The negative impact of ICT overuse on student performance: evidence from OECD countries

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Authors:

Lucía Gorjón
Ainhoa Osés

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Abstract

The increasing presence of technologies at school has triggered a vivid debate on the way ICT influences students' learning process. Using PISA 2018 data for 15-year-old students and hierarchical linear models, we find an inverted U-shaped relationship between ICT use at school and students' performance in mathematics in 22 OECD countries. In all cases, the excessive use of technology is associated with a lower academic performance, although this penalty differs across countries, which points to the importance of addressing country-specific analyses. The differentiated profile of those very intensive users, who suffer from above-average bullying exposure, draws into question whether the effect can be deemed as causal. Based on Inverse Probability Weighting techniques, the findings indicate that the very intensive use of ICT at school causes an underperformance of students equivalent to around half an academic course in Estonia, Finland and Spain. The results highlight the need to ensure that the integration of ICT at schools is based on well-founded pedagogical methodologies; frequently evaluated; and supported by the continuous update of teachers' digital skills.

Keywords technology, learning, empirical, quantitative, assessment, digital, evaluation, cognitive

The rapid process of digitalisation has permeated and transformed a number of aspects of citizens' daily live, from social relationships to labour organisation. The last decade has particularly uncovered that adoption of digital skills is paramount in two key ways. Firstly, because it contributes to enhancing citizen participation due to increasing access to information (Polizzi, 2021). Secondly, because it facilitates the process of reskilling or upskilling in a context where demand for new digital skills has risen steadily. In consolidating the process of digital transformation, education and training play a central role. In this paper, we focus on the role of educational technology applied to the youth, the engine behind the future of work.

Digital technology, when implemented skillfully by educators, has the potential to create a powerful and engaging environment for collaborative and creative learning (European Commission, 2020; Rubach & Lazarides, 2021). However, in absence of a well-founded pedagogical strategy, the use of digital technology at school risks that individuals lag behind (Comi et al., 2017). The past two decades have seen firm attempts by policymakers to reduce the so-called "digital gap" (Szeles, 2018), or the unequal access to Information and Communication Technologies (ICT). Over time, the reduction of this gap has been substantial, particularly in technologically and economically advanced societies (Vassilakopoulou & Hustad, 2021).

In this context, one of the key questions now is to what extent the use of ICT—rather than solely the access to them—ultimately impacts on students' performance. This paper explores the non-linear association between ICT usage at school and student performance in a number of OECD countries and it assesses the causal impact of ICT overuse on student performance. Results from this study contribute to expanding the policymakers and educators' earlier knowledge on the way technology, widely present in the classrooms, influences student performance.

Literature Review and Contribution

Literature on the Linear Relationship between ICT Usage and Student Performance

The existing evidence on the linear effects of ICT usage on student performance fundamentally depends on the nature of the data. Results arising from experimental (or quasi-experimental) studies are mixed, while those based on international survey data, such as PISA, generally point to a negative association between ICT use and student performance (OECD, 2015). Focusing on PISA studies assessing the effects of ICT use at school, Hu et al. (2018) find that a one-score increment in the frequency of use is negatively associated with academic performance on mathematics, science and reading in the 44 countries examined with PISA 2015 data (between 10 and 13 points in the three fields of analysis, which is roughly equivalent to a fourth of a full academic year). These findings are consistent with previous studies which make use a number of waves of PISA (Zhang & Liu, 2016 find a negative effect of 9 points on mathematics and science using 2000-2012 PISA data) or which focus on a specific wave of PISA (Petko et al., 2017 find a negative association between educational use of ICT in the classroom and the PISA results using PISA 2012 data). Other authors (Skryabin et al., 2015) question whether this issue differs by grade, and find a negative impact for secondary school students (between 13 and 15 points for the three PISA areas), but a positive impact for primary school students (between 5 and 7 points depending on the area).

Country-specific literature using PISA data mostly points to a negative association between the educational use of ICT and student performance. For Turkey, the use of computers for educational purposes is found to negatively affect students' reading performance (Gumus & Atalmis, 2011). This negative association is also found for Spain (Gómez-Fernández & Mediavilla, 2021): using PISA 2015 data, the authors find a negative association between the educational use of ICT at school and at home and the performance in all three areas of assessment. With regard to the school effect, the authors suggest that the lack of preparation of teachers in terms of digital competences may explain part of the result. In a recent paper, Fernández-Gutiérrez et al. (2020) find, also for Spain, that the use of ICT at school in an Autonomous Community does not positively affect performance in mathematics and reading (although it does for science). For Italy, it is found that the usage of at least one digital device has a positive impact on students' performance in mathematics (Ferraro, 2018) compared to the absence of usage of digital devices, yet the frequency of use is not captured in the model.

Literature on the Non-Linear Relationship between ICT Use and Student Performance

Previous literature, hence, mostly focuses on analysing the relationship between technology and academic performance in a linear fashion, disregarding the possibility of non-linearity. This may, however, be paramount as the oftentimes found negative relationship might be capturing an average effect that might be overlooking potentially positive effects related to certain degrees of use. The OECD (2015) already suggested that a limited usage of computers in school may trigger better performance than no use at all, but a high use (above the OECD average) could lead to significantly worse academic results.

Some exceptions which have explored the potential existence of non-linearity are identified below. In particular, Woessmann and Fuchs (2004), using data from PISA 2000, find an inverted U-shaped relationship between Internet connectivity at school and student mathematics and reading performance. For the specific case of the Netherlands, Gubbels et al. (2020) find an inverted U-shaped relationship between ICT use and reading performance using data from PISA 2015. Focusing on Hong Kong, a recent study (Zhu & Li, 2022) finds that the use of ICT at school is negatively associated with student performance in a linear fashion, while the usage for other purposes (e.g., for leisure or for off-school learning) follows a hill-shaped relationship with student performance. Relatedly, Hu and Yu (2021) assess the relation of ICT use at school for communication (chatting online with other students and using email at school)—among other variables—and student performance on digital reading by analysing whether the effect varies depending on the frequency of use. The results indicate that over the past decade, adolescents' frequent use of ICT-based social media at school, including chatting online and using email at school, have negative effects on digital reading performance compared to the peers who seldom do so. Lastly, Borgonovi and Pokropek (2021) identify an inverted U-shaped association between different forms of ICT use—including use at school—and reading achievement by using PISA data for 2009-2018 for OECD countries.

Literature on the Causal Impact of ICT Use on Student Performance

As outlined above, the literature using large-scale surveys usually establishes a correlation relationship, rather than a cause-effect analysis, given the difficulty to address non-observable features such as student motivation (Fernández-Gutiérrez et. al, 2020; Fariña et al., 2015). In broad terms, (quasi-) experimental studies allow for a deeper understanding of a potential causal effect between ICT usage and student performance when compared to the usage of large-scale surveys, while the drawback is that these results are mostly not generalisable as they focus on a very particular context (Fernández-Gutiérrez et al., 2020). Overall, the literature assessing the causal impact of ICT use on student performance through experiments generally finds non-significant effects. As an early example, Angrist and Lavy (2002) adopted an Instrumental Variables approach to assess a policy of installing computers into Israeli primary schools on a wide-spread basis, and they did not find evidence of any relevant effect on students' test scores.

Turning to large-scale surveys, the literature measuring the causal impact of the frequency of ICT usage on student performance is scarce, although some other variables, such as ICT investment, have been analysed. For example, Cabras and Tena Horrillo (2016) study the impact of ICT investment on student performance in Spain using PISA 2012 data and applying Bayesian Additive Regression Trees (BART). Results suggest a moderate positive causal effect of ICT investment on student performance. Some additional techniques to overcome the potential endogeneity bias arising from ICT usage have been employed by authors. For example, Agasisti et al. (2020) resort to propensity score matching and Instrumental Variable techniques to examine the effect of ICT use at home and find a negative causal impact on student performance in almost all EU-15 countries.

Rationale for the Present Study

The widespread presence of technology has triggered a vivid debate around its usefulness as a tool to enhance student performance. While the evidence is not conclusive, as shown above, this paper attempts to shed light on two fundamental points related to the impact of the frequency of ICT use at school on student performance. First, it was not until recently that the possibility of a non-linear relationship was formally considered (Zhu & Li, 2022). This is, however, paramount to policy makers, as the establishment of a linear relationship might be capturing an average effect that might not be reflective of the actual relationship. This would happen when the positive or negative effect might vary depending on the degree of usage. If this were the case, instructors and policy makers would need to aim for the optimal frequency of usage, which requires to be combined with an appropriate implementation of digital devices at school (OECD, 2015). Earlier literature in this context has been either country-specific (e.g., based on the Netherlands or Hong Kong) or has provided average results for OECD countries in an aggregate manner, and this study aims to expand the geographical scope to test for the possibility of non-linearity in a wider sphere of OECD countries. This is tested in a non-parametric way, contrary to the vast majority of previous research, where non-linearity is gauged by means of quadratic models. Relatedly, we argue that the separate, country-specific analysis allows to gauge potential geographical divergences in the effects of ICT use on student performance, as found in Agasisti et al. (2020).

Second, most of the previous literature focused on examining the correlation between ICT use and student performance. This approach, while informative, risks offering a blurred picture of the real cause of the impact on account of confounding variables (Busenbark et al., 2021). For instance, if the frequency of use of technology were found to be negatively associated with student performance, then it could well be the case that this be caused by other non-observable variables that correlate with frequency of use (e.g., if more frequent users happened to lack motivation to excel academically, and this was the cause of their underperformance, then the estimate would not be reflective of the causal impact). Addressing causality is, hence, paramount in the development of well-founded public policy recommendations (Athey & Imbens, 2017). This study aims to explore the potential existence of a cause-effect relationship between frequency of ICT use at school and student performance. To our knowledge, this is the first time that the causal impact of frequency of ICT usage at school is analysed, especially in the framework of large-scale surveys. The ultimate goal is to contribute to the guidance of educational policy choices in a context where technology is playing an increasingly central role in the learning process of students.

