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# ICTs and Students' Academic Performance: Analyses on PISA 2018 data in EU27 countries

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# Sommario

Basandosi sui risultati dei test standardizzati PISA (i.e. Programme for International Student Assessment) nei Paesi europei, questo studio analizza l'influenza delle Information and Communication Technologies (ICTs) sul rendimento scolastico degli studenti. In particolare, la ricerca esamina le prestazioni degli studenti di 15 anni nelle materie di lettura, matematica e scienze. Per l'analisi dei dati sono stati utilizzati due principali approcci analitici, ovvero linear mixed models e hierarchical regression trees.

Questi modelli evidenziano importanti risultati sulla relazione tra l'utilizzo delle ICTs e il rendimento scolastico. In particolare, gli studenti ottengono in media il massimo rendimento quando utilizzano i dispositivi digitali per più di 60 minuti a settimana e quando i dispositivi digitali sono utilizzati esclusivamente dagli insegnanti. Inoltre, i risultati indicano che in alcuni casi l'impatto dell'uso delle ICTs varia a seconda della materia. In particolare, considerando scienze, l'utilizzo sinergico dei dispositivi digitali da parte di insegnanti e studenti produce un aumento delle prestazioni statisticamente significativo rispetto allo scenario in cui nessuno li utilizza. Al contrario, considerando le altre due materie, si osserva un effetto leggermente negativo.

Infine, lo studio esamina l'influenza dell'uso di Internet sul rendimento scolastico. Si individua un'associazione positiva quando l'utilizzo quotidiano rimane entro la soglia dei 30 minuti. Tuttavia, quando l'uso di Internet supera questo limite, si nota un corrispondente calo del rendimento. È interessante notare che l’esecuzione di attività come simulazioni e il completamento dei compiti sui computer scolastici mostra un impatto negativo sul rendimento scolastico.

I risultati di questa ricerca hanno importanti implicazioni per le strategie da adottare nell’ambito dell’istruzione, fornendo indicazioni agli educatori ed ai policymakers su come sfruttare efficacemente le ICTs per migliorare l’apprendimento degli studenti.

Parole Chiave: ICTs - Dispositivi Digitali - Educazione - Apprendimento - PISA 2018 - EU27

# Abstract

This study investigates the influence of Information and Communication Technologies (i.e. ICTs) on students' academic performance, focusing on the Programme for International Student Assessment (i.e. PISA) standardized tests in European countries. The research specifically examines the performance of 15-year-old students in the subjects of reading, mathematics, and science. Two primary analytical approaches, namely linear mixed models and hierarchical regression trees, are employed to analyze the data.

The findings reveal valuable insights into the relationship between ICT usage and academic performance. Specifically, students on average achieve the highest performance when utilizing digital devices for more than 60 minutes per week. Additionally, academic performance tends to be higher when digital devices are exclusively employed by teachers. Furthermore, the results indicate that the impact of ICT usage differs across subjects in certain instances. Specifically, in the context of science, the collaborative utilization of digital devices by both teachers and students yields a statistically significant increase in performance compared to scenarios where no one employs them. Conversely, in the case of the other two subjects, a slightly negative effect is observed.

Moreover, the study examines the influence of Internet usage on academic performance. A positive association is identified when daily usage remains within the 30-minute threshold. However, as Internet usage overcomes this limit, a corresponding decline in performance is evident. Interestingly, engaging in activities such as playing simulations and completing homework on school computers shows a negative impact on academic performance.

The findings of this study have significant implications for educational policies and practices, providing guidance to educators and policymakers on leveraging ICTs effectively to enhance students' learning outcomes.

Key Words: ICTs - Digital Devices - Education - Learning - PISA 2018 - EU27

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# List of Acronyms

| *Acronym* | *Meaning* |
|---|---|
| *AI* | Artificial Intelligence |
| *AR* | Augmented Reality |
| *ICTs* | Information and Communication Technologies |
| *IoT* | Internet of Things |
| *ITS* | Intelligent Tutoring Systems |
| *IVR* | Immersive Virtual Reality |
| *LMM* | Linear Mixed Model |
| *MOOCs* | Massive Open Online Courses |
| *OECD* | Organization for Economic Co-Operation and Development |
| *PISA* | Programme for International Student Assessment |
| *SES* | Social Economic Status |
| *ESCS* | Economic, Social and Cultural Status |
| *STEM* | Science, Technology, Engineering, Mathematics |
| *VR* | Virtual Reality |

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# Introduction

Education is a crucial scientific and cultural asset for a nation. It helps promote economic, technological and social change in a country and provides students with valuable knowledge that will contribute to their personal development. In the long run, this will fuel the growth of their nation and may contribute to creating a more equal, fair and advanced society (Ozturk, 2001). Analyzing and understanding the performance of students throughout their academic career is thereby fundamental for nations policymakers. It may provide them with valuable insights on the role that economic, social and technological variables play on a student's academic path. In turn, this may provide guidelines on the levers that policymakers can use for further advancing their countries development.

In the last decades, the way in which education has been delivered at school has significantly changed. The introduction of information and communication technologies (ICTs) within school boundaries have widened the possibilities that teachers have in delivering knowledge to their students. It has changed teachers' pedagogical approaches, impacted the traditional face-to-face interaction between students and teachers during classes, and offered students with great flexibility on the time and place to attend lectures (Youssef and Dahmani, 2008). However, the impact that ICTs have had on education is all but trivial. Researchers have been debating for decades on whether technologies represent an enabler or a threat for a student's academic and personal development.

The question of whether ICTs enhance education holds significant importance. If technologies represent an enabler for a student’s academic and personal development, it becomes necessary to establish policies and procedures to ensure their effective implementation in schools. Moreover, disruptive events like COVID-19 have brought to the forefront the need to evaluate whether technologies can replace or enhance traditional teaching methodologies.

The utilization of digital devices in schools brings with it a multitude of advantages and disadvantages. One notable benefit is the potential economic convenience compared to traditional teaching approaches (Deming et al. 2015), especially during disruptive events such as COVID-19.
Furthermore, ICTs offer opportunities for personalized learning tailored to students’ individual needs and foster collaborative learning environments (Bindu, 2016).
In addition to these benefits, ICTs offer flexibility in terms of time and location for attending lectures. (Youssef and Dahmani, 2008). This flexibility not only accomdates diverse student schedules but also extends educational access to disadvantaged regions where high-quality education is limited.

While there are notable benefits, it is important to acknowledge the potential drawbacks associated with their implementation.
One of the concerns is the widening educational gap between advantaged and disadvantaged students. Scholars from socially and economically vulnerable backgrounds may lack access to computers or high-speed Internet connections, leading to increased disparities in educational opportunities. Additionally, disadvantaged countries may face challenges in improving their infrastructure to support effective online learning.
Youssef and Dahmani (2008) highlight another potential drawback of ICTs, which is the reduction in problem-solving skills. Relying on readily available answers from the Internet may hinder critical thinking and diminish the interactive student-teacher engagement.
Agasisti (2020) raises another concern, suggesting that students may not receive sufficient guidance on the proper use of digital devices, leading to distractions and reduced focus during learning activities.

The importance of the potential impacts of ICTs on students' academic and personal development is recognized by policymakers, leading to proactive measures.
One initiative is the Digital Education Action Plan established by the European Union. Its primary goal is to ensure equitable access to digital education by providing adequate infrastructure and Internet connectivity to schools in disadvantaged and rural areas.
Another objective is to enhance teachers' proficiency in utilizing technology, through the provision of resources and training programs (Muraille, 2020).

Not only at a European level but also at the national level, several countries are actively promoting the widespread adoption of digital devices in schools. A notable example is Italy, where the National Plan for Digital Schools was established in 2007. The purpose of this plan was to exploit the potential of ICTs to transform the educational approach by introducing innovative tools and resources that enhance the quality of teaching. As part of this initiative, pilot schools were selected to test the effectiveness of ICTs, and a dedicated fund was allocated to facilitate the integration of digital tools in classrooms. The Organization for Economic Cooperation and Development (OECD) also played a role in this plan, as the Italian Ministry of Education, Universities, and Research sought their support and expertise (Avvisati et al., 2013).

Given the rapidly evolving nature of Information and Communication Technologies, it is no longer sufficient to study their impact on students' academic performances sporadically. As ICTs evolve, so does their utilization and influence, making it necessary to continuously assess their impact to understand the ways in which they can enhance various aspects of students' learning journeys.

This study directly addresses this issue, providing an in-depth analysis of the impact of ICTs on students' academic performances.
The central research question guiding this investigation is as follows:
*How do ICTs influence students' academic performances?*

This overarching question leads to several interconnected sub-questions that will be explored throughout the study:

*What is the recommended duration of digital device usage in educational contexts?*

*How do the academic performances of students vary when digital devices are exclusively used by students, exclusively used by teachers, or employed collaboratively by both students and teachers?*

*Which specific activities leveraging digital devices contribute most effectively to students' learning paths?*

To investigate these topics, a combination of descriptive analyses and statistical techniques are employed. Additionally, careful attention is given to confounding factors by incorporating relevant control variables in the statistical models, enabling a comprehensive assessment of the impact of ICT-related variables on students' academic performance.

The structure of this study unfolds as follows: the first chapter offers a comprehensive literature review, providing foundation for understanding the current state of research in the field. Chapter 2 focuses on presenting the dataset and its characteristics, facilitating a deeper comprehension of the empirical context, as well as meticulous descriptive analyses to explore the impact of digital devices on students' academic performance. Chapter 3 presents the statistical techniques utilized throughout the study. Chapter 4 presents the findings derived from the application of the latter statistical techniques to the PISA 2018 dataset. Lastly, Chapter 5 covers the conclusion, summarizing the key insights of the study, highlighting limitations of the research, and suggesting opportunities for further research in the field of adopting ICTs for enhancing students' academic performance at school.

# 1. Literature Review

In this chapter, a summary of the existing literature regarding students' education is presented. First, an analysis on the typical variables influencing students' academic performances (e.g. student socio-economic status, student characteristics, school features) is presented. Second, since the focus of the thesis is to discuss the correlation between the use of Information and Communication Technologies at school and students' grades, a literature review concerning the positive and negative effects that ICTs have had on students' academic performances is presented. Lastly, an analysis on the role that ICTs play on education during disruptions (e.g. COVID-19, natural disasters) and an overview on possible future uses of ICTs in education (e.g. AI, neuroeducation) are presented.

## 1.1 Factors Traditionally Related with Students’ Academic Achievement

In this paragraph, a literature review regarding the factors that have traditionally influenced students’ academic performances is presented. An analysis of this nature is also necessary to decide which control variables to include in potential statistical models. There are multiple factors that come into play in this context, and there is general agreement concerning the effects of a great proportion of this set of variables.

One of the most important features that is able to explain significant differences in the students’ academic achievement is the socioeconomic status (SES) of the family (Hanushek, 1979). It comprises various variables, but there is a lack of consensus regarding the aspects to be included in the SES, and many different measures have been proposed in distinct studies (Mueller & Parcel, 1981). The most frequently considered variables are the income of the family, the home possessions, the level of education of the parents, and their occupation.
Sirin (2005) lists some of the reasons behind the relationship between the socioeconomic status and the academic performance. In the first place, parents with higher income and assets could potentially grant more and better resources to their child, increasing the probability of reaching better results in the academic context.
Subsequently, social capital plays an important role. It is defined by OECD (2001) as “networks together with shared norms, values and understandings that facilitate co-operation within or among groups”, and a family with a significant social capital may facilitate access to valuable educational resources, provide positive role models, and establish supportive networks. Each one of these aspects might offer emotional and practical support to the student, who would be guided to overcome possible challenges.

Another important academic aspect on which families have certainly an influence is the choice of the school. Enlarging the concept of SES to the school level, dissimilarities in the materials provided, the teachers' years of experience, and teacher-student ratio have been detected (Sirin, 2005). In a study conducted by Ersan and Rodriguez (2020), an effect on students' academic performances of both the SES of the family, and the aggregated SES of the school, has been identified. In particular, they found a significant and positive correlation between the SES at the student level and his achievement, and also that the SES can be a robust predictor of achievement across different schools. Therefore, it can be deduced that the SES of the family, which in turn may influence the choice of the school, can have an influence on the education of the child.

In the same study another impactful variable, that is usually included in the SES, has been identified: the level of education of the parents. Besides the fact that parents with a higher level of education may provide better direct support to their children, they are also used to spending more for education than parents with a lower level of schooling. Additional expenditures in this field can certainly help pupils to achieve better results.

As previously mentioned, large dissimilarities exist between different schools. In addition to the aspects already provided, such as the quantity and quality of materials furnished, teachers' years of experience, and teacher-student ratio, a further aspect varying across schools that may have an influence on the students' academic performance is the teachers' quality.

As Hanushek (1979) infers, teachers' quality is important to be considered when assessing the factors that have an effect on the students' education, but unfortunately data regarding this aspect are hardly ever available.

Another important feature to be considered, is the expectation of parents and teachers regarding the student. In a study conducted by Benner et al. (2021), a positive and significant relationship is found between this feature and the students' academic achievement. In particular, teachers' expectations seem to have a higher impact than parents' expectations on the students' performance.

A plausible explanation could be that teachers have daily interactions with pupils at school. As a matter of fact, higher educational expectations among teachers were associated with increased connections between teachers and students. This, in turn, has been found to have a positive relationship with students' academic performance.

The evaluation of personality traits should be extended beyond teachers and parents, to include those of the students as well. Two factors that may influence pupil's academic performances are the student's self-esteem, and grit.

The former is defined by Coopersmith (1967) as the "extent to which an individual believes himself to be capable, significant, successful and worthy".

A definition for the latter is provided by Duckworth (2007): "passion and sustained persistence applied toward long-term achievement, with no particular concern for rewards or recognition along the way".

As it was stated in a study conducted by Kim et al. (2021), since it is recognized that academic success is achieved by sustained and persistent effort, the potential effects induced by self-esteem and grit have to be analyzed. Both factors have a positive relationship with students' academic performance; in particular, self-esteem might increase the motivation to pursue academic excellence, while grit allows students to maintain their focus, effort and determination over time.
In this study, the likely relationships between these two variables, the outcome, and a further factor, namely the academic enthusiasm, are examined.
As it is shown in Figure 1, self-esteem influences both grit and academic enthusiasm, and it is also related with academic achievement. Instead, grit influences both academic enthusiasm and students' outcomes.

