ICT use for learning and students' outcomes: Do the country's development level matter?

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Abstract

The use of Information and Communications Technologies (ICT) in educational systems has become a policy priority over the last decades. However, empirical evidence is inconclusive on whether there is a positive relationship between ICT use and students' outcomes. The literature has largely ignored the role that the country context, and in particular the country's development level, may play in shaping this relationship. This paper empirically addresses whether the relationship between ICT use for learning at school and students' outcomes differs from developed to developing countries. We employ data for 236,540 students attending 10,193 schools in 44 countries, obtained from the OECD Programme for International Student Assessment (PISA 2018). We use two alternative measures to classify the countries by their development level: The *Gross National Income* (*GNI*) per capita and the *Human Development Index* (*HDI*). The estimations, based on a Hierarchical Linear Model, show a negative relationship between ICT use for learning at school and students' outcomes. This negative relationship is more negative for students from developing countries than for those from developed countries. These findings imply that policymakers should be cautious about replicating interventions and technological applications from developed to developing countries (and vice versa).

Keywords: ICT use, education, development, income, PISA

1. Introduction

ICT have become an essential part of people's daily life. For this reason, policymakers increasingly acknowledge that students should be immersed in this digital world, which would enable students to be fully engaged in their socioeconomic and cultural environment [1]. In this spirit, educational policy has regarded investment in ICT as a priority over the last years [2,3], with the central goal of improving students' outcomes [4]. This interest has grown even more since the COVID-19 pandemic, as many countries accelerated ICT incorporation into education.

Despite the eagerness of policymakers and software (and hardware) manufacturers, research has not found clear evidence of a positive effect of ICT use for learning on students' outcomes (e.g., [4–6]). Notwithstanding the significant endeavors to understand which is the relationship between ICT use and students' outcomes, it remains an open question [5,7].

With rare exceptions, existing literature has passed over the analysis of third factors that may influence the relationship between ICT use for learning and students' outcomes [8].[1] In particular, the literature has paid little attention to the potential role of country characteristics, such as the country's development level, in shaping the relationship between the use of ICT and students' outcomes [5]. Commonly, empirical analyses on this relationship have been based on a single country or encompassed a sample of countries but did not consider differences in their development level.

ICT use for learning may have positive effects, but also negative effects, on students' outcomes [3]. On the positive side, ICT use can increase access to information and resources for learning, make lessons more attractive and/or interactive, increase students' flexibility and autonomy and facilitate individualized instruction and monitoring of student progress. On the

[1] Some examples are socio-economic status [10], gender [64], and students' experience using ICT [65].

negative side, ICT use may distract students, undermine students' need for work and discipline, restrict their creativity and reduce real interaction between students and teachers. The net effect of ICT use on students' outcomes may depend on whether the positive or the negative effects prevail.

There are arguments to expect that the effects of ICT use for learning on students' outcomes may differ depending on the country's development level. On the one hand, a series of factors positively associated with the effectiveness of ICT use tend to be more prevalent in developed countries than in developing countries. Developed countries usually count on a higher level of human capital [9], better ICT physical and pedagogical resources [1], a better quality of educational software [8], and better integration of ICT into academic curriculum [10,11], together with stronger ICT competences and skills among students [11-13], than their developing counterparts. These factors may facilitate, in developed countries versus their developing counterparts, to achieve positive effects (and to avoid negative effects) of ICT use. As a result, the effect of ICT use for learning on students' outcomes may be more positive (or less negative) in developed countries than in developing countries. On the other hand, however, there are also reasons from theory to expect the opposite. Following Solow's [14,15] neoclassical theory of growth (which assumes technology is a public good and technological change is exogenous), developing countries can reach more benefits from technological adoption than their developed counterparts by leveraging developed countries' investment in ICT [16,17]. Moreover, according to the theory of technological diffusion, developing countries may obtain higher yields in the embracement of technologies previously implemented in developed countries due to the lower costs it implies [18]. As a result, ICT use for learning may render more positive (or less negative) effects on students' outcomes in developing countries than in their developed counterparts.

Based on these theoretical arguments, this paper hypothesizes that the relationship between ICT use for learning at school and students' outcomes may differ from developed to developing countries. To address this empirically, we used a sample of 236,540 students from 44 countries (obtained from the Programme for International Student Assessment, PISA 2018) to estimate the effect of the interaction between ICT use for learning at school and the country's development level on students' outcomes.

As a measure of ICT use for learning at school, we employed the *Subject-related ICT use during lessons* index (PISA code *ICTCLASS*), newly introduced in PISA 2018. Compared to measures of ICT use at school already available in previous rounds of PISA, this index permits a more accurate measurement of the amount of time of ICT use for specific learning purposes in each subject. Indexes of ICT use at school previously available in PISA did not differentiate between academic- or leisure-related ICT use and nor did they incorporate information on the amount of time students devoted to ICT use in each specific subject. We employed two alternative measures to categorize the countries by their development level: The *Gross National Income* (*GNI*) *per capita* and the *Human Development Index* (*HDI*). First, the *GNI per capita* has been traditionally considered a suitable proxy for the country's well-being or economic development [19,20]. Based on the *GNI per capita,* the World Bank periodically released the *Country Classifications by Income Level*. This tool is broadly used to analyze and compare development trends within and among countries [21]. Second, country's *HDI* is periodically computed by United Nations Development Programme to measure its performance and path in human development [22]. Anand and Sen [23] stated that the *HDI* constitutes an alternative to income as a measure of development, which places human well-being as the principal means and the ultimate goal of development. As explained by these authors, the *HDI* incorporates education and longevity as two basic capabilities which, along with *GNI per capita* (as an indirect measure of complementary capabilities to these two), would reflect human well-being.

This paper contributes to the literature on the relationship between ICT use for learning and students' outcomes by providing evidence on whether, and how, this relationship is affected by the country's development level. Our results show that the relationship between ICT use for learning at school and students' outcomes differs from developed to developing countries. We observe a negative relationship between ICT use for learning at school and students' outcomes. This negative relationship is more negative for students from developing countries than for their developed counterparts, regardless of the measure of country's development level used (*GNI per capita* or *HDI*). These findings suggest that educational policy should be cautious in replicating analyses, interventions, and technological applications from developed to developing countries (and vice versa), without careful evaluation of the specific context of the country (including the availability of the educational inputs that may influence the effectiveness of ICT in educational practices).

The paper is organized as follows. Section 2 presents a literature overview on the relationship between ICT use at school and students' outcomes, based on large-scale international surveys, with particular attention to the role of the country's development level. Section 3 explains the methodology, data, and variables used in the paper. Section 4 describes the results. Section 5 concludes and discusses the findings and their implications for educational policy.

2. Literature review

The increasing relevance of ICT for teaching and learning processes [24] has led to the development of a significant amount of research focused on the relationship between access to and use of ICT and students' outcomes [3]. A substantial part of this literature has been based on data from large-scale international surveys on students' outcomes (e.g., PISA, TIMSS, and PIRLS). Its main results and contributions, as well as the mediating effect that the level of development of economies could play, are described in the following subsections.

2.1. ICT use at school and students' outcomes: Evidence from large-scale international surveys

Large-scale international surveys on students' outcomes allow to model patterns of correlations in populations (e.g., schools, teachers, students) and compare their results in a wide range of countries and settings. Their main limitation, however, is the difficulty of inferring cause-and-effect relationships from observational data provided by these surveys [3,6]. The studies on the relationship between ICT use and students' outcomes based on large-scale international surveys have addressed three elements: the purpose of ICT use (learning- or leisure-related), the location of ICT use (at school or home), and the subject assessed (e.g., mathematics or reading). For the purpose of this paper, we focus only on evidence of ICT use for learning purposes at school.

Several studies have used regression methods, applied to data from international surveys (most commonly, PISA), to estimate the relationship between indicators on ICT use at school and students' outcomes. Some of these studies focused on a single country. Mediavilla & Escardíbul [25], based on PISA 2012 data for Spanish students, found that the use of ICT at school was negatively related to mathematics and reading outcomes among boys. Erdogdu & Erdogdu [26], based on PISA 2012 data for Turkish students, concluded that internet access at school was positively related to students' outcomes in science, whilst the frequency of browsing the internet at school was negatively related to outcomes in the three PISA subjects.

