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FACTORS INFLUENCING ITALIAN STUDENTS' DIGITAL LITERACY: A MULTI-LEVEL ANALYSIS OF ICILS RESULTS

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Abstract. *The information and communication technologies (ICTs) has brought into sharp focus the necessity for digital literacy, which is essential for social inclusion and personal development. Notwithstanding its significance, there is considerable variation in digital literacy levels across Europe, with Italy exhibiting a notable deficit, with only 50% of its population aged 16-74 possessing basic digital skills. This paper analyses data from the 2018 International Computer and Information Literacy Study (ICILS) to examine the digital competences of young Italian students. This study examines the influence of individual, school, and territorial factors on the digital competencies of students at grade 8. The research addresses three key questions: firstly, how individual characteristics affect digital competences; secondly, the influence of usage habits and school environments; and thirdly, the existence of regional and school-based inequalities. Due to hierarchical data structure through a multilevel regression analysis, the study provides insights into the pre-pandemic digital literacy situation in Italy, identifying critical issues and suggesting the need for targeted educational policies. These results can also be used to compare the outcomes of surveys conducted after the pandemic.*

Keywords: *Digital literacy, competence assessment, Rasch model, hierarchical data, multilevel regression model.*

1. INTRODUCTION

The development of the global knowledge society and the rapid integration of information and communication technologies (ICTs) have transformed society and the economy, with an increasing impact on daily life, demonstrating the essential need for citizens to acquire digital skills.

The International Telecommunication Union (ITU), the United Nations specialised agency for ICTs, defines digital literacy for the global population in terms of its putative outcomes: “the ability to use ICTs in ways that help individuals achieve beneficial, high-quality outcomes for themselves and others in everyday life and that reduce potential harms associated with more negative aspects of digital engagement” (ITU, 2018).

Digital technology is transforming people's lives. The European Commission (EC) has suggested that digital literacy is increasingly becoming an essential life skill, and the inability to access or use ICT has effectively become a barrier to social inclusion and personal development (European Commission, 2008).

The EC has outlined a set of principles aimed at facilitating a people-centred digital transformation in order to articulate common policy objectives for citizens, businesses, public administrations and policy makers. The articulated digital principles are intended to provide direction for creating a digital environment that prioritises human well-being, security, inclusiveness, and openness, ensuring that no one is left behind (European Commission, 2022).

In Europe, more than 90% of jobs require a basic level of digital literacy, and digital integration permeates different sectors, from commerce to transport and agriculture. However, around 42% of Europeans have deficits in basic digital skills, including 37% of the active workforce (European Commission, 2024).

In the context of technological development, digital literacy has become increasingly crucial in education. The ongoing digital transformation requires the development of education and training systems that are able to support people in developing their digital skills consistently at all levels of the formative process.

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.

In addition, recent global challenges such as the COVID-19 pandemic have further highlighted the importance of digital literacy. The widespread adoption of distance learning modalities has highlighted the need for students to have robust digital skills to engage with online educational content, participate in virtual classrooms, and collaborate with peers and educators across digital platforms. In this context, digital literacy is not just an additional skill, but a cornerstone of modern education, enabling students to adapt to changing learning paradigms and navigate the complexities of the digital age with confidence and efficiency. Promoting the development of digital literacy has therefore become a priority for educators, policymakers and stakeholders alike as they strive to equip the next generation with the tools and skills necessary to thrive in an increasingly digitalised world.

In order 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 situation in Italy with regard to digital skills is rather worrying. According to Eurostat data (Eurostat, 2023), in 2021 the percentage of the population aged 16-74 with basic digital skills is just under 50%. This result places Italy at the bottom of the list of European countries. Action to improve this situation must therefore focus first and foremost on educating the younger generations.

Based on these considerations, 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.

In this paper, we analyse data from the 2018 edition of ICILS. The survey was repeated in 2023, but data will not be available until 2025. Our aim is to delve into the reality of young Italian students in the pre-pandemic period in order to identify the main critical issues that were already present before the emergency of increased use of digital tools. Three main research questions are addressed: 1) what are the individual characteristics that significantly influence the digital skills; 2) what are the habits of using electronic devices and the role of the reference school environment; 3) whether there are school and territorial inequalities.

While the main report of ICILS 2018 (Fraillon et al., 2020b) offers only general results on Italian student scores, our analysis allowed us to investigate individual, school, and territorial inequalities in more detail.

Our paper makes the following contributions to the literature. First, it provides a general overview of the issue of young people's digital literacy, with a focus on assessing their education and identifying factors that influence their performance. The debate on these issues is ongoing, encompassing numerous aspects and a vast body of literature, which risks losing sight of the core problem. More research is needed, particularly on the consequences of digital literacy, causality and

the relationship between different factors, and the review proposes a number of specific hypotheses to be tested in future research. The second contribution is to deepen the Italian results, taking into account the hierarchical structure of the data, and to assess the impact of the main socio-demographic, aptitude and educational characteristics of the students. The Italian results were only briefly reported in the IEA report and, in general, studies on the digital literacy of Italian students are rather limited.