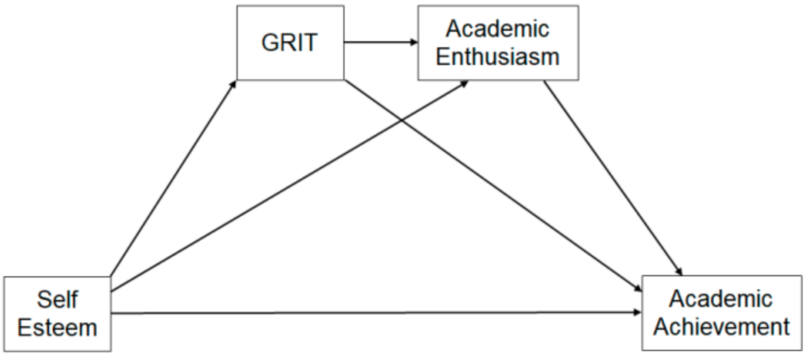


**Figure 1.** Relationships between self-esteem, grit, academic enthusiasm and academic achievement.
Source: Kim et al. (2021).

A positive correlation is observed between these four variables, and the study suggests that self-esteem indirectly affects academic achievement by influencing grit and academic enthusiasm, rather than having a direct effect.

Shifting focus on students' passions, a factor that has been analyzed is the time devoted to computer games.
In a study conducted by Kulikova and Maliy (2015) a negative correlation between the time spent playing computer games and the students' academic performance is observed. The reasons behind this relationship can be numerous, as highlighted by the study: children who devote a significant amount of time to computer games show lower levels of extroversion, self-confidence, honesty, and self-control. They also seem to be less interested and motivated to learn.

In addition to the aforementioned factors, research has shown that gender can play a role in determining students' academic success. When comparing boys' outcomes with the girls' ones, a generally accepted difference concerns subjects such as mathematics, learning and reading. Girls have on average better performances regarding learning and reading, while boys outperform girls in mathematics (García-Jiménez et al. 2020).

In a study conducted by Chen and Liu (2013), interesting insights are found with respect to the influence that siblings may have on educational achievement. Specifically, no significant variation in academic performance was detected between only children and firstborns, regardless of the number of siblings. The same conclusion was observed regarding the comparison between only children and laterborns, but only in cases of families with maximum two children. The only significant difference in academic performances was found contrasting only children with laterborns of families with two or more siblings.

Chen and Liu (2013) mention three established conceptual frameworks that explain the observed dissimilarities in the academic context: the confluence model, the resource dilution model, and the attachment theory.

The former explains that only children and firstborns engage more with adults, which is believed to provide more intellectual stimulation. On the contrary, laterborns also interact with older siblings, whose level of maturity may be influenced by their age.

The resource dilution model states that the family resources (cultural objects, opportunities, personal attention etc.) are shared between every child. Therefore, in the case of only children, all necessary resources are at their disposal, while siblings must share them. Another important concept explained by this model is that parents also have higher expectations in the case of only children, with respect to families with siblings. This can be linked to the aforementioned study conducted by Benner et al. (2021), which described the positive relationship between parents' expectations and academic achievement.

The last theory, namely the attachment theory, explains that parents tend to experience more anxiety when caring for their child for the first time, which can lead them to provide more sensitive care to their only children or firstborn. This can promote the development of secure attachments, which, in turn, may help to develop intellectual abilities and psychological confidence in their child.

When considering students' academic achievement, preschool education may yield further benefits (Ersan and Rodriguez, 2020). A positive relationship between this educational program and mathematics achievement was found also after controlling for the student's socioeconomic status. Indeed, the considered educational program can build a foundation for literacy and numeracy, which, in turn, benefits later academic achievement.

A last variable that has to be taken into account is the origin of the children and of the family. From a study on Slovene pupils conducted by Brecko (2004), it was found that students born in the considered country perform better in the educational context than the ones born abroad. In addition, also the country of birth of the student's parents is crucial: students with at least one parent born in the considered country reached better outcomes when compared with students with parents not born in the country.

Moreover, distinguishing between ethnicities, a research carried out by Hamnett et al. (2007) in London, showed dissimilarities in students' academic performances. In particular, ethnicities classified as "Black Africans" and "Bangladeshis" registered lower outcomes than the average.

Two theories are mentioned to explain this phenomenon. The first one suggests that some ethnic groups may be perceived or perceive themselves as being at a disadvantage, while the second one highlights the potential impact of racial biases among “White teachers”.
Lastly, as shown from a study conducted by Böhlmark (2005), age at immigration has a significant effect on students’ academic performances. The analysis is performed considering Sweden pupils, and the results indicated that a significant achievement gap only exists when the age at immigration is greater than or equal to ten. Below this threshold, children have enough time to learn the new language and develop skills specific to the country. On the contrary, above this threshold, performances constantly decrease as the age at immigration increases.

A plot summarizing the factors traditionally related with students’ academic performance is presented below.

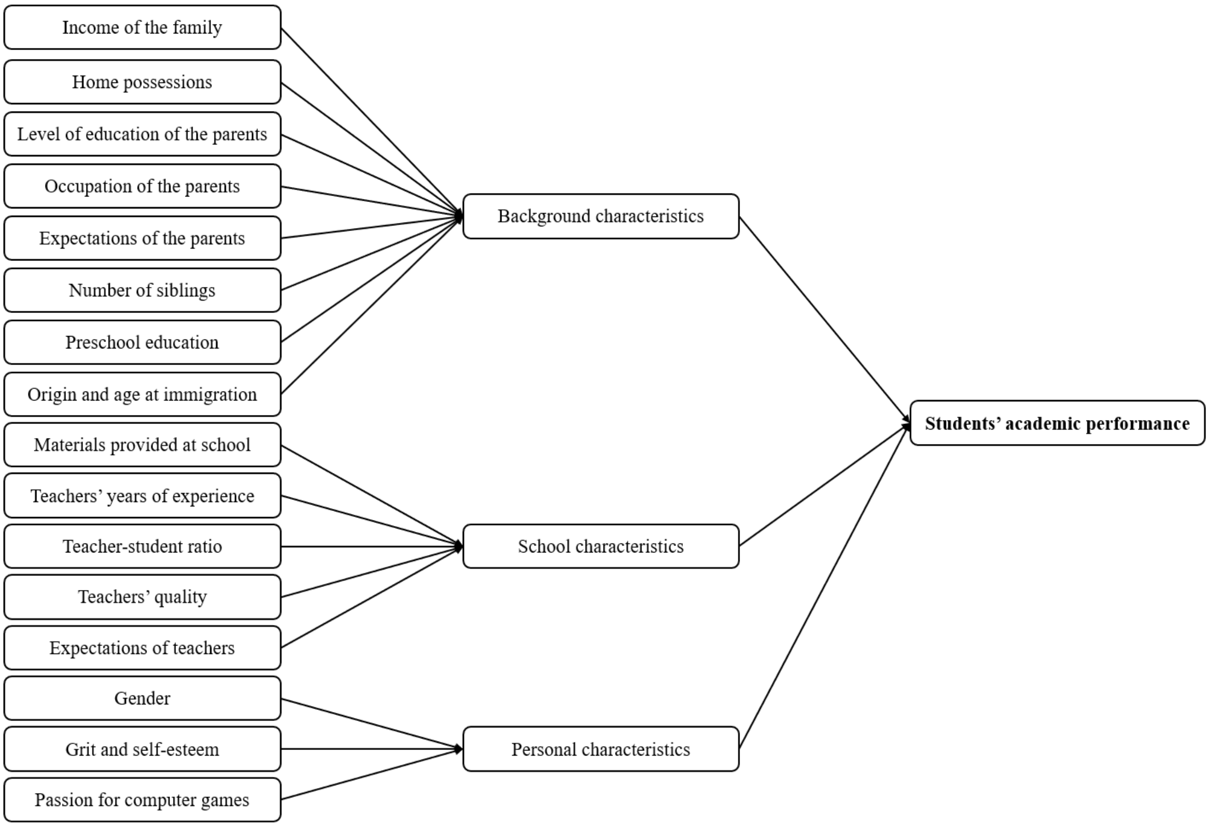


**Figure 2.** Factors traditionally related with students’ academic performance

## 1.2 The Impacts of ICTs on Education

After having analyzed the variables that are traditionally considered to have an impact on students' academic performances, the following paragraph examines the role that Information and Communication Technologies (i.e. ICTs) have played in revolutionizing traditional forms of education. Counterintuitively, the impact of ICTs on schooling is all but trivial. Providing digital-natives, who enjoy and thrive in the use of technologies in their every-day life, with the possibility to use ICTs in classrooms does not guarantee an increase in their academic performances (Livingstone, 2012). In a world in which the pace of technological advancements keeps on increasing, it is thereby fundamental to assess if and how technologies may shape education.

Before deep diving in these effects, a definition of Information and Communication Technologies is needed. Tinio (2003) and Zuppo (2012), describe ICTs as:

"[a] diverse set of technological tools and resources used to communicate, and to create, disseminate, store, and manage information"

"[a] continuum of skills and abilities (…). ICT is being used increasingly by global industry, international media, and academics to reflect the convergence between computer and communication technologies. Summarily, within the realm of education, ICT can be viewed as a set of activities and technologies that fall into the union of IT and telecommunications"

"ICTs" are considered by the authors as an umbrella-term, under which several devices are included. It integrates computers, with broadcasting technologies and the Internet. In schooling, the term includes educational computer games, virtual learning environments, online repositories, interactive whiteboards, tablets, spreadsheets and many more tools. It encompasses both one-to-many technologies (e.g. projectors), used by teachers to deliver frontal lectures, and peer-to-peer technologies (e.g. online education platforms), through which students learn by participating and interacting in group activities (Livingstone, 2012).

Practitioners have been discussing for decades on whether technologies may represent an opportunity and increase the efficiency and effectiveness of teaching activities, or whether they may represent a threat to traditional and more effective forms of instruction. This dichotomy is described in greater detail in the following sub-chapters.

### 1.2.1 The Positive Impacts of ICTs on Education

On one hand, research highlights that the benefits of using technologies at school are manifold.

ICTs allow students to have great flexibility concerning the time and place to attend lectures. This is especially true in Higher Education where physical attendance is not mandatory. Students are granted the opportunity to attend classes from wherever they are, or in whatever moment they deem to be appropriate (Youssef and Dahmani, 2008). This enables them to avoid missing out on potentially important lectures in their academic paths. Not attending classes may create academic gaps in a student's preparation which in turn may result in difficulties in studying for future courses.
According to the authors, the flexibility offered by ICTs may also be used to offer education in disadvantaged or developing countries, where the lack of teachers and the presence of social,

economic and infrastructural boundaries hamper children the right to have access to high quality education.
In addition, not always is it economically convenient for students to commute to university, as the time and cost of the trip may exceed the benefits of attending short lectures.

ICTs are used to enable a more collaborative learning environment both within classes and between courses in different countries (Bindu, 2016). Technologies such as Miro and other visual collaboration platforms are used to brainstorm and share ideas among students during lectures. Through collaboration students develop the soft skills which are of increasing importance for job seekers, as the latter are necessary skills for working in many companies.
The author adds that ICTs are also used to connect scholars studying in nations with different cultures or teaching approaches. This facilitates the internationalization of education, which is the basis of what the researcher defines as “global collaborative learning”.
Students are not the only ones benefiting from this collaboration. The creation of e-libraries and online repositories also facilitates teachers and researchers from different parts of the globe in accessing and sharing academic papers and teaching material.

ICTs are fundamental for the shift from a traditional teacher-centered approach, in which teachers deliver frontal lessons and focus on simply transmitting facts to their students with a top-down methodology, to a learner-centered approach (Bindu, 2016). The latter relies on open-ended learning and on the personalization of classes according to students’ needs. Teaching becomes a process in which both teachers and students may enlarge their knowledge and benefit from it. Lectures become tailored to the needs of single students and strongly rely on the use of multi-media devices, that through the power of visualization and interactive audio-visual effects strongly engage, motivate and nurture a positive attitude of students towards learning. Students may also like classes more and take less time to learn as a result of this increased engagement (Kulik, 1994).

In addition, the use of ICTs in classrooms allows students to learn-by-doing in a hands-on teaching environment. These approaches to education are strongly advised by the supporters of constructivist theory. According to the latter, it is through the application of a concept that students learn more effectively. This is due to the fact that pupils are challenged to find their own path and apply their own methodologies in solving a problem rather than applying pre-determined schemes imposed by an external party. Kirschner (2006) instead, argues that traditional forms of education are more effective than the aforementioned minimal-guidance approaches to education and that the gap between traditional and more innovative forms of education begins to diminish only when students have sufficient prior knowledge on the subject that is being taught. Therefore, it is not necessarily true that students should be provided with no guidance throughout their academic activities. This reasoning is supported by cognitive load theory, according to which, if novel learners are provided with no guidance in performing academic tasks, they spend most of their time searching for information on the topic rather than solving the problem due to their lack of prior knowledge. This activity may be physically and mentally demanding. In turn, as the author highlights, this may result in students getting

confused and lost within the myriad of information they have read, which may lead to an abandonment of the task or in a misconception of the topic.
These contrasting theories suggest that traditional teaching approaches and hands-on ICT-based academic practices may be complementary rather than mutually exclusive. Students should first be taught the basics of a subject and then be asked to apply their knowledge in solving practical problems.

ICTs allow the effectiveness of teaching activities and the consequent student performances to be less teacher-dependent, since learners have access to unlimited academic material online (Youssef and Dahmani, 2008). However, this implies that learners need to understand how to filter, select and cross reference multiple sources of information. Students must be able to construct meaning from what they read, distinguish truthful from biased information, challenge false beliefs, construct mental models, and more. These competences are what Bindu (2016) defines as “high order” thinking skills.
Furthermore, providing learners with wide access to information may also be more inclusive, empowering and democratizing than imposing students to read pre-defined books which are naturally more selective and exclusive (Livingstone, 2012). However, the consequences of potential misinformation must always be kept in mind and limited.

Finally, ICT-based education is more economically convenient than traditional methods to deliver classes (Deming et al. 2015), and may have a significant impact during disruptive events (e.g. COVID-19). The latter will be widely discussed in section 1.3 and are thereby not reviewed in the following sub-chapter.

### 1.2.2 The Negative Impacts of ICTs on Education

On the other hand, supplementary research highlights that ICTs may have a negative impact on students' education and academic performance.