Other studies based on international surveys have carried out similar analyses using samples that include several countries. Skryabin, Zhang, Liu, & Zhang [27] used data from PIRLS 2011 (for a set of 43 countries), TIMSS 2011 (for a set of 38 countries) and PISA 2012 (for a set of 39 countries) to analyze whether ICT use was related to students' outcomes. These authors found that ICT use at school was positively related to 4th grade students' outcomes in mathematics, reading and science, but negatively related to 8th grade students' outcomes in the three subjects. Other authors have carried out their research with data coming exclusively from PISA. Zhang & Liu [28] used data from five rounds of PISA (2000, 2003, 2006, 2009 and 2012) to explore the relationship between indicators on ICT use and students' outcomes in mathematics and science, for the set of countries which had completed the *ICT familiarity questionnaire* in these five rounds of PISA (25 countries in 2000, 32 in 2003, 40 in 2006, 45 in 2009, and 43 in 2012). The authors found that the use of both software and internet at school was negatively related to students' outcomes in mathematics and science. Petko, Cantieni, & Prasse [8] analyzed data for 39 countries of PISA 2012 and found that ICT use at school was negatively related to outcomes in mathematics, reading and science in a vast majority of countries. More recently, Kılıc & Drepen [29] used data from PISA 2018 to compare the factors that influenced the outcomes of Turkish and Chinese students in reading. By using machine learning analysis, these authors found that ICT use for learning at school (as measured by the *Subject-related ICT use during lessons* index) was the third most influential factor to explain Turkish students' outcomes, but in contrast, this factor was not relevant to explain Chinese students' ones. Erdogdu [30] also used data from 41 countries that participated in PISA 2018 to evaluate whether access to ICT at school and home, GDP per capita, and other contextual factors were predictors of outcomes in reading, mathematics and science. By using stepwise regression analysis, this author found that

ICT use at school was not related to students' outcomes in none of these three subjects. Furthermore, he obtained that GDP per capita was negatively related to PISA outcomes.

Other studies have addressed other methodologies to explore the effect of ICT access and use at school on students' outcomes. De Witte & Rogge [2] applied matching techniques to estimate the effect of ICT-related variables on outcomes in mathematics, based on TIMMS 2011 data for Dutch students. They concluded that the estimated effect of ICT was significantly altered depending on whether student, teacher, school, and regional characteristics were considered. Cabras & Tena Horrillo [31] applied a non-parametric approach to estimate the effect of the use of computers at school on outcomes in mathematics, using PISA 2012 data for Spanish students. They found that, with a high probability, the effect of ICT use on students' outcomes was moderately positive. This effect was particularly high for low socioeconomic background students. Falck, Mang, & Woessmann [32] estimated the effects of different uses of computers at school on students' outcomes, employing TIMSS 2011 data for 30 countries. They exploited within-student between-subject variation, leveraging information for each student on two different subjects (mathematics and science). These authors found positive effects of using computers to look up information on students' outcomes, whilst the effects of using computers to practice skills were negative. Finally, Fernández-Gutiérrez, Gimenez, & Calero [3] used data for Spanish regions from three rounds of PISA (2009, 2012, and 2015) to estimate the effect of ICT use at school on students' outcomes in mathematics, reading and science. These authors leveraged the representative samples for Spanish regions and the autonomy and variability of ICT use at school across them. They found that a higher ICT use at school in a region did not have positive effects on outcomes in mathematics and reading, while it had positive effects on outcomes in science.

2.2. ICT use and students' outcomes: The role of the country's development level

Existing literature has shown that the country's development level plays a key role in explaining the differences in access to and use of ICT in education [4]. However, scarce empirical evidence has been conducted on whether, and how, the country's development level influences on the relationship between ICT use and students' outcomes. Among the studies which have (at least indirectly) addressed this issue, we highlight the ones by Skryabin, Zhang, Liu, & Zhang [27], Petko, Cantieni, & Prasse [8], and Falck, Mang, & Woessmann [32].

Skryabin, Zhang, Liu, & Zhang [27] (which used data from TIMSS 2011, PIRLS 2011, and PISA 2012) stated that developing countries have a faster ICT development rate, but a lower ICT level than developed countries. In addition, these authors noted that the ICT level has a stronger positive influence on students' outcomes than its development rate. This would contribute to explain the gap in students' outcomes between developed and developing countries. Petko, Cantieni, & Prasse [8] carried out separate estimations on the relationship between ICT use and students' outcomes for each of the 39 countries included in their analysis, based on PISA 2012 data. They obtained a negative relationship between ICT use and students' outcomes for 37 of the 39 countries. However, they did not find that the differences across countries in this relationship between ICT use and students' outcomes were apparently correlated to the country's development level or to other variables at the country level. Falck, Mang, & Woessmann [32] carried out an empirical analysis to explore the heterogeneity across countries in the relationship they found between the use of computers at school and students' outcomes. To do so, they split their sample of 30 countries (derived from TIMSS 2011 data) according to two different criteria: first, whether the countries were OECD members or not; and second, whether they were above or below the median Gross National Product (GNP) per capita of their sample. These authors found that the effects they had obtained were mostly cramped to OECD members and to countries with GNP per capita above the median, while little significant effects were observed neither in non-OECD members nor in countries with GNP per capita below the median. They argued that the effects of using ICT on students' outcomes (positive or negative) may be less pronounced in developing countries, because ICT-based instruction would have a lower effectiveness in these countries.

Our study has two key novelties with respect to the previous literature. First, in the preceding studies, the influence of the country's development level on the relationship between ICT use and students' outcomes was not the central point of the analysis. As far as we know, the present paper constitutes the first specific, in-depth empirical analysis of whether, and how, the relationship between ICT use for learning at school and students' outcomes depends on the country's development level. Second, we used the new PISA index of *Subject-related ICT use during lessons*, which is a more accurate indicator of subject-specific ICT use for learning purposes at school than those previously available in PISA (as we explain in detail in the next section).

3. Empirical method

3.1. Data

In our analysis, we used PISA 2018 dataset as our main source. This international large-scale survey, created by the Organisation for Economic Co-operation and Development (OECD), measures students' outcomes (in reading, mathematics, and science), for a representative sample of the target population in the participating countries: 15-year-old students attending educational institutions at grade seven or higher.

The survey has been held every three years since 2000. In the 2018 round, PISA surveyed 612,004 students, that assisted to 21,903 schools distributed in 79 countries and economies. Given our focus on the relationship between ICT use for learning at school and students' outcomes, we only worked with countries where the PISA *ICT familiarity questionnaire* (which encompasses the information on ICT use for learning at school) was completed. After excluding missing values, our final sample was reduced to 236,540 students from 10,193 schools and 44 countries.[2]

3.2. Variables

We established a statistical relationship between students' scores in each PISA subject (dependent variables) and the learning factors (predictors). As learning factors, we employed a set of students', schools', and countries' characteristics that, being available in the PISA 2018 dataset, the literature has identified to play a crucial role in the learning process. Table A1 of the Statistical appendix shows the descriptive statistics of the dependent variables and the predictors.

3.2.1. Dependent variables

To increase the accuracy of students' scores measurement in the cognitive tests, PISA generates ten plausible values for each student's score in each subject (reading, mathematics and science). In our case, estimating a HLM in three levels using plausible values analysis for such a large sample of students would make the estimations extremely demanding in computational terms. To deal with this, we defined the dependent variables as the student's average score of the ten plausible values, for each subject.[3] Since we were working with a sample of 236,540

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[2] Due to technical issues, PISA 2018 excluded results for Spain from the reading assessment. For this reason, our sample for reading scores is restricted to students from the remaining 43 countries.