Method

Research Context and Sample

The present study feeds from the PISA 2018 microdata, a programme led by the OECD that measures the ability of 15-year-old students to use their mathematics, science and reading skills to meet real-life challenges. The 2018 edition includes participation of 600,000 students from 79 countries, representing about 32 million students (OECD, 2020). The assessment comprises a number of questionnaires, addressed to a wide range of stakeholders, namely students, teachers, parents and school managers. The key questionnaire for this study is the ICT familiarity questionnaire, which includes detailed information on students' use of ICT and their attitude towards it.

The focus of this paper is placed in Estonia (N = 4,862), Finland (N = 4,898) and Spain (N = 28,319), though Appendix D, as shown later, will extend the empirical results to a number of additional countries in order to test for the robustness of the results.[1] We compare Spain, a relatively low-performing country with room for improvement in terms of ICT integration at school, with the opposite side of the coin: two traditionally top-players in the PISA context and countries where the education policy has made a firm commitment to the integration of ICT into their education system. In total, 22 countries are analysed—including Spain, Finland and Estonia—those for which the questions related to the key variable of interest (i.e., ICT usage in terms of frequency at school) do exist in the database. Those countries are Australia (N =10,830),

[1] This refers to the results on the hill-shaped relationship between use of ICT at school and student performance; the results on the causal impact are undertaken solely for Estonia, Finland and Spain for the sake of simplicity.

Belgium (N = 6,891), Switzerland (N = 5,164), Czech Republic (N = 6.181), Denmark (N = 5,976), the United Kingdom (N = 6,975), Greece (N = 5,641), Hungary (N = 4,717), Ireland (N = 5,049), Island (N = 2,675), Italy (N = 9,484), Lithuania (N = 5,840), Luxembourg (N = 4,706), Latvia (N = 4,630), Poland (N = 5,087), Slovakia (N = 4,997), Slovenia (N = 5,447) and Sweden (N = 4,617).

Variable Description

Dependent Variable

As outlined above, the PISA programme allows to capture students' skills to solve real-life problems in three main areas: mathematics, reading and science. In the present study, the descriptive analysis is presented for these three areas to test whether the observed patterns apply relatively homogeneously. In fact, after confirming that the functional form to relate ICT usage with student performance is comparable across all three knowledge areas, the empirical section specifically focuses on the mathematics field to simplify the analysis. The reason underpinning this choice is that mathematics fosters mental discipline, logical reasoning, mental rigor, and is a paramount element to understanding the content of other fields, such as science. Mathematics is also the engine to STEM-related careers, which are closely related to jobs that will only gain momentum in the future, such as those related to artificial intelligence, machine learning, automation or robotics (Wang & Siau, 2019).

In terms of measurement, the OECD quantifies students' grades around an OECD average of 500 points and a standard deviation of 100 points.

Control Variable of Interest

Drawing on the ICT familiarity questionnaire, this study focuses on the module of the questionnaire tackling the frequency of use of ICT by students at school, rather than at home.

This choice is central to the interpretation of the results, as there are arguments to consider it as more exogenous than usage in other contexts: there is an external factor (such as the teaching staff or the school's policy concerning the use of ICT) which, in principle, determines the use of ICT made at school. This would contrast with the choice of the variable of educational use at home, which may suffer from greater selection bias because it could be determined by the student's own initiative, their socio-economic background or the family environment. Another reason why the analysis focuses on the use of ICT at school is due to its impact on education policy, which is more straightforward to implement as compared to the use of ICT in the private domain.

In order to measure the frequency of use of ICT at school, the questionnaire includes ten different questions. These reflect the extent to which students use a computer at school to do their schoolwork, use the school's computers to do group work or communicate with other students, or surf the Internet in connection with class work. The remaining questions are specified in Appendix A. The possible answers that students can provide are the following: "never or hardly ever", "once or twice a month", "once or twice a week", "almost every day", or "every day".

To synthesise the frequency of use of ICT at school, we create an index that allows to compare students' frequency of use of ICT at school. This index is benchmarked at the country level. This intra- rather than inter-country comparison is most suitable in the context of the present study, especially since cross-country comparisons show a blurred relationship between average ICT use and the average score in mathematics, as described in Appendix B. More broadly, another argument to support this intra-country comparison relates to the fact that reported variables have intrinsic limitations that might hinder inter-country comparisons (for instance, certain cultural aspects of countries might lead students to overstate or understate some questions).

The index summarises the use of ICT at school for student i ($ICT\ *$). It is calculated by obtaining each student's mean reported frequency (ICT)—across the ten questions included in the questionnaire—and normalising it by subtracting country c's mean use, $\overline{ICT}$, and dividing it all by the country's standard deviation σ_{ICT}. This index will therefore have a mean value of zero for each country, and a standard deviation of one.

(1) $$ICT_i * = \frac{ICT_i - \overline{ICT_c}}{\sigma_{ICT,c}}$$

It is important to note that the OECD already offers an index to synthesise the use of ICT at school by students. The index is centered around an OECD mean of zero and a standard deviation of one, and its construction is based on the Item Response Theory (IRT) (see OECD 2017 for further methodological details). While this index is useful for inter-country comparisons, it is not fully suitable for our analysis for the abovementioned reasons. To ensure that the index created here is, however, robust to the OECD's index, we calculated the correlation between the two. In the case of Spain, for instance, the correlation between the ICT index created here and that of the OECD is 0.9406028.

Based on the ICT index ($ICT_i\ *$), five types of users are created, ranging from the very low frequency user to the very intensive one (Table 1). The rationale for the creation of those users is to further explore the possible non-linear relationship between ICT use and academic performance. These users are defined on the basis of the country-specific quintiles of the ICT index created in this analysis. Quintiles are created with the purpose of summarising the average reported frequency of the ten questions on ICT usage, which makes the interpretation more comprehensive than if a continuous variable (i.e., the mean of a variable that was originally categorical) were to be included. As quintiles rely on the country's specific distribution, it is worth noting that users might not be directly comparable across countries.

Table 1

Definition of ICT Users at School

Country-specific quintiles of frequency of use of ICT at school	**Type of ICT user at school**
Quintile 1	Very low ICT user
Quintile 2	Low ICT user
Quintile 3	Medium ICT user
Quintile 4	Intensive ICT user
Quintile 5	Very intensive ICT user

Other Control Variables

The explanatory variables selected here are in line with those commonly used in the literature in this context (see Hu et al. 2018, for instance). At the student level, we include discrete indicators of gender, repetition and immigration status, late introduction to the use of technologies (above nine years of age), the PISA index of economic, social and cultural status (ESCS) and a PISA index on the degree of bullying suffered. The two latter are standarised variables—centered around an OECD mean of zero and a standard deviation of one—that synthesise student responses regarding their family background (e.g., home possession, parents' occupations and parents' highest educational level), for the ESCS index, and other questions related to bullying exposure (e.g, whether other students made fun of them) for the latter index. The inclusion of the bullying index is often overlooked in the literature, while research highlights its negative impact on student performance (Yu & Zhao, 2021). At the school level, we include the school size (in logarithmic terms), the type of school (public or not), and the ratio of computers per student (as a continuous variable).

Research Model and Procedure

The methodological framework is divided into two parts. First, it assesses—through hierarchical linear models—whether the hill-shaped relationship between ICT usage and student performance still holds after taking into account other student-specific determinants. The second part focuses on the very intensive ICT user and adopts a complementary technique to establish a causal relationship between the very intensive ICT usage at school and mathematical performance. This is done through a widely applied technique in the causality literature: Inverse Probability Weighting.

Hierarchical Linear Models

This first part outlines the empirical strategy to assess the relationship between ICT usage and student performance taking into consideration the nested nature of the data. The fact that students are nested within schools implies that multiple regression analysis is not suitable. Instead, the relation is estimated by means of multilevel models, also known as hierarchical linear models (Bryk & Raudenbush, 1992). This is a form of Ordinary Least Squares that analyses the variance in the dependent variable when the predictor variables are at different levels (Woltman et al., 2012).

The rationale for this estimation procedure is described below and is formally specified in Equations 2 and 3. The first-level specification gauges the relationship between student performance (student i attending school j) and the p different explanatory variables considered (i.e., the set of independent variables outlined in the "Variable Description" subsection). More specifically, the variables ranging from *X1* to *X4* are binary variables that denote the type of ICT user each student can be deemed as depending on the level of usage of ICT (based on the country-specific quintiles of ICT usage): low, medium, intensive and very intensive, respectively, and the very low user is taken the as the reference variable. This allows to estimate the relationship between the frequency of ICT usage and mathematics performance when compared to those students who barely ever (or never) make use of it. This is in contrast with most of previous studies that attempt to gauge the non-linear association between ICT use and academic performance, which usually resort to quadratic models, whereas the specification herein used is more flexible by being non-parametric.

The remaining variables entail other features such as the student's gender or socio-economic status, among others (see "Variable Description" subsection). Lastly, e_{ij} refers to the residuals. The second-level specification shows that the intercept varies across schools; that is, the overall mean intercept includes a school-specific random-effect term. The reminder βs are constant across schools. The combination of the equations at level 1 and level 2 gives rise to the final specification as shown in Equation 3.

Level 1 specification

$$(2)\ Y_{ij} = \beta_{0j} + \beta_{1j}X1_{ij} + \beta_{2j}X2_{ij} + \cdots + \beta_{pj} * Xp_{ij} + e_{ij}$$

Level 2 specification

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

$$\beta_{1j} = \gamma_{10}$$

$$\beta_{2j} = \gamma_{20}$$

$$\ldots$$

$$\beta_{pj} = \gamma_{p0}$$

Mixed model specification

(3) $Y_{ij} = (\gamma_{00} + u_{0j}) + \gamma_{10} * X1_{ij} + \gamma_{20} * X2_{ij} + \cdots + \gamma_{p0} * Xp_{ij} + e_{ij}$

In all cases, the 10 plausible values for each student are considered simultaneously, and the 80 weights assigned to each student are taken into account to avoid potential bias in the estimated coefficients (OECD, 2017).

