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Doctoral Thesis

ICT Use at School and Students' Performance: Analysis of Contextual Factors

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ICT USE AT SCHOOL AND STUDENTS' PERFORMANCE: ANALYSIS OF CONTEXTUAL FACTORS

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Thesis Advisor: Gregorio Giménez Esteban
July, 2022

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NOTES

All the tables presented are self-elaborated.

CHAPTER I

INTRODUCTION

CHAPTER I. INTRODUCTION

Information and Communication Technologies (ICT) are an essential part of today's society. It is hard to imagine that our activities, whether work, study, health care, or leisure, are not mediated by the use of ICT. The COVID-19 pandemic has further intensified the relevance of ICT to the functioning of society. Restrictions on mobility and gathering of people as measures to control the spread of the COVID-19 made ICT the main mechanism to enable the continuity of daily activities, including the educational ones (Yang et al., 2020). Before the COVID-19 pandemic, ICT investment in educational systems was already a priority (De Witte & Rogge, 2014; Fernández-Gutiérrez, Gimenez, & Calero, 2020). Since 2020, in the Covid-19 era, policymakers have been betting more decisively on immersing students in the digital world. Digital insertion becomes the vehicle for students' full socio-economic and cultural inclusion.

Despite the enthusiasm for investment in new technologies for education, empirical evidence on the positive effects of ICT use for learning is inconclusive (see, for example, Bulman & Fairlie, 2016; Giambona & Porcu, 2015; Hu, Gong, Lai, & Leung, 2018). Research that has been conducted in recent decades highlight arguments in favor and against the use of ICT for educational purposes. On the one hand, it is argued that ICT favor teaching processes through greater access to pedagogical resources, which translates into a more enriching educational experience (Comi, Argentin, Gui, Origo, & Pagani, 2017). ICT also allow for more agile and timely access to learning processes (Spiezia, 2010) and increase its flexibility and autonomy (De Witte & Rogge, 2014). Other benefits of the use of ICT for education are: to facilitate monitoring of the academic progress of students (Falck, Mang, & Woessmann, 2018) and to improve their attitude towards teaching processes (Alderete, Di Meglio, & Formichella, 2017). However, literature also highlights arguments against the use of ICT for education. First, they reduce the interaction between teachers and students, which weakens their relationship and negatively impacts learning (De Witte & Rogge, 2014; Livingstone, 2012). In addition, the use of ICT can restrict students' creativity (Spiezia, 2010), distract them from teaching processes (De Witte & Rogge, 2014; Spiezia, 2010) and undermine discipline (Falck et al., 2018).

For all of the above, the outcome of ICT use in learning on academic performance remains a controversial topic (Gómez-Fernández & Mediavilla, 2021; Hu et al., 2018). In the present doctoral thesis, we want to deepen this relationship, by introducing an issue to which the literature has paid less attention (Petko, Cantieni, & Prasse, 2017): the mediating factors that may condition the relationship between ICT use for learning and academic performance. In particular, we address three issues. The first is the countries level of economic development. The second is the role of their stock of human capital. The third are the likely differences in the success of ICT use for learning from gifted students to their peers.

A first shortcoming we identify in the literature is the likely differences in the successful use of ICT for learning between students attending educational systems in less-developed countries and those in developed countries. On the one hand, there are theoretical arguments in favor of a more efficient use of ICT for educational purposes in less-developed countries. According to Solow's (1956, 1957) neoclassical economic growth theory, less-developed countries obtain greater benefits from technology adoption than developed countries, due to they carry lower decreasing returns (Barcenilla et al., 2019; Fagerberg, 1995). Technological diffusion theory has also pointed out some advantages; less-developed countries obtain greater benefits from the use of ICT previously implemented in developed countries, due to their subsequent adoption entails lower appropriation costs (Caselli & Coleman II, 2001).

However, on the other hand, some arguments justify that using ICT could bring greater educational benefits to students in developed countries. Among these factors, they are the greater stock of human capital (Gimenez & Vargas-Montoya, 2021) and the advantage in access to physical and pedagogical resources based on ICT (OECD, 2015). Other factors of relevance are the greater effectiveness in the use of ICT for learning in developed countries (Petko et al., 2017); the better integration of ICT in educational strategies (Biagi & Loi, 2012; Spiezia, 2010); and the higher competencies and skills in the use of ICT by teachers and students in developed countries (Luu & Freeman, 2011; OECD, 2010; Spiezia, 2010).

In the second chapter, we empirically address whether the relationship between ICT use for learning at school and students' outcomes differs from developed to less-developed countries. We employ data for 236,540 students attending 10,193 schools in 44 countries from the Programme for International Student Assessment (PISA) 2018 dataset. 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 three-level (students, schools, and countries) hierarchical linear model (HLM), show a negative relationship between ICT use for learning at school and students' outcomes. However, this negative relationship is stronger for students from less-developed countries than for those from developed countries. These findings imply that policymakers should be cautious on replicating interventions and technological applications from developed to less-developed countries (and vice versa). Notably, in the context where less-developed countries mainly adopt ICT-based instructional materials designed for educational systems from developed countries.

The third chapter addresses another of the shortcomings identified in literature. Empirical literature has not considered the possible influence of the countries' stock of human capital on the relationship between ICT use for learning and students' academic performance. As previous theoretical studies highlight, human capital is a catalyst that allows taking advantage of new technologies; by reducing costs and accelerating the speed of their adoption (Barcenilla, Gimenez, & López-Pueyo, 2019; Funke & Strulik, 2000;). A larger stock of human capital is also associated with a more favorable learning environment, by decreasing criminal activity (Lochner & Moretti, 2004), increasing civic engagement (Milligan, Moretti, & Oreopoulos, 2004), and improving responsiveness to contextual socioeconomic changes (Reiter, C., Özdemir, C., Yildiz, D., Goujon, A., Guimaraes, R., & Lutz, 2020).

In this third chapter, we test empirically the existence of complementarities between human capital and technology adoption for learning. We carry out an empirical analysis with data from PISA 2018. We use a large-scale sample of 363,412 students enrolled in 13,215 schools in 48 countries. We estimate a HLM of three levels: students, schools, and countries. Our results strongly support the evidence of a positive externality of the stock of human capital on ICT use for learning. When we consider the moderator-effect of the stock of human capital, we find that the negative outcome of ICT use on students' academic performance in reading, mathematics, and science turns positive (greater and more positive the higher the stocks of human capital are). The greater the stock of human capital an economy has, the more benefits it can get from investments in ICT for learning.

The fourth chapter analyzes the last shortcoming identified in the literature about ICT use and students' performance. Empirical literature lacks for large-scale survey-based studies assessing whether ICT use leveraging for education differs from gifted students and their remaining peers. Gifted students are those who: "...demonstrate excellence relative to age-appropriate standards of exceptional performance or potential, as measured through standardized tests, interviews, and clinical observation of behavior and performance" (Yun-Dai, 2009, p. 41).

Mathematics is considered the most appropriate subject to incorporate the use of ICT in students' learning (Ke, 2014). It is also the one that has received the most attention on the potential effect of using ICT for gifted students' education (Fernández Batanero, Reyes Rebollo, & Montenegro Rueda, 2019). Mathematics will be, so, our subject of interest in the fourth chapter.

In this fourth chapter, we use a large-scale multinational sample of 236,938 adolescents attending 10,213 schools in 44 countries from PISA 2018. We estimate a HLM and find that only gifted students benefit from using ICT in mathematics' performance. The higher their achievement level, the more beneficial the use of ICT is for gifted students. This relationship is negative for all other students. The results illustrate that policymakers should consider a differentiated approach to using ICT in schools based on the performance level of students. Gifted students could benefit more from the use of ICT for learning and their remaining peers from teaching with more human interaction. Table 1 shows an overview of the research question and transmission mechanisms address in each chapter of the thesis.

Table 1. Research Question and Transmission Mechanisms in each Chapter of the Thesis

Chapter	Research question	Transmission mechanisms
<u>Chapter II</u> **ICT Use for Learning and Students' Outcomes: Do the Countries' Development Level Matter?**	Whether the relationship between ICT use for learning at school and students' outcomes differs from developed to less-developed countries	**On the one hand, the educational use of ICT may render higher returns on students' outcomes in less-developed countries:** 1. *Neoclassical theory of growth*. o Less-developed countries can reach more benefits from technological adoption than their developed counterparts by leveraging developed countries' investment in ICT. 2. *Theory of technological diffusion*. o Less-developed countries may obtain higher yields in the embracement of technologies previously implemented in developed countries due to the lower costs of adoption. **On the other hand, the educational use of ICT may render higher returns on outcomes to students from developed countries.** 1. The higher level of human capital in developed countries may favour their success when using ICT for learning. 2. Developed countries usually own better ICT physical and pedagogical resources than less-developed countries and count on a better quality of educational software, leading to higher effectiveness of ICT-based instruction. 3. Developed countries make a better integration of ICT into academic curriculum than their less-developed counterparts.

Chapter	Research question	Transmission mechanisms
<u>**Chapter III**</u> **ICT Use and Successful Learning: The Role of the Stock of Human Capital**	Whether the outcome of ICT use on learning varies when we consider differences in the countries' stock of human capital	**There are solid arguments to expect that the relationship between ICT and educational outcomes may differ depending on the countries' human capital level. Specifically, due to its strong positive externalities, we can point to three effects of the stock of human capital on learning through ICT:** 1. *The assimilation and effective use of technology*. We consider the stock of human capital as a catalyst of new technologies: the process of adoption of new technologies is strongly influenced by the human capital stock, by reducing new technologies' learning costs and accelerating their adoption. 2. *The creation and improvement of a pedagogical and institutional environment more conducive to learning*. Human capital diminishes criminal activity, increases civic participation, improves adaptive capacity to environmental change, and spurs entrepreneurship and business outcomes. 3. *The attraction of better teachers*. Highly educated areas experience faster population and employment growth as individuals flock to be near the highly educated. Moreover, it is mostly educated individuals who are moving to high human capital areas, seeking a better quality of life. These effects have specifically been found in the case of teachers: their well-being and productivity can increase by interacting with and learning from high-skilled teachers.

Chapter	Research question	Transmission mechanisms
<u>**Chapter IV**</u> **ICT Use at School: Differences in Mathematics Performance Between Gifted Students and Their Peers**	Whether the relationship between ICT use for learning at school and performance differs from gifted students to their peers	**On the one hand, ICT tools and activities provide a wide range of possibilities to enhance gifted education:** 1. Gifted students benefit more when using ICT since they are given wider opportunities to utilize their skills, develop their creativity, and expand their learning. 2. Technology-pervasive environments motivate and enable gifted students to perform differently, allowing them to seek challenging tasks with self-supervision to accelerate the manifestation and development of their exceptional abilities. 3. ICT is an essential tool for personalizing the curriculum. It is essential when gifted students learn together with their peers, because incorporating technologies in learning processes helps create challenging activities and provides an individual approach for gifted education. 4. ICT use can facilitate critical thinking and social-emotional needs in gifted students, who should be equipped with substantial digital skills. **But, on the other hand:** 1. ICT-based instruction is designed for average- and low-performing students and not for gifted students. Thus, ICT use for learning not addresses properly gifted students needs and potential. 2. Gifted students are less likely to use ICT, due to they do not perceive a benefit of its use.

The dissertation concludes with a fifth chapter, which includes the main conclusions, limitations, extensions, and policy recommendations arising from this doctoral thesis.

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THESIS ACKOWLEDGEMENTS

PENDING

CHAPTER II

ICT USE FOR LEARNING AND STUDENT'S OUTCOMES: DO THE COUNTRIES' DEVELOPMENT LEVEL MATTER?

II

CHAPTER II. ICT USE FOR LEARNING AND STUDENTS' OUTCOMES: DO THE COUNTRIES' DEVELOPMENT LEVEL MATTER?

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 the existence of 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 less-developed 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. However, this negative relationship is stronger for students from less-developed countries than for those from developed countries. These findings imply that policymakers should be cautious about replicating interventions and technological applications from developed to less-developed countries (and vice versa). Notably, in the context where less-developed countries mainly adopt ICT-based instructional materials designed for educational systems from developed countries.

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 (OECD, 2015a). In this spirit, educational policy has regarded investment in ICT as a priority over the last years (De Witte & Rogge, 2014; Fernández-Gutiérrez, Gimenez, & Calero, 2020), with the central goal of improving students' outcomes (Bulman & Fairlie, 2016). 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., Bulman & Fairlie, 2016; Giambona & Porcu, 2015; Hu, Gong, Lai, & Leung, 2018). Notwithstanding the significant endeavors to understand which is the relationship between ICT use and students' outcomes, it remains an open question (Gómez-Fernández & Mediavilla, 2021; Hu et al., 2018).

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 (Petko, Cantieni, & Prasse, 2017).[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 (Hu et al., 2018). Commonly, empirical analyses

[1] Some examples are socio-economic status (Biagi & Loi, 2012), gender (Meggiolaro, 2018), and students' experience using ICT (Falck, Heimisch, & Wiederhold, 2016).

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.

Nevertheless, there are arguments to expect that the relationship between ICT use for learning and students' outcomes may differ depending on the country's development level. On the one hand, the educational use of ICT may render higher returns on students' outcomes in less-developed countries. Following Solow's (1956, 1957) neoclassical theory of growth (which assumes technology is a public good and technological change is exogenous), less-developed countries can reach more benefits from technological adoption than their developed counterparts by leveraging developed countries' investment in ICT (Barcenilla, Gimenez, & López-Pueyo, 2019; Fagerberg, 1995). Moreover, according to the theory of technological diffusion, less-developed countries may obtain higher yields in the embracement of technologies previously implemented in developed countries due to the lower costs it implies (Caselli & Coleman II, 2001). However, on the other hand, the educational use of ICT may render higher returns on outcomes to students from developed countries. The higher level of human capital in developed countries may favor their success when using ICT for learning (Gimenez & Vargas-Montoya, 2021). In addition, developed countries usually own better ICT physical and pedagogical resources than less-developed countries (OECD, 2015a), and count on a better quality of educational software, higher effectiveness of ICT-based instruction (Petko et al., 2017), and better integration of ICT into academic curriculum (Biagi & Loi, 2012; Spiezia, 2010) than their less-developed counterparts. These factors, together with the stronger ICT competences and skills among students in developed countries, may favor the educational achievement obtained from ICT use (Luu & Freeman, 2011; OECD, 2010; Spiezia, 2010).

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 less-developed 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. Indexes of ICT use at school previously available in PISA did not differentiate between academic- or leisure-related ICT use, 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 (Gimenez, 2017; Romer, 2019). 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 (Fantom & Serajuddin, 2016). Second, country's *HDI* is periodically computed by United Nations Development Programme to measure its performance and path in human development (UNDP, 2020b). Anand & Sen (2000) 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 less-developed countries. While there is a negative relationship between ICT use for learning at school and students' outcomes in both cases, this relationship is more intense for students from less-developed countries than for those from developed countries, 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 less-developed 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 (Comi, Argentin, Gui, Origo, & Pagani, 2017) 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 (Fernández-Gutiérrez et al., 2020). 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 (Fernández-Gutiérrez et al., 2020; Giambona & Porcu, 2015). 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 (educational or leisure), 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 educational 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 (2015), 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 (2015), 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 (2015) 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 (2016) 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 et al. (2017) 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, Kılıç Depren & Depren (2021) 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 (2022) also used data from 41 countries that participated in the 2018 PISA edition 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 (2014) 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 (2016) 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 (2018) 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 et al. (2020) 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 Countries' 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 (Bulman & Fairlie, 2016). 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 et al. (2015), Petko et al. (2017), and Falck et al. (2018).

Skryabin et al. (2015), which used data from TIMSS 2011, PIRLS 2011, and PISA 2012, stated that less-developed 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 less-developed countries. Petko et al. (2017) 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 et al. (2018) 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 1 shows the descriptive statistics of the dependent variables and the predictors.

[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.

Table 1. 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.

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. 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. Since we were working with a sample of 236,540 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 (OECD, 2009). 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.

Predictors

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. The use of *ICTCLASS* constitutes an improvement compared to previous cross-country studies that used the variables on ICT at school available in earlier rounds of PISA: *ICT available at school* (PISA code *ICTSCH*) and *Use of ICT at school in general* (PISA code *USESCH*). *ICTCLASS* lets us to work with a specific measure of ICT use for learning purposes at school, while *ICTSCH* and *USESCH* do not differentiate between educational or leisure ICT uses and nor about the use of ICT for each specific subject.

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)[3] and the *Attitude towards school: learning activities* (PISA code *ATTLNACT*). Male students usually underperform females in reading but overperform them in mathematics and science (OECD, 2015b; Torrecilla Sánchez, Olmos Miguélañez, & Martínez Abad, 2019). Being older (there can be a difference of up to 11 months in students' age in PISA) is related to higher scores (OECD, 2014, 2016). 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 (OECD, 2012; Potochnick, 2018). Previous literature has pointed out that socio-economically disadvantaged students tend to underperform those from advantaged backgrounds (Hu et al., 2018; Zhang & Liu, 2016). Finally, a higher motivation or better attitudes toward learning among students is related to higher outcomes (Dunn & Kennedy, 2019).