Youssef and Dahmani (2008) report that ICTs reduce the student-teacher in-person interaction and the immediate resolution of doubts that students have during lectures. This is particularly true in the case of online learning, where there is an additional physical barrier between the student and the lecturer.
ICTs may be a distraction for scholars both in class and at home. At school, when teachers are not looking, pupils may access websites that differ from those they are supposed to be using during lectures. At home instead, learners may use ICTs to increase their leisure time by chatting or gaming online instead of studying. Agasisti et al. (2020) thoroughly examine the effects that using ICTs at home have on students’ test scores. Their study focuses on 15 year old learners from the PISA 2012 assessment cycle. The research reveals that students from EU 15 nations that use ICTs at home for school related tasks have lower test scores in reading, mathematics and science than those that do not. According to the authors, the reasons are threefold. First, the hardware and the software of the devices that learners use at home may not

be adequate for schoolwork. If the instruments that the students use at home are slow and outdated, they may decrease students' productivity. Second, students may not receive sufficient instructions on how they are supposed to use the digital devices at home. If this is the case, students would not be taught how to extract the value that stems behind the use of the technologies. Simply using technologies more at home does not bring benefits in students' academic achievements if the latter are not aware of how they are supposed to use the technologies. Teachers must educate students on how to productively use ICTs at home in order for them to be effective. Lastly, if students are not mature enough, they may waste time on digital devices by scrolling feeds on social media or listening to music. All these activities are not aimed at increasing students' test scores.

Youssef and Dahmani (2008) also inform that technologies restrict students' creativity and problem-solving skills. Pupils are not stimulated to think and find their own solutions to the specific academic inquiries they are asked to solve, as they may find the answers to their problems readily available online. If students are not taught how to challenge accepted beliefs and the information they read, in the long rung this may create a polarization of information.

Furthermore, the budget that schools have for financing teaching material should be adjusted to include investments in ICTs, otherwise spending on these technologies may reduce the funds that are typically allocated to more effective schooling material.

Deming et at. (2015) argue that online learning also has an impact on students' future careers. That is, if distance learning is perceived to be of lower quality than traditional forms of education, job-hunters may be more skeptical in employing these kinds of students.

Lastly, students' favorability towards the use of ICTs in schools is critical for their successful introduction in classes. Weili et al. (2022), argue that ICTs have a relevant impact on the global emission of carbon dioxide. In a world in which students are increasingly environmentally concerned, it is therefore fundamental to search for ways to reduce the environmental impact that these technologies have on the planet.

Ikeda and Rech (2022), claim that ICTs have reduced the average availability of physical and printed books in students' households. One may argue that, as the Internet has given the possibility to students to access digital libraries and electronic repositories online, the latter does not constitute a threat to pupils' academic performances. However, this theory is dismantled by the authors, that emphasize how students who read books more often in paper format scored 49 points higher on average in the PISA 2018 reading test compared to students that rarely or never read books, after having controlled for confounding variables such as students' and schools' socio-economic profile and students' characteristics. The longitudinal analysis, concerning years 2000, 2009 and 2018 also highlights that not only has the average number of books is students' households been decreasing throughout the years, but also that the average gap between the availability of printed books in advantaged and disadvantaged students' homes has been increasing. This may be an indicator of the increase of inequality in education.

The authors also study the effect that the reading format (i.e. reading books on digital devices, in paper format, or a mixture between the two) has had on the enjoyment that readers perceive while reading books. The results emphasize that students claiming to read more often in paper format have had on average a higher increase in the enjoyment towards reading (with respect to those who rarely or never read books) compared to those using digital devices, as reported in Figure 3. This phenomenon should be monitored closely by policymakers, to avoid that by increasingly reading in digital formats, pupils decrease the average amount of books they read in time, causing a surge in illiteracy and language flattening.

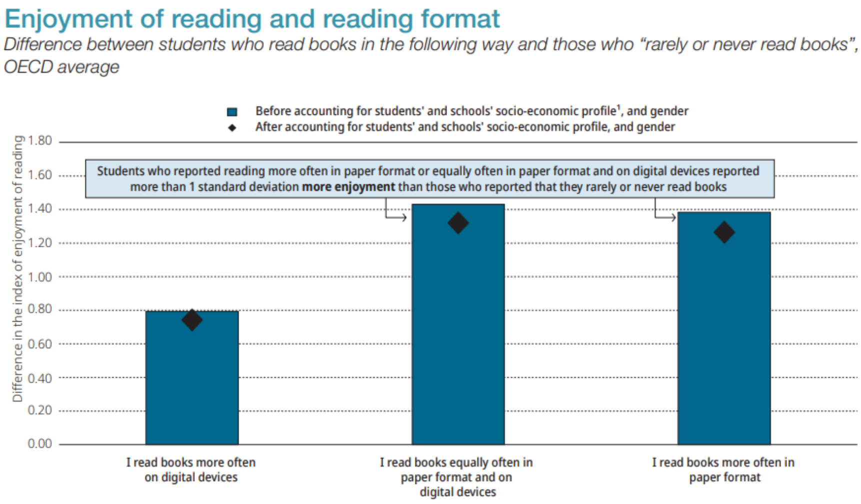


**Figure 3.** Enjoyment of reading and reading format.

Note: the social-economic profile is measured by ESCS.

Source: Ikeda and Rech (2022).

ICTs may increase rather than mitigate the educational gap existing between advantaged and disadvantaged students (Ikeda, 2020). This effect is particularly amplified in case of remote learning, as pupils belonging to socially and economically vulnerable families not always have access to a computer to perform schooling activities, a high-speed Internet connection, broadband bandwidth and a quiet place to study at home. Remote learning may also increase the educational disparity existing between developed and developing countries, as the latter have fewer resources to devote to improving their facilities and infrastructures to enhance online learning. All these variables should be taken into consideration by policymakers to try and reduce the current educational gap existing between advantaged/disadvantaged students and between developed/developing countries.

The use of the Internet also has an impact on students' academic performances. Echazarra (2018), analyzed the difference in the science test scores of students who used the Internet compared to those who did not. The analyses yielded different results according to whether students used the Internet at school during weekdays, outside of school during weekdays, or during the weekends, as reported in Figure 4. In the former, higher Internet usage was correlated with lower student performances. In the latter two cases instead, the curve displayed a concave trend, highlighting a peak at an intermediate level of internet usage. Exceeded that limit, the author argues that the Internet consumption begins to interfere with the pupils' learning time.

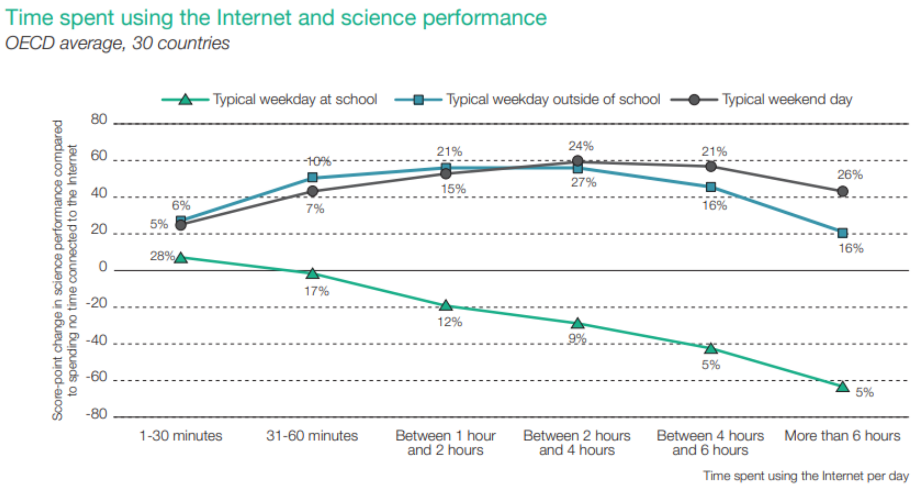


**Figure 4.** Time spent using the Internet and science performance.
Notes: The reference category is *no time*. The percentage of students in each category is shown next to the marker. The remaining students answered *no time*.
Source: Echazarra (2018).

The concave shape of two of the three above-mentioned curves may also suggest an alternative scenario. Not necessarily traditional and ICT-enabled teaching methodologies are incompatible. Combining the strength of both approaches in what Garrison and Kanuka (2004) define as “blended learning” may significantly increase teaching effectiveness in schools. The authors argue that for blended learning to be successful, it is not sufficient to extend traditional forms of education with ICTs, or online learning with well-established teaching practices. Blended learning results from the combination of the strength of these two antipodes in the creation of a new pedagogical approach. For instance, by discussing topics in class and then asking students to write online essays on their discoveries at home, students are challenged to put in practice both their interaction and analytical thinking skills. The former trains students to think and answer questions quickly. These skills are fundamental in fast paced, face-to-face interactions. The latter instead coaches pupils on how to reflect before stating their opinions, how to support their written statements with evidence, and how to write with precision. These abilities are of great importance while writing on the Internet, an environment which by nature is permanent.
The authors also argue that blended learning is more effective and efficient than traditional or fully online teaching approaches.
Additionally, the completion rate of the courses delivered in these modalities are higher, as classes enabled by ICTs are more interactive, engaging, practical and often help facilitate learning. For instance, lectures delivered in these modalities typically involve projects, games, tutorials and more. MOOCs (i.e. Massive Open Online Courses) may be useful to students for filling the gaps in subjects they have not fully understood. They may also be used by schools to deliver top-notch quality education to other institutions around the world.

Shifting from traditional teaching approaches to a blended learning methodology is less of a disruption than moving directly to fully delivering online courses. Semerci and Aydin (2018) state that teachers prior ICT knowledge, skills and experience are amongst the greatest factors that create anxiety towards this change among lecturers. The smaller transformation enabled by blended learning is thereby an advantage, as it most likely would elicit a lower degree of opposition towards the change by the institutions and actors involved in the process.

### 1.2.3 Discussion on the Overall Impacts of ICTs on Education

In the above-presented sub-chapters, a summary on the positive and negative impacts that ICTs have had on education has been presented. However, the scope of the analyses was never to conclude which among traditional or ICT-enabled methods of education have proven to be more effective in enhancing students' academic performances.

This does not mean that addressing such an issue is not important. The latter is and will be a fundamental question that educators and policymakers need to address in the upcoming years. However, conducting such an analysis today may not be fully appropriate for several reasons.

Traditional forms of education have been adopted in schools for centuries. Educators have had the time and opportunity to test several teaching methodologies before developing the optimal approaches they use in schools today. On the other hand, ICTs have been introduced in schools only in the last decades. Livingstone (2012), states that educational institutions are still in the early stages of the adoption of ICTs in schools and that the integration of new technologies in well consolidated, traditional schooling systems, is a lengthy and demanding process. It requires several changes in the schools' educational infrastructures, teaching materials, classroom dispositions, curriculum compositions, teacher training and more. Not only do teachers need to be trained in how to use technologies. They also must be taught how to take advantage of these technologies to improve their teaching activities during class. The above-mentioned theories are also supported by Ikeda (2020), and Youssef and Dahmani (2008).

The former author reports that in OECD countries, only half of 15-year-old students are enrolled in schools that have effective online learning support platforms. In addition, only two thirds of 15-year-olds in OECD nations are enrolled in schools in which their teachers have the necessary skills, or the time to learn the necessary skills to integrate digital technologies in their teaching approaches.

The latter authors inform that for ICTs to help improve students' performances, a deep organizational change is needed in schools. This includes a transformation in the information and communication structures in place, and in how decision-making units are structured within schools.

The authors also classify educational institutions in four levels, according to how deeply ICTs have been integrated in their daily activities at a classroom and institutional level. The higher the level of a school, the more advanced it is from a technology adoption perspective. Schools are classified into levels one or two if ICT skills have been recently introduced in school programs or if these technologies have recently started to impact teachers' pedagogical approaches, whereas schools are classified into level three or four if ICTs have proven to be radically transformational at a classroom or institutional level. According to the report, most schools to date belong to level one or two.

Suarez-Alvarez (2021) also states that, while most students are using ICTs at school, few have properly been instructed on how to use these technologies. Teaching students' additional skills such as how to compare different webpages to decide which is more relevant for their schoolwork, deciding whether online information is trustworthy or not, using keywords in search engines, and being taught the consequences of posting information online is important to improve students' performances and promote responsible Internet behavior.
All the four above-mentioned studies highlight that it is important to wait until ICTs have fully been integrated and that all the necessary skills have been taught in educational institutions before comparing traditional and well-established pedagogical practices to recent ICT enabled teaching methodologies.

Youssef and Dahmani (2008) and Livingstone (2012) also highlight that the traditional practices for evaluating the impact that teaching methodologies have on educating students are not appropriate for assessing the effects that ICTs have had on students' academic and personal developments. Namely, teaching methodologies have traditionally been evaluated on the impact that they have had in improving students' average grades. The latter, however, is only one of the consequences that ICTs may have on students. The authors argue that the evaluation criteria should focus on the effects that ICTs have on the students learning process as a whole instead of focusing on their individual achievements. Specifically, other than improving students' marks, ICTs increase students' motivation, attitude and enjoyment towards learning. They also enhance students' collaboration, discussion, interaction, conflict resolution and meta-cognitive skills. Therefore, deciding whether to integrate ICTs in education, simply by analyzing their impacts on students' academic scores is overly simplistic.

Lastly, researchers need not to generalize the effects that ICTs have on education. Sub-levels of analyses need to be introduced in examining whether ICTs enable more effective teaching practices or represent a threat to traditional forms of education.
On one hand, specific technologies may be more effective than others in improving students' academic performance. Livingstone (2012) cites a study conducted in 2007 on the learning outcomes of American 13-year-old middle school students, reporting how improved grades were only associated to the use of subject-specific technologies (e.g. educational computer games) during science, mathematics and history lessons. These technologies however resulted to be rarely used by educators as they were seen as hard work by students. This represents an interesting insight from a policy-making perspective, as it encourages policymakers to find innovative ways to incentivize students to adopt these technologies.
On the other hand, the impacts that ICTs have on students' academic performances may be subject specific. Namely, the use of technologies during lessons may be more useful in certain subjects than others. The above-mentioned author cites a pan-European literature review, highlighting how interactive whiteboards were associated with a higher national test score in English, mathematics and science. Furthermore, within a specific subject, technologies may also be more effective in teaching certain skills than others.
Lastly, the effect that ICTs have on students' academic performances may also be dependent on the age group the students belong to.