The study provides insights into the pre-pandemic digital literacy situation in Italy. These results are a useful tool for comparing the results of the surveys conducted after the pandemic, particularly with the ICILS2023 data that was recently made available. The overall results seem to show that the impact of Covid period was as important as expected. Further in-depth studies will be necessary for Italian results.

The paper follows this structure: the literature review first provides a summary of the main definitions of digital literacy, followed by a summary of the main aspects of assessment instruments. The structure of the ICILS survey is then presented, followed by an initial exploratory analysis of the results. The results of the analyses conducted to address the research questions are then reported. For this purpose, a multilevel linear regression model has been estimated, with students as the first-level units and schools as the second-level units. Finally, conclusions and future developments are presented.

2. BACKGROUND AND RELATED LITERATURE

2.1 DEFINITION OF DIGITAL LITERACY

Over the years, there have been significant differences in the way digital literacy for young people has been conceptualised and measured in the literature. As a result, different terms such as skills, competence, and knowledge have been used to refer to digital literacy.

The term "digital literacy" was first coined by Paul Gilster, a historian and educator, who defined it as: "the ability to understand and use information in multiple formats from a wide range of sources when presented via computers" (Gilster, 1997). In other words, digital literacy involves the ability to critically evaluate information (presented in different formats) and to make decisions about how to use this information in different real-life contexts.

The challenge in defining digital literacy systems stems from two main factors. First, there is ambiguity about what 'digital' means, whether it focuses on specific technical skills such as programming, or broader skills needed to function in a digital environment. Secondly, determining what constitutes literacy' is complex as it involves practical knowledge and expertise, which is difficult to assess without observing individuals demonstrating their skills.

Some researchers adopt broad definitions that consider multiple dimensions of digital skills, while others focus on specific skills such as information literacy or computer programming (van Laar et al., 2020). Ferrari (2013) attempted to clarify the relationship between these existing labels and the emerging definition as follows: "digital literacy is the ability to safely and appropriately access, manage, understand, integrate, communicate, evaluate and create information through digital technologies for employment, decent work and entrepreneurship. It encompasses competences sometimes referred to as digital literacy, ICT literacy, information literacy and media literacy". All these competences are included in the Digital Competence Framework for Citizens, also known as DigComp (Vuorikari et al., 2022; Wild & Schulze Heuling, 2021), which 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).

For young people, digital literacy is increasingly being formulated as an important educational goal. 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). In this respect, the accuracy, clarity and topicality of curricular guidelines related to these concepts is crucial, which calls for research that investigates how digital literacy and digital competence are represented in curricular documents.

2.2 THE MEASUREMENT TOOLS IN THE EDUCATIONAL CONTEXT

As there is no single definition of digital literacy, the assessment of the level of skills acquired depends strongly on the definition used, the context and the assessment tools. As far as the context is concerned, there are studies ranging from compulsory schooling to higher education, so the assessment may involve different approaches, all within the framework of a definition that refers to an internationally recognised dimension, while respecting individual national contexts.

Instruments can be divided into three main categories according to the approach to data collection (Carretero et al., 2017): performance assessment, where individuals are monitored by a human observer or software while solving authentic, real-life problems using common software tools (e.g. browser, word processor, spreadsheet); knowledge-based assessment, where individuals respond to carefully designed test items that measure both declarative and procedural knowledge; self-assessment, where individuals are asked to assess their knowledge and skills using questionnaires that can range from structured scales to free-form reflections.

In the educational research literature, several papers are dedicated to digital competences in higher education (for a systematic review, see Farias-Gaytan et al., 2023; Saltos-Rivas et al., 2022; Sillat et al., 2021; Spante, 2018).

The digital competences of children and adolescents, which are the main topic of our paper, are the subject of several studies. The systematic review by Haddon et al. (2020) delves into the multifaceted landscape of children and youth digital literacy, examining their ability to navigate the digital realm, critically evaluate online content, and engage safely in digital environments. The review provides a comprehensive overview of the digital competences developed by today's youth. The results of 110 papers were collected. A minimal proportion of the studies include an achievement test; many more focus on self-reported measures. The most commonly studied countries are the US and European countries. In contrast, there are some large regional gaps: no studies cover any part of Africa, Central Asia or Central America, and only a small number of studies cover South America and Asia. This gap can be explained by the availability of data. The main findings of the review underline that digital skills generally improve with age and that, contrary to popular belief, gender differences in digital skills are not consistent; although boys may claim to have better skills, achievement tests often show no difference. Better cognitive skills are associated with better digital skills, and academic achievement positively correlates with digital skills, along with motivation and possibly learning style. In addition, positive attitudes towards ICT are associated with better digital skills in children and, as it is well known, children from higher socio-economic status households tend to have better digital skills.

