensure that everyone has access to high-quality and inclusive digital education and training that promotes a lifelong learning perspective.

6.3 Limitations and future developments

First, the analysis focused on a selected subset of available variables, chosen for their comparability across the two ICILS cycles and based on preliminary relevance. While this approach ensured coherence and methodological rigor, it inevitably excluded other potentially relevant factors, such as parental involvement, teacher practices, or students' emotional engagement with digital learning, that could offer further insights into the determinants of digital competence.

Second, the research was limited to the Italian context, without direct comparison with other participating countries. Although this allowed for a more in-depth and context-sensitive exploration, a cross-national perspective could enrich the understanding of how different education systems, policy frameworks, and socio-cultural environments shape digital skills development. This comparative dimension represents a promising direction for future research, particularly in the aftermath of the global health crisis. However, it should also be reminded that for the 2018 edition, Italy’s results cannot be directly compared with those of the other participating countries, as the test in Italy was administered at the beginning rather than the end of the school year, a limitation that cannot be overlooked.

Finally, the study did not explicitly address the pedagogical approaches employed in the integration of ICT in teaching practices. Future research should delve deeper into the relationship between teaching strategies and digital competence, with particular attention to didactic innovation, teacher training, and student-centered methodologies.

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Appendix A

Table A1. List of Variables.

Variable Name	Meaning	Category
Gender	Gender of the student	0 = Male 1 = Female
Area	Geographical area of the school	0 = North 1 = Centre 2 = South
Continue_school	Level of education that the student intends to achieve	0 = does not want to continue her/his studies after high school 1 = wants to continue her/his studies after high school
Soc_eco_bg	Index of socio-economic background	Real value (standardized to have a mean of 0 and a standard deviation of 1)
ICT_school	How much the student uses ICT at school for non- school works	0 = Never 1 = Quite frequently (qf) 2 = Frequently (f)
ICT_outschool	How much the student uses ICT outside school for school-works	0 = Never 1 = Quite frequently (qf) 2 = Frequently (f)
Use_pc_more5y	Student's use of the pc by more than 5 years	0 = No 1 = Yes
ICT_self_efficacy	Student's confidence about the ability to use ICT	Real value (standardized to have a mean of 50 and a standard deviation of 10 at international level)
ICT_studied_school	ICT studies in the current school year	0 = No 1 = Yes

General_ICT_school	Use of general applications in class	Real value (standardized to have a mean of 50 and a standard deviation of 10 at international level)
Specific_ICT_school	Use of specialist applications in class	Real value (standardized to have a mean of 50 and a standard deviation of 10 at international level)
School_over_devices	Number of students in the school (P_NUMSTD) divided by the number of ICT devices in the school altogether	Positive real number
ICT_avaiability_school	Availability of ICT resources at school reported by the ICT coordinator	Real value (standardized to have a mean of 50 and a standard deviation of 10 at international level)
Soc_eco_bg_school	Average index of socio-economic background at school level	Real value (standardized to have a mean of 0 and a standard deviation of 1 at international level)

Table A2. Frequency distribution of the categorical covariates at student level.

	2018	2023
Gender	Females = 48% Males = 52%	Females = 49% Males = 51%
Area	North = 44% Centre = 20% South = 36%	North = 45% Centre = 21% South = 34%
Continue_school	No = 38% Yes = 62%	No = 35% Yes = 65%
ICT_school	Never = 84% Quite frequently = 12% Frequently = 4%	Never = 69% Quite frequently = 20% Frequently = 11%
ICT_outschool	Never = 25% Quite frequently = 54% Frequently = 21%	Never = 9% Quite frequently = 22% Frequently = 69%
Use_pc_more5y	No = 64% Yes = 36%	No = 58% Yes = 42%
ICT_studied_school	No = 10% Yes = 90%	No = 43% Yes = 57%

Table A3. Summary statistics for quantitative covariates at student level.