In conclusion, in the previous subchapters, an analysis on the existing literature concerning the positive and negative impacts that ICTs have had on education was presented. The analysis showed how researchers have conflicting opinions on whether ICTs represent the future of schooling or a great danger to education as it is known today.
It highlighted how not necessarily the two forms of education are mutually exclusive. The strength of both methodologies may be combined to create a new pedagogical approach (i.e. blended learning) which has been demonstrated to be effective according to existing research to date.
Lastly, attention needs to be paid in comparing traditional and ICT-enabled education, as the former has been adopted for a much longer timeframe than the latter. The latter also requires a deep transformation in schools' organizational structures and in the skills that teachers and students need to have to effectively use these technologies. Finally, the impact of ICTs on education needs not to be generalized. Technologies may be more or less effective in improving students' academic performances according to the discipline that is being taught, the age of the students that are using them, and the typology of the technology itself.

## 1.3 ICTs in the Era of COVID-19

The implementation and utilization of Information and Communication Technologies were considerably accelerated by the spread of the COVID-19 virus. Indeed, due to the adoption of social distancing and quarantine measures, ICTs became fundamental in every professional and academic field, in order to maintain acceptable levels of communication and productivity.
The first, and maybe most crucial tool that was used in the educational context during the COVID-19 era was the videoconference software. It is an instrument that allows people to connect in real time and have virtual meetings or conversations. By using the camera and microphone available on their device, participants are able to see and talk to each other. Some examples of the most used videoconference software during the COVID-19 pandemic are Zoom, Google Meet, Microsoft Teams, Skype and Cisco Webex. All of them have similar key features, such as screen sharing, file sharing and chat messaging.
The pandemic forced the adoption of another basic tool: the learning management system. Its purpose was to facilitate the delivery of academic lessons. Some examples can include Blackboard, Google Classroom, and Moodle.
Teaching during the COVID-19 pandemic was a big challenge, but assessing students was also a necessary task that could not be neglected. In order to make it possible, online assessment tools achieved notoriety. They allowed teachers to create tests, manage them and evaluate students in a completely digital format. Examples of these types of software are Respondus, Google form and Microsoft forms.

Remote learning generally allowed families to have some cost savings, resulting from students not having to travel to the city where the educational institution was located or not having to rent accommodations close to the academic establishment (Al-Ansi et al., 2021). The same

study revealed that online learning also improved time efficiency for both pupils and teachers, increasing the amount of time that everyone could spend with their family.
Due to the high demand for ICTs during the pandemic, numerous new tools were created. These instruments continued to be used also when in-person classes resumed, allowing a broad availability of new instruments to optimize lessons.

Unfortunately, online learning was accompanied by many problems. In the first place, a limited interaction may have caused a lack of motivation in the pupils, which, in turn, may have interfered with their academic performances. Another huge issue during the COVID-19 pandemic was represented by mental health problems, resulting from lack of social interaction. Students affected by mental health problems may have witnessed an increase in the probability of school refusal, truancy, school withdrawal, school exclusion and complicated educational paths in the future (Nathwani et al. 2021). Teachers' situation was certainly not more favorable. The majority of them reported feeling stress and anxiety due to social distancing, while other issues arose regarding the use of ICTs. Specifically, many teachers felt that they were not granted adequate support throughout the disruption and that the training they received on the technological devices they had to use throughout the pandemic was insufficient (Espino-Díaz et al., 2020).

While making these considerations, the huge dissimilarities between developed countries and disadvantaged countries have to be taken into account. As mentioned in a study conducted by Lorente et al. (2020), even the right to education, which is a recognized human right, was hindered in some regions during the pandemic. A starting point to understand these difficult circumstances, is to analyze which regions did not have access to electricity. As reported in the aforementioned study, worrying values are found considering sub-Saharan Africa and South Asia, because respectively around 70% and 50% of primary schools lack access to electricity. In these regions, during whichever pandemic, it would be nearly impossible to switch to an online learning approach. Another problem concerns the proportion of students without a feasible access to remote education: at least one third of the children in the world.
A direct evidence is provided by Sintema (2020), who, after having interviewed mathematics and science teachers in Zambia, states that the country is unable to offer an appropriate platform dedicated to online learning. The resultant lack of interaction with teachers, typical of home schooling, may decrease drastically the students' academic performance.

## 1.4 Potential Academic Uses of ICTs in the Future

After having analyzed how and why ICTs have been introduced in education contexts in the recent years, it is relevant to explore the potential tools that could be implemented in the future, with the related benefits, opportunities, challenges, and drawbacks.

When considering the near future, one of the simplest instruments that may be implemented in academic contexts is augmented reality (AR). It consists of "a combination of technologies that

enable real-time mixing of computer-generated content with live video display" (Mekni and Lemieux, 2014).
One of the most intuitive ways to use AR during lessons is to exploit interactive textbooks that allow the tool to create virtual and dynamic 3D models; this way, students would have a clear representation of what they are studying, which in turn would improve their understanding of the subject. For instance, AR could represent a huge advantage in subjects such as science, chemistry, art, and history, since students can visualize abstract objects which are otherwise difficult to imagine: molecules, the anatomy of the human body, space, chemical reactions, extinct animals, geological features, sculptures, ancient pottery or jewelry, monuments, and more.
This instrument can significantly enhance understanding and the ability to retain knowledge over an extended period, but there are also some drawbacks to consider. Since this is a technology that is not yet widely adopted, there may be challenges with useability; additionally, the tool may draw away the attention from the key takeaways from the lessons (Southgate et al., 2019).

Leaving the world where reality is paired with digital objects, made possible by AR, and increasing the level of abstraction, a completely artificial world can be visualized through the use of virtual reality (VR). It is defined by Bryson (2013) as "the use of computer technology to create the effect of an interactive three-dimensional world in which the objects have a sense of spatial presence".
Firstly, it is necessary to make a distinction between two types of VR: non-immersive VR and immersive VR (Liu et al., 2020). The former defines a virtual environment which is displayed on a screen, and the interaction between the user and the environment occurs only through a mouse and a keyboard. On the contrary, immersive VR allows the user to be fully involved in the digital environment, through a display that covers his entire field of view. The interaction with the simulated space occurs through hand controllers or body tracking systems, but further devices could be implemented to generate sensations such as vibration or touch.
Both types of VR have potential applications in academic contexts, but the immersive VR can present significant challenges due to the high costs associated with providing the necessary technology to an appropriate number of students. On the other hand, it may have higher potential to enhance students' understanding of complex concepts and academic achievement, since the immersive environment can stimulate curiosity and engagement.
Some examples of the implementation of VR technology in educational institutions include simulations of scientific phenomena, recreation of historical events, and virtual scenarios in which students can practice their language skills.
Currently, there are not many experiments or data regarding the implementation of VR in schools, to assess the effect it can have on students' academic performances. Nevertheless, in a quasi-experimental approach followed by Liu et al. (2020), the treatment group obtained significantly higher outcomes with respect to the control group, which did not have the possibility to explore the environment created by VR technologies.

These results can be explained by both the support that these tools provide in understanding complex concepts, as well as the ability to increase motivation and enhance problem-solving skills (Liu et al., 2020).
Certainly, the cost of VR technologies is often prohibitive. However, it is important to note that they have the ability to create simulations and scenarios that would be much more expensive in the real world. This is particularly relevant in educational institutions where there is shortage of laboratories, often due to the high costs to build and maintain them. With VR, it became possible to replicate lab experiments in a virtual world; therefore, from this perspective, VR offers significant cost savings (Bogusevschi et al. 2020).
As Vera et al. (2005) explain, VR offers huge advantages for students with learning disabilities. Some features that could be very helpful for these students include the repetition of the same scenario multiple times, the possibility to manipulate the environment at will, and to deal with dangerous situations such as fire practice or crossing the road.

Comparing the implementation of AR with the one of VR, an experiment cited by Alalwan et al. (2020) revealed that students appreciated both tools, but for different reasons. VR allows them to explore the environment themselves, which may create a higher engagement. On the contrary, AR is easier to use and more accessible even from home since it only requires a smartphone. Regarding teachers' opinions, instead, there is a general preference for the AR for its ease of use and capacity to monitor students, while VR does not provide the same level of oversight.

With the introduction of technologies as AR, non-immersive VR, and immersive VR, gamification in academic contexts takes on a completely new meaning. It is generally defined as "a technique that proposes dynamics associated with game design in the educational environment, in order to stimulate and have direct interaction with students" (Manzano-León et al. 2021).
The most used elements of gamification such as points, badges, and leaderboards, can be implemented in new technological environments, creating new challenges, or even digital worlds in which student avatars can compete.
The positive effects of gamification include higher motivation, greater commitment, promotion of teamwork, a sense of belonging to a group, and increased classroom participation. These advantages are further enhanced when ICTs are involved (Manzano-León et al. 2021). These benefits represent why academic achievement is increased through gamification.
One possible risk, in case physical prizes are awarded to few top-performing students, is that it may create feelings of jealousy among others which in turn may not incentivize pupils to participate in these activities in the future (Çakıroglu et al. 2016).

The technological landscape, at the beginning of 2023, is being dominated by the launch of numerous AI tools. This proliferation included a variety of instruments, such as chatbots, sentiment analysis tools, and image and video recognition tools. Currently, their usage is restricted to leisure time or professional applications, and, apart from some experiments, they have not yet been exploited in academic contexts.

When AI will be introduced in educational institutions, potential benefits which can be reached include increasing motivation, assisting teachers in organizing lessons and selecting the best instructional approach, increasing engagement (Southgate et al. 2019), and most importantly, tailoring educational programs to fit the individual needs of each student (García-Martínez, 2023). All these upsides may contribute to increasing academic performances and reducing achievement gaps.

AI could be also integrated with VR and AR, to take advantage of all the synergies between them.

Southgate et al. (2019) list some possible utilizations of AI in academic contexts. One of the most useful in enhancing students' academic performance is represented by Intelligent Tutoring systems (i.e. ITS). These systems aim at replicating the interaction between a pupil and a teacher, utilizing cameras and sensors to capture emotions and provide personalized learning materials and suggestions. Through adaptive learning, they can also test students in challenging tasks, providing them with hints if needed. As students become better, they may then remove these hints to understand if the pupils have acquired the related skills.

Currently, IoT is widely used in professional environments, but this technology is not exploited in the educational one. If paired with AI, "smart classrooms" can be created. As Southgate et al. (2019) define them, they are "technology-rich classrooms, equipped with wireless communication, personal digital devices, sensors, as well as virtual learning platforms". Through numerous sensors, it could be possible to support students whenever they need it, assess their attention and emotions, and provide suggestions to teachers in real time.

It is always worth to keep in mind that all these technologies need large amounts of data to be stored and analyzed by the software, which may give rise to ethical and privacy problems.

# 2. Data

The Organization of Economic Co-operation and Development pioneered the global initiative known as PISA, which stands for "Programme for International Student Assessment". Every three years, it administers its tests to the students of the participating countries that are between 15 and 16 years old. PISA randomly samples the students to test in order to avoid potential biases.

By combing the test scores of the students in its assessments, with the questionnaires that it administers to the students, the parents, and the teachers of the selected schools, the aim of the OECD is to unveil the factors influencing students' academic scores in reading, mathematics and science. To name a few, students' attitudes, beliefs, the amount of support they receive by their parents or teachers, are examples of aspects that may influence students' test scores. In recent years, educational contexts have significantly changed due to the advent of ICTs and digital devices. Policy makers have been strongly debating on whether ICTs represent an improvement or a threat to traditional forms of education. For this reason, in the following research, a strong focus is posed on ICTs. The analyses are conducted on the EU27 nations of the PISA 2018 dataset, with the aim of unveiling if and how ICTs may enhance students' academic performance in reading, mathematics and science.

In the following chapters, the results of the analyses are presented in greater detail. An outline of how the research was conducted is presented hereafter.

First a description of PISA is presented. The aim of the paragraph is to provide the reader with a general understanding of what PISA is, the typology of assessments it carries out, and a description of how it selects the students to participate in its programs. The reasons behind why PISA assessments are relevant for educators and policy-makers are also provided.

Subsequently, a description of the dataset that is used to conduct the descriptive statistics and the statistical analyses in the research is presented. The aim of this section is to explain how the dataset and the variables are constructed, in order for the study to be replicable in case of future studies. The section provides greater insights on which PISA 2018 datasets are selected and how they are merged together. Additionally, the paragraph describes the variables that are chosen for the study, the reason for which they are selected, and details on potential transformations that are conducted on the latter. Finally, details on the nations on which the research focuses on are also presented.

Lastly, the results of the descriptive statistics are highlighted. It is worth noting that the conclusions that will be drawn are purely descriptive and do not imply any causal inferences. They are foundational for providing an overview of the current adoption of ICTs within schools and assessing which nations are currently the best performing in terms of their students' academic results in reading, mathematics and science. The paragraph also aims at unveiling if there is any spatial dependence among the test scores of students studying in the top performing nations. Furthermore, the section assesses how much ICTs are typically adopted in schools, who among students and teachers are the main users of these technologies, which nations are using ICTs the most, and additionally, for which activities digital devices are currently being adopted in teaching practices. Lastly, a strong focus is posed on the correlation among digital device usage in schools and students' test scores.

## 2.1 PISA

PISA is a global initiative of the OECD, the Organization for Economic Co-Operation and Development, aimed at assessing the academic performance of 15 year-old students in reading, mathematics and science.
Other than merely assessing learners' skills in the latter three subjects, which are considered to be of vital importance for students lifelong learning, PISA also indirectly tries to uncover if students have developed the ability to apply those skills to reason and communicate effectively, and to solve real life problems.
The assessment is held every three years, and each time focuses on evaluating students' performance in one subject among reading, mathematics and science.
Despite being designed for one specific subject, students are assessed in all three fields throughout the year.
The Programme is for students that are 15/16 years-old and that are enrolled in an educational institution at grade 7 or above. This is because within that age range, students are at the end of compulsory education in the majority of OECD countries.
Throughout the sampling process, PISA selects schools and students regardless of the type of educational institution they are enrolled in, and independently of whether learners are attending full-time or part-time education.
Each sampled student is then assigned a weight that indicates the student cohort they are representing. This allows extending the results from the statistical sample to the whole population under analysis.