In sum, while this methodology allows to isolate the correlation between ICT usage at school and the academic performance, causality cannot be inferred. To address this, the following subsection outlines the methodology underpinning the causality analysis.

Inverse Probability Weighting

The second part of the empirical framework focuses on the very intensive ICT user, who is of particular interest on account of the results, which evidence their differentiated socio-demographic profile and their notorious underperformance in mathematics compared to the rest of users. Those results, both at the descriptive and at the empirical levels (through hierarchical linear models), cannot be deemed as causal, which is to be analysed in this second part of the analysis.

The causality analysis attempts to identify whether the variable of interest (very intensive ICT usage in this case) is actually causing the outcome variable (student performance) to decrease. For example, if some non-observable variables shared across very intensive ICT users were determining the low mathematics performance, then these variables—rather than very intensive ICT use—would be the cause of a low performance. The fundamental rationale of the causality analysis is to ideally compare a situation where an individual uses technology very intensively with a situation where that same individual hardly uses it at all. If the comparison were to lead to a significant gap in mathematical performance in favour of the non-intensive user, it could be concluded that the very intensive use of ICT is the cause of poor mathematical skills acquisition. However, since in reality this comparison is not feasible for the same individual, there are a number of econometric techniques that offer an approach to address this issue.

In this paper, the Inverse Probability Weighting (IPW) method is applied. This methodology is based on the idea that random assignment ensures that the distribution of variables among treated and control individuals is probabilistically equivalent. Nevertheless, when the assignment is not random (and this is the case for being a very intensive ICT user), some students have higher probability of being treated, depending on their characteristics. In order to obtain a pseudo-random sample that guarantees that the distribution of covariates would be probabilistically equivalent, we weight students by the inverse probability of being very intensive users (Author, 2019). The aim of this estimation method is, in turn, to approximate the distribution of the observable variables of the treatment group (very intensive users) and of the control group (the rest of the students), assuming that in this way the distribution of the non-observable variables would also be assimilated (see Wooldridge, 2002 and 2010 for a detailed explanation of this methodology).

The estimation method is based on the following procedure. Firstly, a logit model is defined to estimate the probability that student i is a very intensive ICT user ($\Pr(VeryIntensive_i)$) based on a number of explanatory variables reflected in vector X in Equation 4, and include gender, socio-economic level, repetition and immigration status, late introduction to ICT, school size, computer/student ratio, bullying rate, and school ownership (public or not). In addition, the final student weights (sw) are also included as established in the framework proposed by DuGoff et al. (2014), who state that the logit model should not be weighted by sample weights, but that these should be included as an additional variable in the model.

(4) $$\Pr(VeryIntensive_i) = f(X, sw_i)$$

Once the model is estimated, the probability of being a very intensive user is predicted (p_i). These predictions are used to create inverse probability weights (w_i) in the following way:

(5) $$w_i = 1/p_i, \qquad if \;\; VeryIntensive_i = 1$$

(6) $$w_i = 1/(1 - p_i), \quad \text{if}\, VeryIntensive_i = 0$$

These weights enable the over-representation of those individuals who, given their characteristics, are likely to be very intensive users but do not report being so on the basis of the ICT questionnaire. On the contrary, if the student's characteristics lead to a prediction of low probability of being a very intensive user and the student does not report to be one, the weight to be applied to that student will be close to one. Similarly, if the model predicts a high probability of being a very intensive user and this is indeed the case, the weights assigned will also be close to one. Finally, when the user is indeed very intensive but her/his characteristics predict a low probability of being so, this person will also be over-represented. Through the approximation of observable variables between the control and treatment groups, it is assumed that this approximation is also assimilated in the unobservable variables.

The estimation of the model through IPW allows to obtain the Average Treatment Effects (ATE), which measures the potential causal impact of the very intensive usage of ICT on student performance. The ATE requires that the whole population under study is eligible to be treated, given that it compares the whole population were it treated versus were it not treated. To ensure that this is the case in the present paper, we will analyse the distribution of the propensity score (i.e., the predicted probability of being a very intensive ICT user) between the treatment and control groups (“Results” section). If the distribution is comparable, then the estimation of ATE is well founded, as long as extreme values are not present in the distribution (Cunningham, 2021). In fact, the presence of extreme values could bias the estimator and induce excessive variance, given that the weights attained through the IPW methodology (see Equations 5 and 6) could become overly large and could hence give raise to unstable estimates (Avagyan & Vansteelandt, 2018).

Following the approach proposed by DuGoff et al. (2014), the final weights applied to the model are the product of the sample weights and the IPW weights, calculated as detailed in (4), (5) and (6) above. With these final weights, the average impact in mathematics between the very intensive user and the remainder of the users is estimated, in order to capture whether the existing mathematical gap changes when these weights are applied.

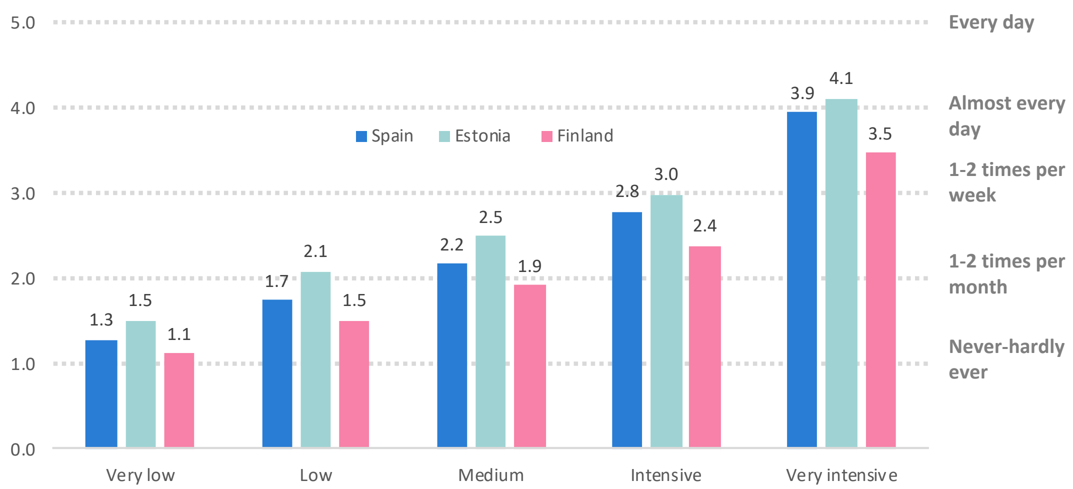
Data Analysis

The descriptive results show, in first place, the mean use of ICT at school for each of the five types of users herein defined and for the three countries. This allows to infer to what extent a specific ICT user is indeed comparable across the three countries.

Figure 1 shows how the average frequency of ICT use at school varies by type of ICT user in all three countries. For each type of user, the average frequency of ICT use at school is similar in Spain and Estonia, and lower than in Finland. Nevertheless, these differences are relatively small. A clear pattern that emerges is the jump in terms of the frequency reported by the very intensive user in the three countries. While the difference between the four reminder users is relatively stable, the very intensive user reports significantly higher frequency, with the use being close “almost every day”, especially for Estonia and Spain. The average frequency reported for each of the ten questions, by country and ICT user type, is provided in Appendix C.

Figure 1

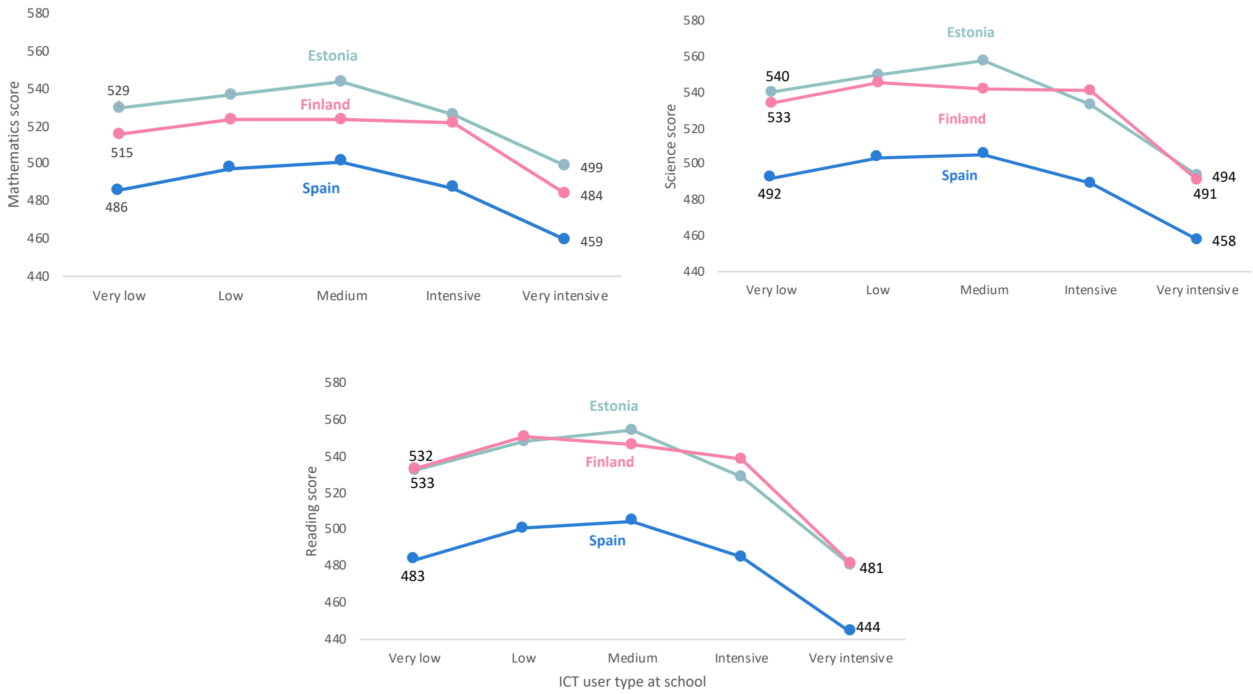
Average Frequency of Use of ICT at School in Spain, Estonia and Finland