2.3 THE MAIN FINDINGS FOR ITALIAN STUDENTS

In Italy, the literature dedicated to the assessment of digital literacy is very limited. The paper by Calvani et al. (2012) presents a research study conducted in Italian schools on the digital competence of adolescents (aged 14-16). A digital literacy questionnaire was developed and administered to a sample of secondary school students. The aim was to verify whether adolescents' digital literacy was limited to simple technical aspects or whether it went beyond them to include a range of more significant knowledge and skills related to conceptual understanding of technology, socio-relational knowledge and higher-order cognitive skills. The authors conclude that the optimistic picture of digital literacy among younger generations is not well founded.

In their paper, Gui and Argentin (2011) present the results of a test covering three main dimensions of digital literacy (theoretical, operational and evaluative skills) administered to a random sample of 65 third-year high school classes. In line with the literature, the sample performed better on operational skills, but particularly poorly on evaluation skills (although the test has reliability problems for the sample dimension). Gender and family cultural background are also collected. It appears that cultural background has a significant effect, which is stronger on operational skills, while gender has a clearer effect on theoretical knowledge.

The paper by Pagani et al. (2016) investigates the impact of digital literacy on educational outcomes by merging data from the INVALSI (National Institute for the Evaluation of the Education and Training System) survey for upper secondary school with an original dataset on performance tests of Internet skills for tenth grade students. A number of individual, family, school and classroom control variables are taken into account. The results indicate that, overall, Internet skills have a positive effect on academic performance. This effect is stronger for students with low academic performance or low family background. It is also stronger for students in technical or vocational schools.

The paper by Caponera et al. (2022) examines gender differences in the results of ICILS 2018 among Italian students aged around 13. The results showed gender differences in the relationship between computer information literacy and self-efficacy in the use of information and communication technologies. In addition, self-efficacy acted as a mediator for girls, strengthening the link between ICT learning and digital literacy. Based on these findings, the study discusses possible implications for the Italian educational system.

Other papers in the literature focus on international surveys and only mention some results of Italian students in a broader context (Ponte, 2019; Areepattamannil & Santos, 2019).

3. DATA: THE ICILS 2018 SURVEY

The IEA-ICILS is a large-scale survey designed to measure the digital literacy of grade 8 students across different educational systems, namely countries and benchmarking units. ICILS has three editions: 2013, 2018 and 2023[1] and is designed to understand how well students are prepared for study, work and life in a digital world (Fraillon et al., 2019). Digital literacy deals with two different dimensions: computer and information literacy (CIL) and computational thinking (CT). The CIL scale is conceptualised as "an individual's ability to use computers to investigate, create and communicate in order to participate effectively at home, school, work and in society", while the CT scale refers to "an individual's ability to recognise aspects of real-world problems that are suitable for computational formulation, and to evaluate and develop algorithmic solutions to these problems so that the solutions can be operationalised using a computer" (Fraillon et al., 2019).

In addition to students' responses to items on the CIL scale and the CT (optional) scale, a student questionnaire was administered to collect individual background information, and separate questionnaires were administered to teachers, school ICT coordinators, school principals, and staff at national research centres. The survey focuses on the home and school contexts in which students develop digital competences and skills.

The CIL test is a computer-based test consisting of a sequence of tasks contextualised by a real-world topic and driven by a plausible narrative (Fraillon et al., 2020b). The CIL includes four strands: understanding computer use, information gathering, information production and digital communication (Fraillon et al., 2019). Using a balanced randomised design, each student completed two of five modules, each lasting 30 minutes. Each module is structured into a series of smaller tasks and a single large task, which takes 15-20 minutes to complete. The major task involves the development of an information product, such as a website, a presentation, a leaflet, etc.

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 Wright, 1997) for polytomous items with more than two response categories. These models belong to item response theory (IRT) and are used both for item calibration (estimation of item parameters, i.e. item characteristics such as difficulty) and

[1] ICILS 2023 data and results will be published in 2025.

for the student scoring phase. The CIL reporting scale has a mean of 500 and a standard deviation of 100. This scale was established in the 2013 edition of ICILS, where the mean is the average CIL score across countries. A set of 5 plausible values for each student is drawn from the marginal posterior distribution of the latent variable (for details see Fraillon et al., 2020a;). The plausible values are used to derive summary performance statistics on the CIL scale. Proficiency levels were also established by analysing item maps and student performance data. The boundaries of the proficiency levels were set at 407, 492, 576 and 662 scale points (each level has a width of 85 scale points) so that students could be classified into one of the five proficiency levels (below level 1, level 1, level 2, level 3, level 4).