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*

[3] 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 (2019) 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.

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 schools with higher average *ESCS* can benefit from positive externalities in the form of peer effects (Ammermueller & Pischke, 2009; Gimenez, Ciobanu, & Barrado, 2021). Previous studies found that teachers' skills to integrate ICT in learning are related to higher students' outcomes (Biagi & Loi, 2012; Spiezia, 2010). Teachers' education tends to correlate positively with students' outcomes (Harris & Sass, 2014). Furthermore, teachers' behavior, attitudes, and relationship with students are critical enablers of learning (Palardy & Rumberger, 2008). The shortage of educational materials and staff tend to be negatively related to students' outcomes (Chin, 2005; Hanushek & Woessmann, 2011). The relationship between disciplinary climate and students' outcomes tends to be positive (Guo, Li, & Zhang, 2018; Kinsler, 2013). Finally, urban schools tend to have better infrastructure and teachers than rural ones, which contributes to increase the students' outcomes (Gimenez, Martín-Oro, & Sanaú, 2018; Sullivan, Perry, & McConney, 2013).

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.[4] 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.

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 (UNDP, 2020a). According to the index thresholds, the countries with a *HDI* index from 0.700to 0.799 are classified as *High-HDI* countries, and those with a *HDI* index above 0.800 are classified as *Very-high-HDI* countries.[5] 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.

[4] 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://cutt.ly/ZFeFU4i.

[5] 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://cutt.ly/uFeFT9t.

Table 2 describes the list of countries we worked with, their *GNI per capita* and *HDI*, and their categorization as developed or less-developed countries 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 less-developed countries.

Table 2. 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	0.85
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	0.68
MAR	Morocco	-0.27	Middle-income	3,190	High	0.77
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) 2020 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.

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 (French, French, & Li, 2015; Hong & Zimmer, 2016; Vegas & Coffin, 2015). Nevertheless, overall, cross-country empirical evidence in this regard is inconclusive (Hanushek & Woessmann, 2017), and the debate on the relationship between expenditure on education and students' outcomes is open (Vegas & Coffin, 2015). 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). This technique improves estimations' efficiency compared to conventional methods, by allowing us to control for unobserved heterogeneity of unknown origin across schools and countries (Zhang & Liu, 2016). By doing this, we mitigated the correlation between the unobserved part of the model and the predictors. We assumed that the intercepts and the slopes varied across schools and countries.

The multilevel model we estimated, using the lme4 package for R software, was given by the following equation:

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

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 (2020) stated, since the relative marginal productivities of ICT use may be specific to the subject assessed, we estimated the equation 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. $\boldsymbol{\beta}_{\boldsymbol{ijk}}$ is the vector of coefficients associated with the student-level predictors $(\boldsymbol{Student}_{\boldsymbol{ijk}})$. $\boldsymbol{\beta}_{\boldsymbol{0qk}}$ is the vector of coefficients associated with the school-level predictors $\left(\boldsymbol{School}_{\boldsymbol{0jk}}\right)$. 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), and 0 for *Middle-income* (less-developed). 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), and 0 for *High-HDI* (less-developed). 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 less-developed 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.[6]

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 (Fuchs & Woessmann, 2007), we also estimated the model imputing missing values as a robustness check. They 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 (Bartlett, Seaman, White, & Carpenter, 2015; Van Buuren, Brand, Groothuis-Oudshoorn, & Rubin, 2006).

4. Results

4.1 Baseline Model Estimation

Table 3 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 would refer to the

[6] For an in-depth explanation about the theoretical and empirical rationale on the random coefficients and slopes estimation, see (Hox, 2010).

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 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 Bradley & Green, 2020).

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. 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 3. Hierarchical Linear Model Predicting Students' Scores in PISA Subjects, with the Countries' 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.

Table 4 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 3). 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* ($p < 0.01$).

The interaction term between the *Subject-related ICT use during lessons* index (*ICTCLASS*) and a country *Very-High-HDI* also 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 also differs between students from *Very-high-HDI* countries to those from *High-HDI* countries, being more unfavorable for those from *High-HDI* countries (as it happened when the country's development level was measured by *GNI per capita*).

The analysis of the variance components for the random intercepts and the slopes (see also Table 4) justifies, as occurred when measuring the country's development level by *GDP per capita*, the inclusion of the three levels in the model and the treatment of the slopes of *ICTCLASS* as random.

Table 4. Hierarchical Linear Model Predicting Sudents' Scores in PISA Subjects, with the Countries' 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
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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
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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
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HDI level									
Very-high-HDI country	**29.491**	**10.388**	**0.005**	**37.778**	**10.687**	**0.000**	**32.693**	**10.133**	**0.001**
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Random effects									
Level 3: Intercept		799.60	28.28		857.98	29.29		769.79	27.75
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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.

4.2 Robustness Checks

As a first robustness check, we performed the estimations by splitting the total sample into four subsamples (*High-income* and *Middle-income* countries, on the one hand, and *Very-high-HDI* and *High-HDI* countries, on the other hand). With these estimations, we aim to determine the coefficient of each predictor (and, in particular, that of the *Subject-related ICT use during lessons* index, *ICTCLASS*) on students' scores specifically for each group of countries. Tables A1 and A2 of the Statistical Appendix show the estimation results.[7]

Regarding the subsamples of *High-income* and *Middle-income* countries, we found out that in both cases, and for the three subjects under analysis (reading, mathematics, and science), there is a negative relationship between *ICTCLASS* and PISA scores. However, this negative relationship is more intense for *Middle-income* countries than for *High-income* countries. A similar result is obtained for the sub-samples of *Very-high-HDI* and *High-HDI* countries: there is a negative relationship between *ICTCLASS* and PISA scores in all cases, but it is more intense for *High-HDI* countries than for *Very-high-HDI*. These results confirm those previously obtained using the total sample and an interaction effect between *ICTCLASS* and the country's development level: the relationship between *ICTCLASS* and PISA scores differs between students from developed and from less-developed countries, being more negative for the latter.

As an additional robustness check, we estimated equations 1 and 2 imputing missing values and obtained 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

[7] Due to the dimension of the tables do not fit to those of this document, they are provided in the following online document shorturl.at/GMO79.

scores. The detail estimation results are shown in Tables A3 and A4 of the Statistical Appendix at pages 57 and 58.

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 less-developed countries. Although the relationship between ICT use and students' outcomes is negative in both cases, it is more intense for students from less-developed countries than those from developed countries. The results are robust for the two measures of the country's development level employed and the method of estimation considered (using the total sample of students and an interaction effect or using separate subsamples of students from developed and less-developed countries). The results are also robust when performing the estimations with and without missing observations treatment.

5. Discussion and Conclusions

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 differed between developed- and less-developed 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' scores in the three subjects under analysis (reading, mathematics, and science) in developed and less-developed countries. However, this relationship differed between both groups of countries. Specifically, the negative relationship between ICT use for learning at school and students' scores was more intense for students from less-developed countries than for those from developed countries.

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.

Most of the previous literature has focused on a single country and has not provided 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, 2014 for The Netherlands; and Mediavilla & Escardíbul, 2015, Cabras & Tena Horrillo, 2016, Alderete, Di Meglio, & Formichella, 2017, and Fernández-Gutiérrez et al., 2020 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 focused on less-developed countries are much scarcer. To the best of our knowledge, only Erdogdu & Erdogdu (2015), 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 less-developed or developing countries can be obtained from experimental studies. Banerjee, Cole, Duflo, & Linden (2007) 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 these results 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 (2017), 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 et al. (2018). These authors completed 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 less-developed countries. These authors attributed this finding to the general lower effectiveness of ICT-based teaching in less-developed 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 less-developed countries than for those from developed countries. This evidence is consistent with the explanation of their findings made by Falck et al. (2018), which they attribute to a general lower effectiveness of ICT-based teaching in less-developed countries. Previous insights from the literature contribute to understanding these results. Theoretical arguments in the literature pointed out that the educational use of ICT may render lower benefits in less-developed- than in developed- countries. These arguments highlight that students from schools with educational software of lower quality and less effective pedagogical use of ICT for educational purposes (Petko et al., 2017), where ICT are worse integrated into academic curriculum (Biagi & Loi, 2012; Spiezia, 2010), and whose competencies in ICT are weaker (Luu & Freeman, 2011; OECD, 2010; Spiezia, 2010) tend to have a less efficient harnessing of ICT. These are conditions expected to be more present in less-developed- than in developed- countries (OECD, 2015a). Also, following Skryabin et al. (2015), the higher ICT level (which characterizes the developed countries), and not the higher ICT development rate (which characterizes the less-developed countries), is critical to explain a lower efficiency of ICT use at school in terms of students' outcomes in the latter. In contrast, we do not find support for theoretical arguments stating that the educational use of ICT may lead to higher outcomes in less-developed countries, based on the higher potential they have to catch up more benefits compared to developed countries (Caselli & Coleman II, 2001; Fagerberg, 1995).

The study has some limitations present also in previous research based on large-scale international surveys on students' outcomes. First, since we use cross-sectional observational data from these surveys, only correlational (and not causal) patterns across variables can be drawn (Zhang & Liu, 2016).[8] Our HLM approach is suitable to control for unobserved heterogeneity of unknown origin across schools and countries, mitigating the endogeneity bias. However, our results on our main research question (whether, and how, the relationship between ICT use for learning at school and students' outcomes vary from developed to less-developed countries) should be understood as such and not as the causal impact of ICT on educational outcomes. 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 (Bulman & Fairlie, 2016) 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. And third, our variable on ICT use for learning at school covers the quantity but not the quality of ICT usage (De Witte & Rogge, 2014; Petko et al., 2017); it also does not identify which activities are performed using ICT (Luu & Freeman, 2011).

[8] As Hanushek & Woessmann (2017) 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).

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 at school and students' outcomes in different settings (such as developed and less-developed countries). These analyses would allow for further insights on 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 and students' outcomes.

The heterogeneity between developed and less-developed 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 et al. (2007), analyses and policies on the educational use of ICT would require a careful understanding and consideration of the specific context of less-developed countries. This is particularly important when less-developed countries are increasingly adopting technologies designed for educational systems from developed countries. Both groups of countries differ in educational inputs that condition the success of educational practices based on ICT use. Some key 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 less-developed countries alongside the investment in new technologies if these countries aim to reproduce successful experiences observed in developed countries. Inability to do so may not lead to leveraging resources, but widening the gap in learning outcomes between less-developed- and developed- countries. Our results also imply that educational systems, specifically those from less-developed countries, should conduct in-depth analysis on whether adopting ICT-based instructional materials (in most cases, designed for developed countries) benefit students learning more than traditional teaching based on human interaction.

6. References

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7. Statistical Appendix

Table A3. Hierarchical Linear Model Predicting Students' Achievement in PISA Subjects with Income Level as Countries' Development Indicator

Variable	Reading			Mathematics			Science		
Fixed effects	*Estimate*	*SE*	*P > |t|*	*Estimate*	*SE*	*P > |t|*	*Estimate*	*SE*	*P > |t|*
(Intercept)	337,188	19,187	0,000	319,455	19,319	0,000	337,170	18,934	0,000
Subject-related ICT use during lessons (ICTCLASS)	**-7,700**	**1,879**	**0,000**	**-5,918**	**1,554**	**0,000**	**-6,663**	**1,817**	**0,000**
Gender									
Male	-20,758	0,271	0,000	10,385	0,225	0,000	3,202	0,236	0,000
Age	9,443	0,458	0,000	10,358	0,381	0,000	8,984	0,400	0,000
Country of birth									
Other country	-14,408	0,567	0,000	-10,867	0,460	0,000	-12,849	0,483	0,000
Economic, social and cultural status (ESCS)	11,891	0,155	0,000	13,389	0,128	0,000	13,035	0,134	0,000
Attitude towards school: learning activities	2,702	0,132	0,000	1,959	0,111	0,000	1,633	0,116	0,000
School average value of ESCS	57,699	0,678	0,000	51,614	0,597	0,000	50,677	0,606	0,000
Does teachers have skills to introduce digital devices in instruction?									
Agree	-0,437	0,836	0,601	-0,508	0,729	0,486	-0,504	0,737	0,494
Proportion of all fully certified teachers	3,805	1,035	0,000	2,384	0,895	0,008	2,999	0,919	0,001
Teacher behaviour hindering learning	0,262	0,297	0,377	0,188	0,259	0,467	0,246	0,266	0,355
Perceived teacher's interest	2,460	0,153	0,000	1,637	0,128	0,000	2,126	0,134	0,000
Shortage of educational material	-0,269	0,366	0,462	-0,202	0,316	0,524	-0,124	0,324	0,700
Shortage of educational staff	-0,920	0,363	0,011	-0,813	0,316	0,010	-0,853	0,324	0,009
Adaptation of instruction	4,141	0,147	0,000	2,909	0,122	0,000	3,315	0,129	0,000
Disciplinary climate in test language lessons	6,322	0,134	0,000	5,814	0,112	0,000	5,716	0,118	0,000
Community in which the school is located									
City or large city (>= 100.000 people)	0,546	0,680	0,422	-0,780	0,589	0,186	-1,103	0,604	0,068
Government expenditure on education (% GDP)	-3,859	3,652	0,291	-5,900	3,782	0,119	-4,593	3,670	0,211
Income level									
High-income country	**23,402**	**10,807**	**0,030**	**27,366**	**11,057**	**0,013**	**24,949**	**10,799**	**0,021**
ICTCLASS · High-income country	**5,555**	**2,221**	**0,012**	**4,939**	**1,829**	**0,007**	**5,215**	**2,139**	**0,015**
Random effects									
Level 3: Intercept		1011,38	31,80		1072,06	32,74		1022,93	31,98
Level 3: ICTCLASS		44,90	6,70		30,62	5,53		42,08	6,49
Level 2: Intercept		1275,02	35,71		1101,49	33,19		1110,95	33,33
Level 2: ICTCLASS		39,43	6,28		30,18	5,49		34,77	5,90
Level 1: Residual		5117,84	71,54		3950,26	62,85		4361,95	66,05
Sample size									
Total sample (students)			324.501			360.444			360.444
Level 2 group (schools)			12.246			13.335			13.335
Level 3 group (countries)			46			47			47

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 46 countries.

Table A4. Hierarchical Linear Model Predicting Students' Achievement in PISA Subjects with HDI as Countries' Development Indicator

Variable	Reading			Mathematics			Science		
Fixed effects	*Estimate*	*SE*	*P > |t|*	*Estimate*	*SE*	*P > |t|*	*Estimate*	*SE*	*P > |t|*
(Intercept)	328,764	20,146	0,000	301,187	19,750	0,000	324,897	19,747	0,000
Subject-related ICT use during lessons (ICTCLASS)	**-9,142**	**2,098**	**0,000**	**-7,196**	**1,730**	**0,000**	**-8,253**	**2,017**	**0,000**
Gender									
Male	-20,757	0,271	0,000	10,386	0,225	0,000	3,203	0,236	0,000
Age	9,443	0,458	0,000	10,358	0,381	0,000	8,984	0,400	0,000
Country of birth									
Other country	-14,407	0,567	0,000	-10,867	0,460	0,000	-12,849	0,483	0,000
Economic, social and cultural status (ESCS)	11,892	0,155	0,000	13,389	0,128	0,000	13,035	0,134	0,000
Attitude towards school: learning activities	2,702	0,132	0,000	1,959	0,111	0,000	1,633	0,116	0,000
School average value of ESCS	57,697	0,678	0,000	51,595	0,597	0,000	50,668	0,606	0,000
Does teachers have skills to introduce digital devices in instruction?									
Agree	-0,441	0,836	0,598	-0,511	0,729	0,483	-0,508	0,737	0,491
Proportion of all fully certified teachers	3,800	1,035	0,000	2,375	0,895	0,008	2,993	0,919	0,001
Teacher behaviour hindering learning	0,260	0,297	0,381	0,185	0,259	0,475	0,244	0,266	0,360
Perceived teacher's interest	2,460	0,153	0,000	1,638	0,128	0,000	2,126	0,134	0,000
Shortage of educational material	-0,268	0,366	0,464	-0,201	0,316	0,526	-0,124	0,324	0,703
Shortage of educational staff	-0,918	0,363	0,011	-0,812	0,316	0,010	-0,852	0,324	0,009
Adaptation of instruction	4,141	0,147	0,000	2,909	0,122	0,000	3,315	0,129	0,000
Disciplinary climate in test language lessons	6,321	0,134	0,000	5,814	0,112	0,000	5,716	0,118	0,000
Community in which the school is located									
City or large city (>= 100.000 people)	0,545	0,680	0,423	-0,774	0,589	0,189	-1,101	0,604	0,068
Government expenditure on education (% GDP)	-2,519	3,574	0,481	-3,626	3,585	0,312	-2,901	3,561	0,415
HDI level									
Very-high-HDI country	**24,119**	**11,487**	**0,036**	**34,715**	**11,399**	**0,002**	**28,370**	**11,370**	**0,013**
ICTCLASS · Very-high-HDI country	**6,932**	**2,373**	**0,003**	**6,159**	**1,952**	**0,002**	**6,810**	**2,275**	**0,003**
Random effects									
Level 3: Intercept		1007,29	31,74		1000,26	31,63		995,05	31,54
Level 3: ICTCLASS		42,96	6,55		29,12	5,40		39,79	6,31
Level 2: Intercept		1274,98	35,71		1101,55	33,19		1111,02	33,33
Level 2: ICTCLASS		39,44	6,28		30,17	5,49		34,77	5,90
Level 1: Residual		5117,84	71,54		3950,26	62,85		4361,94	66,05
Sample size									
Total sample (students)			324.501			360.444			360.444
Level 2 group (schools)			12.246			13.335			13.335
Level 3 group (countries)			46			47			47

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 46 countries.