PISA 2018, the dataset that was used to carry out the following study, was designed specifically to assess students' academic performance in reading.
For the first time in decades, an adaptive testing approach was used. The more students answered questions correctly, the harder the test became. Although this may not seem the best approach to use for comparing students, the reader must always keep in mind that PISA aims at contrasting academic performances among nations, not between students. It is thereby fundamental that students receive tests with different difficulties.
The computer based test lasted approximately two hours and was composed predominantly by multiple choice questions. Up to one third of the questions were instead open-ended. The former typology of questions was preferred to the latter as they are more efficient, robust and allow for

better comparisons during statistical analyses. Within the plethora of the multiple choice questions, the format varied significantly, from highlighting words in a text, to making multiple selections in a drop down menu, and more.
For the first time in a reading assessment, the test also included questions to assess how students were adapting to recent changes in education. The advent of ICTs has significantly increased the availability of materials to read online, causing readers to shift from physical to electronic reading formats. Consequently, the test also aimed at assessing whether students were capable of finding, integrating and contrasting information from multiple sources of text.
After the test, students were asked to complete a “Student questionnaire” concerning their attitudes, beliefs and learning experiences at school. In addition, principals were required to fill out a “school questionnaire” concerning their schools management, organization and learning environment.
Additional questionnaires were completed by students on a voluntary basis. This included the student “ICT familiarity questionnaire”, the student “Wellbeing questionnaire” and the student “Future expectations from education” questionnaire. Parents and teachers could also choose to complete a “Parent questionnaire” and “Teachers questionnaire” concerning the involvement parents had in their children’s education, and a description of the instructor’s teaching practices.
All these questionnaires were, and continue to be, fundamental for educators and policy-makers as they allow to understand the factors behind a nations’ exceptional academic performance. In turn, successful scholastic policies in high performing nations may be replicated in lower performing countries to increase their students’ academic achievements. Lastly, it enables researchers to study potential existing correlations between students’ test scores and the latter’s immigration status, socio-economic background, gender, learning environment and more.
These are all but secondary issues, as the OECD demonstrates that students that perform better in PISA assessments are more likely to reach a higher level of education, and are less likely to be completely out of the labor market further on in their career.

## 2.2 Dataset

In the following paragraph, a detailed description of all the variables used in the statistical models, descriptive analysis, and throughout the entire study are presented.
The first aspect provided is the name of each variable in the original dataset (i.e. the one directly provided by PISA), allowing the reader to eventually replicate in future studies the analyses performed in the following chapters.
Then the new name assigned by the authors of this study to each variable is presented, with the aim of creating outputs and plots that are more comprehensible to the reader.
As the original questionnaire provided to the students was divided into different sections, the group to which each variable belongs is indicated, if it is derived from the questionnaire. These groups include the ICT familiarity questionnaire, the student questionnaire, and the school questionnaire. Additionally, the specific question posed to the students is presented.
If the variable is constructed, a description of the methodology used to build the variable is provided.

Furthermore, the variables related to the students' test scores, the socio-economic status, the country, and the school identification number are directly obtained from the PISA dataset, as they have no corresponding question in the student questionnaire.
Then, the measurement level of each variable is shown. There are only two types of data: numerical and categorical. For categorical variables, the different alternatives are listed, while for numerical variables, the mean and standard deviation are provided.
Lastly, the reasons why each variable has been included in the study is presented.
A table summarizing the information presented is displayed immediately after the detailed description of the variables.

*CNTRYID*

- New name: *Country*.
- Source: directly obtained from the dataset.
- Measurement level: categorical.
- Alternatives: the alternatives of this variable include all the countries to which the questionnaire was administered. This study focuses on the member countries of the EU27.
- Reason: data are distinguished by country, as it is likely that there will be variations in the average student performance across countries.

*CNTSCHID*

- New name: *School*.
- Source: directly obtained from the dataset.
- Measurement level: categorical.
- Alternatives: the alternatives of this variable include all the school identification numbers of the schools to which the questionnaire was administered.
- Reason: data are distinguished by school, as it is likely that there will be variations in the average student performance across schools.

*PV1READ*

- New name*: Reading_score*.
- Source: directly obtained from the dataset.
- Measurement level: numerical.
- Mean: 483.69
- Standard deviation: 99.42
- Reason: this variable is one of the three outputs that are studied in this paper.

*PV1MATH*

- New name: *Math_score*.
- Source: directly obtained from the dataset.
- Measurement level: numerical.
- Mean: 491.40
- Standard deviation: 92.18

- Reason: this variable is one of the three outputs that are studied in this paper.

*PV1SCIE*

- New name: *Science_score*.
- Source: directly obtained from the dataset.
- Measurement level: numerical.
- Mean: 486.47
- Standard deviation: 95.04
- Reason: this variable is one of the three outputs that are studied in this paper.

*IC150Q01HA*

- New name: *Time_digital_devices_reading*.
- Source: ICT questionnaire.
- Question: "In a typical school week, how much time do you spend using digital devices during test language lessons?"
- Measurement level: categorical.
- Alternatives:
  - *No time*
  - *1 – 30 minutes a week*
  - *31 – 60 minutes a week*
  - *More than 60 minutes a week*
- Adjustment: students who responded *I do not study this subject* were categorized as *No time*, since they did not use digital devices. Additionally, a specific dummy variable was created to account for the negative impact of not studying a certain subject on the student's performance. This variable will be presented in greater detail at the end of this paragraph.
- Reason: the purpose is to see if the time spent using digital devices is related with students' academic performances.

*IC150Q02HA*

- New name: *Time_digital_devices_math*.
- Source: ICT questionnaire.
- Question: "In a typical school week, how much time do you spend using digital devices during math lessons?"
- Measurement level: categorical.
- Alternatives:
  - *No time*
  - *1 – 30 minutes a week*
  - *31 – 60 minutes a week*
  - *More than 60 minutes a week*
- Adjustment: students who responded *I do not study this subject* were categorized as *No time*, since they did not use digital devices. Additionally, a specific dummy variable was created to account for the negative impact of not studying a certain subject on the

student's performance. This variable will be presented in greater detail at the end of this paragraph.

- Reason: the purpose is to see if the time spent using digital devices is related with students' academic performances.

*IC150Q03HA*

- New name: *Time_digital_devices_science*.
- Source: ICT questionnaire.
- Question: "In a typical school week, how much time do you spend using digital devices during science lessons?"
- Measurement level: categorical.
- Alternatives:
  - *No time*
  - *1 – 30 minutes a week*
  - *31 – 60 minutes a week*
  - *More than 60 minutes a week*
- Adjustment: students who responded *I do not study this subject* were categorized as *No time*, since they did not use digital devices. Additionally, a specific dummy variable was created to account for the negative impact of not studying a certain subject on the student's performance. This variable will be presented in greater detail at the end of this paragraph.
- Reason: the purpose is to see if the time spent using digital devices is related with students' academic performances.

*IC152Q01HA*

- New name: *Users_digital_devices_reading*.
- Source: ICT questionnaire.
- Question: "Within the last month, has a digital device been used for learning or teaching during test language lessons?"
- Measurement level: categorical.
- Alternatives:
  - *No*
  - *Yes, but only students used it*
  - *Yes, but only the teacher used it*
  - *Yes, both the teacher and students used it*
- Adjustment: students who responded *I do not study this subject* were categorized as *No*, since neither the scholar nor the teacher reported using digital devices during class activities. Additionally, a specific dummy variable was created to account for the negative impact of not studying a certain subject on the student's performance. This variable will be presented in greater detail at the end of this paragraph.
- Reason: the objective is to see if a higher student performance is associated with a specific type of ICT user at school.

*IC152Q02HA*

- New name: *Users_digital_devices_math*.
- Source: ICT questionnaire.
- Question: "Within the last month, has a digital device been used for learning or teaching during math lessons?"
- Measurement level: categorical.
- Alternatives:
  - *No*
  - *Yes, but only students used it*
  - *Yes, but only the teacher used it*
  - *Yes, both the teacher and students used it*
- Adjustment: students who responded *I do not study this subject* were categorized as *No*, since neither the scholar nor the teacher reported using digital devices during class activities. Additionally, a specific dummy variable was created to account for the negative impact of not studying a certain subject on the student's performance. This variable will be presented in greater detail at the end of this paragraph.
- Reason: the objective is to see if a higher student performance is associated with a specific type of ICT user at school.

*IC152Q03HA*

- New name: *Users_digital_devices_science*.
- Source: ICT questionnaire.
- Question: "Within the last month, has a digital device been used for learning or teaching during science lessons?"
- Measurement level: categorical.
- Alternatives:
  - *No*
  - *Yes, but only students used it*
  - *Yes, but only the teacher used it*
  - *Yes, both the teacher and students used it*
- Adjustment: students who responded *I do not study this subject* were categorized as *No*, since neither the scholar nor the teacher reported using digital devices during class activities. Additionally, a specific dummy variable was created to account for the negative impact of not studying a certain subject on the student's performance. This variable will be presented in greater detail at the end of this paragraph.
- Reason: the objective is to see if a higher student performance is associated with a specific type of ICT user at school.

*IC011Q01TA*

- New name: *Chatting_online*.
- Source: ICT questionnaire.

- Question: “How often do you use digital devices for chatting online at school?”
- Measurement level: categorical.
- Alternatives:
  - *Never or hardly ever*
  - *Once or twice a month*
  - *Once or twice a week*
  - *Almost every day*
  - *Every day*
- Reason: the purpose is to see if, and how, this activity is related to students’ academic performances.

*IC011Q02TA*

- New name: *Email*.
- Source: ICT questionnaire.
- Question: “How often do you use digital devices for using email at school?”
- Measurement level: categorical.
- Alternatives:
  - *Never or hardly ever*
  - *Once or twice a month*
  - *Once or twice a week*
  - *Almost every day*
  - *Every day*
- Reason: the purpose is to see if, and how, this activity is related to students’ academic performances.

*IC011Q03TA*

- New name: *Internet_schoolwork*.
- Source: ICT questionnaire.
- Question: “How often do you use digital devices for browsing the internet for schoolwork at school?”
- Measurement level: categorical.
- Alternatives:
  - *Never or hardly ever*
  - *Once or twice a month*
  - *Once or twice a week*
  - *Almost every day*
  - *Every day*
- Reason: the purpose is to see if, and how, this activity is related to students’ academic performances.

*IC011Q04TA*

- New name: *Browsing_school_website*.
- Source: ICT questionnaire.

- Question: “How often do you use digital devices for downloading, uploading or browsing material from the school’s website at school?”
- Measurement level: categorical.
- Alternatives:
  - *Never or hardly ever*
  - *Once or twice a month*
  - *Once or twice a week*
  - *Almost every day*
  - *Every day*
- Reason: the purpose is to see if, and how, this activity is related to students’ academic performances.

*IC011Q05TA*

- New name: *Posting_school_website*.
- Source: ICT questionnaire.
- Question: “How often do you use digital devices for posting your work on the school’s website at school?”
- Measurement level: categorical.
- Alternatives:
  - *Never or hardly ever*
  - *Once or twice a month*
  - *Once or twice a week*
  - *Almost every day*
  - *Every day*
- Reason: the purpose is to see if, and how, this activity is related to students’ academic performances.

*IC011Q06TA*

- New name: *Simulations*.
- Source: ICT questionnaire.
- Question: “How often do you use digital devices for playing simulations at school?”
- Measurement level: categorical.
- Alternatives:
  - *Never or hardly ever*
  - *Once or twice a month*
  - *Once or twice a week*
  - *Almost every day*
  - *Every day*
- Reason: the purpose is to see if, and how, this activity is related to students’ academic performances.

*IC011Q07TA*

- New name: *Practicing_and_drilling*.

- Source: ICT questionnaire.
- Question: “How often do you use digital devices for practicing and drilling, such as for foreign language learning or mathematics at school?”
- Measurement level: categorical.
- Alternatives:
  - *Never or hardly ever*
  - *Once or twice a month*
  - *Once or twice a week*
  - *Almost every day*
  - *Every day*
- Reason: the purpose is to see if, and how, this activity is related to students’ academic performances.

*IC011Q08TA*

- New name: *Homework_school_computer*.
- Source: ICT questionnaire.
- Question: “How often do you use digital devices for doing homework on a school computer?”
- Measurement level: categorical.
- Alternatives:
  - *Never or hardly ever*
  - *Once or twice a month*
  - *Once or twice a week*
  - *Almost every day*
  - *Every day*
- Reason: the purpose is to see if, and how, this activity is related to students’ academic performances.

*IC011Q09TA*

- New name: *Computer_group_work*.
- Source: ICT questionnaire.
- Question: “How often do you use school computers for group work and communication with other students at school?”
- Measurement level: categorical.
- Alternatives:
  - *Never or hardly ever*
  - *Once or twice a month*
  - *Once or twice a week*
  - *Almost every day*
  - *Every day*
- Reason: the purpose is to see if, and how, this activity is related with students’ academic performances.

*IC011Q10HA*

- New name: *Learning_apps*.
- Source: ICT questionnaire.
- Question: “How often do you use learning apps or learning websites at school?”
- Measurement level: categorical.
- Alternatives:
    - *Never or hardly ever*
    - *Once or twice a month*
    - *Once or twice a week*
    - *Almost every day*
    - *Every day*
- Reason: the purpose is to see if, and how, this activity is to with students’ academic performances.

*IC005Q01TA*

- New name: *Time_internet*.
- Source: ICT questionnaire.
- Question: “During a typical weekday, for how long do you use the Internet at school?”
- Measurement level: categorical.
- Alternatives:
    - *No time*
    - *1 – 30 minutes per day*
    - *31 – 60 minutes per day*
    - *Between 1 hour and 2 hours per day*
    - *Between 2 hours and 4 hours per day*
    - *Between 4 hours and 6 hours per day*
    - *More than 6 hours per day*
- Reason: the purpose is to see if, and how, the use of the Internet at school is related to students’ academic performances.

*IC013Q13NA*

- New name: *Enjoyment_digital_devices*.
- Source: ICT questionnaire.
- Question: “Thinking about your experience with digital media and digital devices: to what extent do you disagree or agree with the following statement? I like using digital devices.”
- Measurement level: categorical.
- Alternatives:
    - *Strongly disagree*
    - *Disagree*
    - *Agree*
    - *Strongly agree*

- Reason: the purpose is to control for the passion that students have for digital devices. Students who answered *Agree* or *Strongly agree* could benefit from being more practical with these devices. This would reduce the time needed to learn how to use them, allowing students to take full advantage of the potentialities of these technologies. In this way, digital devices would not be a learning barrier that could be otherwise difficult to overcome.