After identifying the actual average use of ICT at school for each type of user, Figure 2 shows the average score of each user in the three main areas of PISA. The results confirm that, in the three countries, the relationship between frequency of ICT use at school and the performance in mathematics, science and reading follows an inverted U shape, where the highest frequency user group (i.e., very intensive users) obtain a significantly lower average grade than the remainder of users. In Spain and Estonia, the maximum peak score in the three knowledge areas is obtained by the medium user (quintile 3, i.e., those who use ICT at school more than 1-2 times per month). In Finland, low users (those that use the ICT 1-2 times per month) and medium users (less than once a week, approximately)—and intensive users, although slightly less so—are the ones who show the strongest mathematical competences, in contrast to the scientific and reading competences, where it is the low intensity user (quintile 2) who obtains the best average competences. Given the fact that the inverted U-shaped relationship holds for the three knowledge areas (mathematics, science and reading), the empirical analysis will focus on the particular case of mathematics.

Figure 2

Average Score in Spain, Finland and Estonia by Frequency of Use of ICT at School



Lastly, this section presents a descriptive analysis of the characteristics of the students depending on their frequency of use. Behind each ICT user type, there might be certain socio-demographic profiles that make users perform differently. Table 2 aims to compare these features to examine whether patterns emerge depending on the frequency of ICT use.

By gender, male students are more numerous in the extremes of ICT usage: they dominate the groups of analogous users and, more notably, they conform a majority within the group of very intensive ICT users. Immigrants are overrepresented in the group of very intensive users, while they are relatively evenly distributed for the reminder of users. Some other differences can also be observed by country: in Spain, there is a substantial overrepresentation of repeaters within the group of very intensive ICT users. This is also the case in Finland, although the share of repeaters in the country is far lower than in Spain. Additionally, the more frequently students use ICT at school, the higher the proportion of those attending non-public schools is in the Spanish case. This is despite the fact that performance of Spanish students is typically better in private schools than in public ones (Vega-Bayo & Mariel, 2018), as also found later in the empirical results section (Table 3). In Estonia and Spain, there is a positive correlation between ICT usage and the socio-economic profile of students. In those two countries, very intensive users have the largest average ESCS of all the users herein defined. Finally, there is a clear pattern between ICT usage and exposure to bullying. In Spain and Estonia, the average exposure to bullying increases as the frequency of use of ICT at school increases. In fact, analogous users in both countries report, on average, lower exposure to bullying than the average of the OECD, whereas the exposure to bullying for very intensive users is far higher than the country's averages in both cases. Very intensive users, in turn, appear as being much more prone to bullying exposure than the rest of users in those countries, and this applies to the three countries under study.

Table 2

Descriptive Statistics by Type of ICT User

	Very low	Low	Medium	Intensive	Very intensive
% female					
Estonia	50.5%	58.3%	57.3%	50.2%	40.2%
Finland	47.3%	60.2%	59.5%	52.0%	33.5%
Spain	47.9%	56.1%	56.4%	50.4%	38.0%
% immigrant					
Estonia	1.3%	0.9%	0.7%	1.1%	3.0%
Finland	3.1%	2.5%	2.9%	4.1%	5.0%
Spain	8.7%	7.6%	7.6%	8.3%	10.3%
% repeater					
Estonia	3.0%	1.8%	2.2%	2.1%	2.7%
Finland	2.4%	2.4%	2.5%	2.7%	3.7%
Spain	26.7%	21.8%	18.9%	20.8%	28.2%
% public school					
Estonia	95.9%	95.8%	97.0%	96.9%	95.9%
Finland	96.9%	96.5%	94.4%	94.7%	94.9%
Spain	66.4%	65.5%	63.0%	58.6%	54.5%
ESCS					
Estonia	-0.0031	0.0493	0.1397	0.1439	0.0878
Finland	0.2076	0.2647	0.3771	0.4263	0.3678
Spain	-0.1819	-0.0904	-0.0899	-0.0455	-0.0597
Bullying index					
Estonia	-0.0681	0.0203	0.0301	0.0947	0.3262
Finland	-0.0899	-0.1258	0.0033	-0.0118	0.0536
Spain	-0.2990	-0.2767	-0.2974	-0.1691	0.0315

It is important to note that the results presented in this section are merely descriptive. They do not imply that the hill-shaped relationship is necessarily attributed to the frequency of ICT usage, as there might be other variables beyond the ICT usage that are driving the effect. This might be particularly the case for very intensive ICT users, who have a very differentiated socio-economic profile (Table 2). The following section will attempt to infer whether this relationship remains once students' personal characteristics are taken into account.

Results

This section presents the empirical results and is divided in two parts. The first one shows the estimated relationship between each type of ICT user and their mathematical performance to identify whether the hill-shaped relationship found in the descriptive analysis holds when considering students' characteristics. The methodology underpinning these results is based on Hierarchical Linear, or Multi-Level, Models. The second part of this section presents the causal estimates for the very intensive ICT user by applying the IPW framework.

Results of the Multi-Level Analysis

The results underpinning the hierarchical linear model allow to compare the over- or under- performance of low, medium, intensive or very intensive ICT users when compared to very low users, taking into account their socio-demographic features.

The estimated coefficients of the hierarchical linear model are summarised in Table 3 for the three selected countries and expanded to the 22 OECD countries herein considered in Appendix D. On the one hand, the results show that, for practically all the countries under study (including those in the appendix), the low ICT user status (quintile 2, i.e., average ICT usage slightly below once a month for Spain and Finland; and once or twice a month in Estonia) is related to better results than the very low user status (quintile 1). The medium user (quintile 3, i.e., those with an average use between 1-2 times per month and 1-2 times per week in Spain and Estonia, and 1-2 times per month in Finland) also tends to be related with more positive results than the very low user, although this variable is not significant for an important part of the countries. For Spain and Estonia, on the other hand, positive and significant effects of 10 and 12 points, respectively, are found in relation to the less frequent user.

On the other hand, for the intensive user of ICT at school, a clearly negative trend is observed in most of the countries analysed. However, the coefficient associated to this variable is not significant in Spain, Finland and Estonia, among others. The strong and very significant impact in all the countries lies on the very intensive users, i.e., those who use ICT almost every day. In this group of very intensive users of ICT at school (last quintile), a unanimous pattern is observed in all the countries examined: compared to very low frequency users and, broadly, to the reminder of users, very intensive users score significantly lower in mathematics. In order to interpret such results, it is important to recall that a difference of 40 points is roughly equivalent to a full academic year. This means that very intensive users in Spain or Estonia underperform by more than half year compared to non-ICT users, and by three-quarters of year when compared to low or medium ICT users. In the case of Finland, very intensive ICT users perform a full academic year worse than their low ICT user counterparts.

Table 3

Estimated Association between the Mathematics Achievement and the ICT Usage and Other Covariates

	Spain	**Estonia**	**Finland**
Low ICT user	10.21***	6.030	8.759***
	(2.865)	(3.749)	(3.147)
Medium ICT user	10.03***	11.41***	4.503
	(3.050)	(4.061)	(3.639)
Intensive ICT user	-2.963	-4.206	0.245
	(2.965)	(4.537)	(4.009)
Very intensive ICT user	-22.45***	-24.65***	-32.37***
	(3.447)	(4.317)	(3.642)
ESCS (socio-ec. index)	10.36***	19.01***	29.76***
	(0.944)	(1.995)	(1.818)
Immigrant	-19.31***	-25.43**	-25.96***
	(3.663)	(12.95)	(7.091)
Repeater	-86.20***	-48.51***	-59.99***

	(2.853)	(10.47)	(8.595)
Female	-17.57***	-12.30***	-3.310
	(2.313)	(2.832)	(2.817)
Public school	-7.017***	-17.66***	-17.44***
	(1.698)	(4.439)	(2.750)
Number of students at school (log)	3.661***	4.349***	2.358
	(0.774)	(1.552)	(1.515)
Computer-student ratio	-0.708	4.936***	2.263**
	(0.683)	(1.742)	(1.085)
Late ICT users (>9 years old)	-21.19***	-26.93***	-28.40***
	(1.952)	(4.291)	(5.080)
Bullying (index)	-4.015***	0.264	1.164
	(1.322)	(1.679)	(1.324)
Intercept	512.7***	521.3***	512.9***
	(6.138)	(11.72)	(10.98)

Note. Standard errors in parentheses: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$. The reference for the different types of ICT users refers to the category of the very low ICT user.

To expand the analysis, the estimations are disaggregated by gender and socio-economic status (higher or lower than the median). The results, shown in Table E1 of Appendix E, confirm that the existence of the inverted U-shaped relationship between ICT usage at school and students' performance in mathematics still holds for all the four groups herein considered.

Lastly, Appendix F estimates the results for the 22 OECD countries by using the ICT frequency index as a continuous variable—as opposed to the user-specific dummies—and compares it to the results found in Hu et al. (2018), undertaken with the PISA 2015 wave. Results are similar in magnitude when using PISA 2018 and PISA 2015 data, and they point to a negative—and highly significant—relationship between ICT usage and mathematical performance in all the countries analysed.