The student questionnaire, also administered as a computer-based test, collects students' background information, their experience and use of computers and ICT at school and outside school, and their attitudes towards computers and ICT (Fraillon et al., 2020b). Based on the students' responses, specific indices are constructed that combine more items or more scales. Some examples of variables collected in the student questionnaire are: gender, age, immigrant and language background, expected level of education, use of ICT (desktop computer, notebook, laptop, smartphone, etc.), engagement in specific tasks using ICT, and agreement with statements about ICT use and attitudes towards ICT. Scales developed on the basis of the student questionnaire are: students' general engagement with ICT, students' engagement with ICT for school-related purposes, extent of students' learning about ICT at school, ICT self-efficacy and perceptions of ICT. In addition, an index of socio-economic and cultural status is constructed based on students' home environment, including parents' level of education, number of resources available for learning at home, and number of books at home.

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

Italy participated for the first time in the 2018 edition, where the ICILS sample consists of more than 46,000 grade 8 students and more than 26,000 teachers from more than 2,200 schools in 14 education systems. The Italian sample consists of 2,810 students grouped in 150 schools. The Italian data are peculiar in that the test was administered in the first half of the school year, while other countries were surveyed in the second half of the school year. This means that caution should be exercised when comparing Italian results with those of other countries. Furthermore, in 2018 Italy only participated in the CIL assessment.

4. METHOD: THE MULTILEVEL LINEAR REGRESSION MODELS (MVL)

Ignoring the hierarchical nature of the data has two implications. The first is methodological because it leads to biased parameter estimates. With regard to the second, the hierarchical model can also include explanatory variables related to schools, thus deepening the interpretation of the results. Therefore, a multilevel approach allows for more precise parameter estimates and also for a better interpretation of the score differences due to individual variability and those due to school characteristics. A hierarchical model allows the estimation of the total and explained variance at the different levels highlighting the impact of school (Azubuike et al., 2024; Goldstein et al., 2002). MLM's use of random effects captures unobserved heterogeneity and models non-independence among students within the same schools.

The multilevel analysis is carried out in successive steps. In the first step, the differences in the dependent variable between groups (schools) are assessed by estimating the empty model (also called baseline or null model), i.e. the model without covariates. This model provides estimates of the variance at each level (within and between schools) before including the predictors; it provides the point from which to determine how much the subsequent models explain the variance.

If there is a significant effect, the analysis moves to the second step, which includes student-level covariates and estimates a linear regression model for each school. This step can be further divided into two steps: the first step involves models that differ only in the intercept (random intercept); the second step involves estimating different regression coefficients for each school (random slope).

The third stage also includes covariates related to school level. Again, it is possible to include only random intercepts and also random slopes.

When interpreting the results of a multilevel analysis, it is also important to be aware that the student-level variables in a two-level model have a different meaning than in a single-level regression analysis. This is because the student-level coefficients reflect the effect of a variable within schools.

A hierarchical regression model with *i* students nested in *j* clusters (schools) can be estimated as

$$Y_{ij} = \beta_0 + \beta_{ij}X_{ij}^{n} + \beta_j X_j^{m} + U_{0j} + \varepsilon_{ij,} \quad (1)$$

where:
Y_{ij} is the dependent variable,
β_0 is the intercept (the mean of Y),
X_{ij}^{n} is a vector of student-level variables, with its corresponding vector of regression coefficients β_{ij},
X_j^{m} is a school-level variable with its corresponding vector of regression coefficients β_j,
U_{0j} is the residual term at the level of the cluster (school), and ε_{ij} is the student-level residual.

Both residual terms are assumed to have a mean of 0 and variance that is normally distributed at each level. A multilevel model can be thought of as consisting of two components: a fixed part which specifies the relationship between the mean of Y and explanatory variables (covariates) and a random part that contains the level 1 and 2 residuals. The explained variance has to be estimated for each level separately, starting from the empty model:

$$Y_{ij} = \beta_0 + U_{0j(null)} + \varepsilon_{ij(null)}. \quad (2)$$

For the empty model it is useful to calculate the intra-class correlation coefficient (ICC), a statistic that measures how strongly units in the same group resemble each other, in other words it measures the proportion of total variance that is due to difference between groups. It can be computed as:

$$ICC = \frac{\tau_{0j(null)}}{\tau_{0j(null)} + \sigma_{ij(null)}} \quad (3)$$

where $\tau_{0j(null)}$ is the between group variance and $\sigma_{ij(null)}$ is the residual variance. Based on the estimates of variances at school and student level derived from the null model, we can compute for the models including covariates the explained variance at the school level

$$EV_j = 1 - \frac{\tau_{0j}}{\tau_{0j(null)}} \cdot 100 \quad (4)$$

and the explained variance at the student level

$$EV_{ij} = 1 - \frac{\sigma_{ij}}{\sigma_{ij(null)}} \cdot 100. \quad (5)$$

5. DESCRIPTIVE ANALYSIS

5.1 THE INDIVIDUAL STUDENTS' CHARACTERISTICS

The dataset used for our analysis comprises 2713 students grouped in 144 schools, representing 96% of the original 2810 (150 schools) Italian ICILS 2018 sample. The units not considered in our analysis were part of 6 schools that lacked data at school level (because either the ICT coordinator or the principal had not responded to the questionnaire). In Appendix, Table A lists all the variables collected in the survey and used in this study with their coded names and meanings.