*ESCS*

- Source: directly obtained from the dataset.
- Measurement level: numerical.
- Mean: -0.027
- Standard deviation: 0.95
- Reason: ESCS, or "Economic, Social and Cultural Status", is a variable introduced to control for financial, social and human characteristics of the family of each student.
  As stated in subchapter 1.1, the academic performance of students can be influenced by the economic, social and cultural status of their families. This is due to the fact that parents with a higher income are able to provide their children with more resources. Furthermore, parents with a higher level of education are better equipped to offer direct support to their children, and are more likely to invest more in their education than parents with a lower level of schooling.
- Definition: according to OECD (2019), ESCS is derived "from three variables related to family background: parents' highest level of education, parents' highest occupational status, and home possessions". The first one and the last one are obtained from closed-ended questions posed to students, while the second one is developed from open-ended questions.
  In the dataset used in this study, a new way to compute the ESCS was introduced by OECD. In the past, it was calculated taking the factor scores of the first principal component, after having performed a principal component analysis of standardized variables. However, in 2018 an average was computed giving the same weight to the three standardized components: parents' highest level of education, parents' highest occupational status, and home possessions.
  In both cases, the standardization is performed across countries and economies, where each of them contributes likewise.
  Lastly, the obtained variable has been transformed to have average 0 and standard deviation 1.

*ESCS_school*

- Source: constructed.
- Measurement level: numerical.
- Mean: - 0.03
- Standard deviation: 0.53
- How it is constructed: $ESCS\_school_i = \frac{\sum_j^N ESCS_j}{N}$ where:
  - "i" is an index to represent each school

   - “j” is an index to represent each student
   - “N” is the number of students in each school
- Reason: it is important to take into account school characteristics, in addition to the economic, social and cultural status of the student.
  Schools that vary in their average economic, social and cultural status may show dissimilarities in the materials provided, the teachers’ years of experience, and teacher-student ratio.

*ST034Q01TA*

- New name: *Outsider*.
- Source: student questionnaire.
- Question: “Thinking about your school: to what extent do you agree with the following statement? I feel like an outsider (or left out of things) at school.”
- Measurement level: categorical.
- Alternatives:
   - *Strongly disagree*
   - *Disagree*
   - *Agree*
   - *Strongly agree*
- Reason: the purpose is to control for the possible negative impact of feeling like an outsider at school, which in turn can lead to lower student motivation.

*ST004D01T*

- New name: *Gender*.
- Source: student questionnaire.
- Question: “Are you female or male?”
- Measurement level: categorical.
- Alternatives:
   - *Male*
   - *Female*
- Reason: the purpose is to control for the gender differences in certain subjects, as there may be variations in performance.
  It is widely acknowledged that, on average, females tend to excel in reading, while males tend to perform better in mathematics.

*ST160Q01IA*

- New name: *Read_if_have_to*.
- Source: student questionnaire.
- Question: “How much do you agree or disagree with these statement about reading? I read only if I have to.”
- Measurement level: categorical.
- Alternatives:
   - *Strongly disagree*

  - *Disagree*
  - *Agree*
  - *Strongly agree*
- Reason: the purpose is to control for students' passion for reading and their ability to focus on a book.

*ST100Q03TA*

- New name: *Teacher_assistance*.
- Source: student questionnaire.
- Question: "How often do these things happen in your test language lessons? The teacher helps students with their learning."
- Measurement level: categorical.
- Alternatives:
  - *Never or hardly ever*
  - *Some lessons*
  - *Most lessons*
  - *Every lesson*
- Reason: the purpose is to control for the impact that teacher support has towards students' academic performances.

*ST123Q02NA*

- New name: *Parent_assistance*.
- Source: student questionnaire.
- Question: "Thinking about this academic year, to what extent do you agree or disagree with the following statement? My parents support me when I am facing difficulties at school."
- Measurement level: categorical.
- Alternatives:
  - *Strongly disagree*
  - *Disagree*
  - *Agree*
  - *Strongly agree*
- Reason: the purpose is to control for the impact that parental support has towards students' academic performances.
  Chapter 1.1 provides an overview of the potential differences in academic performance between firstborns and laterborns, along with several theories aimed at explaining these dissimilarities.
  One of these theories is the resource dilution model, which suggests that family resources, such as parental attention, are shared between every child, resulting in a better performance of only children, who do not have to share these resources with siblings. Although the dataset under consideration does not include information about the number of siblings of each student, the degree of parental support is examined as a potential variable to explain differences between students who receive high levels of parental

support and those who receive lower levels of parental support. This variable may potentially help to distinguish between only children and students with siblings, as well as between students with different levels of parental support.

It is worth noting that while the number of siblings is a starting factor that can potentially influence the degree of parental support, which in turn may influence students' academic performance, examining parental support directly allows for a better understanding of the potential impact of family resources on academic outcomes.

*ST182Q04HA*

- New name: *Persistence*.
- Source: student questionnaire.
- Question: "How much do you agree with the following statement about yourself? Once I start a task, I persist until it is finished."
- Measurement level: categorical.
- Alternatives:
  - *Strongly disagree*
  - *Disagree*
  - *Agree*
  - *Strongly agree*
- Reason: the purpose is to control for the impact of student persistence on their academic achievements.

  In subchapter 1.1, the potentially favorable impacts of grit were examined, and it should be noted that these effects may also be observed in students who exhibit a high degree of persistence. Specifically, such students may be more adept at maintaining their concentration, effort and determination over an extended period.

*Age_at_immigration*

- Source: constructed.
- Measurement level: numerical.
- Mean: 0.44.
- Standard deviation: 2.05
- Methodology: the new variable is created starting from the variable *ST021Q01TA*, whose related question is "How old were you when you arrived in the country of the test?". The first label is *age 0-1*, and then the answers range from *age 1* to *age 16*. *age 0-1* has been transformed into *age 1*, since they have a similar meaning. Then, the word *age* has been removed from every answer, and the alternative *0* has been introduced for students who were born in the country where they took the test. Therefore, the new variable is a numerical variable ranging from 0 to 16.
- Reason: the purpose of this variable is to control for the impact that the amount of years that a student spent abroad before moving to the country where he has taken the PISA test, has on student's test scores.

  As evidenced by some studies cited in subchapter 1.1, there are situations where students who are native to the country in which they are studying outperform those who were born abroad. Furthermore, the magnitude of this performance gap may vary depending on the number of years that the student spent living outside the country prior to taking the test.

*SC011Q01TA*

- New name: *School_competition*.
- Source: school questionnaire.
- Question: "Which of the following statements best describes the schooling available to students in your location?"
- Measurement level: categorical.
- Alternatives:
  - *There are no other schools in this area that compete for our students*
  - *There is one other school in this area that competes for our students*
  - *There are two or more other schools in this area that compete for our students*
- Reason: the purpose is to control for the competition among nearby schools. It can also serve as a proxy of urban or rural areas.

*SC012Q01TA*

- New name: *Student_selection*.
- Source: school questionnaire.
- Question: "How often are the following factors considered when students are admitted to your school? Student's record of academic performance (including placement tests)"
- Measurement level: categorical.
- Alternatives:
  - *Never*
  - *Sometimes*
  - *Always*
- Reason: the purpose is to control for the difference between schools that admit students based on a specific test and those that accept every student. Controlling for this variable can mitigate the impact of the bias created with the different admission processes.

*Grade_repetition*

- Source: constructed.
- Measurement level: categorical.
- Alternatives:
  - *No*
  - *Yes*
- Methodology: the new variable is created using the variables *ST127Q01TA* and *ST127Q02TA*. *ST127Q03TA* was excluded since most of its answers were missing values.

  The value *Yes* was assigned to *Grade_repetition* if at least one of the two starting variables had the value *Yes, once* or *Yes, twice or more*. If one variable had the value *No, never* and the other variable had a missing value, then a missing value was assigned to *Grade_repetition*. Lastly, if both variables had the value *No, never*, the value *No* was assigned to the new variable.

- Reason: the purpose is to control for the impact of grade repetition on students' performances.

*Reading_not_studied*

- Source: constructed.
- Measurement level: categorical.
- Alternatives:
  - *No*
  - *Yes*
- Methodology: the variables *IC150Q01HA* and *IC152Q01HA* previously mentioned included the response option *I do not study this subject*, referring to the reading subject. If a student answered *I do not study this subject* in at least one of these two questions, the alternative *Yes* was assigned to the variable *Reading_not_studied*, otherwise it was assigned the alternative *No*.
- Reason: the purpose of this variable is to control for students who do not study the reading subject.

*Math_not_studied*

- Source: constructed.
- Measurement level: categorical.
- Alternatives:
  - *No*
  - *Yes*
- Methodology: the variables *IC150Q02HA* and *IC152Q02HA* previously mentioned included the response option *I do not study this subject*, referring to mathematics. If a student answered *I do not study this subject* in at least one of these two questions, the alternative *Yes* was assigned to the variable *Math_not_studied*, otherwise it was assigned the alternative *No*.
- Reason: the purpose of this variable is to control for students who do not study mathematics.

*Science_not_studied*

- Source: constructed.
- Measurement level: categorical.
- Alternatives:
  - *No*
  - *Yes*
- Methodology: the variables *IC150Q03HA* and *IC152Q03HA* previously mentioned included the response option *I do not study this subject*, referring to science. If a student answered *I do not study this subject* in at least one of these two questions, the alternative

*Yes* was assigned to the variable *Science_not_studied*, otherwise it was assigned the alternative *No*.

- Reason: the purpose of this variable is to control for students who do not study science.

A table summarizing various aspects of the variables is presented below.
The first column displays the newly assigned names of the variables as stated by the authors of this paper. The second column provides information on the domain of each variable, indicating whether it refers to the characteristics of the student, school, or ICT usage and familiarity. The third column indicates the measurement level of each variable, while the final column reports the mean for numerical variables only.

| *Name* | *Domain* | *Measurement level* | *Mean* |
|---|---|---|---|
| *Country* | Student & School | Categorical | - |
| *School* | School | Categorical | - |
| *Reading_score* | Student | Numerical | 483.69 |
| *Math_score* | Student | Numerical | 491.40 |
| *Science_score* | Student | Numerical | 486.47 |
| *Time_digital_devices_reading* | ICT | Categorical | - |
| *Time_digital_devices_math* | ICT | Categorical | - |
| *Time_digital_devices_science* | ICT | Categorical | - |
| *Users_digital_devices_reading* | ICT | Categorical | - |
| *Users_digital_devices_math* | ICT | Categorical | - |
| *Users_digital_devices_science* | ICT | Categorical | - |
| *Chatting_online* | ICT | Categorical | - |
| *Email* | ICT | Categorical | - |
| *Internet_schoolwork* | ICT | Categorical | - |
| *Browsing_school_website* | ICT | Categorical | - |
| *Posting_school_website* | ICT | Categorical | - |
| *Simulations* | ICT | Categorical | - |
| *Practicing_and_drilling* | ICT | Categorical | - |
| *Homework_school_computer* | ICT | Categorical | - |
| *Computer_group_work* | ICT | Categorical | - |
| *Learning_apps* | ICT | Categorical | - |
| *Time_internet* | ICT | Categorical | - |
| *Enjoyment_digital_devices* | ICT | Categorical | - |
| *ESCS* | Student | Numerical | - 0.027 |
| *ESCS_school* | School | Numerical | - 0.03 |
| *Outsider* | Student | Categorical | - |
| *Gender* | Student | Binary | - |
| *Read_if_have_to* | Student | Categorical | - |
| *Teacher_assistance* | Student | Categorical | - |
| *Parent_assistance* | Student | Categorical | - |
| *Persistence* | Student | Categorical | - |

| | | | |
|---|---|---|---|
| *Age_at_immigration* | Student | Numerical | 0.44 |
| *School_competition* | School | Categorical | - |
| *Student_selection* | School | Categorical | - |
| *Grade_repetition* | Student | Binary | - |
| *Reading_not_studied* | Student | Binary | - |
| *Math_not_studied* | Student | Binary | - |
| *Science_not_studied* | Student | Binary | - |

**Table 1.** Summary of variables

In order to perform descriptive statistics and statistical analyses on the above mentioned variables, the 2018 "Student questionnaire data file" and "School questionnaire data file" datasets were downloaded directly from the PISA official website. The two datasets were then merged according to the country school ID: *CNTSCHID*.

## 2.3 Descriptive Statistics

After having described in greater detail the dataset that was used throughout the study, in the following paragraphs the descriptive statistics that were conducted on the dataset are presented. First an analysis on the students' test scores in reading, mathematics and science is presented. The objective of the analysis is to benchmark students' mean test performance across EU27 nations, with the aim of unveiling top performing countries, uncovering didactic best-practices and highlighting spatial dependence among educational systems in the European Union.
Second, a description of the use of the Internet and digital devices in the schools of the European Union is provided. Additional insights on who uses ICTs at schools (i.e. teachers, students, both), the activities digital devices are deployed for (e.g. simulations, homework etc.), and on the amount of time students use ICTs in class are also presented.

### 2.3.1 Heatmap of the Average Student Performance Across Nations

A heatmap representing the average test scores of students in EU27 nations is presented in Figure 5. All test scores are normalized to have mean of 500 and standard deviation of 100. The brighter a nation's label is on the chart, the higher the country's average test score is considered to be. Switzerland, Norway, Kosovo, Serbia, Montenegro, Albania, Bosnia and Herzegovina, North Macedonia and the United Kingdom are represented as a whitespace on the map as they are not EU27 nations. Therefore, they are omitted from the analysis.

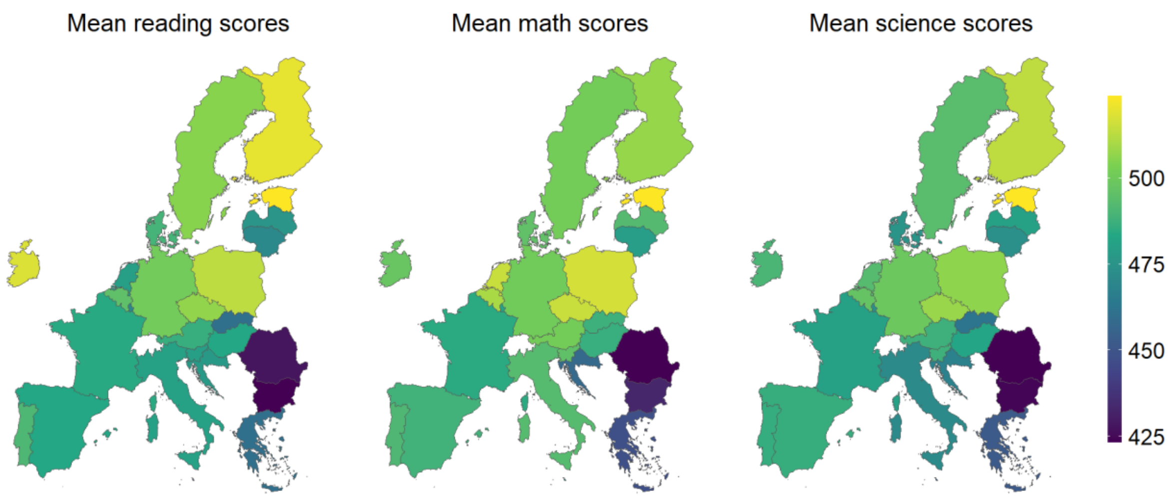


**Figure 5.** Average student test scores in reading, mathematics and science.
Variables used: Reading_score, Math_score and Science_score.