CHAPTER III

ICT USE AND SUCCESSFUL LEARNING: THE ROLE OF THE AGGREGATE STOCK OF HUMAN CAPITAL

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III

CHAPTER III. ICT USE AND SUCCESSFUL LEARNING: THE ROLE OF THE AGGREGATE STOCK OF HUMAN CAPITAL

Abstract

Previous empirical studies have found a weak nexus between the use of Information and Communication Technologies (ICT) for learning and students' outcomes. However, this literature has not taken into account the role that the countries' stock of human capital can have in the successful use of ICT for learning, despite the important complementarities between human capital and technology adoption. We carry out an empirical analysis with PISA data from a large-scale sample of 363,412 students enrolled in 13,215 schools of 48 countries. We estimate a Hierarchical Linear Model (HLM) of three levels: students, schools, and countries. Our results strongly support the evidence of a positive externality of the stock of human capital on ICT use for learning. When we consider the moderator-effect of the stock of human capital, we find that the negative outcome of ICT use on students' outcomes in mathematics, reading and science turns positive (greater and more positive the higher the stocks of human capital are). The greater the stock of human capital one economy has, the more benefits it can get from the investment in ICT for learning.

Keywords: ICT; technology; Internet; computers; human capital; students, schools; teaching; academic achievement; PISA

1. Introduction

Information and Communication Technologies (ICT) have changed the world. In the last decades, both work and leisure, have undergone a profound transformation.

Today, it is difficult to conceive life without computers, cell phones, social networks and permanent access to information. Everything has become accessible and instantaneous.

Education has not been immune to this profound transformation in the last decades. Computers, at first, and access to knowledge through the Internet, later, were identified as revolutionary educational tools. Computers and connectivity would make possible, definitely, to democratize and universalize education. The teaching and learning applications available would allow to standardize quality. Following these premises, policy makers in education have been investing, during the last decades, huge amounts of resources in making schools more technological and facilitating access to new technologies for students (Comi et al., 2017; Fernández-Gutiérrez et al., 2020; González-Betancor, López-Puig, & Cardenal, 2021; Spiezia, 2010). This interest has grown even further since the COVID-19 pandemic, as many countries are accelerating the incorporation of ICT into education (M. A. White & McCallum, 2021).

However, it is clear that digital transformation is coming at a cost. Digitization is meaning an increasing human beings' dependence on technological devices, and even its advantages in terms of productivity and efficiency are being questioned, as there is a discrepancy between measures of investment in information technology and measures of output (Turban, McLean, & Wetherbe, 2004).

This critical vision has become very evident in the educational field, where the effectiveness of new technologies in learning is increasingly questioned. The impact of ICT on educational achievements has become a controversial issue, and scientific evidence has not clearly found that the use of ICT in the classroom has a positive effect on learning (Bulman & Fairlie, 2016; Falck, Mang, & Woessmann, 2018b; Fernández-Gutiérrez et al., 2020; Giambona & Porcu, 2015b; Hu, Gong, Lai, & Leung, 2018b). One major motive is that the empirical studies carried out have paid little attention to the potential role of country characteristics in shaping the relationship between the use of ICT and educational achievement (Hu et al., 2018b). Among these characteristics, the stock of human capital, and specifically the interaction between it and the use of new technologies, emerges as a factor of singular importance. Economic literature has highlighted the important complementarities that surge between human capital accumulation and technology adoption (Barcenilla, Gimenez, & López-Pueyo, 2019; Benhabib & Spiegel, 2005; Giménez, López-Pueyo, & Sanaú, 2015; Lentini & Gimenez, 2019; López-Pueyo, Barcenilla, & Giménez, 2018; Vandenbussche, Aghion, & Meghir, 2006).

Following this line, in the present article, we formulate the hypothesis that the outcome of ICT use on learning varies when we consider differences in the countries' stock of human capital. We conjecture that the countries with greater stock of human capital can benefit more from the use of ICT in learning. In the next subsections, we explain what the literature has found about the relationship between ICT and learning success and why we think that this can be conditioned by the stock of human capital.

2. ICT and Educational Outcomes

There are both positive and negative arguments about the effectiveness of ICT for teaching and learning. On the one hand, ICT may ease individualized and flexible instruction, leading to improve students' outcomes by attending their own needs and potential (Rubach & Lazarides, 2021). The availability of vast ICT educational resources and information on internet also amplifies the scope of teaching and learning beyond the educational system (Sangrà & González-Sanmamed, 2016), which might enhance students' outcomes. ICT also provides audiovisual materials capable to stimulate motivation (Marco et al., 2021), creativity and innovation (Allegra et al., 2001) in learning and teaching processes, leading to improve academic outcomes. On the other hand, when

ICT are not well integrated into the curriculum due to pedagogical barriers, they might hinder students learning (Shan Fu, 2013). ICT may also discourage students effort and logical thinking if educational systems do not fit technology to their ICT-instructional needs (Wheeler et al., 2002). The ICT might further provide a lot of wrong or incomplete information, which can be used for education, diminishing students learning (Gómez-Fernández & Mediavilla, 2021). The effectiveness of ICT on educational systems will depend on the net effect of these likely positive and negative contributions to academic outcomes.

Over the past two decades, a substantial amount of empirical research as regards the effectiveness of access to and use of ICT on academic outcomes using large-scale international surveys have been developed (for a literature review, see Bulman & Fairlie, 2016). Studies based on large-scale international surveys (e.g. PISA, TIMSS, and PIRLS) allow to compare a broad range of setting and to estimate correlations among populations (e.g. schools, professors, and students) within countries and across them. Nevertheless, with these studies using cross-sectional data, it is hardly probable to infer causal relationships (E. A. Hanushek & Woessmann, 2011).

Since this paper is based on a large-scale international survey (Programme for International Student Assessment, PISA) and analyzes the educational ICT use at school, in the following paragraphs we present the main results of research conducted from international assessments and which analyzed the effectiveness of access to and use of ICT at school. Several studies have used international surveys (most commonly, PISA) to conduct analyses in single countries. Based on Spanish students' data from PISA 2012, Cabras & Tena Horrillo (2016) estimated the effect of computers use at school on mathematics outcomes. They found that, with a high probability, computers use had a moderate positive effect on mathematics outcomes, which was particularly high among low socioeconomic background students. Also based on PISA 2012 data from Spain, Alderete et al. (2017) found a negative relationship between ICT use at school and reading-, mathematics-, and science- outcomes. In another study for Spain, Gómez-Fernández & Mediavilla (2021) used PISA 2015 to estimate the relationship between the access to and use of ICT at school and reading-, mathematics-, and science- outcomes. These authors found a positive relationship between the availability of computers and academic outcomes, whereas for the use of computers it was negative. Using data from 2009, 2012, and 2015 PISA rounds for Spanish students, Fernández-Gutiérrez et al. (2020) estimated the effect of ICT use at school on the three PISA subjects' outcomes. Leveraging the availability of representative samples for Spanish regions and the autonomy and variability of ICT use at school across them, they found that increasing ICT use at school in an Autonomous Community did not have positive effects on reading and mathematics outcomes, whilst in science it had positive effects. Based on PISA 2012 data for Turkish students, Erdogdu & Erdogdu (2015) found a positive relationship between internet access and science outcomes, whereas for the frequency of internet browsing it was negative in the three PISA subjects (reading, mathematics, and science). Using TIMMS 2011 data for Dutch students, De Witte & Rogge (2014) estimated the effects of distinct ICT variables on mathematics outcomes. The authors found that these effects were rather modified whether or not different student, teacher, school, and regional features were considered.

Other studies based on international assessments have conducted analyses for a set of countries. Using samples of 38 countries from TIMSS 2011 data, 43 countries from PIRLS 2011 data, and 39 countries from PISA 2012 data, Skryabin et al. (2015) analyzed the relationship between ICT use and subjects' academic outcomes. They found a positive relationship between ICT use and reading-, mathematics-, and science- outcomes of 4th grade students, while for 8th grade students it was negative. D. Zhang & Liu (2016) used a set of 25 countries from PISA 2000, 32 from PISA 2003, 40 from PISA 2006, 45 from PISA 2009, and 43 from PISA 2012, to estimate the relationship between various ICT use indicators and mathematics- and science- outcomes. These authors found a negative relationship between software- and internet- use and both subjects' outcomes. Using data for 39 countries from PISA 2012, Petko et al. (2017) estimated the relationship between ICT use and reading-, mathematics-, and science- outcomes. They found a negative relationship between ICT use and academic outcomes in the vast majority of countries. Finally, based on a set of 30 countries from TIMSS 2011, Falck et al. (2018b) estimated the effects of distinct school computers uses on academic outcomes. The authors applied a within-student between-subject identification, which leverage the availability of information for each student on two different subjects (mathematics and science). They found positive effects of practicing skills and procedures on academic outcomes, whilst for processing and analyzing data they were non-significant.

3. The Role of Human Capital

By human capital, we understand the knowledge and skills embodied in people. Thus, the term is explained by the fact that it is seen as a form of capital incorporated into persons (Gimenez, 2005). Nevertheless, for the purposes of this study, the key aspect of human capital has to do with its externalities. Human capital has shown to be a key driver of economic growth and poverty reduction, as it relates to economies' ability to maintain competitiveness, develop novel business ideas, and to spur innovation and technology diffusion (Gimenez, 2017; Gimenez & Simón, 2004; Winters, 2013).

There are solid arguments to expect that the relationship between ICT and educational achievement may differ depending on the countries' human capital level.

Specifically, due to its strong positive externalities, we can point to three effects of the stock of human capital on learning through ICT:

The assimilation and effective use of technology. We consider the stock of human capital as a catalyst of new technologies: the process of adoption of new technologies is strongly influenced by human capital stock, by reducing the new technologies learning costs and accelerating its adoption (Barcenilla et al., 2019; Funke & Strulik, 2000; Gimenez, 2006; Labordeta & Giménez, 2012).

The creation and improvement of a pedagogical and institutional environment more conducive to learning. Human capital diminishes criminal activity (Lochner & Moretti, 2004), increases civic participation (Milligan, Moretti, & Oreopoulos, 2004), improves adaptive capacity to environmental change (Reiter, C. , Özdemir, C., Yildiz, D. , Goujon, A. , Guimaraes, R. , & Lutz, 2020), and spurs entrepreneurship and business outcomes .

The attraction of better teachers. Highly educated areas experience faster population and employment growth as individuals flock to be near the highly educated (Doms, Lewis, & Robb, 2010). Moreover, it is mostly educated individuals who are moving to high human capital areas, seeking a better quality of life (Shapiro, 2006; Winters, 2011). These effects have specifically been found in the case of teachers: their well-being and productivity can increase by interacting with and learning from high-skilled teachers (Berlinski & Ramos, 2018; Correa, Parro, & Reyes, 2015).

The goal of the present study is to provide a theoretical and empirical underpinning towards a better understanding of the role of the stock of human capital in the successful use of ICT in the learning process. To do so, we estimate an education production function that empirically establish the relationship between the student's outcomes, in the form of tests' scores in mathematics, reading and science (output), and a wide set of explaining variables (inputs), among them, the subject-related ICT use in schools. In the function, we include the stock of human capital and its interaction with the subject-related ICT use, to assess whether, and how, human capital has a moderator-effect on the relationship between ICT use and students' outcomes. This approach constitutes, as far as we now, a novelty in the literature. We find that, although subject-related ICT use in schools has a negative relationship with students' outcomes, when we consider the moderator-effect of the stock of human capital in the estimations, this relationship turns positive. The relationship between subject-related ICT use in schools and students' outcomes is greater (more positive) the higher the level of the stock of human capital is. The higher the stock of human capital one economy has; the more benefits can be got from the investment in ICT for learning. Similarly, the higher the subject-related ICT use, the greater (more positive) the result of the stock of human capital on students' outcomes.

The remainder of the paper is organized as follows. In the next section, we explain the data, variables and methodology used in the paper. Section 3 describes the results. Section 4 discusses the findings and concludes.

4. Materials and Methods

The current study developed an empirical analysis with data of 363,412 students, enrolled in 13 215 schools in 48 countries (12 middle-income and 36 high-income economies). It aimed to answer the following question: Whether and how, the countries' stock of human capital has a moderator-effect on the relationship between subject-related ICT use in schools and students' outcomes.

4.1 Data

The empirical analysis used, as the main source, data coming from the 2018 edition of the PISA questionnaire, released in 2020. Table 1 shows the classification and descriptive statistics of the variables.

Table 1. Variables Classification and Its Descriptive Statistics

Type of variable	Variable	Mean	SD	Missing (%)
Dependent variables	Reading score	465	104.0	9.9[1]
	Mathematics score	472	95.1	0.0
	Science score	470	95.5	0.0
Student-level predictors	Subject-related ICT use during lessons (CI)[2]	-0.05	1.0	15.9
	Age	15.8	0.3	0.0
	Economic, social and cultural status (CI)	-0.2	1.1	2.4
	Gender[3]			0.0
	Female	181,3	49.9	
	Male	182,07	50.1	
	Country of birth			2.8
	Country of the test	339,1	93.3	
	Other country	24,31	6.7	
School-level predictors	Proportion of all teachers fully certified (CI)	0.84	0.3	16.9
	Teacher behavior hindering learning (CI)	0.17	1.1	4.5
	Perceived teacher's interest (CI)	0.08	1.0	4.9
	Shortage of educational material (CI)	0.06	1.1	4.8
	Shortage of educational staff (CI)	-0.02	1.0	4.9
	Adaptation of instruction (CI)	0.02	1.0	5.6
	Disciplinary climate in test language lessons (CI)	0.07	1.1	3.4
	Which of the following definitions best describes the community in which your school is located?			5.4
	A large city (with over 1,000,000 people)	52,02	14.3	
	A city (100,000 to about 1,000,000 people)	98,08	27.0	
	A small town (3,000 to about 15,000 people)	70,4	19.4	
	A town (15,000 to about 100,000 people)	110,2	30.3	
	A village, hamlet or rural area (fewer than 3,000 people)	32,70	9.0	
	Is your school a public or a private school?			12.7
	Private school	74,73	20.6	
	Public school	288,7	79.4	
Country-level predictors	Years of schooling (BL)	10.50	1.8	0.0
	Years of schooling (PWT)	3.21	0.4	0.0
	Gross domestic product per capita (GDP per capita)[4]	40,70	21,7	0.0

[1] Since PISA 2018 excluded Spain results from the reading assessment for technical issues, reading score has 35,943 missing values. [2] Many questionnaire items were designed to be combined as part of composite indicators (CI) built by the PISA project work group. In this case, Cronbach's alpha was used to check the internal consistency of each scale. [3] In categorical variables, values reflect respectively the number of observations of each category and the percentage it represents. [4] This variable was obtained from: https://data.worldbank.org/indicator/NY.GDP.PCAP.PP.CD.

The PISA questionnaire is carried out by the Organisation for Economic Co-operation and Development (OECD) every three years since 2000. Its objective is to evaluate educational systems by measuring 15-year-olds' ability to use their reading, mathematics and science knowledge and skills to meet real-life challenges ("PISA - PISA," n.d.). In addition to the cognitive test, students are asked to answer a background questionnaire, which brings information about themselves, their homes, and their school. School principals are asked to complete an additional questionnaire, which covers the school system and the learning experiences. These questionnaires contain key information concerning subject-related ICT use at schools, and its student-and-school-level predictors, that we use in our study.