Performance data had no missing values, while the covariates related to student characteristics and device use had low percentages of missing data (always less than 5%). The percentage of missing data increased for the school-related covariates. In this case, the presence of significantly different percentages is natural, as the data on school structures were collected from individuals other than the students (the units of the database). Therefore, only variables with an acceptable percentage of missing data, never exceeding 10%, were considered.

Missing data were imputed using the mean for numerical variables and the mode for categorical variables, following the guidelines suggested in the ICILS documentation. This choice was also motivated by the fact that the missing values in the dataset were completely random. A study of the distributions of all variables was carried out to ensure that imputing the mean and mode was indeed the best approach. The chosen imputation method did not lead to substantial changes in the distributions of the variables involved.

The table 1 synthetizes the main socio demographic characteristics of the students.

Table 1 Socio-demographic characteristics of students

Gender		Born		Parents	Home address		
Female	Male	Italy	Abroad	At least one non-Italian	Northern Italy	Central Italy	Southern Italy
48%	525	95%	5%	10%	44%	19%	37%

A composite indicator (s_nisb) is calculated as a proxy for the socio-economic and cultural status of the student, taking into account three indices: highest occupational status of parents, highest educational level of parents, and the number of books at home. After converting the resulting variables into z-standardized variables (with a mean of 0 and a standard deviation of 1 for each national dataset), principal component analysis of these indicator variables were conducted separately for each weighted national sample. The final s_nisb scores consists of factor scores for the first principal component with national averages of 0 and national standard deviations of 1.

The values ranged from -2.46 to a maximum of 2.05, with the 75th percentile being rather low (0.74). The variable was categorised into 4 classes: low (<1.25), medium-low (-1.25; 0), medium-high (0;1.25) and high (>1.25). In Figure 1 the distribution of the levels is represented.

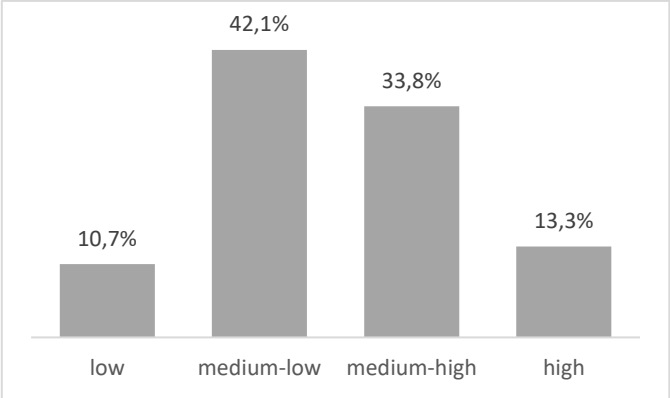


Figure 1. Level distribution for socio-economic and cultural background index

The figure shows a slight prevalence of students with a socio-economic and cultural background in the low and medium-low levels.

Another important information is collected about the level of education that student intends to achieve. The 62% of students stated that they intended to continue their studies after leaving the high school.

5.2 ICT EQUIPMENT, USE, AND ATTITUDES

In terms of ICT equipment ownership, use and attitudes towards technology, almost all students have a computer (95%), an Internet connection at home (94%) and 90% have both. Slightly fewer reported owning a tablet (88%). More than half of the students have been using different devices for between 1 and 5 years, both for computers and for tablets and smartphones. However, 14% said they had never used a computer, 16% a tablet and 8% a smartphone. Therefore, although the ICILS 2018 survey aims to investigate the CIL skills of digital native students, and indeed many of them report having years of experience with technology, there remains a small proportion of students in the sample who have never used a computer, smartphone or tablet.

About 95% of students use devices for personal purposes, while 75% also use them for studying. The main use is to communicate with friends or to access online platforms. Girls use communication tools more than boys. For all, is most common to use general application for editing videos, making music, etc., rather than specific applications such as Word, PowerPoint and Excel.

In terms of attitudes towards technology, students are more confident in using basic tools and less confident in using applications. However, they are positively motivated to pursue future careers that involve extensive use of computer tools. Males consider themselves more experienced in specific applications and have a more positive view of technological tools.

In terms of use at school, 91% of students have studied computer science, but less than half claim to have acquired the maximum level of skills. It should be noted, however, that only 41% use PCs at school. Another negative aspect is the percentage (only 53%) of students who claim to have learnt basic concepts of computer security at school.

5.3 SCHOOL CHARACTERISTICS

The situation in terms of staff and infrastructure varies greatly between schools, and this has a relevant impact on the interpretation of the results and possible conclusions. The average number of pupils per school is 480 **(minimum 8, maximum 2000) and the average number of teachers is 75 (minimum 6, maximum 200).**

The percentage of students attending schools that have been using technological tools for at least 5 years is 72%. The average number of PCs per school is 76, of which 56 are dedicated to pupils. Most schools show

little interest in developing the digital skills of their students; as for teachers, there is interest from the school in increasing computer equipment and improving their skills, but training initiatives are scarce.