The following section will delve deeper into whether causality can be inferred regarding the impact of the very intensive ICT usage, who experienced large penalties in the mathematical performance, on students' mathematical performance.

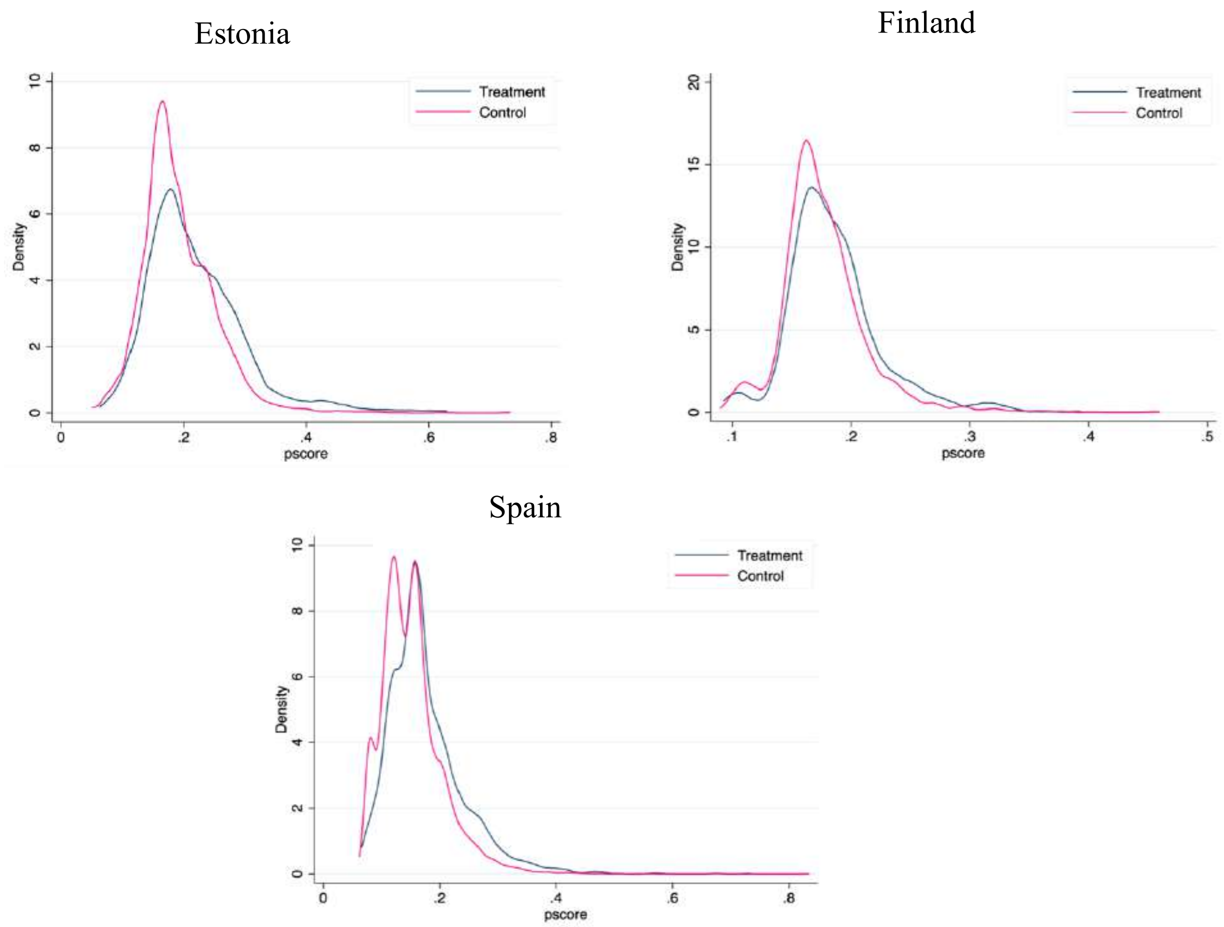
Results of the Inverse Probability Weighting Analysis

This subsection focuses on the causal impact of the very intensive user to assess whether the underperformance related to the very intensive ICT user seen in the previous subsection can actually be attributed to the very frequent use of ICT.

Before presenting the causal estimates, it is important to first ensure that the distribution of the propensity score (i.e., the predicted probability of being a very intensive ICT user) between the treatment and control groups are comparable such that the ATE is well founded, as long as extreme values are not present in the distribution (Cunningham, 2021). Figure 3 shows the distribution of the propensity scores to ensure that the application of IPW would not lead to biased estimates. In the three countries under study, the propensity scores are comparably distributed across treatment and control groups. In addition, extreme cases are uncommon, ensuring that the ATE estimation through IPW is justified.

Figure 3

Propensity Score Distribution of Treatment and Control Groups



Note. The table presents the predicted probability of very intensive ICT user for the treatment and control groups, attained through a logit model as set out in Equation 4.

The Inverse Probability Weighting estimates are presented in Table 4. In particular, the table shows the Predicted-outcome means (Pomeans) and the ATE, that is, the estimated mean difference in performance of the very intensive user compared to the performance if she/he were to use ICT at school less frequently. For context, the observed gap in the math mean score is also included in the table.

Table 4

Inverse Probability Weighting Estimates of Very Intensive ICT Usage

	Spain	Estonia	Finland
Inverse probability weighting estimates			
Pomeans	491.8***	533.5***	516.7***
	(0.873)	(1.332)	(1.158)
ATE	-26.28***	-32.38***	-32.83***
	(2.015)	(2.821)	(2.858)
Observed statistics			
Observed math mean score not very intensive ICT user	485.3	529.0	512.0
Observed gap math mean score very intensive user vs not	-25.9	-30.4	-27.9

Note. Standard errors in parentheses: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$. Pomeans refers to the predicted-outcome means; and ATE, to the average treatment effect.

The results shown in Table 4 confirm that very intensive ICT usage causes significant underperformance in mathematics. That is, after approximating the observed variables between the treatment and control group (and assuming that the unobserved features are also assimilated), there is evidence that a very intensive usage of ICT causes substantial underperformance in mathematics. The usage of ICT at school more than 1-2 times per week reduces very significantly students score in mathematics. This penalty is equivalent to more than half an academic year for very intensive users in Spain, and ¾ of an academic year for the homologous users in Finland and Estonia.

As done earlier, the analysis is extended by socio-economic status and gender, with the aim of assessing whether the causal impact of the very intensive ICT usage on the mathematical performance holds across these groups. These results, shown in Appendix E (Table E2), confirm this fact and show that the relative impact of very intensive ICT usage is more negative for female students in Estonia and Finland, and for male students in Spain. In Spain and Estonia, the relative impact is more negative for students from high socio-economic profiles, while the opposite is found for Finland.

Discussion

In sum, after confirming the existence of an inverted U-shaped relationship between frequency of use of ICT at school and academic performance, which is significantly negative for very intensive users, the present study has confirmed that the penalty associated to the very intensive ICT usage is causal, rather than explained by the particular socio-demographic features of this student subgroup. Below, we discuss the results arising from this study and put them into context based on related literature.

The hill-shaped relationship between ICT usage and student achievement in OECD countries

The results on the inverted U-shaped relationship between ICT usage and student performance are aligned with Gubbels et al. (2020), who focused on the specific case of the Netherlands. While the setting of the study is slightly different—particularly regarding the field of study (reading), the measurement of the frequency of use of ICT at school (a continuous variable based on the OECD index) and the quadratic functional form of the model—results are still comparable. After controlling for similar covariates as in the present study, a hill-shaped relationship is found, and the difference in the mean predicted performance between the least and the most intensive user amounts to the equivalent of over an academic course. This is similar to the difference in the predicted mean in the reading performance found by the OECD (2015). Again, these magnitudes are not directly comparable to the present study, but the overall conclusions do concur. Similarly, the broad conclusions are in line with Borgonovi and Pokropek (2021) and Hu and Yu (2021), while they cover a number of countries in an aggregate manner, as in OECD (2015), and assess the relation with regard to students' reading performance. In contrast, recent findings by Zhu and Li (2022) for Hong Kong are slightly different. While accounting for non-linearity, the authors assess a linear and negative relationship between ICT use at school and student performance in reading. However, the relatively less time available to efficiently use ICT tools compared to OECD peers might partly explain this divergence (Zhu & Li, 2022).

The negative impact of a very intensive ICT usage on student performance

Concerning the causal negative impact of very intensive use of ICT at school on the mathematical performance found in this paper, to our knowledge there is no directly comparable paper to contrast the results with. However, the study by Agasisti et al. (2020) would constitute a close example assessing causality through analogous econometric techniques. The findings reveal that the intensive use of ICT at home has a negative causal impact on all subjects in most EU-15 countries. The present study focuses on the use of ICT at school, and hence further studies are needed to further delve into the direction of the impact, as well as the factor that might be driving the results.

Overall, the reasons underpinning the negative impact between the very intensive ICT usage on the mathematical performance are beyond the scope of the paper, but some potential hypotheses are explored here. On the one hand, students could possibly get distracted by using ICT at school for activities unrelated with the educational purpose of the usage of these devices. This might lead them to over-report the amount of time spent using technology at school (Agasisti et al., 2020). The possibilities that ICT offers students for "multitasking", i.e., performing a large number of tasks at the same time, can prove detrimental to students' ability to capture information (OECD, 2018; Vedechkina & Borgonovi, 2021; Borgonovi & Pokropek, 2021). On the other hand, deficiencies in training teachers towards digitalisation have also been identified by the OECD (Echezarra, 2018) and other authors (e.g., Hu et al., 2018) as an obstacle to successfully foster student learning through digital devices. This might be the case when teachers' ICT knowledge is not regularly updated, although since the outbreak of the COVID-19 pandemic—which is not gauged in this study—many teachers and educators were forced to rapidly develop and learn ICT skills to optimise their instruction (Vedechkina & Borgonovi, 2021).