[3] Using just one plausible value or an average measure of them is a quite common procedure in the empirical literature when working with large PISA samples [9,67–69]. Indeed, the PISA data analysis manual itself recognizes that *using one plausible value or five plausible values* [ten, as available from the 2015 PISA round] *does not really*

students, this approach allowed us to obtain an unbiased estimation and relatively small imputation error (which reflects estimation reliability) of the average score for each student and subject [37].[4] In our total sample, the average PISA score was 461 for reading, 469 for mathematics, and 466 for science, while their standard deviations were, respectively, 104, 96, and 96.

3.2.2. Predictors

3.2.2.1. Student-level predictors

A central variable in our study was the PISA index of *Subject-related ICT use during lessons* (PISA code *ICTCLASS*). The 2018 round was the first in which PISA included the *ICTCLASS* variable, computed from information about the time that, in each specific subject, students devoted to learning using ICT at school. Previous cross-country studies based on PISA used the variables on ICT at school available in earlier rounds of this source: *ICT available at school* (PISA code *ICTSCH*) and *Use of ICT at school in general* (PISA code *USESCH*). These variables already available in earlier rounds of PISA focus on "the access to" (*ICTSCH*) and the "the use of ICT at school in general" (*USESCH*). *ICTCLASS* provides three crucial advantages with respect to *ICTSCH* and *USESCH* variables, as it enables: (1) to specifically analyze ICT use for learning purposes, separated from other purposes such as those leisure-related; (2) to obtain a measure of ICT use that is specific for each subject; and (3) to obtain a measure of the time

make a substantial difference on large samples ([70], p. 46) and that, *on average, analyzing one plausible value instead of five plausible values provides unbiased population estimates as well as unbiased sampling variances on these estimate. s*ee [70], p. 129). The impact appears to be minimal on the results, with only *trivial changes to the estimated effect sizes and associated standard errors*, and the additional imputation error calculated working with all the plausible values *is almost always of negligible magnitude, with key conclusions continuing to hold if it is simply ignored* ([71], p. 55).

[4] For a complete technical justification, see [71–73].

devoted to ICT use. The time dimension is fundamental, as it provides information on the actual intensity of use of ICT (and not just on ICT availability).

PISA 2018 constructed the *Subject-related ICT use during lessons* index (*ICTCLASS*) from items *IC150Q01HA* to *IC150Q05HA*. These items asked about the time students spent using digital devices during classroom lessons in a typical school week in five subjects: test language lessons, mathematics, science, foreign language, and social sciences. Each item considers four possible responses: “No time”, “1-30 minutes a week”, “31-60 minutes a week”, and “More than 60 minutes a week”. Applying the *item response theory* scaling to this information, PISA computed the standardized single *Subject-related ICT use during lessons* index.

We also included student-level characteristics available in PISA 2018 which have been commonly used in the related literature as predictors of students’ outcomes: *Gender* (PISA code *ST004D01T*), *Age* (PISA code *AGE*), *Country of birth* (PISA code *ST019AQ01T*), and the composite indexes for the *Economic, social and cultural status* (PISA code ESCS)[5] and the *Attitude towards school: learning activities* (PISA code *ATTLNACT*). Male students usually underperform females in reading but overperform them in mathematics and science [38,39]. Being older (there can be a difference of up to 11 months in students’ age in PISA) is related to higher scores [40,41]. Students born out of the country of the test are more susceptible to language and integration issues that cause them to underperform compared to native students in terms of outcomes [42,43]. Previous literature has pointed out that socio-economically

[5] PISA built the *ESCS* index by attributing equal weight to its three standardized components: *highest parental education in years of schooling* (*PARED*), *highest parental occupational status* (*HISEI*), and *home possessions* (*HOMEPOS*). See OECD [74] for a description of the method and variables used to build the three components. In a final step, the *ESCS* index was transformed, 0 being the score of an average OECD student and 1 being the standard deviation across equally weighted OECD countries.

disadvantaged students tend to underperform those from advantaged backgrounds [5,28]. Finally, a higher motivation or better attitudes toward learning among students is related to higher outcomes [44].

3.2.2.2. School-level predictors

As school-level predictors of students' outcomes, we took schools' characteristics available in PISA 2018 commonly used in the related literature. We included, first, each *School average value of the index ESCS* as a measure of peer effects. Second, the principals' perception of teachers' skills to introduce digital devices in instruction, to control for ICT-related knowledge among teachers in each school (PISA code SC155Q06HA). Third, a set of composite indexes which measure the educational climate and resources: *Proportion of all teachers fully certified* (PISA code *PROATCE*), *Teacher behavior hindering learning* (PISA code *TEACHBEHA*), *Perceived teachers' interest* (PISA codes *TEACHINT*), *Shortage of educational material* (PISA code *EDUSHORT*), *Shortage of educational staff* (PISA code *STAFFSHORT*), *Adaptation of instruction* (PISA code *ADAPTIVITY*) and *Disciplinary climate in test language lessons* (available for the core subject, with code *DISCLIMA*). And fourth, the categorical variable *School location* (PISA code *SC001Q01TA*), which captured the size of the community where the school was located.

Students attending to schools with higher average *ESCS* can benefit from positive externalities in the form of peer effects [45,46]. Previous studies found that teachers' skills to integrate ICT in learning are related to higher students' outcomes [10,11]. Teachers' education tends to correlate positively with students' outcomes [47]. Furthermore, teachers' behavior, attitudes, and relationship with students are critical enablers of learning [48]. The shortage of educational materials and staff tend to be negatively related to students' outcomes [49,50]. The relationship between disciplinary climate and students' outcomes tends to be positive [51,52]. Finally, urban schools tend to have better infrastructure and teachers than rural ones, which contributes to increase the students' outcomes [53,54].

3.2.2.3. Country-level predictors

As country-level predictors, we focus on the country's development level. We used two alternative variables: the *GNI per capita* and the *HDI*. Information on the country's *GNI per capita* was retrieved from the *Country Classifications by Income Level* of the World Bank, which was based on the country *GNI per capita* in current USD in 2020. According to its thresholds, *Middle-income* countries are those with a *GNI per capita* between 1,036 and 12,535 current USD (1,036 to 4,045 for *Lower-middle-income* countries and 4,046 to 12,535 for *Upper-middle-income* countries); while *High-income* countries are those with a *GNI per capita* above 12,535 USD.[6] In our final sample, 13 countries were *Middle-income* countries, whose *GNI per capita* ranged from USD 3,190 in Morocco to USD 11,700 in Costa Rica; whereas 31 countries were *High-income* countries, with *GNI per capita* ranging from 14,980 in Croatia to 85,500 in Switzerland. According to this criterion, we take *High-income* countries as developed countries, and *Middle-income* countries as developing countries.

The second measure, the *HDI,* was retrieved from the *Human Development Report 2020* elaborated by United Nations. This index is based on three dimensions (health, education, and standard of living), and it is computed by the normalized index of the geometric mean of each of these three dimensions [59]. According to the index thresholds, the countries with a *HDI* index from 0.700 to 0.799 are classified as *High-HDI* countries, and those with a *HDI* index above

[6] The Country Classifications of the World Bank includes four categories: Low-income, Lower-middle-income, Upper-middle-income and High-income. To obtain further details see, https://blogs.worldbank.org/opendata/new-world-bank-country-classifications-income-level-2020-2021.

0.800 are classified as *Very-high-HDI* countries.[7] In our final sample, 10 countries were classified as *High-HDI* countries, whose *HDI* ranged from 0.676 in Morocco to 0.799 in Serbia; while 34 countries were classified as *Very-high-HDI* countries, whose *HDI* ranged from 0.807 in Turkey to 0.946 in Switzerland. According to this criterion, we take *Very-high-HDI* countries as developed countries, and *High-HDI* countries as developing countries.

Table A2 of the Statistical appendix describes the list of countries we worked with, their *GNI per capita* and *HDI*, and their categorization based on these two variables. Table A2 also describes the statistics on ICT use for learning at school (*ICTCLASS*) for each country. In our total sample, *ICTCLASS* was, on average, -0.08 and its standard deviation was 1.01. Japan had the lowest value (-0.59), and Denmark had the highest (1.35). Among students enrolled from *High-income* countries, *ICTCLASS* was, on average, -0.06, while among those from *Middle-income* countries it was -0.14. Among students from *Very-high-HDI* countries, *ICTCLASS* was, on average, -0.03, while for those from *High-HDI* countries the average was -0.27. These data show that the average ICT use for learning at school was higher in developed countries than in developing countries.