6. THE MAIN INEQUALITIES IN CIL RESULTS

6.1 THE OVERALL PERFORMANCE

In the Italian sample, the CIL score has an average of 461.47 (se=2.8) which is below the international average of around 538. The median of 467 refers to level 1, which means that half of the students are at or below the lowest level of proficiency. The third quartile of the distribution is also quite low, with a score of 513.88, corresponding to proficiency level 2. Only Kazakhstan and Uruguay had lower average scores than Italian students. However, since the Italian data were collected at the beginning of the school year, and not in the middle as was the case for other countries, it is not entirely accurate to make a direct comparison of the results.

As illustrated in Figure 2, most students show a lack of developed skills (23.7% scored below level 1) or have basic skills (38.9% in level 1) that do not go beyond using the computer for basic communication or research. However, some (30.5%) demonstrate the ability to use the computer for data collection and management tasks (level 2), but very few (4.9%) show high level skills that translate into independence and autonomy in performing more complex tasks involving computer use (level 3) and only 2% reach the highest level (level 4), demonstrating a sophisticated ability to apply critical thinking skills when searching for information online.

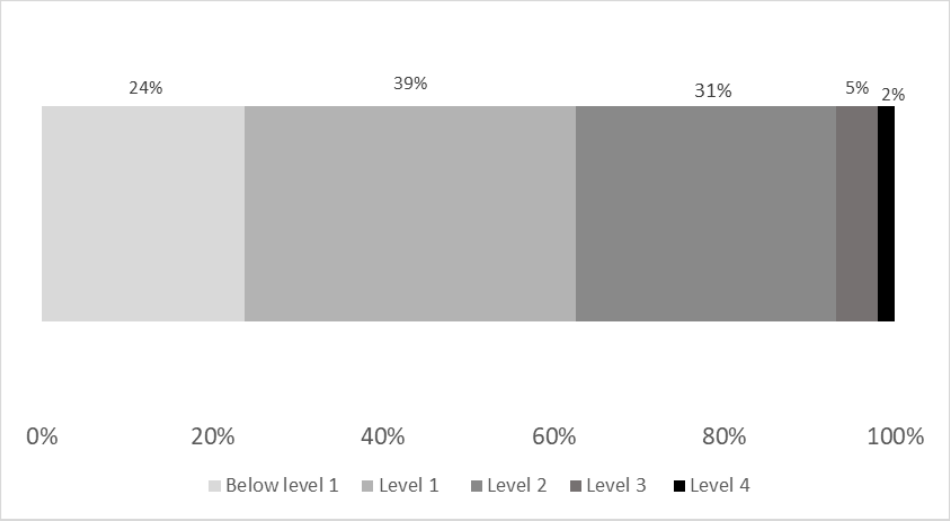


Figure. 2. The distribution of performance levels

6.2 PERFORMANCE INEQUALITIES BY SOCIO-DEMOGRAPHIC CHARACTERISTICS

The analysis of the gender gap shows that males have an average proficiency level of 454, while females have an average proficiency level of 570, which is 16 points higher than males. Again, the differences between the two groups depend on the distribution across the different score levels. There are more boys than girls with scores below the minimum, while there are fewer boys than girls with proficiency level 2. In addition, there is a significant gap between those expressing an intention to go on to higher education after leaving school and other students in the sample. The former group has an average score of 478, while the latter group has an average score of 435.

As concern the main territorial disparities, students from the north and centre of Italy have significantly higher average scores than those from the south: students from the north score on average 41 points higher and

those from the centre 35 points higher than their southern counterparts. However, the difference in average scores between the North and the Centre is not significant. In the South, there is a higher percentage of students scoring below the minimum level (35% compared to 17% in the North and 19% in the Centre) and fewer students reaching level 2 compared to other areas (22% compared to 33% and 36%).

6.3 PERFORMANCE INEQUALITIES BY ICT TOOLS USE AND BY ATTITUDE

Considering the ownership and use of technology, both at home and at school, there is a significant difference in test scores between those who have a personal computer at home and those who do not, with the former group scoring on average 49 points higher. Similarly, there is a 47-point difference in scores between those who have an internet connection at home and those who do not. Owning a tablet, however, does not appear to produce significantly different averages.

There are also significant differences in whether students use computers for study, personal reasons or at school. Students who use computers for these purposes achieve significantly higher scores. Another significant difference is observed between the results of students from schools with a higher number of students from better socio-economic backgrounds and those from schools with more economically disadvantaged students. On average, the former group scores 25 points higher than the latter. As with the geographical distribution and the gender distribution, the difference in performance can be attributed to the fact that a higher percentage of students from disadvantaged schools score below the first level (lack of skills) and a lower percentage score at the higher level 2 compared to the distribution of students from the other group. Thus, groups of students from schools with different socio-economic compositions in the sample effectively achieve different scores.