In the dataset that was built merging both questionnaires, there were a substantial set of predictors that presented missing values. The exclusion of this missing values (see figures in Table 1) would have generated a loss of 142,569 observations (39% of our final sample). This would have represented biases in the statistical inference (G. Castro Aristizabal, Giménez, & Pérez Ximénez-De-Embún, 2017; Geovanny Castro Aristizabal, Giménez, & Pérez Ximénez-de-Embún, 2018; Gimenez & Barrado, 2020). We used data imputation as a way to carry out the analyses avoiding the reduction of the sample size and mitigating the estimation bias (Fuchs & Wößmann, 2007). The missing values were imputed with the R package *Multivariate Imputation by Chained Equations*, which computes incomplete multivariate data by Fully Conditional Specification (FCS).

The key variable that we incorporated into our study was the PISA index *subject-related ICT use during lessons* (PISA code *ICTCLASS*). PISA constructed this index from five question that asked about the time students spent using digital devices during classroom lessons in a typical school week in five domains: test language lessons, mathematics, science, foreign language, and social sciences. Each question considered 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 index *ICTCLASS*. As this variable allowed us to work with a subject-specific measure of ICT use for teaching purposes, it constituted a substantial novelty compared to previous cross-country studies that used ICT measures, mostly based on access to and general use of ICT, without distinguish between academic- and leisure- purposes.

Since our paper analyzed the relationship between academic achievement and subject-related ICT use in schools, mediated by the stock of human capital from an international perspective, we merged the PISA dataset with two measures of the stock of human capital widely used in the literature: the stock of human capital indicator coming from Barro and Lee (BL) dataset (Barro & Lee, 2013) and the one coming from the Penn World Table (PWT) (“PWT 10.0 | Penn World Table | Groningen Growth and Development Centre | University of Groningen,” n.d.).

For decades, schooling has been used as the main proxy for human capital, which has mostly been measured in terms of the highest educational attainment distribution of the population or the aggregated mean years of schooling (Angrist, Djankov, Goldberg, & Patrinos, 2021). Following this mainstream, we incorporated in our study a measure of the average years of schooling constructed by BL, based on the percentage of population, aged 25 years old and above, that have completed primary, secondary, and tertiary education.

In recent years, some researchers have made valuable efforts to build more elaborated and accurate indicators (López-Pueyo et al., 2018). Among these new attempts, the index of human capital included in the PWT is widely used. This index is constructed making a Mincerian transformation of the average years of schooling calculated by BL, and estimates the stock of human capital (hc) of a country i at time t as a function of the average years of schooling (s):

$$hc_{it} = e^{\phi(s_{it})}, \qquad (1)$$

Where $\phi(s)$ are the Mincerian rates of return to education defined by Psacharopoulos (1994) (Psacharopoulos, 1994).

The countries' average values of the ICTCLASS index and those for the BL and PWT stock of human capital indicators are shown in the Table 2. The average *ICTCLASS* index in our sample was of -0.07 and its standard deviation of 0.34. It ranged from the one of Japan (-0.59) to the one of Denmark (1.35). The BL indicator average was of 10.54 with a standard deviation of 1.95. It ranged from the one of Morocco (4.24) to the one of the United States (13.42). The average value of the PWT indicator was of 3.23 and its standard deviation was of 0.41. It ranged from the one of Morocco (1.89) to the one of Singapore (3.97).

Table 2. List of Countries in the Sample, and Its Average Value in the PISA Index Subject-Related ICT Use During Lessons (ICTCLASS), Years of Schooling (BL), and Years of Schooling (PWT)

Country code	Country name	ICTCLASS	BL	PWT
ALB	Albania	-0.23	9.85	2.95
AUS	Australia	0.61	11.77	3.52
BEL	Belgium	-0.20	10.78	3.14
BRA	Brazil	-0.48	7.66	2.95
BRN	Brunei	-0.25	8.77	2.77
BGR	Bulgaria	-0.02	11.45	3.16
CHL	Chile	-0.09	9.71	3.11
CRI	Costa Rica	-0.28	7.84	2.66
HRV	Croatia	-0.31	11.42	3.52
CZE	Czech Republic	-0.28	13.16	3.67
DNK	Denmark	1.35	11.53	3.56
DOM	Dominican Republic	-0.35	7.46	2.72
EST	Estonia	0.00	12.48	3.62
FIN	Finland	0.08	10.21	3.47
FRA	France	-0.18	10.64	3.19
GBR	Great Britain	-0.11	12.32	3.76
GRC	Greece	-0.39	10.26	3.09
HKG	Hong Kong	-0.37	11.02	3.24
HUN	Hungary	-0.30	12.14	3.38
ISL	Iceland	0.41	10.59	3.23
IRL	Ireland	-0.36	12.20	3.15
ISR	Israel	-0.06	12.76	3.81
ITA	Italy	-0.06	9.54	3.12
JPN	Japan	-0.59	11.52	3.57
KAZ	Kazakhstan	0.32	11.42	3.14
KOR	Korea	0.07	11.89	3.69
LVA	Latvia	-0.12	10.48	3.13
LTU	Lithuania	0.03	11.05	3.26
LUX	Luxemburg	-0.31	11.22	3.51
MAC	Macao	-0.05	8.09	2.86
MLT	Malta	-0.07	10.33	3.13
MEX	Mexico	-0.29	8.33	2.74
MAR	Morocco	-0.27	4.24	1.89
NLD	Netherlands	-0.05	11.60	3.37
PAN	Panama	-0.40	9.15	2.86
POL	Poland	-0.20	11.42	3.40
RUS	Russia	0.06	11.73	3.40
SRB	Serbia	-0.22	10.97	3.39
SGP	Singapore	-0.33	10.63	3.97
SVK	Slovakia	0.00	13.07	3.79
SVN	Slovenia	-0.34	12.13	3.53
ESP	Spain	-0.05	10.30	2.94
SWE	Sweden	0.77	11.89	3.42
CHE	Switzerland	-0.24	13.42	3.69
THA	Thailand	0.13	7.30	2.74
TUR	Turkey	0.22	6.56	2.44
USA	United States	0.38	13.42	3.74
URY	Uruguay	-0.11	8.11	2.73

4.2 Model

We established a statistical relationship between the students' outcomes in each PISA domain (dependent variables) and the learning factors (predictors). To increase the accuracy of students' scores measurement, PISA generated ten plausible values, for each student, in the three domains (mathematics, reading, and science). To calculate the ten plausible values, a set of random values were drawn from the estimated distributions of the scores computed around the reported values in the tests (OECD, 2009, p. 95). We used the same methodology as previous studies that defined the dependent variable as the student's mean scores of the plausible values (Ammermueller, 2007; L. Zhang et al., 2015).

The dataset that we used presented a nested structure: students were grouped in schools, and schools in countries. This type of clustered data violates the assumption of independence of the observations. This is, observations within each group were probably correlated, because the individuals belonging to the same groups share common characteristics. Some probable causes were that the students enrolled in the same schools might have similar social background, they might influence each other, or their school might deliver education in a particular manner that made its students' outcomes to differ from those enrolled in other schools. The same can be applied to students of the same country, who share the same culture, values and idiosyncratic educational issues. So, we expected the correlation between the residuals of the predicted students' outcomes, for every school or country in the sample, to be different from zero. Hierarchical Linear Models (HLM) are suitable to deal with data that present this nested structure. They consider this cluster structure by identifying random effects. In our case, we included school- and country-specific random intercepts, allowing schools and countries to differ with respect to average PISA scores when the covariates were zero. This allowed us to estimate robust standard errors.

Specifically, the three-level model that we used can be expressed as:

$$Y_{ijk} = \beta_0+\boldsymbol{\beta_1 X_{1ijk}} + \boldsymbol{\beta_2 Z_{jk}} + \beta_3 ICTCLASS_{1ijk} + \beta_4 GDP_k + \beta_5 H_k + \beta_6 ICTCLASS_{1ijk} \cdot H_k + \varepsilon_{ijk} \quad (2)$$

$$\beta_0 = \gamma_{00} + u_{0jk} + v_{0k} \quad (3)$$

In Eq. (2), Y_{ijk} was the expected PISA score for student *i* enrolled in school *j* in a country *k*; $\boldsymbol{X}_{ijk}$and $\boldsymbol{Z}_{jk}$ were respectively vectors of predictors at the student-and-school-levels; $ICTCLASS_{1ijk}$ measured the time devoted to subject-related ICT use for student *i* in school *j* and country *k*; GDP_k and H_k were, respectively, the GDP per capita and the stock of human capital at the country- level; $ICTCLASS_{1ijk} \cdot H_k$ was the term that reflected the interaction of the stock of human capital with the subject-related ICT use at schools; and ε_{ijk} was the unexplained component. Our hypothesis was that students who lived in environments with higher stock of human capital could benefit directly and indirectly (via the use of ICT) by obtaining better outcomes.

$\boldsymbol{X}_{ijk}$and $\boldsymbol{Z}_{jk}$ included a set of students', teachers' and schools' characteristics that are considered standard in the literature to predict students' outcomes. Specifically, *gender* (PISA code ST004D01T), *age* (PISA code AGE), *immigrant background* (PISA code CNTBIRTH), a composite index of *economic, social and cultural status* of the household (PISA code ESCS), an index showing the *proportion of all teachers fully certified* (PISA code PROATCE), an index of *teacher behaviour hindering learning* (PISA code TEACHBEHA), an index of *perceived teacher's interest* (PISA code TEACHINT), an index of *shortage of educational material* (PISA code EDUSHORT), an index of *shortage of educational staff* (PISA code STAFFSHORT), an index of *adaptation of instruction* to improve learning (PISA code ADAPTIVITY), an index of *disciplinary climate in test language lessons* (PISA code DISCLIMA), the *size of the community* in which the school was located (PISA code SC001Q01TA), and if the school was *public* or *private* (PISA code SC013Q01TA). For an in-depth justification of the inclusion of these predictors that act as control variables and the role that they play in the learning process, see (Bradley & Green, 2020b; Hanushek & Welch, 2006; Bulman & Fairlie, 2016; Hanushek & Woessmann, 2011; Hanushek, Woessmann, & Machin, 2011). We expected to find gender differences, as girls used to score higher in reading, but lower in mathematics and science. Students who were older, did not have immigrant background, lived in households with higher *economic, social and cultural status*, lived in richer countries, attended private schools or schools that were situated in larger communities, were expected to have better outcomes, measured by PISA scores. The index showing the *proportion of all teachers fully certified,* the index of *perceived teacher's interest,* the index of *adaptation of instruction,* and the index of *disciplinary climate in test language lessons* were expected to correlate positively with students' outcomes. Conversely*,* the index of *teacher behaviour hindering learning*, the index of *shortage of educational material,* and the index of *shortage of educational staff* were expected to correlate negatively.

Eq. (3) was estimated simultaneously with Eq. (2) and allowed us to model the school and country specific intercepts and the associated complex error structure u_{0jk} and v_{0k} were the respective deviation of the schools' and the countries' means from the overall mean γ_{00}. They were assumed to be normally distributed, with mean zero, and uncorrelated with ε_{ijk} .

To obtain a more clear and intuitive evidence of the interaction between subject-related ICT use during lessons and human capital, we conducted the estimations centered at the country mean of the stock of human capital indicators (Wooldridge, 2009). It facilitates the interpretation of the results.

5. Results

Table 3 (for the BL indicator of the stock of human capital) and Table 4 (for the PWT indicator of the stock of human capital) show the results of the estimations of Eq. (2) and Eq. (3) for mathematics, reading and science. They include the fixed-and-random-effects. The latter, at the bottom of the table, shows the standard deviations from the overall mean, with origin in the school-and-country-level variance unaccounted for in the model and the residual variance component.

Table 3. Hierarchical Linear Models Predicting Students' Outcomes and Considering Years of Schooling (BL) as Indicator of the Countries' Stock of Human Capital

Type of variable	Variable	Reading		Mathematics		Science	
		Estimate	SE	Estimate	SE	Estimate	SE
Fixed effects	Intercept	303.10***	11.48	271.80***	11.05	298.20***	10.95
	Gender - Female (base)						
	Male	-21.00***	0.27	10.02***	0.22	2.93***	0.24
	Age	9.58***	0.46	10.46***	0.38	9.14***	0.40
	Country of birth - Country of the test (base)						
	Other country	-13.55***	0.56	-10.19***	0.45	-12.21***	0.48
	Economic, social and cultural status	13.75***	0.15	14.85***	0.13	14.60***	0.13
	Proportion of all teachers fully certified	2.58**	1.19	0.93	1.01	1.75*	1.04
	Teacher behavior hindering learning	-0.11	0.34	-0.23	0.29	-0.17	0.30
	Perceived teacher's interest	2.73***	0.15	1.81***	0.13	2.27***	0.13
	Shortage of educational material	-3.38***	0.43	-3.04***	0.37	-2.98***	0.37
	Shortage of educational staff	-2.27***	0.42	-1.90***	0.36	-2.05***	0.37
	Adaptation of instruction	4.35***	0.15	3.08***	0.12	3.48***	0.13
	Disciplinary climate in test language lessons	6.43***	0.14	5.85***	0.11	5.77***	0.12
	School location - A large city (with over 1,000,000 people) (base)						
	A city (100,000 to about 1,000,000 people)	-3.38***	1.24	-2.57**	1.07	-2.58**	1.10
	A small town (3,000 to about 15,000 people)	-13.46***	1.35	-10.02***	1.16	-9.97***	1.20
	A town (15,000 to about 100,000 people)	-8.45***	1.23	-6.95***	1.06	-6.58***	1.09
	A village, hamlet or rural area (fewer than 3,000 people)	-21.04***	1.48	-14.69***	1.28	-15.09***	1.32
	Public or a private school? - Private school (base)						
	Public school	-4.25***	0.78	-4.03***	0.66	-3.98***	0.69
	Gross domestic product per capita (GDP per capita)	0.75***	0.18	0.92***	0.19	0.80***	0.18
	Subject-related ICT use during lessons (ICTCLASS)	-3.62***	0.14	-1.82***	0.12	-2.28***	0.12
	Years of schooling (BL)	8.87***	2.29	9.53***	2.40	7.62***	2.31
	Interaction between ICTCLASS and years of schooling (BL)	1.28***	0.07	1.02***	0.06	1.15***	0.06
Random effects	Level 2: Intercept	2275.00	47.70	1903.90	43.63	1901.70	43.61
	Level 3: Intercept	848.20	29.12	943.50	30.72	870.40	29.50
	Level 1: Residual	5204.60	72.14	3983.60	63.12	4430.30	66.56
Sample size	Total sample (students)	327,469		363,412		363,412	
	Level 2 groups (schools)	12,126		13,215		13,215	
	Level 3 groups (countries)	47		48		48	

Note: ***p<0.01, **p<0.05, *p<0.1.

Table 4. Hierarchical Linear Models Predicting Students' Outcomes and Considering Years of Schooling (PWT) as Indicator of the Countries' Stock of Human Capital

Type of Variable	Variable	Reading		Mathematics		Science	
		Estimate	SE	Estimate	SE	Estimate	SE
Fixed effects	Intercept	305.80***	11.32	274.00***	11.09	300.80***	10.85
	Gender - Female (base)						
	Male	-21.00***	0.27	10.00***	0.22	2.92***	0.24
	Age	9.57***	0.46	10.45***	0.38	9.14***	0.40
	Country of birth - Country of the test (base)						
	Other country	-13.56***	0.56	-10.20***	0.45	-12.23***	0.48
	Economic, social and cultural status	13.76***	0.15	14.86***	0.13	14.61***	0.13
	Proportion of all teachers fully certified	2.62**	1.19	0.95	1.01	1.78*	1.04
	Teacher behavior hindering learning	-0.11	0.34	-0.23	0.29	-0.17	0.30
	Perceived teacher's interest	2.73***	0.15	1.82***	0.13	2.27***	0.13
	Shortage of educational material	-3.39***	0.43	-3.04***	0.37	-2.98***	0.37
	Shortage of educational staff	-2.26***	0.42	-1.90***	0.36	-2.04***	0.37
	Adaptation of instruction	4.34***	0.15	3.08***	0.12	3.48***	0.13
	Disciplinary climate in test language lessons	6.43***	0.14	5.85***	0.11	5.77***	0.12
	School location - A large city (with over 1,000,000 people) (base)						
	A city (100,000 to about 1,000,000 people)	-3.34***	1.24	-2.54***	1.07	-2.55**	1.10
	A small town (3,000 to about 15,000 people)	-13.41***	1.35	-9.99***	1.16	-9.94***	1.20
	A town (15,000 to about 100,000 people)	-8.40***	1.23	-6.92***	1.06	-6.54***	1.09
	A village, hamlet or rural area (fewer than 3000 people)	-20.98***	1.48	-14.65***	1.28	-15.05***	1.32
	Public or a private school? - Private school (base)						
	Public school	-4.28***	0.77	-4.05***	0.66	-4.01***	0.69
	Gross domestic product per capita (GDP per capita)	0.66***	0.18	0.85***	0.19	0.72***	0.18
	Subject-related ICT use during lessons (ICTCLASS)	-3.77***	0.14	-1.82***	0.12	-2.27***	0.12
	Years of schooling (PWT)	48.40***	10.88	47.72***	11.70	41.73***	11.02
	Interaction between ICTCLASS and years of schooling (PWT)	6.94***	0.34	4.44***	0.29	5.54***	0.31
Random effects	Level 2: Intercept	2271.40	47.66	1899.70	43.59	1902.80	43.62
	Level 3: Intercept	786.70	28.05	820.60	28.65	926.50	30.44
	Level 1: Residual	5203.50	72.13	4430.30	66.56	3984.10	63.12
Sample size	Total sample (students)	327,469		363,412		363,412	
	Level 2 groups (schools)	12,126		13,215		13,215	
	Level 3 groups (countries)	47		48		48	

Note: ***p<0.01, **p<0.05, *p<0.1.