We also included, as a country-level predictor, the information on the *Government expenditure on education* (measured as % of GDP), to control for the effect that the general effort (beyond ICT) that each country dedicates to education may have on students' outcomes. Previous research found a positive relationship between countries' expenditure on education and students' outcomes in particular contexts [55–57]. Nevertheless, overall, cross-country empirical evidence in this regard is inconclusive [58], and the debate on the relationship between

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[7] The Human Development Classification of the United Nations includes four categories: Low-HDI, Medium-HDI, High-HDI and Very-high-HDI. To obtain further details see, https://hdr.undp.org/system/files/documents/2018humandevelopmentstatisticalupdatepdf.pdf.

expenditure on education and students' outcomes is open [57]. Data on this predictor were retrieved from the *World Development Indicators* of the World Bank.

3.3. Model

We model the students' outcomes in the PISA subjects (reading, mathematics and science) by using a set of predictors distributed into three levels (respectively, student, school, and country). Given this nested structure (students enrolled at the same schools may have similar characteristics, while schools from the same countries have comparable contexts), it is suitable to apply a Hierarchical Linear Model (HLM). The use of HLM is more appropriate in this case than the use of other nested models' estimation techniques, such as fixed effects. HLM assumes that observations within groups (schools and countries) are likely to be correlated and allows us to distinguish effects due to observed and unobserved group characteristics that affect students' outcomes. In contrast, if we were to estimate students' outcomes by adding level fixed effects, we could not make that distinction. In addition, the estimation through HLM allows inference to a population of groups, whereas estimation with fixed effects does not allow inference beyond the groups in the sample. See Hox [28] for an in-depth explanation of the advantages of HLM estimation.

The multilevel model we estimated, using the lme4 package for R software, was given by the following equation, which assumes that the intercepts and the slopes vary across schools and countries:

$$Y_{ijk}^{s} = \gamma_{000} + \beta_1 ICTCLASS_{ijk} + \boldsymbol{\beta_{ijk} Student_{ijk}} + \boldsymbol{\beta_{0jk} School_{0jk}} + \beta_2 GE_{00k} + \beta_3 DL_{00k}^{m} + \beta_4 ICTCLASS_{ijk} \cdot DL_{00k}^{m} + \varepsilon_{ijk} + u_{0jk} + \mu_{00k} + u_{1jk} ICTCLASS_{ijk} + \mu_{01k} ICTCLASS_{ijk} \quad (1)$$

Y_{ijk}^{s} is the expected PISA subject *s* score of student *i*, enrolled in school *j*, in country *k* (that is, the student's outcome). As Sulis, Giambona, & Porcu [33] stated, the relationship between ICT use and students' outcomes, as well as the relationships between the other predictors and students' outcomes, may differ across subjects. For this reason, we estimated the equation separately for each of the three PISA subjects reading, mathematics, and science.

On the right side of the equation, for every subject, γ_{000} is the grand mean of the students' scores for all countries included in the sample. β_1 is the coefficient associated with the *Subject-related ICT use during lessons* index $(ICTCLASS_{ijk})$, which we use to measure ICT use at school for learning. $\boldsymbol{\beta_{ijk}}$ is the vector of coefficients associated with the student-level predictors ($\boldsymbol{Student_{ijk}}$). $\boldsymbol{\beta_{0qk}}$ is the vector of coefficients associated with the school-level predictors $(\boldsymbol{School_{0jk}})$. β_2 is the coefficient associated with the country-level predictor of *Government expenditure on education (% GDP)* (GE_{00k}). β_3 is the coefficient associated with the country's development level (DL_{00k}^{m}), where m represents the *Development level*. This *Development level* is measured in two ways. First, through the income level estimated by the *GNI per capita*. We define a binary variable, which takes a value of 1 if the country is classified as *High-income* (developed country), and 0 for *Middle-income* (developing country). And second, through the Human Development Index (*HDI*). We define a binary variable, which takes a value of 1 if the country is classified as *Very-high-HDI* (developed country), and 0 for *High-HDI* (developing country). β_4 is the coefficient associated with the interaction term $ICTCLASS_{ijk} \cdot DL_{00k}^{m}$, which captures the hypothesized differential effect of ICT use for learning at school from developed countries to developing countries. ε_{ijk} is a student-level random effect that represents the deviation of $Student_{ijk}$ score from the predicted score based on the student-level model.

u_{0jk} and μ_{00k} are the random effects that allow the intercept to vary randomly by the school and country, respectively. Furthermore, we consider that the effect of ICT may vary across schools or countries. So, we treat these slopes as random by introducing the interaction term between the random effect u_{1jk} and $ICTCLASS_{ijk}$, which allows the *ICTCLASS* slope to vary randomly by the school; and the interaction term between the random effect μ_{01k} and $ICTCLASS_{ijk}$, which allows the *ICTCLASS* slope to vary randomly by country.[8]

4. Results

Table 1 presents the estimations of the HLM for PISA scores in the three subjects (reading, mathematics, and science) using the *GNI per capita* as a measure of the country's development level. The estimations include the fixed-and-random effects. The fixed effects refer to the overall expected effects of the students', schools', and countries' characteristics on test scores. The random-effects, at the bottom of the table, show the standard deviations from the overall mean, with origin in the school-and-country-level variance unaccounted for in the model.

The analysis of the fixed effects shows that the *Subject-related ICT use during lessons* index (*ICTCLASS*) was negatively related to PISA scores ($p < 0.01$) in the three subjects. This coefficient captures the relationship between *ICTCLASS* and PISA scores when the interaction term is null (that is, for the group of *Middle-income* countries). Female students scored higher than males in reading, whereas in mathematics and science they scored lower ($p<0.01$). A higher student's age was related to higher scores ($p<0.01$). Students who were born in the country of the

[8] For an in-depth explanation about the theoretical and empirical rationale on the random coefficients and slopes estimation, see [66].

test scored higher than immigrant students ($p<0.01$). Students' *Economic, social and cultural status (ESCS)* was positively related to their scores ($p<0.01$), as well as students' attitudes towards learning activities ($p<0.01$). The school's average *ESCS* was positively related to students' scores ($p<0.01$). The coefficient that shows the relationship between principals' perception of teachers' skills to introduce digital devices in instruction and students' scores was non-significant. The *Proportion of all teachers fully certified* was positively related to students' scores ($p<0.01$), while *Teacher behavior hindering learning* was negatively related to the scores ($p<0.05$). The *Perceived teachers' interest* was positively associated with students' scores ($p<0.01$). The *Shortage of educational material* was negatively related to students' reading scores ($p<0.10$), while in mathematics and science this relationship was non-significant. The *Shortage of educational staff* was positively associated with students' reading scores ($p<0.05$), while it was not significantly related to scores in mathematics and science. Both the *Adaptation of instruction* and the *Disciplinary climate in test language lessons* were positively associated to students' scores ($p<0.01$). Attendance at schools located in larger cities was related to higher reading scores ($p<0.05$), whereas it was not significantly related to the scores in mathematics and science. The *country's government expenditure on education (% GDP)* was not significantly associated to students' scores in none of the three subjects. Finally, the students from *High-income* countries scored higher than those from *Middle-income* countries ($p<0.01$). Overall, the coefficients of the control variables were significant and showed the usual signs found in the empirical literature (for an in-depth analysis of the expected relations, see [60]).

As we explained above, our objective was to test whether the relationship between the *Subject-related ICT use during lessons* index (*ICTCLASS*) and PISA scores was conditioned by the country's development level (in this case, measured by the *GNI per capita*). To do so, we estimated the interaction term between *ICTCLASS* and a *High-income* country, which shows a positive and significant coefficient in the three subjects under analysis: reading, mathematics, and science ($p < 0.01$). This result indicates that the relationship between the *ICTCLASS* index and PISA scores differs between students from *High-income* countries and those from *Middle-income* countries, being more unfavorable for students from *Middle-income* countries.