	2018	2023
Soc_eco_bg	Min = -2.461 Max = 2.051 Mean = -0.013 S.d.= 0.019	Min = -2.382 Max = 2.097 Mean = 0.300 S.d.= 0.017
ICT_self_efficacy	Min = 13.000 Max = 61.120 Mean = 49.940 S.d. = 0.177	Min = 14.310 Max = 71.570 Mean = 51.030 S.d. = 0.148
General_ICT_school	Min = 31.480 Max = 75.890 Mean = 46.470 S.d. = 0.187	Min = 26.620 Max = 78.120 Mean = 47.220 S.d. = 0.160
Specific_ICT_school	Min = 37.120 Max = 87.710 Mean = 50.250 S.d. = 0.176	Min = 31.810 Max = 86.180 Mean = 47.770 S.d. = 0.151

Table A4. Summary statistics for quantitative covariates at school level.

	2018	2023
School_over_devices	Min = 0.610 Max = 108.80 Mean = 14.460 s.d. = 0.261	Min = 0.690 Max = 31.280 Mean = 6.102 s.d. = 0.084
ICT_avaiability_school	Min = 23.190 Max = 41.420 Mean = 46.230 s.d. = 0.145	Min = 27.740 Max = 72.060 Mean = 46.920 s.d. = 0.120
Soc_eco_bg_school	Min = -1.180 Max = 1.463 Mean = -0.013 s.d. = 0.009	Min = -1.178 Max = 1.256 Mean = 0.030 s.d. = 0.008

APPENDIX B

Table B1. Estimated quantile regression model parameters for seven quantiles, 2018 data (*p*-value in brackets).

	Quantile						
	0.05	0.10	0.25	0.50	0.75	0.90	0.95
Intercept	206.545	238.041	295.996	351.415	394.818	436.198	457.495
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Female	1.940	6.186	7.656	8.746	9.630	4.239	4.780
	(0.853)	(0.420)	(0.275)	(0.133)	(0.129)	(0.678)	(0.626)
Centre	-6.480	-6.838	-5.938	-8.779	-5.905	-5.083	-6.174
	(0.695)	(0.546)	(0.578)	(0.286)	(0.518)	(0.664)	(0.599)
South	-41.391	-38.841	-30.804	-27.630	-25.175	-23.094	-24.365
	(0.012)	(0.003)	(0.002)	(0.000)	(0.000)	(0.025)	(0.005)
Continue_school	26.46	27.434	26.963	26.586	25.518	22.955	21.856
	(0.051)	(0.015)	(0.002)	(0.000)	(0.000)	(0.03)	(0.023)
Soc_eco_bg	13.385	13.49	14.569	13.667	12.149	12.887	14.486
	(0.036)	(0.025)	(0.001)	(0.000)	(0.000)	(0.007)	(0.002)
ICT_school_qf	-17.27	-17.431	-17.734	-18.394	-13.558	-11.807	-9.069
	(0.397)	(0.258)	(0.141)	(0.050)	(0.133)	(0.326)	(0.606)
ICT_school_f	-27.601	-29.800	-32.556	-34.190	-23.816	-17.285	5.328
	(0.403)	(0.415)	(0.094)	(0.07)	(0.191)	(0.769)	(0.9)
ICT_outschool_qf	26.913	24.427	21.438	17.751	16.535	15.768	14.947
	(0.039)	(0.039)	(0.018)	(0.002)	(0.049)	(0.071)	(0.161)
ICT_outschool_f	14.976	13.239	8.165	8.481	10.585	11.222	9.816
	(0.374)	(0.396)	(0.515)	(0.315)	(0.38)	(0.258)	(0.49)
Use_pc_more5y	22.860	20.46	16.726	19.437	15.389	15.700	15.962
	(0.051)	(0.042)	(0.020)	(0.001)	(0.013)	(0.054)	(0.109)
ICT_self_efficacy	2.676	2.619	2.470	2.388	2.597	2.515	2.458
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
ICT_studied_school	-19.127	-19.341	-19.811	-13.274	-12.153	-7.461	-5.052
	(0.387)	(0.155)	(0.074)	(0.178)	(0.108)	(0.508)	(0.714)
General_ICT_school	1.987	1.879	1.801	1.483	1.245	1.089	0.820
	(0.008)	(0.003)	(0.0)	(0.001)	(0.006)	(0.072)	(0.136)
Specific_ICT_school	-1.803	-1.759	-1.780	-1.743	-1.750	-1.658	-1.388
	(0.016)	(0.01)	(0.001)	(0.000)	0(0.000)	(0.010)	(0.006)