In view of the results, a number of policy implications can be drawn. A relevant implication is the need for teachers, educators and school principals to carefully identify their context-specific deficiencies (which the paper has shown to geographically differ in a substantial manner) and support that the teaching and learning processes are adapted to the needs of both sides. Incorporating the experience of remote technology-enhanced learning and online activities into the school agenda on a regular basis is particularly crucial in view of the COVID-19 outbreak, as it would help students and teachers develop important digital competencies and be prepared for the next emergency event (Shamir-Inbal & Blau, 2021). Another implication is the need for assessing the quality of the technological material that is used at school, both in terms of its technical capacity and, probably even more importantly, regarding the way it is implemented. This requires an exhaustive evaluation of the tools and methodologies that would best serve the ultimate purpose of using technology as a means of enhancing student performance. In this context, reinforcing teachers' ICT competences and their perceptions towards ICT usage has been shown to be related to the successful implementation of ICT in teaching settings (Rubach & Lazarides, 2021). Overall, the purpose of using digital devices is not to be limited to merely modifying earlier means of teaching, such as the usage of physical books; rather, the efficient use of technology to facilitate the learning process should be an objective on its own.

Conclusions, Limitations and Future Research

The present study contributes to the field in two key ways. First, this study captures the varying effects of ICT at school in the performance in mathematics depending on the intensity of use for a number of OECD countries. Second, it applies the Inverse Probability Weighting technique to gauge the potential causal impact of ICT overuse on student performance, while most of previous studies using large-scale surveys limit the results to the correlation sphere.

The results from this study confirm the existence of a hill-shaped relationship in explaining the frequency of ICT usage at school and students' performance in mathematics in 22 OECD countries, with varying magnitudes across countries. The study reveals that even in the most advanced countries in terms of ICT integration at school—such as Finland or Estonia—the group of very intensive frequency users experiences a significant penalty in terms of their performance in mathematics, while the low and medium ICT user status is related to better results than the very low user status. However, these very intensive have a very differentiated socio-economic profile compared to the rest of users: they report above-average levels of bullying, and they are over-represented by male, repeaters and immigrant students. Given this, the study further explores whether the observed underperformance is attributed to such differentiated profiles or, conversely, whether the penalty can be attributed to the excessive use of ICT at school. Results indicate that the overuse of ICT causes an underperformance in mathematics, which is of the order of more than half academic year in Estonia, Finland and Spain.

The present study is not without limitations, which could be addressed in future research. The first relates to the measurement and definition of the main variable of interest, use of ICT at school, which is made on the basis of quantity of time spent, as opposed to quality of usage (Petko et al., 2017). In fact, the definition of the variable of interest is broad, which limits the interpretation of the results. For instance, future research could further explore whether the impact differs when looking at other computer-related activities that might be more specifically addressed to improving student performance, such as computer thinking applied to digital devices. This would help inform whether very intensive users' underperformance could partly be explained by an inappropriate use of technologies. The second limitation refers to the absence of other covariates that might be of relevance to the model. One question that arises in view of the results is how the performance of students clustered in the same classroom where ICT is very intensively used might vary. This is currently unattainable with the PISA database due to the lack of an identifier that links students with classrooms. The availability of this data would also allow to identify whether specific ICT methodologies implemented by teachers, as well as ICT training received, entail a differential impact on student performance, which has been noted to be paramount in this research context (Pérez-San Agustín et al., 2017). The third limitation relates to the cross-sectional nature of the database: the usage of panel data (or quasi-experimental studies) would further enrich the analysis and, notably, the causality analysis. A fourth limitation related to the causality analysis lies on the assumption that the unobserved features between treatment and control groups are assimilated, which might not always be the case if unobserved variables proved relevant in either of the two groups (whether treatment or control). Lastly, although this paper covers a wide range of countries and population subgroups, results cannot necessarily be generalised to other contexts, whether geographic or temporal. Despite the gaps that are yet to be overcome, the present paper has intended to further contribute to the exploration of the way ICT—which is increasingly present in schools—affects student performance, a paramount topic for instructors and policy makers in their search for an optimal use of technology that enhances students' learning processes.

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Appendix A

Student Questionnaire on the Frequency of Use of ICT

This Appendix lists the ten different questions regarding frequency of ICT use in schools as part of the ICT familiarity questionnaire:

1. Chatting online at school.
2. Using email at school.
3. Browsing the Internet for schoolwork.
4. Downloading, uploading or browsing material from the school's website (e.g. intranet).
5. Posting my work on the school's website.
6. Playing simulations at school.
7. Practicing and drilling, such as for foreign language learning or mathematics.
8. Doing homework on a school computer.
9. Using school computers for group work and communication with other students.
10. Using learning apps or learning websites.

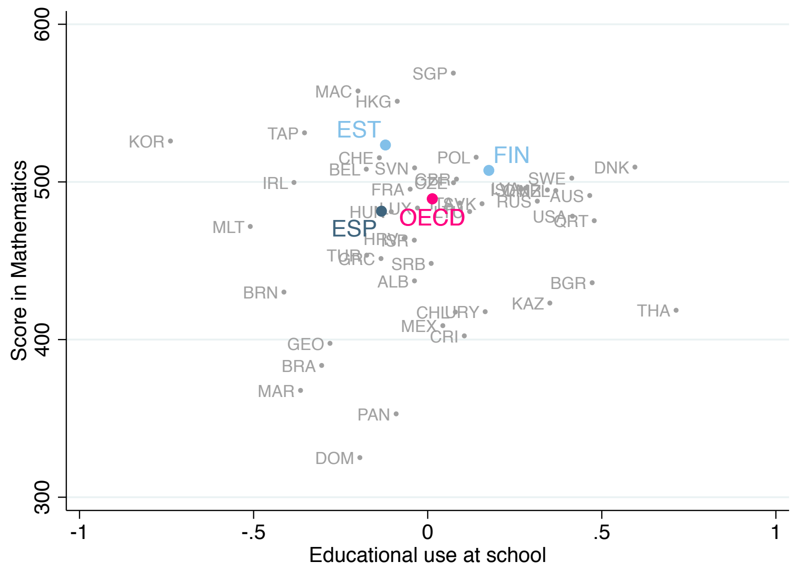
Appendix B

Descriptive Relationship between ICT Usage and Student Performance in Mathematics

In the search for the relationship between the use of ICT at school and students' performance, the first question that arises is how these two factors relate in the different countries participating in the ICT questionnaire. Figure B1 depicts the standard ICT index developed by the OECD in terms of countries' average use of ICT at school and the average score in mathematics. The results do not seem to show a clear association with the average performance of the countries. This is used as the main argument to undertake an intra-country (rather than inter-country) analysis. As with most reported data, certain biases in terms of over/understatement might arise at the country level, hindering the direct comparability across countries.

Figure B1

OECD Indices on ICT Use and their Relation with the Average Score in Mathematics



Note. The educational use at school refers to the OECD-created index that measures the frequency of ICT use at school. It is centered around an OECD mean of zero and a standard deviation of one.

Appendix C

Average Frequency of Use of ICT at School by Activity

Table C1 shows the average frequency reported per country and for each of the five types of users defined in this paper. There exist five possible answers for students to answer in each question listed below, and those are scored as follows: 1, never-hardly ever; 2, once-twice per month; 3, once-twice per week; 4, almost every day; 5, every day.

It is important to note that frequency of use increases uniformly across all questions by type of user. In addition, extreme answers to the individual ICT questions are generally uncommon. These two facts justify the usage of the average, rather than other measures such as the maximum reported frequency.

Table C1

Average Reported Frequency of ICT at School by Activity, Type of User and Country

Very low ICT user			
	Spain	Estonia	Finland
Chatting online at school	1.065	1.008	2.566
Using email at school	1.076	1.149	1.284
Browsing the Internet for schoolwork	1.269	1.313	1.944
Downloading, uploading or browsing material from the school's website (e.g. intranet).	1.018	1.054	1.098
Posting my work on the school's website	1.027	1.011	1.137
Playing simulations at school	1.014	1.021	1.083
Practicing and drilling, such as for foreign language learning or mathematics	1.047	1.045	1.174
Doing homework on a school computer.	1.031	1.043	1.074
Using school computers for group work and communication with other students	1.072	1.058	1.358
Using learning apps or learning websites	1.016	1.044	1.189
Low ICT user			
	Spain	Estonia	Finland
Chatting online at school	1.756	1.086	3.789

Using email at school	1.502	1.669	1.858
Browsing the Internet for schoolwork	2.010	2.141	2.741
Downloading, uploading or browsing material from the school's website (e.g. intranet).	1.201	1.300	1.256
Posting my work on the school's website	1.156	1.033	1.290
Playing simulations at school	1.099	1.091	1.207
Practicing and drilling, such as for foreign language learning or mathematics	1.350	1.289	1.408
Doing homework on a school computer.	1.224	1.229	1.170
Using school computers for group work and communication with other students	1.447	1.326	1.743
Using learning apps or learning websites	1.142	1.284	1.495
Medium ICT user			
	Spain	Estonia	Finland
Chatting online at school	2.111	1.417	3.809
Using email at school	1.988	2.135	2.317
Browsing the Internet for schoolwork	2.550	2.597	3.041
Downloading, uploading or browsing material from the school's website (e.g. intranet).	1.574	1.691	1.586
Posting my work on the school's website	1.352	1.134	1.552
Playing simulations at school	1.246	1.178	1.417
Practicing and drilling, such as for foreign language learning or mathematics	1.645	1.592	1.771
Doing homework on a school computer.	1.543	1.440	1.413
Using school computers for group work and communication with other students	1.837	1.563	1.990
Using learning apps or learning websites	1.424	1.598	1.874
Intensive ICT user			
	Spain	Estonia	Finland
Chatting online at school	2.342	2.159	4.101
Using email at school	2.572	2.551	2.828
Browsing the Internet for schoolwork	2.969	2.995	3.488
Downloading, uploading or browsing material from the school's website (e.g. intranet).	2.252	2.348	2.239
Posting my work on the school's website	1.906	1.538	1.956
Playing simulations at school	1.645	1.573	1.602
Practicing and drilling, such as for foreign language learning or mathematics	2.158	2.152	2.160
Doing homework on a school computer.	2.152	1.817	1.774
Using school computers for group work and communication with other students	2.379	2.006	2.369
Using learning apps or learning websites	2.049	2.121	2.369
Very intensive ICT user			
	Spain	Estonia	Finland
Chatting online at school	3.189	3.204	4.146
Using email at school	3.488	3.417	3.478
Browsing the Internet for schoolwork	3.718	3.706	3.927
Downloading, uploading or browsing material from the school's website (e.g. intranet).	3.504	3.605	3.560