Regarding the random effects, the variance components for the random intercepts are large relative to their standard error. This shows that some school-and-country-level variance remains unaccounted for in the model, which justifies the inclusion of the school and the country levels. By comparison, the variance components corresponding to the slopes are smaller relative to their standard errors, justifying the treatment of these slopes as random.

Table 2 shows the fixed- and random- effects estimations of the HLM for PISA scores in the three subjects, using the same predictors but considering the *HDI level* (instead of the *GNI per capita*) as a measure of the country's development level. The sign and statistical significance of the predictors were consistent with respect to those obtained when using the *GNI per capita* (described in Table 1). The *Subject-related ICT use during lessons* index (*ICTCLASS*) kept a negative relationship with PISA scores ($p < 0.01$) in the three subjects, which indicates that *ICTCLASS* was negatively related to PISA scores when the interaction term was null (that is, in this case, for the group of *High-HDI* countries). The students from *Very-high-HDI* scored higher than those from *High-HDI* ($p < 0.01$).

Our objective here was to test whether the relationship between *ICTCLASS* and PISA scores was conditioned by the country's development level (in this case, measured by the *HDI level*). The interaction term between the *Subject-related ICT use during lessons* index (*ICTCLASS*) and a country *Very-High-HDI* shows a positive and significant coefficient in all the three subjects reading, mathematics, and science ($p < 0.01$). This indicates that the relationship between *ICTCLASS* and PISA scores differs between students from *Very-high-HDI* countries to those from *High-HDI* countries, being more unfavorable for those from *High-HDI* countries. This result is coherent with that obtained when the country's development level was measured by the *GNI per capita*. [i]

The analysis of the variance components for the random intercepts and the slopes (see also Table 2) justifies, as occurred when measuring the country's development level by the *GNI per capita*, the inclusion of the three levels in the model and the treatment of the slopes of *ICTCLASS* as random. To assess the relative size of the effects found on the differences in the relationship between the *Subject-related ICT use during lessons* index and PISA scores by country's development level, we calculate the interaction between the estimated coefficients and the standard deviations of the predictors. When we measure the country's development level by the *GNI per capita*, an increase of one SD in the *Subject-related ICT use during lessons* index (*ICTCLASS*) is associated with an average reduction in the PISA reading, mathematics, and science scores that is higher (more intense) by .06 SD (6 PISA points) in middle-income than in high-income countries. When we measure the country's development level by the *HDI*, the difference between *Very-High-HDI* and *High-HDI* countries is .07 SD (7 PISA points). To contextualize the importance of these effects, a variation of one SD in the school-level predictors associated with students' outcomes, which measure the educational climate and resources (the indexes of *Proportion of all teachers fully certified*, *Teacher behavior hindering learning*, *Perceived teachers' interest*, *Shortage of educational material*, *Shortage of educational staff*, and *Adaptation of instruction*), would lead to smaller reductions in PISA scores (between .01 and .04 SD).

It is important to point out that, when working with PISA data, the presence of missing observations represents a significant problem. In our dataset, the deletion of all the students with a missing value for at least one variable reduced the sample size by around 38%. The frequency of the missing values varies across countries and between variables. To test whether the missing values would have generated biases on the statistical inference [34], we estimated the model imputing missing values as a robustness check. Missing values were imputed with the R package *Multivariate Imputation by Chained Equations*, which computes incomplete multivariate data by Fully Conditional Specification (FCS). The main advantages of this method are its flexibility and efficiency, as it permits to select and compute appropriate regression models for each variable [35,36].

The estimation of equations 1 and 2 imputing missing values yielded consistent results. The interaction term between the *Subject-related ICT use during lessons* index (*ICTCLASS*) and developed countries (both if measured by *GNI per capita* for *High-income* countries, or by *HDI* for *Very-high-HDI*) was positively and significantly related to PISA scores. See Tables S3 and S4 of the supplementary material available at:
https://docs.google.com/spreadsheets/d/1B4uRAxBGOEoYl7XidGhn-OU5pGZ29L7D/edit?usp=sharing&ouid=102720823307982166811&rtpof=true&sd=true

Finally, as a key contribution of this paper was to use a new variable that provides a more accurate measure of ICT use for learning at school (*ICTCLASS*), we aim to check if the same results applied when other variables on ICT use at school available in PISA were considered instead. To do so, we reproduced the analysis, substituting the PISA index of *Subject-related ICT use during lessons* (*ICTCLASS*) with the PISA index of *ICT available at school* (*ICTSCH*); and at a later stage with the PISA index of *Use of ICT at school in general* (*USESCH*). We obtained, again, a negative relationship between ICT use (*ICTSCH* and *USESCH*, respectively) and students' outcomes. However, we found significant differences as regards the interaction effect between ICT use and the country's level of development, whose sign and significance depended on the variable chosen for measuring ICT use. These results highlight the conceptual differences between variables in the measurement of ICT use. We include these results in Tables S5 to S8 of the supplementary material, available at https://docs.google.com/spreadsheets/d/1B4uRAxBGOEoYl7XidGhn-OU5pGZ29L7D/edit?usp=sharing&ouid=102720823307982166811&rtpof=true&sd=true

All in all, our findings supported our hypothesis that the relationship between ICT use for learning at school and students' outcomes differs from developed to developing countries, both when the country's development level is measured by the *GNI per capita* and by the *HDI*. There is a negative relationship between ICT use for learning at school and students' outcomes. This negative relationship is more negative for students from developing countries (*Middle-income* countries and *High-HDI* countries, if measured by the *GNI per capita* or by the *HDI*, respectively) than for those from developed countries (High-income and Very-High-HDI countries, respectively). The results are robust for the two measures of the country's development level employed and to performing the estimations with and without missing observations treatment.

5. Discussion and conclusions

ICT use may render positive but also negative effects on students' performance, and the net effect of ICT use on students' performance is unclear. The existing literature based on large-scale international surveys has not found conclusive evidence of a positive relationship between ICT use at school and students' outcomes. Based on insights from economic theory and previous literature on the role of ICT in education, we looked into a new avenue, hypothesizing that this relationship differs between developed and developing countries. We used a sample of 236,540 students from 44 countries from the PISA 2018 dataset to test this hypothesis. Our findings showed a negative relationship between ICT use for learning at school and students' outcomes. However, this relationship differed between students from developed and developing countries. Specifically, the negative relationship between ICT use for learning at school and students' outcomes was more negative for students from developing countries than for their developed counterparts. We obtain consistent results in the three subjects under analysis (reading, mathematics, and science).

To the best of our knowledge, this paper constitutes the first empirical analysis based on a large-scale international survey that focused on whether the relationship between ICT use at school and students' outcomes depends on the country's development level. In addition, another important contribution of this paper is the use of the variable *Subject-related ICT use during lessons* index, newly introduced in PISA 2018. The use of this new variable, versus those available in earlier rounds of PISA, enables us to analyze the time devoted, in each subject, to ICT use specifically for learning purposes, providing a more accurate measure of ICT use for learning at school. We show that the choice of this variable, with respect to those available in earlier rounds of PISA (which measure availability of ICT at school and ICT use at school in general), it is crucial for explaining the main results obtained in this paper. We conclude that the subject-specific effective time devoted to ICT use for learning at school, and not the mere availability of ICT at school or ICT general use (beyond learning purposes and specific subjects) is behind the differences in the successful use of ICT for learning we found between developed and developing countries.

Most of the previous literature on the relationship between ICT use at school and students' outcomes focused on a single country and did not provide cross-country evidence of this relationship. Existent studies used different surveys, variables, and methodologies to capture ICT use and its relationship with students' outcomes which, along with the different country settings, hinders comparability across them. The majority of existent studies focused only on a developed country (e.g. De Witte & Rogge [2] for The Netherlands; and Mediavilla & Escardíbul [25], Cabras & Tena Horrillo [31], Alderete, Di Meglio, & Formichella [61], and Fernández-Gutiérrez, Gimenez, & Calero [3] for Spain). These studies found mixed evidence on the relationship between ICT use and students' outcomes, depending on the variables used, the country, the subject under study, and the methodology used.