We found that the following results, that are robust regardless of the stock of human capital indicator and subject analyzed. First, *male* students scored higher in mathematics and science but less in reading (p < .01). Second, *age* was positively correlated with students' outcomes (p < .01). Third, students that had an i*mmigrant background* got lower outcomes (p < .01). Fourth, *economic, social cultural status* was positively related with outcomes (p < .01). Fifth, the *proportion of all teachers fully certified* was correlated positively for reading (p < .05) and science (p < .10); while for mathematics it was not significant ($p > .1$). Sixth, the index of *teacher behaviour hindering learning* correlated negatively and was not significant ($p > .1$). Seventh, the index of *perceived teacher's interest* correlated positively ($p < .01$). Eight, the index of *shortage of educational material* correlated negatively ($p < .01$). Nineth, the index of *shortage of educational staff* correlated negatively ($p < .01$). Tenth, the index of *adaptation of instruction* correlated positively ($p < .01$). Eleventh, the index of *disciplinary climate in test language lessons* correlated positively ($p < .01$). Twelfth, students that attend schools situated in larger cities scored higher with a highly significant coefficient ($p < .01$) in nearly all cases. Thirteenth, students attending public schools scored lower ($p < .01$). Fourteenth, *GDP per capita* correlated positively with students' outcomes ($p < .01$).

As regards our central variables of study, the estimated coefficients and standard errors showed that the time devoted to subject-related ICT use in schools was associated negatively with students' outcomes ($p < .01$). The stock of human capital, both measured by the BL and PWT indicators, was correlated positively ($p < .01$). And, finally, the interaction between the time devoted to subject-related ICT use in schools and the stock of human capital was correlated positively with students' outcomes ($p < .01$). A positive value for the coefficient of the interaction term between the *stock of human capital* and *subject-related ICT use* implies that the higher the *stock of human capital*, the greater (more positive) the relationship between the *subject-related ICT use* and students' outcomes. Similarly, the higher the *subject-related ICT use*, the greater (more positive) the relationship between the *stock of human capital* and students' outcomes. For any given level of the stock of human capital for the countries included in our sample, the partial effect (relationship between *subject-related ICT use* and students' outcomes moderated by the stock of human capital) turned positive. Even in the case of the country with the lowest stock of human capital, Morocco, (values for BL of 4.24 and for PWT of 1.89), the partial effect turned positive. The results are robust for both definitions of human capital: average years of schooling (BL) and average years of schooling weighted by the Mincerian rates of return to education (PWT).

All in all, the estimations showed that there was a negative correlation between subject-related ICT use in schools and students' outcomes. However, when we considered the moderator-effect of the stock of human capital, we found that the effect of ICT use on students' outcomes was greater the higher the stock of human capital was. that is, the higher the stock of human capital one economy has, the more benefits can be got from the investment in ICT for learning.

6. Discussion

Previous empirical studies have found a weak nexus between the use of ICT for learning and students' outcomes. However, this literature has not taken into account the role that the countries' stock of human capital can have in the successful use of ICT for learning. In the empirical application that we have carried out, with data from a large-scale sample of 363,412 students enrolled in 13,215 schools of 48 countries, the results that we obtained strongly supported the evidence of a positive effect of the stock of human capital on ICT use for learning. When we considered the moderator-effect of the stock of human capital, we found that the relationship between ICT use and students' outcomes was greater the higher the countries' stock of human capital was. Regardless of the stock of human capital of the countries included in our sample, the relationship between students' outcomes and ICT use turned positive when we considered the average stock of human capital of the countries as a moderator-effect.

When we focused just in the variable ICT use at school, we found a negative relationship between students' outcomes and ICT use at school, in line with previous empirical research based on large-scale assessments data and a broad set of countries (Falck et al., 2018b; Petko et al., 2017; Skryabin et al., 2015; D. Zhang & Liu, 2016). Petko et al. (2017) stated that the relationship between students' outcomes and ICT might be influence more by students' positive experience in terms of quality using ICT than the quantity of its use. D. Zhang & Liu (2016) suggested that this negative relationship could be explained by the overall unproductive use of ICT students did, due to the mismatch between students' learning necessities and ICT pedagogical resources used in educational processes. Skryabin et al. (2015) argued that this negative relationship might be influenced by specific uses of ICT and the narrow participation ICT programs have had in the curriculum. The study conducted for Falck et al. (2018b) was the only one that found a null effect of ICT use at school on students' outcomes. The authors stated that this null effect was explained by the opposite effects (positive or negative) depending on the ICT activity carried out. Other studies, overall, reached similar results as ours but based on a single country subsample from a large-scale assessments (Alderete et al., 2017; Cabras & Tena Horrillo, 2016; De Witte & Rogge, 2014; Erdogdu & Erdogdu, 2015; Fernández-Gutiérrez et al., 2020; Gómez-Fernández & Mediavilla, 2021).

Nevertheless, we looked in a different direction to understand the relationship between ICT use at school and students' outcomes, hypothesizing that the countries' stock of human capital might have a positive externality that influenced the relationship between students' outcomes and ICT use. We confirmed our hypothesis according to previous arguments which supported the role of the stock of human capital as a catalyst of new technologies (Barcenilla et al., 2019; Funke & Strulik, 2000; Gimenez, 2006; Labordeta & Giménez, 2012; López-Pueyo et al., 2018), its capacity to create and improve a pedagogical and institutional educational environment (Doms et al., 2010; Lochner & Moretti, 2004; Milligan et al., 2004; Reiter, C. , Özdemir, C., Yildiz, D. , Goujon, A. , Guimaraes, R. , & Lutz, 2020), and its function engaging better teachers (Berlinski & Ramos, 2018; Correa et al., 2015). Regardless of the subject assessed and the human capital indicator considered, average years of schooling (BL) and average years of schooling weighted by the Mincerian rates of return to education (PWT), the moderator-effect of the stock of human capital turned a negative relationship between students' outcomes and ICT use at school into a positive one.

A key limitation of this study is that we have used a concept of human capital focused just on its educational dimension. The indicator of average years of schooling is the most commonly used in empirical studies, nevertheless it does not account for other dimensions of the concept of human capital different from formal education, as are health, experience, or on-the-job training (Winters, 2013). A further line of analysis could include new perspectives in the measurement of human capital. In this sense, working with measurements of the stock of human capital based on the skills that individuals possess become crucial. Surveys such as the Programme for the International Assessment of Adult Competencies (PIAAC), carried out by the OECD, have pointed out the big differences that exist in labour force skills in developed countries. Therefore, the incorporation of data coming from (PIAAC) results a promising idea to extend the present analysis in further studies to smaller samples that just include developed countries.

In line with the prior limitation, it is important to highlight that the measures of human capital we have incorporated in the analysis do not account for the quality of education, specifically measured by the results of international cognitive test. This is becoming a very popular approach in the literature. We point out that, in the present study, was not possible to account for these measures, as this was indeed the independent variable we explained in the model. Nevertheless, we have to point out that, as the stock of human capital measured in the PWT is weighted by the rates of return to education, this measure can be considered to be accounting indirectly for the quality of the education.

From a policy making perspective, our results warn scholars and policy makers about the role of the stock of human capital as a mediator to leverage the use of ICT for learning purposes. Our findings suggest that, at a time when a critical view of the role of ICT in education is beginning to prevail, policy makers should bear in mind that the effect of ICT could be mediated by intermediate variables that offer a new perspective in the calculation of the true contribution of ICT to learning.

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CHAPTER IV

ICT USE AT SCHOOL: DIFFERENCES IN MATHEMATICS PERFORMANCE BETWEEN GIFTED STUDENTS AND THEIR PEERS

IV

CHAPTER IV. ICT USE AT SCHOOL: DIFFERENCES IN MATHEMATICS PERFORMANCE BETWEEN GIFTED STUDENTS AND THEIR PEERS

Abstract

Previous empirical studies have paid little attention to whether the relationship between ICT use and performance differs between gifted students and their peers. We tested it using a large-scale multinational sample of 236,938 adolescents attending 10,213 schools in 44 countries, from the Programme for International Student Assessment Questionnaire (PISA) 2018. We estimated a hierarchical linear model (HLM) and found that only gifted students benefit from ICT use in mathematics performance. The higher their level of performance, the more beneficial ICT use is for gifted students. This relation is negative in the case of the rest of the students. The findings illustrate that policymakers should consider a differentiated approach to ICT use at school depending on the students' level of performance. Gifted students could benefit more from ICT use in learning and the rest of the students from teaching with more human interaction.

Keywords: ICT use, mathematics learning, gifted students, talented students, adolescents, PISA

1. Introduction

Nowadays, ICT plays an essential role in people's daily life, including in the educational field (Comi, Argentin, Gui, Origo, & Pagani, 2017). Fluency in ICT use allows adolescents to fully participate in the economic, social, and cultural life around them and stay connected with each other (OECD, 2015). In this regard, investment in education has not been immune to the recent and rapid digital transformation (De Witte & Rogge, 2014; Fernández-Gutiérrez, Gimenez, & Calero, 2020). This digital transformation has accelerated even further during the Covid-19 pandemic, when ICT has been crucial to ensuring educational systems functioning (König, Jäger-biela, & Glutsch, 2020; OECD, 2021).

According to theoretical arguments supporting ICT use at school, they may facilitate students' learning by a) widening didactic material and learning experience, making lessons more complete and interactive (Comi et al., 2017); b) providing faster access to information (Spiezia, 2011); c) increasing students' flexibility and autonomy and reducing long-term educational costs (de Witte & Rogge, 2014); d) improving students' learning attitude (Alderete et al., 2017); e) contributing to closer monitoring students' progress (Falck, Mang, & Woessmann, 2018); and d) enhancing the quality of education, by creating new directions and possibilities (Chen, Yun Dai, & Zhou, 2013). However, the benefits of ICT use are contingent on the educational systems' capacity to adapt them to their conditions and teaching methods (Spiezia, 2011), as well as the abilities of teachers and students to use them effectively (de Witte & Rogge, 2014). Contrariwise, the arguments against ICT use for education claim that they a) reduce human interaction and undermine the teachers-students relationship (de Witte & Rogge, 2014; Livingstone, 2012); b) restrict students' creativity (Spiezia, 2011); c) distract them (de Witte & Rogge, 2014; Spiezia, 2011); and d) undermine discipline (Falck et al., 2018). The contribution of ICT to students' performance depends on the net effect of these likely ICT use arguments in favor and against learning.

An extensive body of empirical research has not found clear evidence to support the positive effect of ICT on performance. Some authors have suggested that this effect may differ depending on the subject (Fernández-Gutiérrez et al., 2020), the level of the students' performance (Giambona, & Porcu, 2015), and other contextual student-, school- and country-related factors. Despite efforts to understand the relationship between ICT use and performance, the question remains open (Hu, Gong, Lai, & Leung, 2018).

Previous empirical studies have paid little attention to whether the relationship between ICT use and performance differs between gifted students and their peers (Fernández Batanero, Reyes Rebollo, & Montenegro Rueda, 2019). By gifted student is understood "*demonstrated excellence by age-appropriate standards, through authentic, exceptional performance or potential for excellence, demonstrated through aptitude tests, interviews, and clinical observations of behavior and performance*" (Yun-Dai, 2009, p. 41). Theoretical investigations have addressed the capacity of ICT to meet gifted education, leading to better performance (García-Perales & Almeida, 2019). The ICT has the potential to stimulate students' engagement and commitment by providing teachers with instructional tools to challenge gifted students (Blair Heald, 2016). The ICT tools may also enable tailored instruction and self-learning for gifted students by giving them a broader scope of resources (Chen et al., 2013). The ICT-based learning might also enhance gifted students' motivation and creativity due to the greater flexibility to accelerate and enrich the learning processes they support (Housand, & Housand, 2012).

Mathematics has been considered a more suitable subject to incorporate computer-based teaching (Ke, 2014; McCoy, 1996; Wiest, 2001). Mathematics is also the subject with relatively more research analyzing the effect of ICT use on gifted education (Fernández Batanero et al., 2019). However, the existing literature focuses on developed countries and particular contexts; without comparing the effect of ICT use on the mathematics performance of gifted students and their peers (for example, see, Cooper, 2018; Gadanidis, Hughes, & Cordy, 2011; Subhi, 1999; Wang, Huang, & Hwang, 2016).

The present study provides theoretical and empirical evidence on whether gifted students and their peers perform differently from ICT use in mathematics. We suppose that 1) the use of ICT at school is related to students' mathematics performance; 2) gifted students and their peers perform differently from ICT use in mathematics performance. To the best of our knowledge, the present study is the first research addressing these hypotheses based on a large multinational sample. We use a sample of 236,938 students enrolled in 10,213 schools from 44 developed- and developing- countries coming from the Programme for International Student Assessment Questionnaire (PISA). Additionally, this rich dataset lets us employ two indexes measuring ICT use at school and control a vast set of student-, school- and country-level learning factors.

Our main findings show that the relationship between the ICT use at school and the mathematics scores is positive and significant for gifted students. For their peers, it is negative and significant. The higher the gifted student's performance level, the greater (more positive) the relationship between ICT use at school and mathematics' performance. These findings suggest that educational policy should implement ICT-based activities cautiously and circumspectly by distinguishing gifted students from their peers.

The paper organizes as follows. Section 2 presents a literature overview on the relationship between ICT use at school and mathematics' performance and whether it may vary between gifted students and their peers. Section 3 explains the methodology and data used in the research. Section

4 describes the estimation results. Section 5 covers the discussion on the main findings. Section 6 concludes and presents implications for educational policy.

2. ICT Use and Students' Mathematics Performance

In recent years, many studies have analyzed the relationship between the availability and use of ICT and students' performance in different subjects, including mathematics. These studies are based on experimental and quasi-experimental analyses and statistical estimations that use large international datasets (such as PISA or Trends in International Mathematics and Science Study, TIMMS). Overall, the experimental studies found ICT's positive- or non-significant- effects on mathematics performance. The studies based on large-scale samples found that ICT availability tends to be positively related to mathematics performance, while ICT use tends to show a negative relationship. For a thoughtful literature review, see Bulman & Fairlie (2016) and Fernández-Gutiérrez et al. (2020).

3. Do Gifted Students Use and Leverage ICT Differently for Mathematics Learning?

Previous literature has argued that ICT tools and activities provide a wide range of possibilities to enhance gifted education (Pyryt, 2009). These are related to gifted students' unique features, such as outstanding intelligence, excellent performance, and high potential to excel or perform flawlessly (Pfeiffer, 2015). Gifted students benefit more when using ICT since they are given wider opportunities to utilize their skills, develop their creativity, and expand their learning (Sheffield, 2007). The technology-pervasive environments motivate and enable gifted students to perform differently, allowing them to seek challenging tasks with self-supervision to accelerate the manifestation and development of their exceptional abilities (Housand & Housand, 2012).

Many scholars agree that ICT is an essential tool for personalizing the curriculum. It is essential when gifted students learn together with their peers, because incorporating technologies in learning processes helps create challenging activities and provides an individual approach for gifted education (Goodhew, 2009; Swan et al., 2015). ICT use can facilitate critical thinking and social-emotional needs in gifted students, who should be equipped with substantial digital skills (Periathiruvadi & Rinn, 2014). However, considering ICT as an essential tool, it is necessary to create effective and independent environments for individualized gifted education (Kontostavlou & Drigas, 2019). ICT use was proposed not only for the effective teaching of gifted students (Mustafayeva, 2020), but also for recognizing gifted students by using ICT as a target experimental group for designing and applying appropriate digital teaching and assessment methods at schools (Ahmad et al., 2014). This potential of ICT use for gifted education has also been acknowledged in mathematics learning, particularly by providing gifted students with more challenging learning activities to ensure their excitement and manifest mathematical abilities (Gadanidis et al., 2011).