7. THE MULTILEVEL REGRESSION MODEL RESULTS

Before estimating the multilevel models, an analysis to identify the covariates with significant impact on the CIL score was performed using a classical multiple regression model.

This analysis confirmed the relevance of several covariates. Socio-economic background, being born in Italy, and higher education aspirations positively impact performance. Access to the Internet, using a computer for studying and for personal purposes all improve scores. Besides Long-term technology use increases scores. Self-confidence in digital skills contributes to better scores, however, frequent use of the computer to exchange information on websites or to do homework does not seem to help students in terms of digital literacy, as it has a negative impact on the CIL score, while Computer science study and the Frequent use of specific applications negatively impacts performance. Using general applications like Word and Excel in the classroom has a positive effect.

These results are consistent with the main evidence illustrated in literature dedicate to ICILS (Fraillon et al., 2020b) and in other papers concerning the use and attitude towards technological tools (Livingstone et al, 2023; Min & Seo, 2024; Scheerder et al., 2017; Wang & Wang, 2023).

Moving from these considerations, several multilevel models have been estimated. The anlysis has been developed using the statistical package EdSurvey of R. This tool is tailored to processing large-scale education data with appropriate procedures to analyze these data efficiently, taking into account their complex sample survey design and the use of plausible values.The evaluation of the goodness of the model is based on parsimony (fewer parameters to estimate), significance of the parameters, explanatory power of the model, and interpretability of the results.

M0: Empty model

The units of level 1 (students) are 2713 clustered in 144 schools (units of level 2). The results are reported in Table 2a e Table 2b.

Table 2a Variance terms (random part) for the M0 model

Level		Variance	Std.error
2	School	1403	264.5
1	Residual	5354	175.7

Table 2b Fixed effects for the M0 model

	Estimate	Std.error	p-value
Intercept	459.374	4.538	0.000

The empty model revealed a significant difference in the score among schools. The ICC is equal to 0.208, indicating that approximately 20% of the variability in score results may be attributed to school membership.

M1: Random-intercept model with first level covariates

The second model included the student covariates which were found to be significant in the classical regression model.

Table 3a Variance terms (random part) for the M1 model

Level		Variance	Std.error
2	School	656.4	119.5
1	Residual	3835.5	124.4

The comparison with the empty model M0 showed a decrease $of\ EV_j = 53\%$ at school level and a decrease of $EV_{ij} = 28\%$ at student level.

Table 3b Fixed effects for the M1 model

	Estimate	Std.error	p-value
Intercept	332.127	14.237	0.000
s_sex1	8.050	3.049	0.008
s_sborn1	17.970	7.395	0.015
s_nisb	12.309	1.533	0.000
s_isced1	23.647	3.050	0.000
s_intnet1	13.772	6.536	0.035
s_usestudy1	11.519	3.397	0.001
s_usepersonal1	22.357	5.083	0.000
s_useinf	-0.613	0.158	0.000
s_usestd	-0.834	0.179	0.000
s_excomp1	8.157	4.624	0.078
s_excomp2	23.250	4.906	0.000
s_geneff	2.392	0.154	0.000
s_ictstud1	-15.790	5.653	0.005
s_genclass	1.3198	0.196	0.000

s_speclass	-1.480	0.216	0.000
s_ictlrn	0.348	0.187	0.062

The level of education that the student intends to achieve is the variable with the higher impact on the CIL score, with an average increase of about 24 points. The use of the computer for purposes other than studying showed a high regression coefficient (22 points) and also if the student started using the computer more than 5 years ago had a positive influence on the score (23 points). Studying computer science in the current year again showed a negative effect, as did the number of times during the current year that the student used the computer in classroom-specific applications. The competence acquired during the school year was not significant.

M2: Random-intercept model with first and second level covariates

Table 4aVariance terms (random part) for the M2 model.

Level		Variance	Std.error
2	School	428.7	82.37
1	Residual	3832.5	126.30

The comparison with the null model showed a decrease of $EV_j = 64\%$ for the variance at school level. The residual variability at student level is very similar to the one of model M1.

Table 4b Fixed effects for the M2 model.

	Estimate	Std.error	p-value
Intercept	339.321	14.075	0.000
s_sex1	7.863	3.0389	0.010
s_sborn1	18.807	7.352	0.011
s_isced1	23.911	3.050	0.000
s_nisb	11.359	1.522	0.000
s_intnet1	11.986	6.351	0.059
s_usestudy1	11.595	3.387	0.001
s_usepersonal1	22.087	5.0342	0.000
s_useinf	-0.583	0.158	0.000
s_usestd	-0.817	0.180	0.000
s_excomp1	7.899	4.633	0.088
s_excomp2	23.098	4.896	0.000
s_geneff	2.399	0.1534	0.000
s_ictstud1	-14.674	5.573	0.008
s_genclass	1.299	0.195	0.000
s s_speclass	-1.414	0.214	0.000
s_ictlrn	0.337	0.186	0.069
Area1	-29.963	6.166	0.000
Area2	-3.264	7.005	0.641
school_nisb	9.681	6.299	0.124

The results for individual covariates remain similar to the previous model. Among the second level covariates, only the coefficient of the South (explictistratum1) is significant different from the North, while the school_nisb is not significant.