Studies based on large-scale international surveys which focused on developing countries are much scarcer. Erdogdu & Erdogdu [26], using data from PISA for Turkish students, analyzed this issue specifically for a developing country. These authors found that the frequency of internet browsing at school was negatively related to students' outcomes in reading, mathematics, and science. Nevertheless, they also found that internet access at school was positively associated with outcomes in the three subjects. These authors stated that one reason to explain these results might be not having considered whether the students were using ICT for academic purposes or not. Further insights on the relationship between ICT use and students' outcomes in the specific setting of developing countries can be obtained from experimental studies. Banerjee, Cole, Duflo, & Linden [62] carried out an experiment on the impact of a computer-assisted learning program for teaching mathematics among children from poor Indian families. These authors found a positive effect of the program on outcomes, a conclusion that differed from previous studies carried out in developed countries. They explained this result by the specific context of India: a large social distance between teachers and students from poor families, which hindered communication between them. In another experimental study, Cristia, Ibarraran, Cueto, Santiago, & Severín Campo [63] evaluated a program that provides a laptop to children from rural schools in Peru. They found that the program increased the use of computers at home and school and positively affected outcomes in tests measuring cognitive skills. However, they found non-significant effects on mathematics and language outcomes measured by national standardized tests. These authors stressed that to increase students' outcomes by using ICT, it is necessary to implement an aimed pedagogical model.

The most important previous evidence on how the relationship between ICT use at school and students' outcomes may depend on the country's development level came from Falck, Mang & Woessmann (2018) [32]. These authors complemented their study on the effects of computer use at school on students' outcomes in mathematics and science (based on TIMMS data for 30 countries) with a heterogeneity analysis, in which they split their sample into subgroups of countries according to their development level: OECD and non-OECD countries, and countries with GNP per capita above and below the sample median. This approach allowed the coefficient associated with each variable to vary among the subgroups of countries. However, it limits the ability to test whether the coefficients statistically differ from one subgroup to the other. These authors observed that the effects they had found on students' outcomes (i.e., a positive effect of using computers to look for information, and a negative effect of using computers for practicing skills and procedures) applied to developed countries (OECD countries and those with a GNP over the median), but most of the effects vanished when looking at developing countries. These authors attributed this finding to the general lower effectiveness of ICT-based teaching in developing countries.

The results of our paper show that the relationship between ICT use for learning at school and students' performance depends on the country's development level. In particular, the negative relationship between both variables is more intense for students from developing countries than for those from developed countries. This evidence is consistent with the explanation of their findings made by Falck, Mang & Woessmann (2018) [32], which they attribute to a generally lower effectiveness of ICT-based teaching in developing countries. Additional insights from the literature contribute to the understanding of these results. Theoretical arguments in the literature pointed out that a series of factors correlated with the effectiveness of ICT use tend to be less prevalent in developing than in developed countries, hindering the achievement of positive effects (and increasing the risk of getting negative effects) of ICT use for learning in the former. Students from countries with a lower level of human capital [9], worse ICT physical and pedagogical resources [1], schools with educational software of lower quality [8], where ICT is worse integrated into academic curriculum [10,11], and whose competences and skills in ICT are weaker [11–13] tend to have a less efficient harnessing of ICT. These are obstacles expected to be more present in developing countries than in their developed counterparts [1]. In contrast, we do not find support for theoretical arguments stating that the educational use of ICT may lead to higher outcomes in developing countries, based on the higher potential they have to catch up more benefits compared to developed countries [16,18]. Following Skryabin, Zhang, Liu, & Zhang [27], the lower ICT level, and not the higher ICT development rate (both being characteristics of developing countries), is critical to explain a lower efficiency of ICT use at school in terms of students' outcomes, as observed in developing countries.

The study has some limitations present also in previous research based on large-scale international surveys on students' outcomes, such as PISA. First, since we use cross-sectional observational data from PISA, only correlational (and not causal) patterns across variables can be drawn [28].[9] Our HLM approach is suitable to control for unobserved heterogeneity of unknown origin across schools and countries, mitigating the endogeneity bias. However, our results should be understood as correlational patterns and not as the causal impact of ICT use on educational outcomes. This is particularly important to be taken into account for interpreting the relationship between ICT use for learning at school and students' outcomes, as well as the result on our main research question: whether this relationship varies from developed to developing countries. Second, also related to this, we acknowledge that other unobserved factors may influence students' outcomes and its relationship with ICT use, particularly those related to teachers' ICT use and knowledge [4] and class-related characteristics. To control for ICT-related knowledge among teachers, we introduced a predictor that measures teachers' skills to integrate digital devices in instruction (as perceived by principals of each school). This predictor has non-significant effects on students' outcomes regardless of the subject assessed and of the measure of the country's development level considered. Unfortunately, PISA does not provide any information at the classroom level or about which students teachers work with. Regarding the lack of class-related predictors in the PISA dataset, we pointed out that teachers might not be the same in different classrooms, being this an unobservable source of heterogeneity in ICT instruction between classrooms. Third, as described above, our variable on ICT use (*ICTCLASS*) provides key advantages, with respect to those variables used in the existing literature, for

[9] As Hanushek and Woessmann [58] stated, "*…cross-country associations reveal to what extent different input factors can descriptively account for international differences in student achievement, studies that focus more closely on the identification of causal effects have reverted to using the within-country variation in resources and achievement.*" (p. 132).

accurate measurement of ICT-specific use for learning at school. However, *ICTCLASS*, as the other variables available in PISA, still holds some limitations for the analysis of ICT use: it covers the quantity but not the quality of ICT usage [2,8], and it does not identify which activities are performed using ICT [12]. Related to this, we should also point out that, albeit our analysis focused on ICT use for learning at school, other uses of ICT (such as leisure-related ones) both at school and outside school may have an impact on students' outcomes, and it may differ between developed and developing countries. Finally, a fourth limitation is related to the representativeness of the countries included in the analysis. Neither PISA sample of 79 countries nor our final sample of 44 countries for which PISA provides information on ICT use are representative of all the countries at the world level. In particular, data from the least developed countries (those with a low level of income, or the lowest levels of HDI) are not available, and thus these countries are not considered in the analysis.

Based on these limitations, we see multiple avenues for follow-up research. First, to conduct further experimental or quasi-experimental studies with suitable approaches to establish cause-and-effect relationships between ICT use for learning at school and students' outcomes in different settings (such as developed and developing countries). These analyses would allow for further insights into the optimal amount of ICT used in educational processes in different country contexts and on whether governments should increase or reduce their investment in ICT for educational purposes. Second, large-scale international surveys on students' outcomes should incorporate new items assessing teachers' knowledge and performance on ICT use and class-related characteristics, as well as measures of ICT quality and particular ICT-based academic activities (e.g., software specialized in solving mathematical problems). This evidence would allow insights on important factors that may influence the relationship between ICT use for learning at school and students' outcomes. Third, availability of new PISA rounds providing comparable information on ICT use for learning at school (such as the *ICTCLASS* variable) will also allow to conduct pseudo-panel analyses, which can provide further evidence of the effects of ICT use on students' outcomes. Similarly, information on other uses of ICT, rather than those for learning (i.e., leisure-related), either at school or outside school, will allow analyzing whether these other uses of ICT may have positive or negative effects on students' outcomes. And fourth, data on ICT use at school and students' outcomes in the least developed countries, from PISA or other sources, would be needed to analyze the relationship between both issues in the specific setting of these countries and whether it confirms (or not) the results found in this paper.