Table B2. Estimated quantile regression model parameters for seven quantiles, 2023 data (*p*-value in brackets).

	Quantile						
	0.05	0.10	0.25	0.50	0.75	0.90	0.95
Intercept	274.864	295.534	355.8	427.568	473.715	497.86	518.575
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Female	19.078	16.688	11.050	8.006	7.821	8.116	9.195
	(0.159)	(0.100)	(0.080)	(0.158)	(0.034)	(0.160)	(0.150)
Centre	-12.271	-11.015	-9.324	-4.433	-3.438	-3.180	-4.424
	(0.38)	(0.446)	(0.269)	(0.430)	(0.546)	(0.663)	(0.580)
South	-59.113	-51.426	-44.006	-39.000	-33.808	-31.471	-32.889
	(0.006)	(0.004)	(0.000)	(0.000)	(0.000)	(0.000)	(0.001)
Continue_school	31.444	27.553	27.554	24.431	21.972	21.347	23.495
	(0.033)	(0.015)	(0.001)	(0.001)	(0.000)	(0.001)	(0.032)
Soc_eco_bg	17.002	15.755	13.534	11.984	11.368	11.288	11.126
	(0.008)	(0.01)	(0.000)	(0.000)	(0.000)	(0.001)	(0.024)
ICT_school_qf	0.878	-2.765	-1.067	2.195	1.457	1.073	1.246
	(0.944)	(0.801)	(0.881)	(0.710)	(0.768)	(0.883)	(0.889)
ICT_school_f	-12.429	-13.783	-17.176	-10.619	-7.412	-5.326	-4.362
	(0.538)	(0.366)	(0.035)	(0.084)	(0.206)	(0.535)	(0.748)
ICT_outschool_qf	31.247	34.539	28.602	32.721	31.746	31.017	30.132
	(0.178)	(0.033)	(0.014)	(0.001)	(0.001)	(0.015)	(0.068)
ICT_outschool_f	31.740	35.369	31.446	32.271	30.667	30.816	29.383
	(0.138)	(0.020)	(0.004)	(0.000)	(0.000)	(0.013)	(0.068)
Use_pc_more5y	19.414	16.291	13.702	11.254	11.123	8.798	8.396
	(0.106)	(0.076)	(0.025)	(0.007)	(0.011)	(0.141)	(0.233)
ICT_self_efficacy	1.497	1.649	1.496	1.302	1.194	1.334	1.308
	(0.018)	(0.003)	(0.000)	(0.000)	(0.000)	(0.000)	(0.019)
ICT_studied_school	-15.029	-9.845	-7.486	-4.064	-1.604	-1.888	-1.436
	(0.252)	(0.297)	(0.136)	(0.424)	(0.693)	(0.739)	(0.843)
General_ICT_school	1.615	1.732	1.554	1.003	0.737	0.684	0.590
	(0.055)	(0.002)	(0.000)	(0.001)	(0.005)	(0.099)	(0.192)
Specific_ICT_school	-1.702	-1.887	-1.819	-1.704	-1.501	-1.421	-1.370
	(0.045)	(0.004)	(0.000)	(0.000)	(0.000)	(0.004)	(0.037)

Table B3. Variance terms (random part) for the null W-MQRE model, 2018 data (s.e. in brackets).