Posting my work on the school's website	3.277	3.191	3.461
Playing simulations at school	3.004	3.111	3.159
Practicing and drilling, such as for foreign language learning or mathematics	3.373	3.479	3.480
Doing homework on a school computer.	3.364	3.227	3.342
Using school computers for group work and communication with other students	3.401	3.319	3.562
Using learning apps or learning websites	3.408	3.457	3.610

Appendix D

Estimation Results (Multi-Level Models) for All Countries

This appendix shows the estimation results from the multi-level models for all countries under study.

Table D1

Estimation Coefficients of the Hierarchical Linear Model for All Countries

	AUS	BEL	CHE	CHL	CZE	DNK	ESP	EST	FIN	GBR	GRC
Low ICT user	9.838**	5.636*	15.40***	2.802	3.368	4.189	10.21***	6.030	8.759***	13.63***	17.41***
	(3.849)	(3.077)	(5.193)	(4.406)	(3.879)	(3.868)	(2.865)	(3.749)	(3.147)	(4.033)	(4.506)
Medium ICT user	14.92***	-0.0687	6.325	3.058	-1.127	0.816	10.03***	11.41***	4.503	6.901*	7.431
	(4.043)	(2.967)	(5.033)	(3.738)	(4.161)	(3.948)	(3.050)	(4.061)	(3.639)	(4.006)	(4.606)
Intensive ICT user	-1.188	-2.817	-2.521	-9.813**	-14.05***	-3.410	-2.963	-4.206	0.245	5.749	-15.89***
	(4.050)	(3.230)	(4.952)	(4.333)	(4.177)	(4.532)	(2.965)	(4.537)	(4.009)	(4.119)	(4.478)
Very intensive ICT user	-13.36***	-26.24***	-26.60***	-26.12***	-25.69***	-23.53***	-22.45***	-24.65***	-32.37***	-22.53***	-29.52***
	(4.819)	(3.043)	(4.862)	(4.535)	(3.828)	(4.987)	(3.447)	(4.317)	(3.642)	(4.265)	(4.814)
ESCS (socio-ec. level)	19.26***	14.93***	18.23***	8.751***	15.49***	26.32***	10.36***	19.01***	29.76***	14.92***	15.40***
	(1.511)	(1.635)	(2.449)	(2.230)	(1.816)	(2.541)	(0.944)	(1.995)	(1.818)	(1.674)	(1.779)
Immigrant	1.195	-17.46***	-12.92**	-15.07*	-36.83***	-11.92	-19.31***	-25.43**	-25.96***	-6.406	-22.85***
	(3.537)	(4.591)	(5.441)	(8.280)	(8.207)	(9.108)	(3.663)	(12.95)	(7.091)	(4.871)	(7.195)
Repeater	-34.92***	-59.29***	-46.42***	-51.21***	-53.64***	-47.38***	-86.20***	-48.51***	-59.99***	-48.79***	-35.29***
	(5.761)	(3.272)	(6.214)	(3.718)	(9.850)	(8.771)	(2.853)	(10.47)	(8.595)	(10.33)	(12.60)
Female	-9.203***	-23.94***	-22.20***	-18.47***	-18.91***	-12.64***	-17.57***	-12.30***	-3.310	-12.28***	-17.12***
	(3.094)	(2.597)	(3.425)	(3.008)	(3.295)	(3.100)	(2.313)	(2.832)	(2.817)	(2.632)	(3.286)
Public school	-19.48***		-20.53***	-49.06***	-10.88***	-23.58***	-7.017***	-17.66***	-17.44***	-13.86***	-35.31***
	(1.369)		(5.785)	(2.725)	(3.011)	(2.198)	(1.698)	(4.439)	(2.750)	(4.720)	(3.042)
School size (log)	22.38***	8.028***	19.76***	19.77***	14.79***	9.450***	3.661***	4.349***	2.358	4.872	0.167
	(1.432)	(1.145)	(0.700)	(1.202)	(0.912)	(1.481)	(0.774)	(1.552)	(1.515)	(3.669)	(3.136)
Ratio computer/student	-1.182**	-4.666***	-1.911**	4.130**	2.307	-3.134	-0.708	4.936***	2.263**	-1.024	-46.71***
	(0.509)	(0.985)	(0.861)	(1.945)	(1.438)	(1.924)	(0.683)	(1.742)	(1.085)	(1.966)	(6.643)
Late ICT user (age >9)	-18.78***	-15.55***	-17.39***	-10.33***	-20.40***	-23.67***	-21.19***	-26.93***	-28.40***	-30.41***	-12.77***
	(2.488)	(2.442)	(3.133)	(3.856)	(3.942)	(4.114)	(1.952)	(4.291)	(5.080)	(3.311)	(3.013)
Bullying (index)	-4.86***	-0.133	-4.905**	-1.025	-2.458	0.495	-4.015***	0.264	1.164	-2.442**	-2.153
	(1.132)	(1.545)	(1.950)	(1.362)	(1.531)	(1.674)	(1.322)	(1.679)	(1.324)	(1.152)	(1.669)
Constant	359.8***	506.6***	443.0***	341.5***	451.6***	471.4***	512.7***	521.3***	512.9***	500.6***	514.7***
	(10.70)	(8.527)	(8.291)	(9.205)	(6.051)	(9.846)	(6.138)	(11.72)	(10.98)	(26.62)	(19.40)

	HUN	IRL	ISL	ITA	LTU	LUX	LVA	POL	SVK	SVN	SWE
Low ICT user	3.679	12.86***	14.19**	8.512**	16.21***	11.85***	5.251	5.579	5.534	11.63***	13.80***
	(3.605)	(4.087)	(5.848)	(3.774)	(3.754)	(3.898)	(4.077)	(4.477)	(4.056)	(3.946)	(4.846)
Medium ICT user	4.668	13.25***	17.47**	0.225	-1.966	9.387***	-0.805	-10.01**	-11.62**	3.906	9.534*
	(3.772)	(3.442)	(7.228)	(4.626)	(4.218)	(3.608)	(4.272)	(4.524)	(4.518)	(4.166)	(4.895)
Intensive ICT user	-11.27***	4.418	-4.843	-12.31***	-18.17***	-3.702	-12.11**	-26.40***	-18.05***	-4.992	-6.891
	(3.632)	(3.901)	(7.027)	(3.897)	(3.260)	(3.976)	(4.846)	(4.491)	(4.201)	(4.217)	(4.957)
Very intensive ICT user	-21.67***	-31.42***	-28.63***	-22.18***	-19.97***	-38.51***	-26.63***	-44.73***	-27.72***	-15.91***	-29.14***
	(3.479)	(4.003)	(7.107)	(5.660)	(4.495)	(4.158)	(4.526)	(4.949)	(4.778)	(4.956)	(5.381)
ESCS (socio-ec. level)	8.742***	19.73***	24.07***	6.560***	16.98***	13.05***	17.43***	23.00***	16.95***	6.951***	25.39***
	(1.912)	(1.646)	(2.575)	(2.112)	(1.559)	(1.861)	(1.689)	(1.946)	(2.176)	(2.256)	(1.856)
Immigrant	-20.06	-4.734	-25.56***	-16.37**	-27.00**	-5.290	16.46	-55.94***	-40.86***	-34.64***	-33.55***
	(12.83)	(4.257)	(9.703)	(6.563)	(12.05)	(4.135)	(13.61)	(20.24)	(9.458)	(8.516)	(5.719)
Repeater	-33.29***	-39.81***	-26.23	-41.16***	-68.27***	-57.44***	-69.14***	-83.53***	-102.9***	-60.96***	-42.65***
	(6.164)	(4.988)	(18.26)	(5.329)	(12.19)	(3.179)	(8.016)	(10.69)	(10.14)	(14.48)	(13.44)
Female	-25.77***	-8.420**	2.051	-22.99***	-14.45***	-16.03***	-16.59***	-13.97***	-17.39***	-22.66***	-6.553**
	(2.982)	(4.098)	(4.068)	(3.487)	(3.164)	(2.675)	(2.924)	(3.096)	(3.585)	(3.062)	(3.013)
Public school	-27.48***		-39.64**	-20.60***	-49.75***	-19.01***	-15.28**	-40.66***	-20.56***	-75.35***	
	(3.602)		(17.38)	(3.695)	(5.230)	(5.705)	(7.524)	(3.240)	(2.406)	(7.769)	
School size (log)	35.09***	19.05***	3.593	15.44***	20.52***	10.70***	10.38***	3.119**	11.85***	12.12***	20.49***
	(1.752)	(1.565)	(3.921)	(1.460)	(1.801)	(3.953)	(1.855)	(1.309)	(1.986)	(1.240)	(2.475)
Ratio computer/student	-0.0965	-1.520	-2.131	5.180***	-11.19***	-1.876***	0.611	-12.82***	-9.011***	7.249***	2.582***
	(3.117)	(1.302)	(2.579)	(1.767)	(1.018)	(0.513)	(1.799)	(3.818)	(1.096)	(1.719)	(0.698)
Late ICT user (age >9)	-15.09***	-17.30***	-30.48***	-12.16***	-18.24***	-16.21***	-15.00***	-20.75***	-20.46***	-19.12***	-24.12***
	(2.760)	(2.997)	(4.956)	(2.712)	(3.981)	(3.462)	(3.546)	(4.289)	(3.846)	(3.236)	(4.092)
Bullying (index)	0.373	-0.568	-5.440**	-4.856***	-5.488***	-4.865***	-7.924***	-1.392	-2.289	-1.445	-2.688
	(1.417)	(1.303)	(2.208)	(1.219)	(1.474)	(1.485)	(1.111)	(1.483)	(1.570)	(1.347)	(1.915)
Constant	306.3***	392.7***	505.8***	430.3***	425.6***	468.7***	468.9***	576.8***	478.0***	515.2***	390.9***
	(10.83)	(10.49)	(27.50)	(8.658)	(12.91)	(27.32)	(17.02)	(10.90)	(12.88)	(10.63)	(14.86)