The heterogeneity between developed and developing countries found in this study warns scholars and policymakers about attempting to generalize ICT-educational analyses, interventions, and technological applications from developed- to developing countries (and vice versa) without further consideration of the country's context. As demonstrated by experimental studies such as the one by Banerjee, Cole, Duflo, & Linden [62], analyses and policies on the educational use of ICT would require a careful understanding and consideration of the specific context of developing countries. This is particularly important when developing countries are increasingly adopting technologies designed for educational systems from developed countries. Both groups of countries differ in key educational inputs that condition the success of educational practices based on ICT use. Some examples are infrastructure, teachers' (and students') abilities, and training and integration of ICT into the educational curriculum. It would be necessary to undertake the transformation of these inputs in developing countries alongside the investment in new technologies if these countries aim to reproduce successful experiences observed in developed countries. The inability to do so may not lead to leveraging resources, but to widening the gap in learning outcomes between developing- and developed- countries. Our results imply that educational systems, specifically those from developing countries, should conduct an in-depth analysis on whether adopting ICT-based instructional materials (in most cases, designed for developed countries) benefits students learning more than traditional teaching based on human interaction.

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Table 1. *Hierarchical linear model predicting students' scores in PISA subjects, with country's development level measured by their GNI per capita*

Variable	Reading			Mathematics			Science		
Fixed effects	*Estimate*	*SE*	*P > |t|*	*Estimate*	*SE*	*P > |t|*	*Estimate*	*SE*	*P > |t|*
(Intercept)	299.039	18.747	0.000	308.855	19.977	0.000	326.714	18.033	0.000
Subject-related ICT use during lessons (ICTCLASS)	**-9.826**	**1.790**	**0.000**	**-7.083**	**1.430**	**0.000**	**-8.157**	**1.723**	**0.000**
Gender									
Male	-14.606	0.331	0.000	14.741	0.267	0.000	8.184	0.285	0.000
Age	10.766	0.564	0.000	10.327	0.455	0.000	8.620	0.485	0.000
Country of birth									
Other country	-15.269	0.862	0.000	-12.023	0.685	0.000	-13.658	0.730	0.000
Economic, social and cultural status (ESCS)	13.145	0.193	0.000	13.278	0.155	0.000	12.863	0.166	0.000
Attitude towards school: learning activities	2.397	0.166	0.000	1.742	0.134	0.000	1.327	0.143	0.000
School average value of the ESCS	48.989	0.862	0.000	46.414	0.757	0.000	44.486	0.769	0.000
Do teachers have skills to introduce digital devices in instruction?									
Principals' perception: Agree	-0.223	1.065	0.834	0.050	0.925	0.957	0.047	0.938	0.960
Proportion of all teachers fully certified	5.585	1.588	0.000	3.877	1.407	0.006	5.625	1.427	0.000
Teacher behavior hindering learning	-1.100	0.460	0.017	-0.955	0.406	0.019	-0.992	0.412	0.016
Perceived teachers' interest	3.564	0.197	0.000	2.186	0.159	0.000	2.571	0.170	0.000
Shortage of educational material	-0.952	0.539	0.077	-0.545	0.471	0.247	-0.532	0.478	0.265
Shortage of educational staff	1.136	0.555	0.041	0.631	0.490	0.198	0.776	0.498	0.119
Adaptation of instruction	3.076	0.187	0.000	2.794	0.151	0.000	2.969	0.161	0.000
Disciplinary climate in test language lessons	6.753	0.175	0.000	5.829	0.141	0.000	6.258	0.150	0.000
School location									
City or large city (>= 100.000 people)	2.396	1.049	0.022	-1.063	0.915	0.245	-0.432	0.928	0.641
Government expenditure on education (% GDP)	0.074	3.420	0.983	-2.939	3.922	0.454	-0.950	3.382	0.779
Income level									
High-income country	**28.373**	**9.679**	**0.003**	**29.315**	**10.466**	**0.005**	**29.097**	**9.592**	**0.002**
ICTCLASS · High-income country	**6.647**	**2.210**	**0.003**	**5.612**	**1.757**	**0.001**	**5.972**	**2.106**	**0.005**
Random effects									
Level 3: Intercept		789.42	28.10		936.15	30.60		788.74	28.09
Level 3: ICTCLASS		36.46	6.04		23.06	4.80		34.57	5.88
Level 2: Intercept		973.41	31.20		895.01	29.92		877.28	29.62
Level 2: ICTCLASS		191.19	13.83		132.75	11.52		147.36	12.14
Level 1: Residual		5755.75	75.87		3831.32	61.90		4354.72	65.99
Sample size									
Total sample (students)			212,537			236,540			236,540
Level 2 group (schools)			9,314			10,193			10,193
Level 3 group (countries)			43			44			44

Notes: In random effects, values reflect variance and standard deviation. In sample size, values reflect observations. Since PISA 2018 excluded Spain results from the reading assessment for technical issues, reading score estimation sample has 43 countries.

Table 2. *Hierarchical linear model predicting students' scores in PISA subjects, with the country's development level measured by their HDI level*

Variable	Reading			Mathematics			Science		
Fixed effects	*Estimate*	*SE*	*P > |t|*	*Estimate*	*SE*	*P > |t|*	*Estimate*	*SE*	*P > |t|*
(Intercept)	292.187	19.670	0.000	293.073	20.241	0.000	317.292	18.774	0.000
Subject-related ICT use during lessons (ICTCLASS)	**-11.159**	**2.079**	**0.000**	**-8.089**	**1.677**	**0.000**	**-9.387**	**1.994**	**0.000**
Gender									
Male	-14.605	0.331	0.000	14.741	0.267	0.000	8.185	0.285	0.000
Age	10.766	0.564	0.000	10.327	0.455	0.000	8.621	0.485	0.000
Country of birth									
Other country	-15.266	0.862	0.000	-12.022	0.685	0.000	-13.656	0.730	0.000
Economic, social and cultural status	13.145	0.193	0.000	13.278	0.155	0.000	12.863	0.166	0.000
Attitude towards school: learning activities	2.398	0.166	0.000	1.742	0.134	0.000	1.327	0.143	0.000
School average value of the ESCS	48.992	0.862	0.000	46.376	0.758	0.000	44.472	0.770	0.000
Do teachers have skills to introduce digital devices in instruction?									
Principals' perception: Agree	-0.233	1.065	0.827	0.042	0.925	0.964	0.038	0.938	0.968
Proportion of all teachers fully certified	5.561	1.589	0.000	3.843	1.407	0.006	5.599	1.427	0.000
Teacher behavior hindering learning	-1.107	0.460	0.016	-0.966	0.406	0.017	-1.000	0.412	0.015
Perceived teachers' interest	3.565	0.197	0.000	2.186	0.159	0.000	2.571	0.170	0.000
Shortage of educational material	-0.948	0.539	0.079	-0.542	0.471	0.250	-0.529	0.478	0.268
Shortage of educational staff	1.143	0.555	0.039	0.637	0.490	0.194	0.782	0.497	0.116
Adaptation of instruction	3.076	0.187	0.000	2.794	0.151	0.000	2.968	0.161	0.000
Disciplinary climate in test language lessons	6.752	0.175	0.000	5.828	0.141	0.000	6.258	0.150	0.000
School location									
City or large city (>= 100.000 people)	2.391	1.049	0.023	-1.043	0.915	0.254	-0.427	0.928	0.646
Government expenditure on education (% GDP)	0.928	3.365	0.783	-1.379	3.696	0.709	0.051	3.292	0.988
HDI level									
Very-high-HDI country	**29.491**	**10.388**	**0.005**	**37.778**	**10.687**	**0.000**	**32.693**	**10.133**	**0.001**
ICTCLASS · Very-high-HDI country	**7.646**	**2.404**	**0.001**	**6.272**	**1.931**	**0.001**	**6.939**	**2.293**	**0.002**
Random effects									
Level 3: Intercept		799.60	28.28		857.98	29.29		769.79	27.75
Level 3: ICTCLASS		35.90	5.99		23.13	4.81		34.02	5.83
Level 2: Intercept		973.60	31.20		895.01	29.92		877.34	29.62
Level 2: ICTCLASS		191.20	13.83		132.74	11.52		147.35	12.14
Level 1: Residual		5755.70	75.87		3831.32	61.90		4354.72	65.99
Sample size									
Total sample (students)			212,537			236,540			236,540
Level 2 group (schools)			9,314			10,193			10,193
Level 3 group (countries)			43			44			44

Notes: In random effects, values reflect variance and standard deviation. In sample size, values reflect observations. Since PISA 2018 excluded Spain results from the reading assessment for technical issues, reading score estimation sample has 43 countries.