By taking a closer look at Figure 5, nations can be clustered into four macro-regions. Hereafter, they are referred to as: "Northern Europe", "Central Europe", "South Eastern Europe" and "South Western Europe".

Students in Northern Europe, including Sweden, Finland, Denmark, Estonia, Latvia and Lithuania are performing around the EU27 average or well above the average in all the three subjects. This is especially due to the strong achievements of scholars in Estonia and Finland.
Particular attention is instead needed for Danish students in science, and for Latvian/Lithuanian learners in reading. Students in these countries are lagging behind their cohort's mean performance.

Scholars in Central Europe, including Belgium, Luxembourg, Netherlands, Germany, Austria, Czech Republic, Ireland and Poland are also performing well above the EU27 average in all the three assessments. Poland is a clear example in all subjects.
Additionally, scholars in the Czech Republic, Belgium and Netherlands are great achievers in mathematics. In reading instead, while learners in Ireland are performing outstandingly, students in the Netherlands and Luxembourg are trailing behind their macro-region's average.
Lastly, in this geographic area, learners test scores in science are inferior to the ones in the other two subjects, on average.

While the typical student in the above-mentioned macro-regions has proven to be a strong academic achiever in reading, mathematics and science, the same result cannot be generalized to the scholars of the South Eastern Europe and South Western Europe macro-regions.

Learners in South Eastern Europe are performing well below the EU27 average. Within the macro-region, including Hungary, Croatia, Slovenia, Bulgaria, Romania, the Slovak Republic

and Greece, exceptionally negative performances are delivered by students in Bulgaria, Romania and Greece in all subjects.
Additionally, Croatian students are struggling in mathematics, while scholars in the Slovak Republic are under achieving in reading and science.

Lastly, in South Western Europe, including Italy, Spain, Portugal, France and Malta, students seem to be performing around or below the EU27 average.
Unlike previous areas, the performance of students in this macro-region appears to be approximately homogenous. More precisely, students in Portugal are slightly outperforming the others in reading, while students in Italy and France are marginally underperforming in science and mathematics respectively.

### 2.3.2 Geo-Statistics of the Average Student Performance Across Nations

The aforementioned heatmap provides an overview of the performance of students within the EU27 nations.
To complete the outline, some geo-statistics are implemented, with the objective of unveiling if there is spatial dependence among nations belonging to the same macro-regions. The analyses provide answers to the following questions:

*Do students of neighboring nations display similar test scores?*
*Are there clusters of nations in which the average student performs outstandingly?*
*Are there clusters of nations in which the mean scholar underperforms?*
*Within their macro-regions, do some nations have an average student test score that significantly differs from the regional average?*

To implement the geo-statistics, first a distance metric needed to be defined to determine when two nations were considered as neighbors. Two solutions were examined throughout the analysis.

The first method categorized nations as neighbors according to the “queens contiguity” metric. This meant that sharing a border was sufficient for two nations to be labeled as neighbors.
However, this procedure was discarded. The reasons are twofold:
On one hand, nations that are separated by a sea would not have been considered as neighbors. Although it may not seem like a big issue, the latter was considered wrong from a conceptual standpoint. Denmark and Sweden are an example. Even though the nations are separated by a body of water, the countries are similar from a social, cultural and economic perspective. Assuming no spatial dependence among the nations’ educational systems is therefore not appropriate.
On the other hand, nations that are geographically close but do not share a border would also not be considered as neighbors. Italy with Germany, or Estonia with Lithuania are an example. Omitting the spatial correlation among these nations is overly simplistic.

The second method instead labels nations as neighbors according to an "inverse distance function". This means that all the countries that fall within a pre-defined radius from the nation under analysis are considered to be its neighbors. This is the procedure that is adopted further on in the analyses.
Once defined as neighbors, not all the nations within the radius are attributed the same spatial dependence. As an inverse distance function is used, the bigger the distance among the nations, the less spatially correlated the nations are considered to be. This is especially true since distances are penalized to the power of five.
A large penalization factor is used in order for very distant nations within the same macro-region to be considered less spatially dependent than closer nations in the same region.
Using smaller penalization factors instead, like the distance to the power of four, was considered to be not appropriate as very distant nations, for example Latvia with Bulgaria, would have been considered as neighbors.

The outputs of the geo-statistics are presented in Figure 6. It is worth noting that Ireland is excluded from the analysis as it is considered to be neighbor of no other nation. Including the latter would have made sense if the United Kingdom had been part of the research. However, since the latter is not part of EU27, Ireland was also excluded from the analysis as well. The nation is treated as an isolated point in Figure 6.

Local Moran Is are computed to study the spatial correlation among all the remaining nations at a 5% significance level. The findings can be used to enrich the qualitative analysis previously carried out on the heatmap.

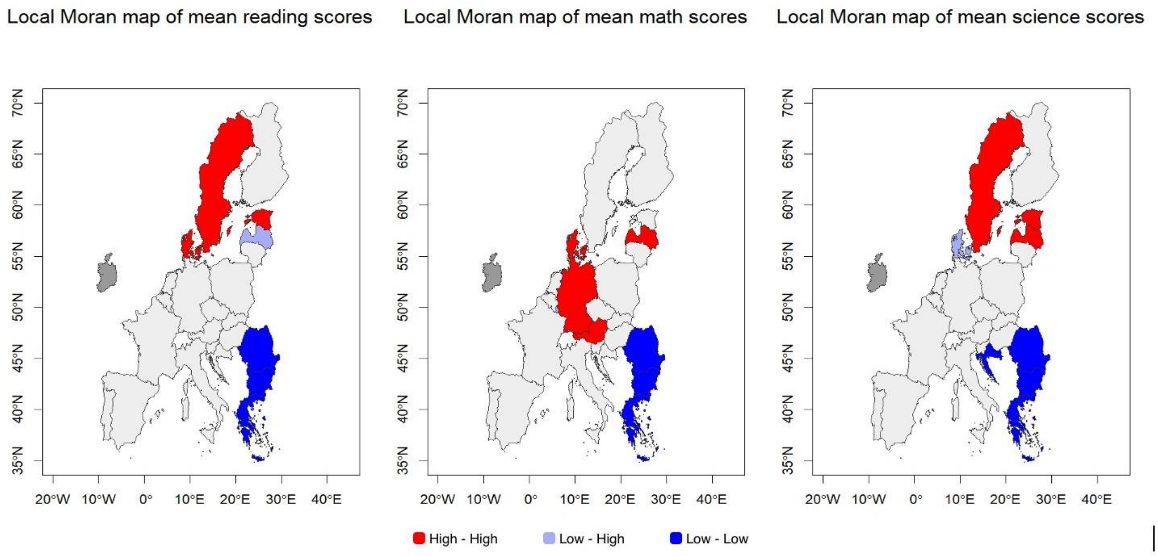


**Figure 6.** Geo-statistics on the average reading, mathematics and science test scores.
Variables used: Reading_score, Math_score and Science_score.

According to the geo-statistics, three types of spatial correlations among EU27 nations persist. The latter are specified in the labels of Figure 6 as: "High-High", "Low-High" and "Low-Low".

High-High spatial dependence, which is indicated in bright red in the above figure, represents nations in which both the students of the highlighted nations and the scholars of their neighboring countries perform above average in the PISA 2018 assessments. They are clusters of excellence.
According to the graph, the top performing nations are all in the Northern Europe and Central Europe macro-regions.
More precisely, students in Sweden and Estonia are among the top achievers in reading and science tests. Scholars in Germany and Austria instead, together with their neighbors, are successful in mathematics assessments.

On the contrary, the students of the nations that are highlighted in dark blue in Figure 6 are underperformers. These nations are all situated in the South Eastern Europe macro-region and have Low-Low spatial correlation. This means that the students of these nations and of their neighbors perform worse than the average learner.
Students in Bulgaria, Romania and Greece are underachievers in all three tests. Additionally, Croatian students are having difficulties in the PISA science tests.

Finally, Denmark and Latvia show mixed results.
On one hand, Danish students are among the top performers in reading and mathematics assessments, while Latvian students are strong achievers in mathematics and science.
On the other hand, Danish and Latvian students' test scores have Low-High spatial correlation with the test scores of their neighbors' students in science and reading respectively. This means that while their students are performing worse than the average scholar in the aforementioned tests, their neighbors' scholars are outperforming the average learner. These nations are outliers in the latter subjects.

All the above-mentioned results provide valuable insights for educators, policy-makers and local governments from a macro-region, national and long term perspective.

From a macro-region perspective, policy makers should try to unveil the reason behind the exceptional student performance in the Northern and Central European countries.
This applies especially for nations that are part of the same macro-region. These nations are more likely to share social, cultural and economic communalities than nations that are far apart from each other. Educators may try to uncover what the top performing countries in each macro-region are doing differently from the rest of the neighboring nations and use the former as a benchmark for the less performing countries.
Denmark is a clear example. Its students are performing worse in science than the ones of its neighbors in the Northern Europe macro-region. Compared to nations that are part of a different macro-region, the latter is more likely to share the approach, mentality and culture its schools have towards education with a nearby nation, like Finland. Their students are also more likely to have a similar average socio-economic background. It is important for the Danish government to unveil what its schools are doing differently, or what they are not doing compared to its neighboring nations, like Finland (e.g. lower investments in education, lower

use of ICTs etc.), in order for the country to bridge the gap in its students' academic achievements.
It may be tempting to apply a similar approach to nations that are part of different macro-regions as well. However, this approach is not the most appropriate.
Take for instance Finland and Romania, whose students are among the top and least performing students in reading respectively. Simply replicating successful Finnish scholastic policies to the Romanian educational system may not be appropriate, as the two nations significantly differ form a social, cultural and economic perspective. Policy makers must always keep in mind that there is no "one size fits all" educational system. Policies of other countries must always be adapted to a nation's specific needs and context.
Lastly policy makers from top performing nations may also learn from the ones of less performing countries. Take for instance the Northern Europe and the South Western Europe macro-regions. Despite students in the former significantly outperform scholars in the latter, the variability of the performance of the students in the former is much higher than the one of the latter. This means that in South Western Europe there is a higher homogeneity in the students' performance. This macro-region is more capable of assuring a homogenous quality of education among its nations. In Northern Europe instead, inequality concerns may arise in the long run if the issue is not addressed carefully.

A similar reasoning may apply at a national level. Educators within a country may be interested in understanding why their students are performing exceptionally well in certain subjects compared to others.
This is the case of the nations that have a Low-High spatial dependence in the geo-statistics. For example, Denmark's policy makers may want to unveil the reasons behind their students' relatively strong performance in reading and weak achievements in science.

Lastly, interesting insights may also be drawn in a long term perspective. Better student test scores in the Northern Europe and Central Europe macro-regions may highlight a better quality of education. In the long run, the latter may foster a nation's economic growth, stimulate innovation and enhance social cohesion and equality. From an individual's perspective, it may also increase the average citizen's earnings, employment status and the quality of the health services they receive. In turn, this may encourage students to study, causing an increase in student enrollment rates and a decrease in student dropouts. All these factors may then create a positive cycle that further increases a nation's growth.
This positive effect persists only for top achieving nations.
European policy makers must try to bridge the gap in the different quality of education among macro-regions in the long run. Otherwise, students in lower performing nations may be seen as less skilled on the labor market further on in their careers. This may result in difficulties for these students in finding jobs in better performing countries. Not only would they be granted an inferior quality of education throughout their studies, they would also have repercussions in their careers in the long run. In turn, this may create a lack of incentive to study and an increase in dropout rates. All the latter may then further increase the existing gap in the quality of education among top performing and worse performing macro-regions.

## 2.3.3 Time Series of the Average Student Performance Across Nations

Finally, time series of the average student test scores between 2012 and 2018 are presented in Figures 7, 8 and 9. They provide an overview of the temporal evolution of each nation's average test scores in the last PISA assessment cycle in reading, mathematics and science. In order to create the time series, the "Student questionnaire data files" of years 2012, 2015 and 2018 are used. The datasets are available in the "Data" section of the PISA website.

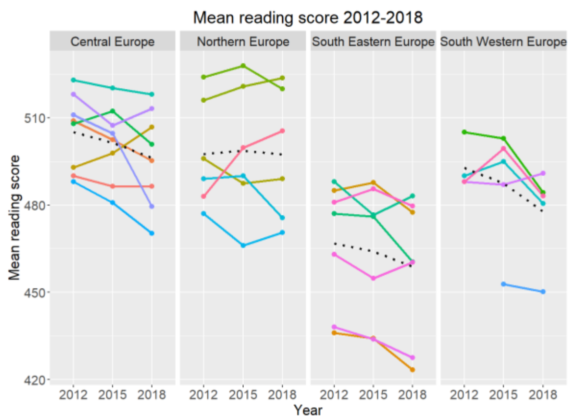


**Figure 7.** Time series of average student reading test score.

Variable used: *Reading_score.*

Dotted line: Macro-region average.

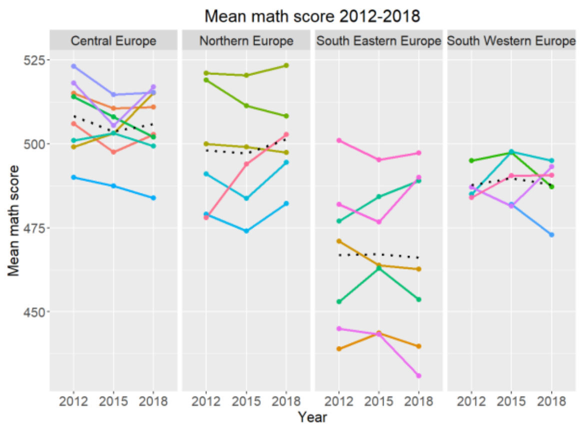


**Figure 8.** Time series of average student mathematics test score.

Variable used: *Math_score*.

Dotted line: Macro-region average.