Level		Quantile						
		0.05	0.10	0.25	0.50	0.75	0.90	0.95
2	School	285.004	634.837	1356.352	1404.585	638.313	180.884	66.170
	variance	(132.542)	(275.303)	(554.507)	(279.328)	(165.930)	(63.547)	(28.145)
1	Residual	1179.976	2165.784	4243.730	5254.211	3269.270	1492.865	799.074
	variance	(225.783)	(356.717)	(551.761)	(252.102)	(269.897)	(206.373)	(141.540)
	ICC	0.195	0.227	0.242	0.211	0.163	0.108	0.076

Table B4. Fixed effects for the null W-MQRE model, 2018 data (p-value in brackets).

	Quantile						
	0.05	0.10	0.25	0.50	0.75	0.90	0.95
Intercept	350.053	377.210	418.786	461.828	499.978	531.912	551.395
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)

Table B5. Variance terms (random part) for the conditional W-MQRE model, 2018 data (s.e. in brackets).

Level		Quantile						
		0.05	0.10	0.25	0.50	0.75	0.90	0.95
2	School	65.688	164.518	415.226	536.445	258.855	70.805	25.964
	variance	(26.756)	(60.786)	(132.849)	(123.842)	(66.138)	(20.649)	(8.804)
1	Residual	872.542	1503.161	2914.493	3855.905	2457.599	1057.402	547.145
	variance	(162.756)	(251.277)	(317.413)	(205.494)	(186.326)	(120.789)	(78.154)
	ICC	0.070	0.099	0.125	0.122	0.095	0.063	0.045
2	EV_j	77%	74%	69%	62%	59%	61%	61%
1	EV_{ij}	26%	31%	31%	27%	25%	29%	32%

Table B6. Fixed effects for the conditional W-MQRE model, 2018 data (*p*-value in brackets).

	Quantile						
	0.05	0.10	0.25	0.50	0.75	0.90	0.95
Intercept	216.446	241.416	281.772	326.067	359.607	381.28	393.648
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Female	7.407	8.484	10.273	11.250	10.597	9.427	9.078
	(0.174)	(0.07)	(0.019)	(0.008)	(0.007)	(0.024)	(0.044)
Centre	-29.495	-31.15	-31.56	-29.041	-26.943	-25.716	-25.887
	(0.042)	(0.020)	(0.003)	(0.000)	(0.000)	(0.000)	(0.000)
South	11.019	8.803	5.599	3.936	4.367	4.969	4.682
	(0.454)	(0.514)	(0.606)	(0.670)	(0.607)	(0.546)	(0.595)
Continue_school	17.43	19.949	24.871	27.175	27.318	26.148	25.037
	(0.031)	(0.005)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Soc_eco_bg	14.136	13.272	12.049	10.903	9.482	9.397	9.601
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.001)
ICT_school_qf	-22.532	-18.248	-12.085	-9.806	-9.223	-10.626	-11.708
	(0.101)	(0.089)	(0.074)	(0.061)	(0.093)	(0.087)	(0.091)
ICT_school_f	-20.488	-23.947	-26.158	-22.718	-11.168	0.627	6.807
	(0.123)	(0.037)	(0.019)	(0.029)	(0.339)	(0.963)	(0.645)
ICT_outschool_qf	16.197	17.073	18.111	18.170	18.302	18.231	18.300
	(0.108)	(0.055)	(0.003)	(0.000)	(0.000)	(0.001)	(0.007)
ICT_outschool_f	8.334	6.563	4.256	5.547	7.312	7.491	6.655
	(0.296)	(0.377)	(0.553)	(0.389)	(0.247)	(0.272)	(0.411)
Use_pc_more5y	20.375	20.88	21.851	20.742	19.585	19.896	20.83
	(0.008)	(0.001)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
ICT_self_efficacy	2.736	2.572	2.388	2.347	2.438	2.536	2.594
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
ICT_studied_school	-29.245	-27.639	-24.077	-18.153	-13.072	-9.359	-7.445
	(0.006)	(0.005)	(0.002)	(0.003)	(0.012)	(0.055)	(0.142)
General_ICT_school	1.984	1.934	1.771	1.477	1.279	1.169	1.083
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Specific_ICT_school	-2.138	-2.031	-1.859	-1.766	-1.725	-1.621	-1.533
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
School_over_devices	0.084	0.074	0.041	-0.045	-0.081	-0.047	-0.010
	(0.856)	(0.873)	(0.925)	(0.901)	(0.789)	(0.859)	(0.972)
ICT_avaiability_school	0.951	0.901	0.733	0.580	0.471	0.393	0.365
	(0.234)	(0.228)	(0.216)	(0.224)	(0.248)	(0.335)	(0.383)
Soc_eco_bg_school	13.321	12.989	11.553	10.251	10.361	10.928	11.382
	(0.177)	(0.159)	(0.183)	(0.194)	(0.147)	(0.116)	(0.108)