Note. Standard errors in parentheses: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

Appendix E

Empirical Results by Student Groups

This appendix shows the empirical results disaggregated by gender and socio-economic status. The aim of the first part is to further explore whether the hill-shaped relationship found on an aggregate basis still holds, or, conversely, whether the form changes for certain groups of students (male and female students, and students from high or low socio-economic backgrounds). The second part explores whether the causal impact of very intensive ICT usage is confirmed for those four student groups. The control variables included in these models are the same as those outlined in the "Variable Description" subsection.

The results presented in Table E1 confirm that the inverted-U relationship between ICT usage at school and students' performance in mathematics still holds for all the four groups herein considered. Male students that are categorised as low or medium ICT users perform better than analogous (very low users) male students across the three countries under analysis. However, the effect of male students with a medium ICT usage on the mathematics performance is found to be non-significant. For both male and female students, very intensive ICT users relate with a significantly lower performance than the reminder of users, and this is particularly the case for female students. By socio-economic status, the hill-shaped relationship is also confirmed: low and medium ICT usage entails improved mathematical performance relative to analogous users, and this is the case for students from both high and low socio-economic status. For very intensive ICT users, a negative and significant relationship is, again, found regardless of the socio-economic status of students.

Table E1

The Estimated Impact of the ICT Users on the Mathematics Score by Gender and Socio-Economic (ESCS) Level

	Spain		Estonia		Finland	
	Female	**Male**	**Female**	**Male**	**Female**	**Male**
Low ICT user	4.000	16.96***	0.427	12.17**	2.897	16.16***
	(3.455)	(3.888)	(4.573)	(5.951)	(4.490)	(5.705)
Medium ICT user	4.160	15.31***	4.640	19.83***	0.891	7.231
	(3.999)	(3.789)	(5.903)	(5.677)	(5.222)	(5.036)
Intensive ICT user	-8.226**	2.074	-5.168	-3.543	0.149	-0.919
	(3.744)	(3.652)	(6.008)	(5.881)	(5.439)	(5.511)
Very intensive ICT user	-25.87***	-19.92***	-26.94***	-21.87***	-36.30***	-29.50***
	(5.451)	(3.794)	(6.251)	(5.072)	(5.644)	(5.084)
	High ESCS	**Low ESCS**	**High ESCS**	**Low ESCS**	**High ESCS**	**Low ESCS**
Low ICT user	12.16***	8.058**	4.530	8.438	-1.011	11.41***
	(3.761)	(3.270)	(6.201)	(5.245)	(8.874)	(4.337)
Medium ICT user	9.057**	9.373***	12.32*	12.84**	17.60**	-2.751
	(4.046)	(3.360)	(7.144)	(5.518)	(8.921)	(5.463)
Intensive ICT user	-2.254	-4.938	-2.122	-5.660	8.360	-1.123
	(3.585)	(4.282)	(6.434)	(5.856)	(9.601)	(5.815)
Very intensive ICT user	-19.55***	-26.79***	-27.69***	-22.21***	-28.66***	-31.58***
	(4.535)	(4.191)	(6.442)	(5.661)	(8.576)	(6.118)

Note. Standard errors in parentheses: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$. The reference for the different types of ICT users refers to the category of the very low ICT user. High and low ESCS refer to the socio-economic index being above or below the country's median, respectively. The usual additional covariates are not shown for simplicity purposes, and full estimation results are available upon request.

Table E2 presents the Average Treatment Effect of very intensive users on the mathematical performance for the four groups considered. By gender, results indicate that the causal impact of the treatment (i.e., the very intensive user) on the mathematical performance for women is -26 points in Spain, and -37 in Estonia and Finland. That is, the very intensive usage of technology at school for women has a more negative impact in Estonia and Finland than it does in Spain, although it is important to note that the two earlier countries have a higher Predicted Outcome Means (in the mathematical performance) than the latter. For men, the ATE amounts to -29 points in Spain, -32 in Estonia, and -31 in Finland. Therefore, a very intensive use of technology causes an underperformance in mathematics that can be equivalent to over half an academic course both for men and women. When looking at the relative impact of the very intensive ICT usage (the quotient between the ATE and the Predicted Outcome Mean), this is comparable across male and female users in Spain, and it is notably larger (i.e., more negative) for female students in Estonia and Finland compared to their male counterparts.

Analogous to the results by gender, the findings by socio-economic status evidence that the very intensive usage causes an underperformance of close to half an academic year for students, irrespective of their socio-economic status. However, as noted before, the Predicted Outcome Mean in the mathematical performance is larger for students with higher socio-economic status as compared to those with a lower socio-economic background. In fact, when looking at the relative impact (the quotient between the ATE and the Predicted Outcome Mean), this appears relatively comparable for high and low ESCS students in Spain and Estonia, while Finland exhibits a much larger relative impact for lower ESCS students compared to those from higher socio-economic profiles.

The causal impact of a very intensive technology usage at school for students from high socio-economic status amounts to -28 points for Spain and Finland, and -34 for Estonia. For students from lower socio-economic status, the corresponding ATE amount to -24, -30 and -34 points for Spain, Estonia and Finland, respectively. In Spain, the ATE is hence more negative for students with high socio-economic background, in contrast with the findings through hierarchical linear models.

Table E2

Inverse Probability Weighting Estimates of Very Intensive ICT Usage by Gender and Socio-Economic Status

	Spain		Estonia		Finland	
	Female	**Male**	**Female**	**Male**	**Female**	**Male**
Pomeans	487.36***	496.61***	528.47***	539.17***	516.39***	517.09***
	(1.13)	(1.35)	(1.71)	(2.07)	(1.50)	(1.80)
ATE	-25.65***	-28.60***	-37.07***	-31.54***	-36.94***	-30.96***
	(3.13)	(2.68)	(4.16)	(3.84)	(4.81)	(3.65)
Obs. Mean [a]	489.84	481.05	524.68	533.72	514.15	509.61
Obs. Gap [b]	-28.43	-24.95	-37.15	-27.74	-32.74	-24.26
	High ESCS	**Low ESCS**	**High ESCS**	**Low ESCS**	**High ESCS**	**Low ESCS**
Pomeans	516.74***	465.10***	553.45***	512.24***	538.54***	493.88***
	(1.12)	(1.20)	(1.80)	(1.83)	(1.54)	(1.58)
ATE	-28.08***	-23.63***	-34.41***	-30.29***	-28.43***	-34.39***
	(2.49)	(2.90)	(3.92)	(3.80)	(3.94)	(3.71)
Obs. Mean [a]	509.65	460.32	548.88	508.12	533.70	489.72
Obs. Gap [b]	-25.28	-28.15	-31.57	-28.45	-24.29	-33.04

Note. Standard errors in parentheses: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$. High and low ESCS refer to the socio-economic index being above or below the country's median, respectively. Pomeans refers to the predicted-outcome means; and ATE, to the average treatment effect. [a] The Obs. Mean refers to the observed mean in mathematics for the non-very-intensive ICT users. [b] The observed gap refers to the difference between the average points of the non-very-intensive ICT users with respect to the very intensive ICT users.

Appendix F

Estimation Results of the Relation between ICT Use and Mathematical performance when ICT is Defined as a Continuous Variable

In this appendix we estimate Equation 2 by including the ICT variable of frequency of use in the school as a continuous variable, as shown in Identity (1). That is, the standardised variable created in this study is used, which is interpreted as the average impact on the mathematics score if the frequency of use increases by one standard deviation.

Figure F1 shows that a one standard deviation increase in the use of ICTs at school is associated with a negative —and highly significant— effect on the mathematics scores in all the countries analysed. The figure also evidences that the magnitude of the coefficient differs markedly by country: in Poland, an increase in the frequency of use implies a substantially higher penalty than in Australia (an increase in the use of ICT entails penalties of 21 points and 9 points, respectively). Of the countries analysed, Spain is the fourth with the lowest estimated penalty: an increase in use implies an estimated reduction in the mathematical score of around 10 points. In the case of Finland and Estonia, the penalty is higher than that of Spain (with an estimated negative impact of 15 and 13 points, respectively). In summary, this analysis provides very robust results on the negative relationship between the frequency of use of ICT and the performance in mathematics in the 22 countries analysed.

Furthermore, these estimated effects, based on the PISA 2018 data, have similar magnitudes to those found by Hu et al. (2018) for PISA 2015 (with an estimated average effect of -9.67 points). It should be noted that the analysis of Hu et al. (2018) is carried out simultaneously for all countries, with models at three levels, while in this exercise the regressions are carried out for each country separately.

Figure F1

The Estimated Association between an Increase in the Use of ICT at School and the Mathematical Performance

Note. Full estimation results available upon request.