However, empirical research focusing on whether ICT use benefits gifted students in their mathematics performance is scarce (Chen et al., 2013; Fernández Batanero et al., 2019). The empirical literature is even more limited when analyzing the differences in ICT use between gifted students and their peers. Bartelet, Ghysels, Groot, Haelermans, & van den Brink (2016) compared the effect of ICT on low-, middle-, and high-achieving students' mathematics performance. They found that the low- and middle-achieving students improved mathematics performance more than those who did not use ICT. Wang et al. (2016) compared the differential benefits of an ICT-based program for mathematics performance between gifted students and their peers. They found that gifted students obtained better results in mathematics problem-solving tasks, were more motivated, and had better attitudes towards learning than their peers.

Among the studies analyzing the effects of ICT use on gifted mathematics performance, most of them did not compare it with the performance of their peers. Ravaglia et al. (1995) found that the average performance of the gifted students participating in APGY Advanced Placement in mathematics was considerably higher than those obtained by nationwide students enrolled in higher schooling levels. Subhi (1999) found that gifted students using *LOGO* programming performed significantly higher in mathematics and manifested higher creativity in figural and verbal domains than gifted students who did not use *LOGO*. Gadanidis et al. (2011) found that using software that integrated mathematics and art stimulated gifted students' engagement, creativity, excitement, and collaborative knowledge. Finally, Cooper (2018) found non-significant differences in mathematics performance between the treated group that used digital game-based learning (DGBL) and the control group, even conducting gender analysis. They state that this result may be explain due to the differences in the curricular design of mathematics learning.

4. Method

We conducted an empirical analysis based on the PISA 2018 dataset to evaluate whether the relationship between ICT use at school and PISA mathematics scores differed between gifted students and their peers. We employed a large-scale sample of 236,938 students enrolled in 10,213 schools in 44 countries.

4.1 Empirical Approach

We estimated a mathematical function in which the dependent variable is the student's average PISA score in mathematics and the independent variables a set of learning predictors. The nested structure of our dataset (students were grouped into schools and schools into countries) violated the assumption of independence of the observations (Hox, 2010). The estimation method that we used, HLM, allowed us to obtain unbiased estimations considering this nested structure. The HLM we estimate can be expressed as:

$$\boldsymbol{Y}_{ijk} = \beta_0 + \beta_1 ICT_{ijk}^{m} + \beta_2\, Gifted_{ijk} + \beta_3 ICT_{ijk}\, Gifted_{ijk} + \boldsymbol{\beta_{ijk}} \boldsymbol{X}_{ijk} + \boldsymbol{\beta_{0jk}} \boldsymbol{Z}_{0jk} + \boldsymbol{\beta_{00k}} \boldsymbol{W}_{00k} + \varepsilon_{ijk} \quad (1)$$

$$\beta_0 = \gamma_{000} + u_{0jk} + v_{0k} \quad (2)$$

In Eq. (1), $\boldsymbol{Y}_{ijk}$ was the expected mathematics' score for student *i* enrolled in school *j* in country *k*; ICT_{ijk} was the ICT used at school for student *i* enrolled in school *j* in country *k*; $Gifted_{ijk}$ indicated whether the student was gifted; $\boldsymbol{X}_{ijk}$ is the vector of student-level predictors; $\boldsymbol{Z}_{0jk}$ the vector of school-level predictors; $\boldsymbol{W}_{00k}$ the vector of country-level predictors; ε_{ijk} the unexplained component.

Eq. (2) represented the complex error structure of the model, in which the intercept may vary randomly by school- and country-level. γ_{000} was the mathematics grand mean for the total sample; u_{0jk} and v_{0k} were the random effects to allow the intercept to vary randomly by school- and country-level, respectively.

4.2 Data

The primary data source for this study was the PISA 2018 questionnaire round, released in 2020. This large-scale multinational assessment, carried out by the Organization for Economic Co-operation and Development (OECD), measures reading, mathematics, and science knowledge and skills to meet real-life challenges in a representative sample of the total population of 15-year-old students attending educational institutions at grade seven or higher in participating countries or economies (OECD, 2019). PISA further conducts background questionnaires, which provide information about students' context: family background, school organization, and learning environment. Additionally, an *ICT familiarity questionnaire* asks about students' access to- and use of- ICT devices and media at home and school and their confidence in performing ICT-based activities (OECD, 2019a, 2021).

PISA 2018 edition included 612,004 students enrolled in 21,903 schools in 79 countries and economies. Among them, 47 countries completed the PISA background *ICT familiarity questionnaire*. After excluding missing values, our final sample consisted of 236,938 students, enrolled in 10,213 schools in 44 countries

Dependent Variable

To increase the accuracy of students' scores measurement, PISA computes ten plausible values. However, since we estimate a three-level HLM and have a large sample of students, using plausible values analysis makes the estimations extremely computationally demanding. We compute the mathematics score as the student's average of the ten plausible values to deal with it. Using only one plausible value or an average is a relatively common procedure in literature when working with large PISA samples (Ammermueller, 2007; Gimenez & Vargas-Montoya, 2021; Lavy, 2015; L. Zhang, Khan, & Tahirsylaj, 2015).

Independent Variables

We focused on two PISA ICT use at school indexes: *Subject-related ICT use during lessons* (PISA code *ICTCLASS*) and *use of ICT at school in general* (PISA code *USESCH*). The *ICTCLASS* index is based on five PISA items (*IC150Q01HA* to *IC150Q05HA*), asking students' time spent using digital devices during classroom lessons in a typical school week in the following subjects: test language lessons, mathematics, science, foreign language, and social sciences. The possible responses are: "No time", "1–30 min a week", "31–60 min a week", and "More than 60 min a week". The *ICTCLASS* index is an essential innovation in PISA 2018, because it accounts for the effective time spent in learning activities using ICT. The *USESCH* index is based on nine PISA items (*IC011Q01TA* to *IC011Q09TA*), which asks students' frequency of using digital devices for the following activities at school: chatting online; using email; browsing the internet; downloading, uploading or browsing material from school's website; posting work on school's website; playing simulations; practicing and drilling; doing homework on a school computer; and using school computers for group work and communication with other students. The possible responses are: "never or hardly ever", "once or twice a month", "once or twice a week", "almost every day", and "every day". Both standardized indexes are constructed by applying the item response theory scaling (IRT) to the information provided by the single items on which they are based.

We computed a categorical variable ($Gifted_{ijk}$ in eq. 1) to classify the students' mathematics performance levels. It is based on the PISA mathematics proficiency scale, which includes seven proficiency levels from 0 to 6 (for an in-depth explanation of the methodology used to construct the scale, see OECD, 2019b). This categorical variable was composed of three possible values: level 0 to 4 PISA proficiency scale, level 5 PISA proficiency scale, and level 6 PISA proficiency scale.[9] PISA categorizes the students classified in these two latter levels of proficiency as top performers. Following Yun-Dai's (2009) definition, we considered PISA top performers as gifted students. The gifted students represented 7.78% of our total sample. To test whether the relationship between ICT use at school and mathematics scores varies between gifted students and their peers, we estimate an interaction term between ICT_{ijk} and $Gifted_{ijk}$.

Table 1 shows the average students' PISA mathematics scores for the sample countries, the *ICTCLASS* and *USESCH* indexes average values and the students' distribution in the PISA mathematics proficiency scale. The average mathematics score in the total sample of students was

[9] The OECD distinguishes seven levels of academic performance. Level 0 is the lowest and, in the case of mathematics, it is composed of the students who obtained a result below 189.33 points. Levels 5 and 6 are considered the levels of excellence. They group students who obtained results between 625.61 and 698.32 (level 5) or above 698.32 points (level 6).

470.72, with a standard deviation of 95. It ranged from 327.72 in the Dominican Republic to 568.29 in Singapore. The *ICTCLASS* index average was -0.06, with a standard deviation of 1.01. From -0.63 in Brazil to 1.58 in Denmark. The average *USESCH* index was 0.02, with a standard deviation of 1.04. From -1.11 in Japan to 0.71 in Thailand. Of the students in the sample, 1.39% achieved level 6 of proficiency, and 6.39% achieved level 5.

Table 1. Countries' Average PISA Score in Mathematics, Subject-Related ICT Use During Lessons (ICTCLASS) and Use of ICT at School in General (USESCH), Average Values, and Its Students' Percentual Distribution by the PISA Mathematics Proficiency Scale

Country name	Country code	Mathematics score	ICTCLASS	USESCH	Level 6	Level 5	Level 0 to 4
Singapore	**SGP**	568.29	-0.336	0.083	11.58	25.36	63.06
Hong Kong	**HKG**	553.92	-0.403	-0.118	7.34	21.43	71.23
Korea	**KOR**	527.55	0.074	-0.724	5.62	14.29	80.09
Czech Republic	**CZE**	515.71	-0.307	0.071	3.21	13.75	83.05
Switzerland	**CHE**	516.09	-0.274	-0.144	3.19	12.04	84.76
Poland	**POL**	516.42	-0.223	0.144	2.88	10.88	86.24
Japan	**JPN**	526.59	-0.611	-1.112	2.62	14.27	83.11
Estonia	**EST**	523.48	0.005	-0.119	2.48	10.46	87.06
Belgium	**BEL**	510.77	-0.239	-0.160	2.09	12.65	85.26
Australia	AUS	490.71	0.741	0.471	1.60	6.89	91.51
Slovenia	**SVN**	496.85	-0.374	0.020	1.39	7.81	90.80
Slovak Republic	SVK	488.59	-0.003	0.171	1.31	7.90	90.80
Italy	ITA	495.07	-0.067	0.049	1.27	7.70	91.02
Thailand	THA	491.16	0.128	0.712	1.20	4.82	93.98
Luxembourg	LUX	483.81	-0.347	-0.031	1.17	8.05	90.78
United Kingdom	**GBR**	495.18	-0.205	0.077	1.11	7.44	91.45
Malta	MLT	473.79	-0.082	-0.506	1.07	5.71	93.22
Iceland	**ISL**	494.78	0.453	0.263	0.97	7.34	91.69
Finland	**FIN**	507.51	0.089	0.178	0.90	8.43	90.67
Israel	**ISR**	465.03	-0.071	-0.040	0.89	6.15	92.96
France	**FRA**	487.01	-0.201	-0.050	0.89	7.96	91.15
Lithuania	LTU	478.90	0.030	0.134	0.89	5.43	93.68
Denmark	**DNK**	497.27	1.581	0.622	0.85	6.79	92.36
United States	USA	473.31	0.400	0.419	0.76	5.60	93.63
Russian Federation	RUS	488.76	0.062	0.316	0.66	5.70	93.64
Bulgaria	BGR	438.69	-0.036	0.474	0.49	2.66	96.85
Serbia	SRB	448.80	-0.292	0.012	0.44	3.21	96.35
Turkey	TUR	452.61	0.231	-0.174	0.42	3.25	96.33
Spain	ESP	491.16	-0.058	-0.131	0.41	5.66	93.93
Ireland	**IRL**	499.55	-0.371	-0.393	0.34	6.42	93.24
Croatia	HRV	462.57	-0.328	-0.062	0.33	3.45	96.22
Greece	GRC	454.22	-0.432	-0.149	0.30	2.26	97.44
Kazakhstan	KAZ	440.59	0.333	0.408	0.25	2.67	97.09
Albania	ALB	437.73	-0.252	-0.041	0.11	1.18	98.71
Brunei Darussalam	BRN	430.24	-0.278	-0.414	0.10	2.33	97.57
Chile	CHL	434.62	-0.104	0.091	0.07	1.26	98.67
Brazil	BRA	384.99	-0.630	-0.312	0.05	0.57	99.38
Georgia	GEO	399.59	-0.493	-0.308	0.02	0.65	99.34
Mexico	MEX	415.58	-0.334	0.074	0.01	0.25	99.74
Costa Rica	CRI	401.37	-0.331	0.093	0.00	0.08	99.92
Dominican Republic	DOM	327.72	-0.442	-0.210	0.00	0.00	100.00
Morocco	MAR	366.54	-0.310	-0.365	0.00	0.03	99.97
Panama	PAN	354.74	-0.480	-0.050	0.00	0.02	99.98
Uruguay	URY	417.69	-0.145	0.174	0.00	0.44	99.56

Notes. Countries fill in light blue are the ones classified by PISA as highest-performing educational systems (hereafter, countries with higher PISA mathematics scores) (OECD, 2019b, pp. 17). Countries were sorted from those with the highest to the lowest share of students classified at the level 6 of the PISA proficiency scale.

In addition to ICT use at school, we identified a set of predictors for academic success commonly used in related literature. At the student-level, *gender* (PISA code *ST004D01T*), *age* (PISA code *AGE*), *country of birth* (PISA code *ST019AQ01T*), and the composed indexes of *economic, social and cultural status* (PISA code *ESCS*) and *attitude towards school: learning activities* (PISA code *ATTLNACT*). Male students usually overperform females in mathematics (Torrecilla Sánchez, Olmos Miguélañez, & Martínez Abad, 2019). Being older (there can be a difference of up to 11 months in students' age) is related to higher performance (OECD, 2014, 2016). Students born out of the country are susceptible to language and integration issues that cause them to catch up behind native students in terms of performance (Potochnick, 2018). Socio-economically disadvantaged students tend to underperform those from advantaged backgrounds (Hu et al., 2018; D. Zhang & Liu, 2016). Finally, a higher motivation or attitude to learning from students is related to higher performance (Dunn & Kennedy, 2019).

As school-level predictors, we included every school's average value of the index *ESCS* as a peer effect proxy; the principals' perception of teachers' skills to introduce digital devices in instruction (PISA code *SC155Q06HA*); and a set of composed indexes that 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*), *disciplinary climate in test language lessons* (PISA code *DISCLIMA*); and, the categorical variable *school location* (PISA code *SC001Q01TA*) which captured the size of the community where the school was located.

Students attending schools with higher average *ESCS* can benefit from positive externalities (Ammermueller & Pischke, 2009; Gimenez, Ciobanu, & Barrado, 2021). Teachers' skills in integrating ICT in learning are related to higher students' performance (Biagi & Loi, 2012; Spiezia, 2010). The education of the teachers tends to correlate positively with students' performance. Furthermore, teachers' behavior, attitudes, and relationship with students are vital enablers of learning (Palardy & Rumberger, 2008). The shortage of educational materials and staff tends to be negatively related to students' performance (Chin, 2005; Hanushek & Woessmann, 2011). The relationship between disciplinary climate and students' performance tends to be positive (Gimenez, Barrado & Arias, 2019; Guo, Li, & Zhang, 2018; Kinsler, 2013). Urban schools tend to have better infrastructure and teachers than rural ones, increasing their students' performance (Gimenez, Martín-Oro, & Sanaú, 2018; Sullivan, Perry, & McConney, 2013).

As country-level predictors, we considered the *government expenditure on education (% GDP)* and the country's level of development, measured through the *Human Development Index (HDI)*. The data on expenditure on education was retrieved from the World Development Indicators of the World Bank. The HDI was retrieved from the Human Development Reports 2020 of the United Nations. There is a debate about the relationship between the expenditure on education and students' outcomes (Vegas & Coffin, 2015). Despite some previous research finding a positive relationship in particular contexts (French, French, & Li, 2015; Hong & Zimmer, 2016; Vegas & Coffin, 2015), overall, cross-country empirical evidence is inconclusive (Hanushek & Woessmann, 2017). The countries' human development tends to be positively related to students' outcomes (Campbell, McIntyre, & Kucirkova, 2021). Table 2 shows the descriptive statistics of the variables we worked with.