Table B7. Fixed effects for the conditional W-MQRE model, 2023 data (*p*-value in brackets).

	Quantile						
	0.05	0.10	0.25	0.50	0.75	0.90	0.95
Intercept	339.248	353.333	382.875	422.76	459.153	481.505	493.523
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Female	16.464	14.792	12.289	10.832	10.109	9.721	9.89
	(0.001)	(0.000)	(0.000)	(0.000)	(0.000)	(0.001)	(0.002)
Centre	-53.345	-49.334	-44.352	-39.998	-36.397	-34.28	-33.566
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
South	-15.162	-13.017	-10.451	-7.315	-5.895	-5.354	-5.449
	(0.115)	(0.108)	(0.148)	(0.254)	(0.321)	(0.37)	(0.376)
Continue_school	28.542	27.754	26.361	24.668	22.988	22.304	22.528
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Soc_eco_bg	9.336	9.808	10.195	10.182	10.100	10.186	10.11
	(0.001)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
ICT_school_qf	0.812	0.459	1.823	3.316	3.531	2.83	2.432
	(0.888)	(0.925)	(0.668)	(0.379)	(0.301)	(0.476)	(0.592)
ICT_school_f	-13.096	-12.738	-11.801	-9.676	-7.231	-6.228	-6.631
	(0.135)	(0.085)	(0.035)	(0.044)	(0.128)	(0.233)	(0.248)
ICT_outschool_qf	23.728	23.606	22.379	22.215	23.642	24.404	25.292
	(0.022)	(0.009)	(0.001)	(0.000)	(0.000)	(0.000)	(0.001)
ICT_outschool_f	21.316	22.585	23.134	22.923	23.780	24.44	25.241
	(0.040)	(0.008)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Use_pc_more5y	16.881	15.151	12.889	11.337	10.677	9.935	8.923
	(0.006)	(0.001)	(0.000)	(0.000)	(0.000)	(0.000)	(0.003)
ICT_self_efficacy	1.387	1.437	1.442	1.384	1.337	1.381	1.417
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
ICT_studied_school	-16.389	-13.081	-9.903	-7.796	-5.654	-3.804	-2.64
	(0.012)	(0.01)	(0.006)	(0.008)	(0.029)	(0.151)	(0.361)
General_ICT_school	1.07	1.204	1.178	0.920	0.692	0.607	0.606
	(0.01)	(0.0)	(0.000)	(0.000)	(0.000)	(0.001)	(0.003)
Specific_ICT_school	-1.394	-1.543	-1.614	-1.540	-1.441	-1.369	-1.367
	(0.003)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
School_over_devices	0.332	0.191	0.123	0.165	0.178	0.072	-0.015
	(0.627)	(0.734)	(0.792)	(0.663)	(0.590)	(0.842)	(0.968)
ICT_avaiability_school	-0.138	-0.082	0.006	0.020	-0.040	-0.081	-0.097
	(0.775)	(0.85)	(0.988)	(0.951)	(0.894)	(0.791)	(0.761)
Soc_eco_bg_school	30.541	23.869	15.285	9.317	6.466	5.713	5.835
	(0.001)	(0.002)	(0.012)	(0.065)	(0.189)	(0.292)	(0.303)