Statistical appendix

Table A1. *Descriptive statistics of the dependent variables and the student-, school-, and country-level predictors*

Variable	*Mean*	*SD*	*Missing (%)*
Dependent variables			
Reading score	461	104	10.4%
Mathematics score	469	96	0
Science Score	466	96	0
Student-level predictors			
Subject-related ICT use during lessons (CI)	-0.07	1.01	14.5%
Gender			0
Female	49.9%		
Male	50.1%		
Age	15.80	0.29	0
Country of birth			2.9%
Country of the test	90.9%		
Other country	6.3%		
Attitude towards school: learning activities (CI)	0.01	1.02	7.9%
Economic, social and cultural status (CI)	-0.25	1.11	2.4%
School-level predictors			
School average value of the ESCS (CI)	-0.25	0.75	0.2%
Do teachers have skills to introduce digital devices in instruction?			4.6%
Principals' perception: Disagree	32.4%		
Principals' perception: Agree	63.1%		
Proportion of all teachers fully certified (CI)	0.83	0.32	13.4%
Teacher behavior hindering learning (CI)	0.17	1.11	4.6%
Perceived teachers' interest (CI)	0.09	1.00	4.9%
Shortage of educational material (CI)	0.08	1.06	4.9%
Shortage of educational staff (CI)	-0.04	1.04	5.0%
Adaptation of instruction (CI)	0.02	1.01	5.6%
Disciplinary climate in test language lessons (CI)	0.08	1.09	3.6%
Community in which the school is located			4.0%
Village, small town or town (< 100.000 people)	56.5%		
City or large city (>= 100.000 people)	39.5%		
Country-level predictors			
Government expenditure on education (% GDP)	4.60	1.22	0

*Not*es: Dependent variables are computed as the students' average of 10 plausible values. Since PISA 2018 excluded Spain's results from the reading assessment for technical issues, the reading score has 35,943 missing values (10,4% of the sample). Many questionnaire items were designed to be combined as part of composite indicators (CI) built by the PISA project work group. They are denoted with the acronym CI in parenthesis. In this case, Cronbach's alpha was used to check the internal consistency of each scale. In categorical variables, values reflect respectively the number of observations of each category and the percentage it represents. In categorical variables, the value in the mean column reflects the percentage of observations that represents each category, excluiding missing values. The *Government expenditure on education (% GDP)* was retrieved from https://data.worldbank.org/indicator/SE.XPD.TOTL.GD.ZS. We used the latest *Government expenditure on education (% GDP)* value available for each country.

Table A2. *Sample of countries, average value in the PISA index Subject-related ICT use during lessons (ICTCLASS), GNI per capita and HDI*

Country ID	*Country name*	*ICTCLASS*	*Income level*	*GNI per capita*	*HDI level*	*HDI value*
AUS	Australia	0.61	High-income	55,100	Very-high	0.94
BEL	Belgium	-0.2	High-income	48,030	Very-high	0.92
BRN	Brunei Darussalam	-0.25	High-income	32,230	Very-high	0.85
CHL	Chile	-0.09	High-income	15,010	Very-high	0.95
HRV	Croatia	-0.31	High-income	14,980	Very-high	0.85
CZE	Czech Republic	-0.28	High-income	91,940	Very-high	0.89
DNK	Denmark	1.35	High-income	63,950	Very-high	0.93
EST	Estonia	0	High-income	23,260	Very-high	0.89
FIN	Finland	0.08	High-income	50,010	Very-high	0.88
FRA	France	-0.18	High-income	42,450	Very-high	0.93
GRC	Greece	-0.39	High-income	19,750	Very-high	0.89
HKG	Hong Kong	-0.37	High-income	50,800	Very-high	0.92
ISL	Iceland	0.41	High-income	72,850	Very-high	0.94
IRL	Ireland	-0.36	High-income	64,000	Very-high	0.84
ISR	Israel	-0.06	High-income	43,110	Very-high	0.85
ITA	Italy	-0.06	High-income	34,530	Very-high	0.94
JPN	Japan	-0.59	High-income	41,710	Very-high	0.94
KOR	Korea	0.07	High-income	33,790	Very-high	0.91
LVA	Latvia	-0.12	High-income	17,740	Very-high	0.88
LTU	Lithuania	0.03	High-income	19,080	Very-high	0.92
LUX	Luxembourg	-0.31	High-income	73,910	Very-high	0.91
PAN	Panama	-0.4	High-income	14,950	High	0.91
POL	Poland	-0.2	High-income	15,350	Very-high	0.79
SGP	Singapore	-0.33	High-income	59,590	Very-high	0.89
SVK	Slovak Republic	0	High-income	19,210	Very-high	0.80
SVN	Slovenia	-0.34	High-income	25,940	Very-high	0.87
ESP	Spain	-0.05	High-income	30,390	Very-high	0.94
CHE	Switzerland	-0.24	High-income	85,500	Very-high	0.90
GBR	United Kingdom	-0.11	High-income	42,240	Very-high	0.94
USA	United States	0.38	High-income	65,850	Very-high	0.81
URY	Uruguay	-0.11	High-income	16,230	Very-high	0.92
ALB	Albania	-0.23	Middle-income	5,220	High	0.79
BRA	Brazil	-0.48	Middle-income	9,130	High	0.82
BGR	Bulgaria	-0.02	Middle-income	9,570	Very-high	0.76
CRI	Costa Rica	-0.28	Middle-income	11,700	High	0.79
DOM	Dominican Republic	-0.35	Middle-income	8,080	High	0.75
GEO	Georgia	-0.38	Middle-income	4,780	High	0.79
KAZ	Kazakhstan	0.32	Middle-income	8,820	Very-high	0.82
MEX	Mexico	-0.29	Middle-income	9,480	High	0.77
MAR	Morocco	-0.27	Middle-income	3,190	High	0.68
RUS	Russian Federation	0.06	Middle-income	11,260	Very-high	0.82

SRB	Serbia	-0.22	Middle-income	7,030	High	0.80
THA	Thailand	0.13	Middle-income	7,260	High	0.77
TUR	Turkey	0.22	Middle-income	9,690	Very-high	0.81

Note: Countries are sorted according to their Income level and alphabetical order. The Country Classifications by Income Level (latest available) was retrieved from https://blogs.worldbank.org/opendata/new-world-bank-country-classifications-income-level-2020-2021. All the countries in the Middle-income category were categorized by the World Bank as Upper-middle-income countries except Morocco, which was categorized as a Lower-middle-income country. The Human Development Index (HDI) was retrieved from http://hdr.undp.org/en/data. We used the Human Development Report (HDR) 2018 edition. All the countries in the High-HDI category were categorized by the United Nations as High-HDI countries except Morocco, which was categorized as a Medium-HDI country and it was included in the High-HDI group in our estimations.

Endnotes

[i] Based on the suggestion of an anonymous referee, we performed an additional estimation that included the triple interaction between *Subject-related ICT use during lessons (ICTCLASS) + the country's development level + Economic, social and cultural status (ESCS)*. Overall, the coefficients of the predictors maintained their signs and significance, and the coefficient of the triple interaction was positive and significant at the 1% threshold level. Thus, the positive mediator effect of *Economic, social and cultural status* on ICT use for learning is reinforced at the country and family levels. However, the coefficient of the double interaction between *Subject-related ICT use during lessons (ICTCLASS) + Economic, social and cultural status (ESCS)* was negative and significant at the 5% threshold level, indicating that the positive mediator effect of income on ICT use for learning was not found at the family level alone. See tables S1 and S2 of the supplementary material available at https://docs.google.com/spreadsheets/d/1B4uRAxBGOEoYl7XidGhn-OU5pGZ29L7D/edit?usp=sharing&ouid=102720823307982166811&rtpof=true&sd=true