Table 2. Dependent and Independent Variables Descriptive Statistics

Variable	Mean	SD	Median	Min	Max	N	Missing
Dependent variable							
Mathematics score	470	95.00	471	90.60	825	360,444	0
Student-level predictors							
Subject-related ICT use during lessons (ICTCLASS) (CI)	-0.06	1.01	-0.03	-1.22	2.44	309,162	51,282
Use of ICT at school in general (USESCH) (CI)	0.02	1.04	0.11	-2.54	3.35	290,473	69,971
Performance level							
Level 0 to 4 PISA proficiency scale	92.20%						
Level 5 PISA proficiency scale	6.43%						
Level 6 PISA proficiency scale	1.37%						
Gender						360,444	0
Female	49.90%						
Male	50.10%						
Age	15.80	0.29	15.80	15.10	16.30	360,444	0
Country of birth						350,273	10,171
Country of the test	93.60%						
Other country	6.40%						
Economic, social and cultural status (CI)	-0.24	1.10	-0.15	-8.17	4.21	351,730	8,714
Attitude towards school: learning activities (CI)	0.01	1.01	0.03	-2.54	1.08	332,429	28,015
School-level predictors							
School average value of ESCS (CI)	-0.24	0.07	0.15	-3.99	2.25	359,726	718.00
Proportion of all teachers fully certified (CI)	0.83	0.31	1.00	0.00	1.00	303,131	57,313
Teacher behavior hindering learning (CI)	0.15	1.10	0.23	-2.09	3.83	344,177	16,267
Perceived teacher's interest (CI)	0.08	1.00	0.17	-2.22	1.82	343,156	17,288
Shortage of educational material (CI)	0.07	1.06	0.10	-1.42	2.96	343,333	17,111
Shortage of educational staff (CI)	-0.03	1.04	0.01	-1.86	4.04	342,835	17,609
Adaptation of instruction (CI)	0.03	1.01	0.10	-2.27	2.01	340,598	19,846
Disciplinary climate in test language lessons (CI)	0.08	1.09	-0.04	-2.71	2.03	347,678	12,766
Community in which the school is located						341,053	19,391
Village, small town or town (< 100.000 people)	58.97%						
City or large city (>= 100.000 people)	41.03%						
Country-level predictors							
Government expenditure on education (% GDP)	4.54	1.27	4.21	2.05	7.82	360,444	0
Human Development Index (HDI)	0.86	0.06	0.88	0.68	0.95	360,444	0

Notes. 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, the values in the mean column reflect the percentage of observations that represents each category excluding missing values. The *government expenditure on education (%GDP)* was retrieved from https://data.worldbank.org/indicator/SE.XPD.TOTL.GD.ZS on January 13th, 2020. We used 2017 data, which was the most recent year with least missing information and in the case of missing data we used the most recent value available. The *Human Development Index* (*HDI*) was retrieved from http://hdr.undp.org/en/data. We used the most recent value available for each country

5. Results

Tables 3 and 4 show Equations (1) and (2) estimations, considering our two key ICT use variables: *ICTCLASS* and *USESCH*. The fixed effects would refer to the overall expected effects of the students', schools', and countries' characteristics on mathematics scores. The random-effects, at the bottom of the table, determine whether these effects differ between schools or countries, showing the standard deviations from the overall mean with origin in the school-and-country-level variance unaccounted for in the model.

Table 3. Hierarchical Linear Models Predicting PISA Mathematics' Scores with Subject-Related ICT Use During Lessons (PISA code ICTCLASS)

Variable	Value		
Fixed effects	*Estimate*	*SE*	*P > |t|*
(Intercept)	151.749	46.496	0.001
Subject-related ICT use during lessons (ICTCLASS)	-2.828	0.138	0.000
Proficiency level [a]			
Level 5 PISA proficiency scale	108.693	0.517	0.000
Level 6 PISA proficiency scale	158.699	1.165	0.000
(ICTCLASS) x (Level 5 PISA proficiency scale)	6.430	0.501	0.000
(ICTCLASS) x (Level 6 PISA proficiency scale)	7.357	1.101	0.000
Gender			
Male	10.296	0.242	0.000
Age	7.682	0.411	0.000
Country of birth			
Other country	-12.397	0.618	0.000
Economic, social and cultural status	10.825	0.141	0.000
Attitude towards school: learning activities	1.834	0.121	0.000
School average value of economic, social and cultural status	39.123	0.657	0.000
Proportion of all teachers fully certified	1.741	1.220	0.153
Teacher behaviour hindering learning	-0.545	0.348	0.118
Perceived teachers' interest	1.703	0.144	0.000
Shortage of educational material	-0.835	0.407	0.040
Shortage of educational staff	0.558	0.423	0.187
Adaptation of instruction	2.131	0.137	0.000
Disciplinary climate in test language lessons	5.108	0.127	0.000
School location			
City or large city (>= 100.000 people)	-0.846	0.793	0.286
Government expenditure on education (% GDP)	-2.101	2.804	0.454
Human Development Index (HDI)	241.796	53.815	0.000
Random effects			
Level 3: Intercept		493.30	22.21
Level 2: Intercept		641.70	25.33
Level 1: Residual		3,230.50	56.84
Sample size			
Total sample (students)			236,938
Level 2 group (schools)			10,213
Level 3 group (countries)			44

Notes. In random effects, values reflect variance and standard deviation. In sample size, values reflect observations.
[a] The OECD distinguishes 7 levels of proficiency, from level 0 to 6. The group students who obtained results between 625.61 and 698.32 are categorized at level 5, while those who obtained results above 698.32 points at level 6. The students from levels 5 and 6 are categorized as top performers.

Table 4. Hierarchical Linear Models Predicting PISA Mathematics' Scores with ICT at School in General (PISA code USESCH)

Variable	Value		
Fixed effects	*Estimate*	*SE*	*P* > |*t*|
(Intercept)	157.537	46.777	0.001
Use of ICT at school in general (USESCH)	-8.722	0.128	0.000
Proficiency level [a]			
Level 5 PISA proficiency scale	110.131	0.532	0.000
Level 6 PISA proficiency scale	160.967	1.254	0.000
(USESCH) x (Level 5 PISA proficiency scale)	11.541	0.524	0.000
(USESCH) x (Level 6 PISA proficiency scale)	12.444	1.271	0.000
Gender			
Male	10.665	0.247	0.000
Age	7.493	0.419	0.000
Country of birth			
Other country	-11.679	0.626	0.000
Economic, social and cultural status	11.566	0.144	0.000
Attitude towards school: learning activities	1.892	0.123	0.000
School average value of economic, social and cultural status	38.418	0.663	0.000
Proportion of all teachers fully certified	1.666	1.227	0.175
Teacher behaviour hindering learning	-0.518	0.350	0.139
Perceived teachers' interest	2.009	0.146	0.000
Shortage of educational material	-1.093	0.409	0.007
Shortage of educational staff	0.520	0.425	0.221
Adaptation of instruction	2.307	0.139	0.000
Disciplinary climate in test language lessons	4.835	0.129	0.000
School location			
City or large city (>= 100.000 people)	-0.815	0.797	0.307
Government expenditure on education (% GDP)	-1.642	2.820	0.560
Human Development Index (HDI)	236.075	54.121	0.000
Random effects			
Level 3: Intercept		498.90	22.34
Level 2: Intercept		630.10	25.10
Level 1: Residual		3,232.30	56.85
Sample size			
Total sample (students)			225,860
Level 2 group (schools)			10,187
Level 3 group (countries)			44

Notes. In random effects, values reflect variance and standard deviation. In sample size, values reflect observations.
[a] The OECD distinguishes 7 levels of proficiency, from level 0 to 6. The group students who obtained results between 625.61 and 698.32 are categorized at level 5, while those who obtained results above 698.32 points at level 6. The students from levels 5 and 6 are categorized as top performers.

The *ICTCLASS* and *USESCH* were, in general terms, negatively and significantly related to mathematics scores ($p < 0.01$). The gifted students scored significantly better than their peers; and the students at level 6 of the PISA mathematics proficiency scale scored higher than those at level 5 ($p < 0.01$). The coefficient associated with the interaction term between ICT use at school and mathematics performance level was positive and significant ($p < 0.01$). It means that the *ICTCLASS* and *USESCH* were positively related to mathematics scores of the gifted students. This coefficient was greater (more positive) for the students at level 6 of the PISA mathematics proficiency scale than for those at level 5. We came to robust results regardless of the ICT use variable employed.

Regarding the remaining covariates, *male* students scored higher than *females* ($p < 0.01$). The *age* was positively related to students' scores ($p < 0.01$). *Non-native students* scored lesser ($p < 0.01$). The indexes *economic, social and cultural status* and *attitude towards school: learning activities* were positively related to students' scores ($p < 0.01$). The *school average value of ESCS* was positively related to students' scores ($p < 0.01$). The index *proportion of all teachers fully certified* were positively and non-significantly related to students' scores. The index *teacher behaviour hindering learning*) were negatively and non-significantly related to students' scores. The index *perceived teachers' interest* was positively related to students' scores ($p < 0.05$). The index *shortage of educational materials* was negatively related to students' scores with ($p < 0.05$) for the estimation with ICTCLASS and ($p < 0.01$) for the estimation with USESCH. The index *shortage of educational staff* was positively and non-significantly related to students' scores. The index *adaptation of instruction* was positively related to students' scores ($p < 0.01$). The index *disciplinary climate in test language lessons* was positively related to students' scores ($p < 0.01$). The *school location* was negatively and non-significantly related to students' scores. The *government expenditure on education (%GDP)* was negatively and non-significantly related to students' scores. The *Human Development Index (HDI)* value of the students' country was positively related to students' scores ($p < 0.01$).

Altogether, these findings supported our hypotheses: 1) the use of ICT at school is negatively related to mathematics performance; 2) gifted students and their peers perform differently from ICT use at school in terms of mathematics performance. The gifted students benefited from ICT use at school, while their peers did not. The higher the gifted students' level of performance was, the higher (more positive) the benefit they obtained from ICT use at school in terms of performance.

6. Discussion

To interpret this study's findings is crucial to emphasize the main attributes of gifted students and how they may influence their performance by using ICT. Gifted students have an exceptional cognitive ability, which may be defined as a "*mental capability that ... involves the ability to reason, plan, solve problems, think abstractly, comprehend complex ideas, learn quickly and learn from experience*" (Gottfredson, 1997, p. 13). It is believed that gifted students are given natural talent (Tannenbaum, 2003) in potential and opportunities (Sternberg, 2003). They demonstrate rapid information processing (Singh, & O'Boyle, 2004; Paz-Baruch, Leikin, Aharon-Peretz, & Leikin, 2014), advanced development of the executive function, manifesting in more efficacious working memory (Aubry, Gonthier, & Bourdin, 2021), sustained attention (Shi et al., 2013), cognitive control (Vaivre-Douret, 2011), and higher capacity for solving problems in comparison with their peers (Vogelaar, Sweijen, & Resing, 2019). They are also very selective in their preferences for group or individual work. As they have their own pace of activity, they do not like to depend on their peers in the dynamics of their educational advances (Wismath & Orr, 2015). Neither do they appreciate collaborative problem solving since they weigh the risks and benefits associated with the context of the educational situation (Kanevsky et al., 2021).

There are also some peculiarities in the interaction between gifted students and ICT use, which are noteworthy to understand our findings. ICT use in the classroom provides gifted students with an opportunity to take responsibility for their own learning and acquire the skills they need to succeed (Blair Heald, 2016). Some researchers emphasize that certain technologies are particularly beneficial to gifted students for enhancing the efficiency and quality of their education (Chen et al., 2013). This is correspondent with the understanding that educational interventions shall be personalized to the specific characteristics of gifted students, who have particular needs and potential (Fernández Batanero, 2019; García-Martínez et al., 2021). Goodhew (2009) recommended providing gifted students with access and instruction to use ICT fluently to expand their independence and competence.

Furthermore, to understand our results, important distinctions regarding ICT use between gifted students and their peers should be made. Overall, gifted students are highly motivated when they seek the opportunity to learn, which is considered a crucial factor in developing their outstanding potential into high levels of academic performance (Plucker & Peters, 2016). Gifted students outperform their peers in speed and accuracy of new skills acquisition (Leikin, Leikin, & Waisman, 2017), including digital ones (Neumann & Ronksley-Pavia, 2021). They use abundant cognitive resources to think and learn more effectively (Navas-Sanchez et al., 2016). Such cognitive resources are associated with more complex and unique patterns of brain activity (Geake, 2009), enchanted bilateral communication (Mrazik, & Dombrowski, 2010), and heightened frontal-parietal activation during task performance (Anomal et al., 2020; Jung, & Haier, 2007). They can stay focused on the task over time much longer, while their peers get distracted more easily (Shi et al., 2013).

Mathematics'performance and its relationship with ICT use depends on many other factors, among them, logical reasoning (Cresswell, & Speelman, 2020), domain-specific numerical skills and knowledge (Jordan, Glutting, & Ramineni, 2010), general intelligence and motivation (Winne, & Nesbit, 2010), self-regulation (Malanchini, Engelhardt, Grotzinger, Harden, & Tucker-Drob, 2019), executive function (Cragg, & Gilmore, 2014), working memory (Raghubar, Barnes, & Hecht, 2010), students' selfconcept in mathematics (Peteros et al., 2020). High mathematical performance can be considered as an indicator of mathematical giftedness, which is connected with mathematical creativity (Leikin, 2019), understood as an ability to perceive original, non-algorithmic, and often insight-based solutions (Leikin, 2021). Since ICT provides a learner with a diversity of tasks and encourages focusing on reflection, verification, decision-making, and problem-solving (Kaushik, 2019), it is not surprising that gifted students benefit the most in terms of their performance from using ICT. Overall, our results support theoretical arguments in favor of ICT use for gifted education

When we compare our findings to those from previous empirical research, we find that, on the one hand, our results support former research that found a positive effect of ICT use on gifted mathematics education (Gadanidis et al., 2011; Ravaglia et al., 1995; Subhi, 1999). Overall, these authors found that ICT benefits gifted students by stimulating their creativity and engagement in mathematics learning. Our results also support empirical research that found differential effects of ICT use on mathematics performance between gifted students and their peers (Wang et al., 2016). The authors explain that this result is due to higher gifted students' problem-solving performance, motivation, and attitude to mathematics learning. On the other hand, however, our findings contradict previous empirical research, which found that gifted students did not benefit from ICT use (Bartelet et al., 2016; Cooper, 2018). The authors argued that the main reason behind this result could be that ICT use was not properly integrated into gifted students' learning strategy.[10] Our results also contradict previous research which found that less-achieving students got more out of ICT use in terms of mathematics performance (Bartelet et al.,

[10] In the case of Bartelet et al. (2016), they studied the effectiveness of a web-based intelligent tutoring system (ITS) that a school offered to its students as an optional assignment; and in the case of Cooper (2018), the purpose of her quasi-experimental non-equivalent control group study was to determine the presence of a statistically significant difference in the mathematics achievement of gifted students when using digital game-based learning.

2016). The authors explained that despite all students having access to the ICT application, gifted students were less likely to use it, due to they did not perceive a benefit of its use.

Summing up, aligned with previous theoretical and empirical research, ICT use at school has a different effect on mathematics performance for gifted students and their peers, by facilitating the process for the first ones and slowing it down for the latter. Thus, it has crucial implications from the policy-making perspective, regarding tuning ICT use during classroom lessons according to students' performance levels.

7. Conclusion and Policy Implications

Educational authorities have invested substantial resources in ICT implementation at schools for learning. Nevertheless, empirical research is inconclusive on the positive effect of ICT use on educational performance. Our results show that the effect of these resources is noteworthily differentiated from gifted students and their remaining peers. We found a net positive relationship between ICT use at school and mathematics performance for gifted students, while for their peers, it was negative. The higher the gifted students' level of performance, the more they get out of ICT use.

This evidence has relevant educational policy implications in designing and tuning curricular programs and teaching resources to meet students' needs and potential. It provides evidence in favor of targeting ICT use programs directly towards mathematically gifted students, who benefit from ICT-based teaching. Students with an adverse effect of the ICT use could benefit from more traditional teaching, higher based on human interaction and lesser based on ICT use. Currently, where full participation in economic, social, and cultural life is mediated by technology, educational systems should better integrate ICT use in learning. In particular, for non-gifted students who have not been leveraging them in performance. With ICT help, diversified educational programs should be designed to teach mathematics, accounting for the student's performance level. The mathematics' teacher can create a unique learning environment, challenging gifted students by using ICT to support their particular needs and potential. Such an approach can also serve as a distributional process of mathematics teaching time, where self-learning using ICT may partially cover gifted education. Consequently, teachers may dedicate more time to the traditional teaching (face-to-face) of their remaining students, increasing their performance. This approach may also motivate non-gifted students to improve their mathematical skills and gain access to individual tasks based on ICT use.

8. References

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CHAPTER V

FINAL CONSIDERATIONS

V

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The empirical literature has not found conclusive evidence on the positive effects of ICT use on students' academic performance. This doctoral thesis addresses three contextual factors that could condition this relationship: the countries' level of economic development, the countries' stock of human capital, and the likely differences in ICT use between gifted students and their peers.

In the second chapter of the thesis, we obtain that the negative relationship between the use of ICT for learning at school and students' academic performance in reading, mathematics, and science is stronger for students enrolled in education systems in less-developed countries than for those enrolled in developed countries.

From the third chapter of the thesis, we conclude that countries' stock of human capital has positive externalities on the use of ICT for educational purposes. The negative relationship that we initially found between the use of ICT for learning and academic performance in reading, mathematics, and science became positive once we consider the moderating effect of the countries' stock of human capital. Countries with a higher stock of human capital obtain greater benefits from ICT investment.

In the fourth chapter of the thesis, we evidence differences in ICT use between gifted students and their peers. Gifted students benefit from using ICT for learning mathematics, while their peers do not. We also conclude that the higher the achievement level of the gifted students, the more they benefit from using ICT for mathematics' learning.

The empirical analysis we have carried out allows us to conclude that the successful use of ICT for learning depends on the students' specific context. We find that in certain environments and for specific students, traditional (face-to-face) learning may be more appropriate, while in others it may be more convenient to learn employing ICT.