In conclusion, it can be affirmed that, in addition to the significant impact of attending different schools on digital literacy, being from Northern or Central Italy and having a more advantageous socio-economic and cultural background, as well as having ambitions for future academic pursuits, certainly have a positive influence on the competencies demonstrated by students.

8. CONCLUDING REMARKS AND FURTHER DEVELOPMENTS

Digital natives are not digital experts. The use of digital devices does not necessarily lead to deeper digital skills. The 2018 ICILS survey shows that while most students have reached a basic level of digital literacy, only 2% have reached the highest level, demonstrating a sophisticated ability to apply critical thinking skills when searching for information online.

An unexpected finding, already highlighted in the 2013 survey, relates to gender differences: contrary to 'conventional wisdom' (see for example, Punter et al. , 2017) average scores on the digital literacy scale are significantly higher for females than for males.

Socio-economic status is one of the most important factors influencing the acquisition of digital skills. Therefore, special attention must be given to innovative and effective projects to reduce inequalities. Schools are the main actors that need to intervene decisively to this end. Compared to the international average, Italian students use computers less at school, both for academic purposes (-11 percentage points) and for non-academic purposes (-25 percentage points). However, if the socio-economic conditions do not allow a student to have adequate computer tools, it is within the school system that they should have the opportunity to deepen their digital skills in order to mitigate the impact of their family background.

Digital literacy needs to be increased, focusing on the role of information and data in the development of a knowledge-based, networked society. In this context, an introduction to logical and computational thinking and expertise with information technologies should be included. Students need to be aware users of digital environments and tools, but also producers, creators and designers. Teachers should be given the right conditions to act as facilitators of innovative educational pathways based on content more familiar to their students. In this context, a key action is to support teachers in their role as facilitators of innovative learning pathways by defining with them didactic strategies to enhance key competences. Engaging students through innovative and purposeful educational formats and the development of innovative curricula are the main challenges for the coming years.

It is also essential to introduce computational thinking at primary school level and to update the technology curriculum at lower secondary level.

Although it is likely that the type of school makes a difference, future studies could verify the causality by assessing the orientations and skills of children at the time when they first enter these different types of secondary schools.

In this study, as just underlined, the data refers to pre-pandemic period. However, the results allow a direct comparison regarding the impact of the pandemic. Besides the new preliminary results of the 2023 reveals that while average performance has improved, the underlying inequalities have not diminished, both for gender and territorial area.

While young people and teachers have had to adapt to new learning tools, geographical and socio-economic differences are likely to have widened the skills gap for the most disadvantaged categories.

Another limitation concerns the age of administration, which was lower in 2018 compared to other countries. However, this limitation was addressed in the subsequent survey.

From a methodological point of view, the approach used provided more robust results compared to the classical linear model. However, an area for further exploration is the possibility of an additional level of analysis that takes into account territorial aspects.

An interesting future development would be the possibility of a quantile analysis to further explore the results over the whole distribution to investigate deeply the effect of student characteristics.

APPENDIX

Table A List of Variables

Area	Geographical area	0 = Northern 1 = Southern 2 = Center
s_sex	Gender	0 = male 1 = female
s_tlang	Spoken language	0 = not Italian 1 = Italian
s_sborn	Country of birth	0 = not Italy 1 = Italy
s_isced	Level of education that the student intends to achieve	0= does not want to continue her/his studies after high school 1= want to continue her/his studies after high school
s_nisb	Index of socio-economic background	Real value
s_comput	Computer availability at home	0=no 1=yes
s_intnet	Internet line availability at home	0=no 1=yes
s_usestudy	Use the computer to study	0=no 1=yes
s_usepersonal	Use the computer for non-school related purposes	0=no 1=yes
s_useinf	Index of how often the student uses ICT devices to exchange information	Positive Real number
s_usestd	Index of how often the student uses ICT devices for school-related purposes	Positive Real number
s_excomp	Years of experience using computers	0=never used 1= 1 to 5 years 2= more than 5 years
s_geneff	Index of how student is confident about her/his ability to use Information and Communication Technology	Positive Real number
s_ictstud	ICT studies in current school year	0=No 1=yes
s_genclass	Use of general applications in class	Positive Real number
s_ictlrn	Learning of ICT tasks at school	Positive Real number
s_speclass	Use of specialist applications in class	Positive Real number
school_nisb	Average Index of socio-economic background of the school	Real value

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