It is important to identify the optimal levels of ICT-related versus traditional learning to optimize existing resources. To this end, it is also necessary to determine which subjects and topics within these subjects are more suitable for ICT-based learning and prioritize ICT use for them (e.g., teaching a particular topic such as geometry in mathematics). One of the main advantages of ICT is the possibility of adapting them to the learning needs of students. This advantage could be exploited in the design of "tailor-made" ICT-based educational strategies (e.g., remedial programs for students who are lagging behind, or special achievement programs for outstanding students). Finally, investment in ICT must be accompanied by critical factors to ensure their effectiveness: a) the appropriate incorporation of ICT-based learning into curricula, b) the provision of the necessary physical and pedagogical infrastructure, and c) the adequate training in the use of ICT for teachers and students.

We recognize that the methodologies we have applied in the different chapters have limitations. First, the data on which the results are obtained are cross-sectional. This allows us to get correlation patterns between variables, but PISA does not provide us with longitudinal data that would allow us to use econometric techniques that would make it possible to estimate causality. Second, PISA database lacks control variables at the classroom and teacher levels (among them, their knowledge and skills in using technology). This means that we cannot introduce these elements into our models, even though, they affect students' academic performance. This becomes a source of endogeneity. Third, additionally, there are multiple country context' variables not available in the PISA database that could affect students' academic performance and its relationship with ICT use (e.g., the average expenditure on ICT teacher training, the quality of the country's and educational centers' broadband, or their investment in educational software, among others). Fourth, as previous literature suggests, there is a need in the PISA survey for questions that allow greater precision in measuring ICT use (e.g., quality of use and not just time of use). Fifth, estimating an HLM in three levels using plausible values analysis for such a large sample of students as we use makes the estimations extremely demanding in computational terms. To deal with this, we defined the dependent variables as the student's average score of the PISA ten plausible values, instead of using the imputation of all of them. Although this is a quite standard procedure in the empirical literature when working with large PISA samples, this might conduct to minor changes (of negligible magnitude, as highlighted in chapter two) to the estimated effect sizes and associated standard errors.

From these limitations, we identify future lines of research. We note that experimental and quasi-experimental studies on ICT applications in specific contexts are still very scarce. Their use is an excellent way of ascertaining the true effectiveness of ICT use in learning through estimating causal effects. Both experiments in particular contexts and large-scale surveys should not just lay on variables that measure the access and use of ICT; the empirical studies should pay more attention to the measurement of students' knowledge and skills in the use of ICT. Studies incorporating these variables would provide more robust estimates of academic achievement mediated by ICT use. Finally, a future line of research could take advantage of the new paradigms in the ICT industry, such as machine learning, artificial intelligence, robotic automation, gaming, and the metaverse. All of them can change the way students engage with machines and learning.

The thesis also allows us to arise policy recommendations in a scenario where ICT are crucial in society. The first aspect to highlight is the contextualization of educational investments in ICT. Policymakers are challenged to consider the countries' contexts of the educational systems. An ICT-based educational technology that has been successful in one group of countries will not necessarily be successful in other countries where it is implemented. For example, as the thesis shows, the country's level of development and its stock of human capital are two factors that condition the successful use of ICT for learning. This consideration is even more relevant for less-developed countries, which mainly adopt educational technologies designed for developed countries. Today, it is a reality that educational contexts within and outside countries have significant asymmetries that must be considered in the design of educational strategies. Some of these asymmetries are the countries' educational expenditure, the quality of the teaching staff, the educational institutions' physical and didactic resources, and the student's socioeconomic context.

An additional consideration for successful public policy design is understanding the advantages and disadvantages of ICT for learning. One advantage of particular interest is that ICT offer the possibility of adapting teaching processes to the needs of students. The use of ICT could be a pivotal instrument to address groups of students with learning difficulties or those who require additional support to take advantage of an exceptional learning capacity. Prioritizing ICT for the learning of certain groups of students could free up teaching time to attend face-to-face teaching with other classmates and thus optimize the use of pedagogical resources. Education systems also face the challenge of better integrating ICT into curricula. To this end, it is necessary to precisely identify the optimal levels of ICT use versus traditional teaching and define the subjects and topics within these subjects that are more suitable for ICT-based teaching. For example, the literature highlights that mathematics is one of the most compatible subjects for using ICT for educational purposes. However, empirical evidence also shows that the use of ICT for mathematics' learning must define precisely the topics in which the use of ICT is more efficient than traditional teaching. In summary, this thesis contributes to the understanding that the role of ICT on learning is a cross-cutting and multidimensional phenomenon, which involves studying contextual factors beyond those traditionally analyzed.

Finally, we would like to highlight that the mission of the educational system not only involves the appropriate use of ICT. In a context of accelerated technological change and in which technologies play a central role in today's society, the adequate insertion of people into the digital world is a necessary condition to compete in a globalized world; and this insertion becomes a fundamental goal of the educational system.

APPENDIX. RESÚMENES DE CAPÍTULOS DE RESULTADOS Y CONSIDERACIONES FINALES EN IDIOMA ESPAÑOL

Resumen del II Capítulo

En las últimas décadas, el uso de Tecnologías de Información y Comunicación (TIC) se ha convertido en una prioridad para los sistemas educativos. Sin embargo, no hay evidencia empírica concluyente de una relación positiva entre el uso de TIC y el rendimiento académico de los estudiantes. La literatura ha pasado por alto el rol que los factores contextuales pueden jugar en esta relación, en particular, el del nivel de desarrollo del país. Este artículo aborda empíricamente si la relación entre el uso de TIC para el aprendizaje en los centros educativos y los resultados académicos de los estudiantes difiere entre los países desarrollados y los menos desarrollados. Utilizamos datos de 236,540 estudiantes que asisten a 10,193 escuelas en 44 países, los cuales, se obtienen del Programa para la Evaluación Internacional de Alumnos (PISA) 2018 de la OCDE. Consideramos dos medidas alternativas para clasificar los países según su nivel de desarrollo: el Ingreso Nacional Bruto (INB) per cápita y el Índice de Desarrollo Humano (IDH). Las estimaciones, basadas en un modelo lineal jerárquico, muestran una relación negativa entre el uso de TIC para el aprendizaje y el rendimiento académico de los estudiantes. Esta relación negativa es más fuerte para los estudiantes matriculados en sistemas educativos de países menos desarrollados que para aquellos matriculados en países desarrollados. Los resultados encontrados implican que los *policymakers* deben ser cautelosos al replicar intervenciones y aplicaciones tecnológicas diseñadas para países desarrollados en países menos desarrollados (y viceversa). En especial, en un contexto en el que los países menos desarrollados adoptan, mayoritariamente, materiales pedagógicos basados en TIC que fueron ideados para contextos educativos de países desarrollados.

Resumen del III Capítulo

La literatura empírica ha encontrado una relación débil entre el uso de TIC para el aprendizaje y los resultados académicos de los estudiantes. Sin embargo, esta literatura no ha considerado el rol que el capital humano de los países puede jugar en el aprovechamiento de las TIC con fines educativos, el cual, responde a las complementariedades entre el stock capital humano y la apropiación tecnológica. Nosotros realizamos un análisis empírico con datos de PISA para una muestra a gran escala de 363,412 estudiantes matriculados en 13,215 escuelas de 48 países. Estimamos un modelo lineal jerárquico de tres niveles (estudiantes, escuelas y países), cuyos resultados confirman que el stock de capital humano es una externalidad positiva en el uso de TIC para el aprendizaje. Cuando se considera el efecto moderador del stock de capital humano, la relación negativa entre el uso de las TIC para el aprendizaje y el rendimiento educativo de los estudiantes en lectura, matemáticas y ciencias se vuelve positiva. Cuanto mayor es el stock de capital humano de una economía, mayores son los beneficios que puede obtener de la inversión en TIC para el aprendizaje.

Resumen del IV Capítulo

Los estudios empíricos han prestado poca atención a si la relación entre el uso de las TIC y el rendimiento educativo difiere entre los estudiantes superdotados y sus compañeros de clase. Nosotros evaluamos esta relación utilizando una encuesta multinacional a gran escala de 236,938 adolescentes matriculados en 10,213 escuelas en 44 países, la cual se obtiene de PISA 2018. Estimamos un modelo lineal jerárquico, cuyas estimaciones muestran que solo los estudiantes superdotados obtienen beneficios del uso de TIC en el aprendizaje de matemáticas. Cuanto mayor es el nivel de rendimiento de los estudiantes superdotados, más se benefician del uso de las TIC para el aprendizaje de matemáticas. Para los demás estudiantes, la relación entre el uso de TIC y el rendimiento académico en matemáticas es negativa. Estos resultados ilustran que los *policymakers* deben considerar distintos métodos de enseñanza basados en TIC, dependiendo del nivel de rendimiento de los estudiantes. Los estudiantes superdotados se podrían beneficiar más del uso de TIC para el aprendizaje; mientras que sus compañeros de la enseñanza tradicional basada en interacción humana.

Consideraciones finales

La literatura empírica no ha encontrado evidencia concluyente respecto a los efectos positivos del uso de las TIC en el rendimiento académico de los estudiantes. En la presente tesis se abordan tres factores contextuales que podrían condicionar esta relación: el nivel de desarrollo económico de los países, su stock de capital humano y las diferencias en el uso de las TIC entre estudiantes de alto rendimiento y sus compañeros.

En el primer capítulo de la tesis, obtuvimos que la relación negativa entre el uso de las TIC para el aprendizaje en la escuela y el rendimiento académico de los estudiantes en lectura, matemáticas y ciencias es más fuerte para los estudiantes matriculados en sistemas educativos de países menos desarrollados que para aquellos matriculados en países desarrollados.

Del segundo capítulo de la tesis concluimos que el stock de capital humano de los países tiene externalidades positivas sobre el uso de las TIC con fines educativos. La relación negativa que inicialmente encontrábamos entre el uso de las TIC para el aprendizaje y el rendimiento académico en lectura, matemáticas y ciencias (sin considerar el efecto moderador del stock de capital humano) se tornaba positiva una vez que tuvimos en cuenta este efecto moderador. Los países con un mayor stock de capital humano obtienen mayores beneficios de la inversión en TIC.

En el tercer capítulo de la tesis, pusimos en evidencia diferencias en el uso de las TIC entre estudiantes superdotados y el resto de sus compañeros. Los primeros se benefician del uso de las TIC para el aprendizaje de matemáticas, mientras que los segundos no se benefician. También, concluimos que conforme mayor es el nivel de rendimiento de los estudiantes superdotados, mayor es el beneficio que obtienen del uso de las TIC para el aprendizaje de matemáticas.

De la tesis también se obtienen conclusiones más allá de las relacionadas directamente con las preguntas de investigación de cada capítulo de resultados. Primero, hay que tener en consideración que el uso de las TIC para el aprendizaje no es beneficioso en todos los contextos. Obtenemos que, en ciertos entornos y para determinados estudiantes, puede resultar más conveniente el aprendizaje tradicional (cara a cara), mientras que en otros el llevado a cabo con TIC. Segundo, la inversión en TIC debe estar acompañada por factores clave para asegurar su efectividad: a) la apropiada incorporación del aprendizaje basado en TIC en los planes de estudio, b) la provisión de la infraestructura física y pedagógica necesaria, c) la adecuada capacitación en el uso de TIC a docentes y estudiantes. Tercero, las TIC tienen como una de sus principales ventajas la capacidad de adaptación a las necesidades de aprendizaje de los estudiantes. Esta ventaja se podría explotar en el diseño de estrategias educativas basadas en TIC “a la medida” (v.g. programas de nivelación para estudiantes rezagados y de aprovechamiento para estudiantes sobresalientes). Cuarto, es importante identificar los niveles óptimos de enseñanza basada en TIC versus la tradicional, de manera que se optimicen los recursos existentes. Para ello, también es necesario identificar qué asignaturas y temas dentro de estas son más adecuados para el aprendizaje basado en TIC y priorizar su uso en ellas (v.g. enseñanza de un tema en particular, como geometría en matemáticas).

Las metodologías que hemos aplicado en los diferentes capítulos presentan limitaciones. Primero, los datos en los que se basan los resultados obtenidos son de corte transversal, lo que nos permite obtener patrones de correlación entre variables y no efectos causales. Segundo, la base de datos PISA carece de variables de control a nivel de clase y profesor (entre ellas, su conocimiento y habilidades en el uso de tecnología). Esto podría afectar el rendimiento académico de los estudiantes. De igual manera, los datos PISA tampoco cuentan con una medición del conocimiento y habilidad de los estudiantes en el uso de las TIC, lo cual podría afectar su rendimiento académico. En tercer lugar, tal como sugiere la literatura previa, es necesario contar con mayor precisión en la medición del uso de TIC (v.g. la calidad del uso y no solo el tiempo de uso). En cuarto lugar, existen otras variables del contexto del país no disponibles en la base PISA, que podrían afectar el rendimiento educativo de los estudiantes y su relación con el uso de TIC (v.g. el gasto medio en formación de docentes en materia de TIC, la calidad de la banda ancha del país y de los centros educativos, o la inversión en software educativo, entre otros).

De la mano de las limitaciones de la tesis, identificamos futuras líneas de investigación. En primer lugar, nos gustaría resaltar el interés que supondría que las encuestas a gran escala, entre ellas PISA, incorporaran en futuras ediciones más variables de control (a nivel de estudiante, clase y profesor) sobre conocimientos y habilidades de los estudiantes en el uso de TIC. Los estudios que incorporaran estas variables permitirían contar con estimaciones más robustas del rendimiento académico mediatizado por el uso de las TIC. En segundo lugar, apuntamos que los estudios experimentales y cuasiexperimentales sobre las aplicaciones TIC en contextos específicos son todavía muy escasos. Su uso supone una excelente manera de constatar la verdadera eficacia en el uso de las TIC en el aprendizaje. Tercero, tanto las encuestas a gran escala como los experimentos en contextos particulares, deberían prestar más atención al análisis de la calidad en el uso de las TIC y no solo centrarse en su tiempo de uso. Cuarto, es aconsejable realizar estudios académicos sobre los potenciales efectos de tecnologías revolucionarias en la industria de las TIC (v.g. *machine learning*, inteligencia artificial, automatización robótica y metaverso) en el aprendizaje.

La tesis también nos permite obtener recomendaciones de política en un escenario social en el que las TIC tienen cada vez más importancia. Un primer aspecto por destacar es la contextualización de las inversiones educativas en TIC. Los *policymakers* tienen como reto considerar el contexto país del sistema educativo. No necesariamente una tecnología educativa basada en TIC que haya sido exitosa en un grupo de países, vaya a serlo en los demás países donde se implemente. Por ejemplo, como muestra la tesis, el nivel de desarrollo del país y su stock de capital humano son dos factores que condicionan el aprovechamiento de las TIC para el aprendizaje. Esta consideración es aún más relevante para países menos desarrollados, los cuales, mayoritariamente, adoptan tecnología educativa diseñada para países desarrollados y tienen importantes limitaciones presupuestarias. Hoy, es una realidad que los contextos educativos dentro y fuera de los países cuentan con asimetrías significativas, que deben ser consideradas en el diseño de las estrategias educativas. Algunas de estas asimetrías son el gasto en educación del país, la calidad del profesorado, los recursos físicos y didácticos de los centros educativos y el contexto socioeconómico del estudiante.

Una consideración adicional en materia de política pública es entender las ventajas y desventajas de las TIC para el aprendizaje. Una ventaja de particular interés es que, las TIC ofrecen la posibilidad de adaptar los procesos de enseñanza a las necesidades de los estudiantes. Las TIC podrían ser un instrumento clave para atender grupos de estudiantes con dificultades de aprendizaje o para aquellos que requieren acompañamiento adicional para aprovechar una capacidad de aprendizaje excepcional. Priorizar las TIC para el aprendizaje de ciertos grupos de estudiantes podría liberar tiempo de docencia para atender presencialmente a otros compañeros y así optimizar el uso de los recursos pedagógicos. Los sistemas educativos también tienen el reto de realizar una mejor integración de las TIC en los planes de estudio. Para ello, es necesario identificar con precisión los niveles óptimos de uso de TIC versus la enseñanza tradicional; así como identificar las asignaturas y temas dentro de estas, que son más adecuados para la enseñanza basada en TIC. Por ejemplo, la literatura resalta que matemáticas es una las asignaturas más compatibles para el uso de las TIC con fines educativos. Sin embargo, la evidencia empírica también demuestra que el aprovechamiento de las TIC para el aprendizaje de matemáticas tiene que identificar de manera precisa los temas en los cuales el uso de TIC es más eficiente que la enseñanza tradicional.

En síntesis, la presente tesis tiene como principal implicación de política el contribuir a entender que el análisis del efecto de las TIC en el aprendizaje es un fenómeno transversal y multidimensional, que conlleva el estudio de factores contextuales más allá de los analizados tradicionalmente. En un contexto de acelerado cambio tecnológico y en el que la TIC tienen un rol central en la sociedad actual, la adecuada inserción de las personas en el mundo digital desde los sistemas educativos condiciona la ventaja competitiva de las economías en un mundo globalizado.