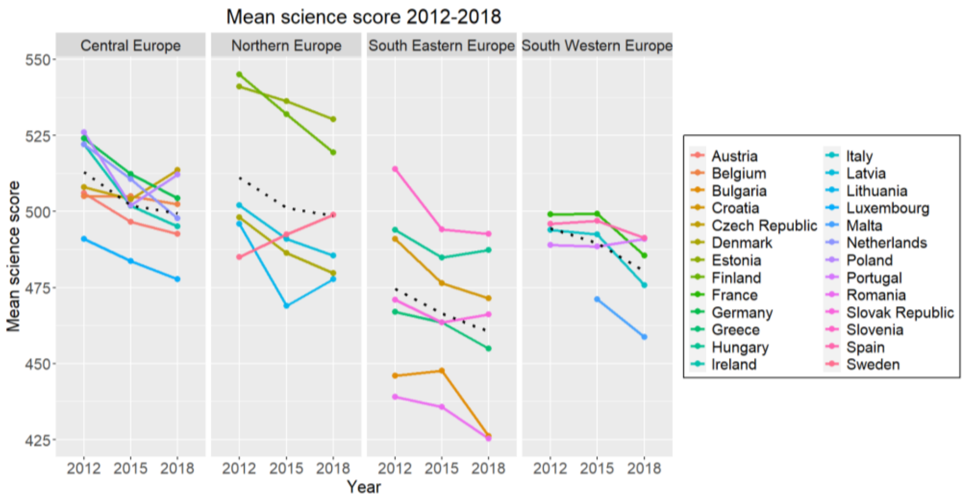


**Figure 9.** Time series of average student science test score.

Variable used: *Science_score*.

Dotted line: Macro-region average.

On one hand, the graphs confirm the previously mentioned conclusions. In South Eastern and South Western Europe, students perform well below the EU27 average. In Central and Northern Europe instead, students match or outperform the average learner.

On the other hand, the time series highlight a substantial difference between the average learner in Northern Europe and the ones of the other macro-regions. In reading, while the average student performance has been decreasing over time in all macro-regions, students in Northern Europe have maintained their performance approximately constant. Additionally, in mathematics, while the average scholar in each macro-region has seen a decrease or no variation in their performance throughout the years, scholars in Northern Europe have improved their average test scores.
To try and explain the relatively strong performance of students in Northern Europe, the time series are paired to Figures 11 and 13. The objective is to try and unveil what nations in Northern Europe are doing differently than countries in least performing macro-regions like South Eastern Europe.

From one point of view, Figures 11 and 13 clearly highlight that nations in Northern Europe are leading the digital transformation of educational institutions across Europe. Their students are among the ones that report the highest use of the Internet and digital devices in schools.
From another point of view instead, the higher use of ICTs cannot be the only explanation behind the better student performance in Northern Europe. The reasons are threefold.
First, not all nations in Northern Europe are improving their performance in time. Students in Finland for instance have experienced a sharp decrease in their mean test scores in the last three years.
Second, other top achieving students, like the ones in Central Europe, currently have a similar adoption of ICTs to students of less performing nations like the ones in South Eastern Europe. All these nations report a low daily use of ICTs.
Lastly, scholars in every EU27 nation have increased their average use of ICTs at school in the last decades. If ICTs were the only explanatory variable for a better student performance, the average student achievement should have increased in time, unlike the results displayed in the above three plots.

By examining Figures 7, 8 and 9 from a country's perspective, additional insights may be drawn.
In Northern Europe, while students in Sweden have increased their average performance in the last three PISA assessments, scholars in Finland and Denmark have decreased their average test scores. The insight is particularly interesting considering that learners in Finland are among the top achievers in all three assessments. It highlights that nations must not only aim at increasing their average student performance in time. It is equally important for a country to maintain the strong student performance steady throughout the years.
In Central Europe, students in Luxembourg are the least performing in all three subjects. Additionally, learners in the Netherlands have significantly decreased their average test scores in reading and science, while scholars in the Czech Republic have notably been improving.
Lastly, in South Eastern and South Western Europe, students in Malta, Bulgaria and Romania have been scoring well below the EU27 average in all three assessments.

It is worth noting that all the above mentioned conclusions are purely qualitative and imply no casual inferences. For example, assessing which variables explain the better student performance in Northern Europe requires more than simple descriptive statistics. Further analyses will be addressed in section 4 with the use of statistical techniques.
The above analyses conclude the assessment of the average student test scores in EU27 nations. The following paragraphs provide a description of the use of the Internet and digital devices in the schools of the European Union. Additional insights on who uses ICTs at schools (i.e. teachers, students, both), the activities digital devices are deployed for (e.g. simulations, homework etc.), and on the amount of time students use ICTs in class are also described.

### 2.3.4 Time Spent Using Digital Devices

This paragraph focuses on the usage of digital devices, starting with an analysis of the time and frequency with which students use them.
It includes a general descriptive analysis of the student response distribution regarding how much time they used digital devices in a typical school week, as well as a country specific analysis.
Additionally, a plot is presented illustrating the frequency of activities that students engage in with digital devices.
Lastly, a descriptive analysis of the time spent using the Internet each day is provided.

Figure 10 displays a clustered column chart to illustrate the frequency of the student responses to the question: “In a typical school week, how much time do you spend using digital devices during classroom lessons?”.
The chart is divided into four answer options, each one containing three columns, representing the reading, mathematics, and science subjects.

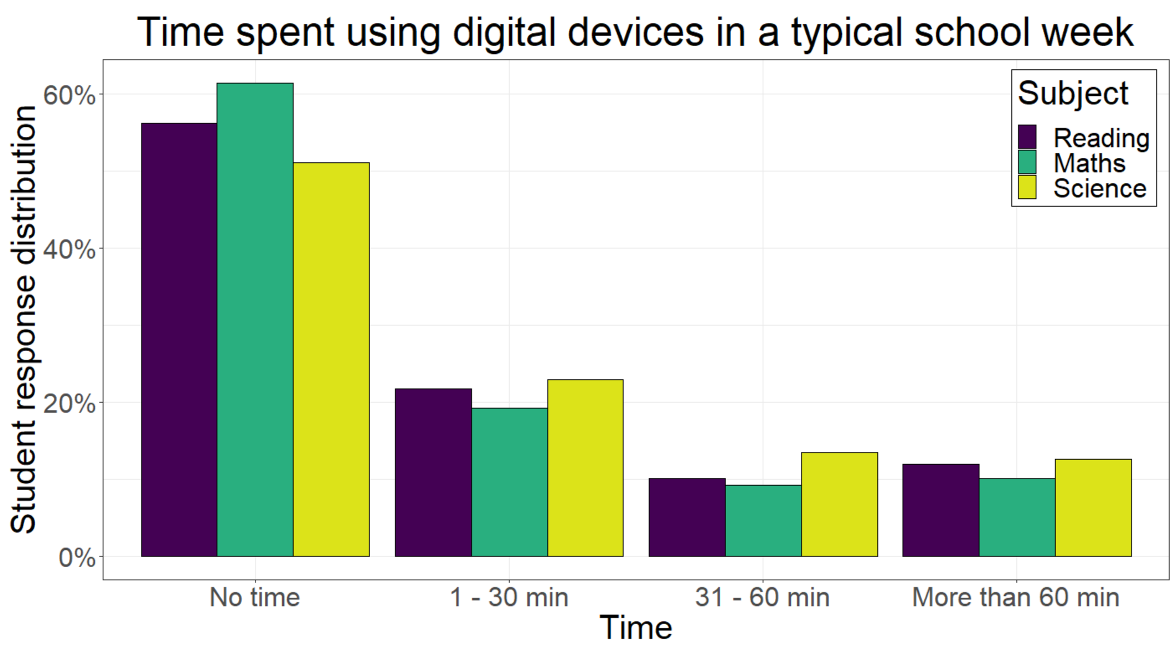


**Figure 10.** Clustered column chart of the student response distribution regarding the time spent using digital devices in a typical school week.
Variables used: Time_digital_devices_reading, Time_digital_devices_math, Time_digital_devices_science.

The first cause for concern that is observable is that over 50% of students in the selected countries do not use digital devices during lessons.
In the alternative *No time*, science has the lowest frequency. This may be attributed to the valuable assistance that ICTs provide in visualizing and comprehending abstract concepts during science lessons. On the other hand, mathematics is the subject with the highest frequency: over 60% of students do not use ICTs.
Two of the remaining three factors indicate low levels of digital device usage, with only the final category indicating a considerable amount of time spent on devices per week.
Across the remaining three factors, the percentage of students using ICTs in mathematics lessons is consistently the lowest, while science has always the highest usage.
Comparing the remaining three factors, the first one, which indicates from one to thirty minutes per week of digital device use, has the highest frequency in all three subjects, suggesting that many students are still not widely adopting ICTs during lessons. Finally, only around 10% of students use digital devices for more than 60 minutes per week.

To dig deeper in the use of digital devices among EU27 nations, a country specific analysis is conducted in Figure 11. This is particularly relevant due to the different social and cultural contexts that nations of the European Union are exposed to.

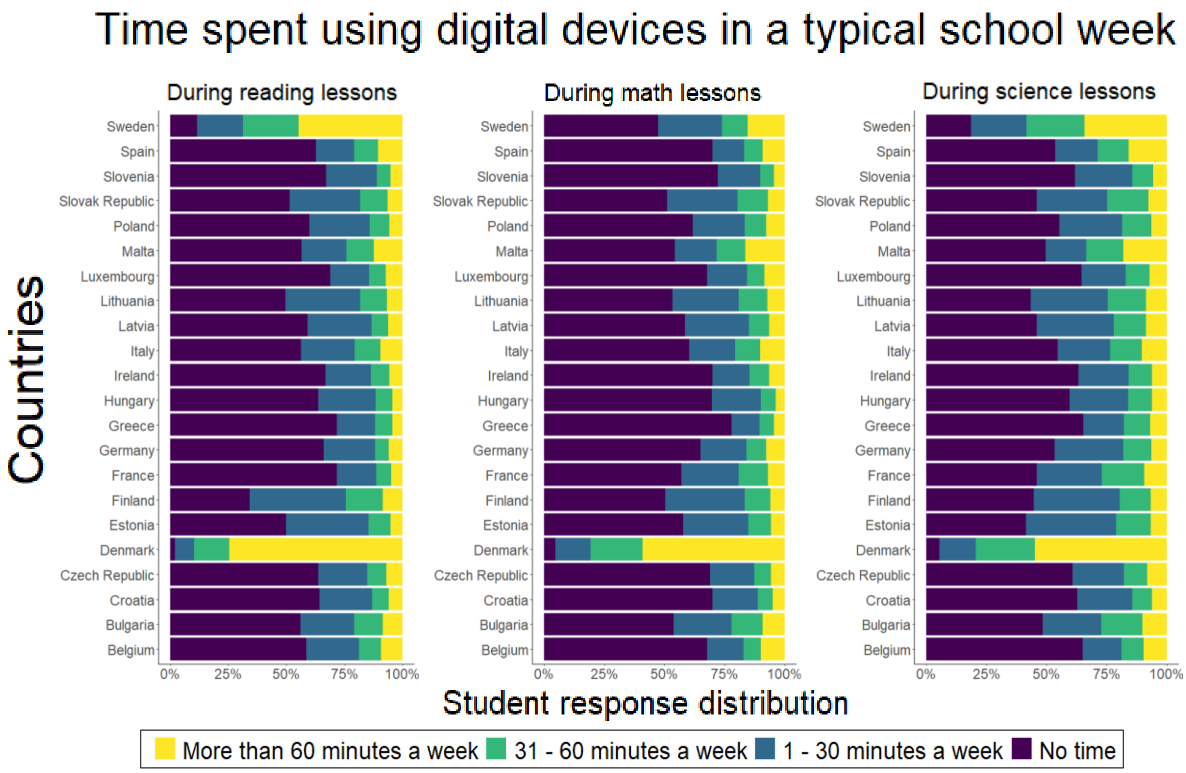


**Figure 11.** Stacked column chart of the student response distribution regarding the time spent using digital devices in a typical school week among EU27 nations. Variables used: Time_digital_devices_reading, Time_digital_devices_math, Time_digital_devices_science, Country.

Considering the overall picture, it is evident that the alternative *No time* prevails in most of the countries, as indicated by the student response distributions that often show a value which is higher than 50% for this category. On the other hand, the only factor that demonstrates a satisfactory level of digital device usage, namely *More than 60 minutes a week*, is reported by fewer than 20% of students in the majority of the nations.

Beginning from the plot on the left, which shows the time spent using digital devices during reading lessons in a typical school week, it is immediately evident that only two countries, Sweden and Denmark, exhibit a high level of digital device usage; Finland, Lithuania, and Slovak Republic follow closely behind.

The heatmap illustrated in Figure 5 reveals that several of these countries, including Sweden, Denmark and Finland have a relatively high average reading score. Lithuania instead is performing poorly in this regard.

Conversely, Slovenia, Luxembourg, Greece, and France appear to have the lowest level of digital device usage in the considered subject.

There are significant differences in terms of reading performance within this group. Luxembourg and Greece are performing below average, while France and Slovenia maintain a relatively good level of academic performance among their students.

Shifting the focus to mathematics lessons, it is evident how Sweden and Finland exhibit a significant decrease in digital device usage. France shows an opposite trend. The other countries instead maintain a similar level of usage as the one observed for reading lessons.
In the final subject under consideration, science, the majority of countries maintain a similar hierarchy as observed in the plot on the left. Germany, France, and Estonia instead show an increase in digital device usage during science lessons.

Furthermore, an analysis on the activities that students perform with digital devices at school is presented in Figure 12. This allows to gain a deeper understanding on how digital devices are currently being used at school in each country. The following plot displays the mode of digital device usage for each activity in each country. It provides insights into how frequently the majority of students engage in using digital devices in each activity. For example, if a nation is reported in the plot using digital devices for "Using email at school" in a quantity *Never or hardly ever*, it means that the majority of students within the nation are currently not adopting digital devices for the latter activity.

The question posed to students is "How often do you use digital devices for the following activities at school?", followed by a list of ten activities, each requiring an exclusive answer regarding how often the student used digital devices for that specific activity. The activities listed included "Chatting online at school", "Using email at school", "Browsing the Internet for schoolwork", "Downloading, uploading or browsing material from the school's website", "Posting my work on the school's website", "Playing simulations at school", "Practicing and drilling, such as for foreign language learning or mathematics", "Doing homework on a school computer", "Using school computers for group work and communication with other students", and "Using learning apps or learning websites". These activities are listed from left to right on the horizontal axis, while the vertical axis illustrates the time usage of digital devices for each activity.
The plot focuses exclusively on the mode response for each nation, resulting in a significant loss of information. However, if the mode is not *Never or hardly ever*, it indicates that the technologies are widely adopted by countries.

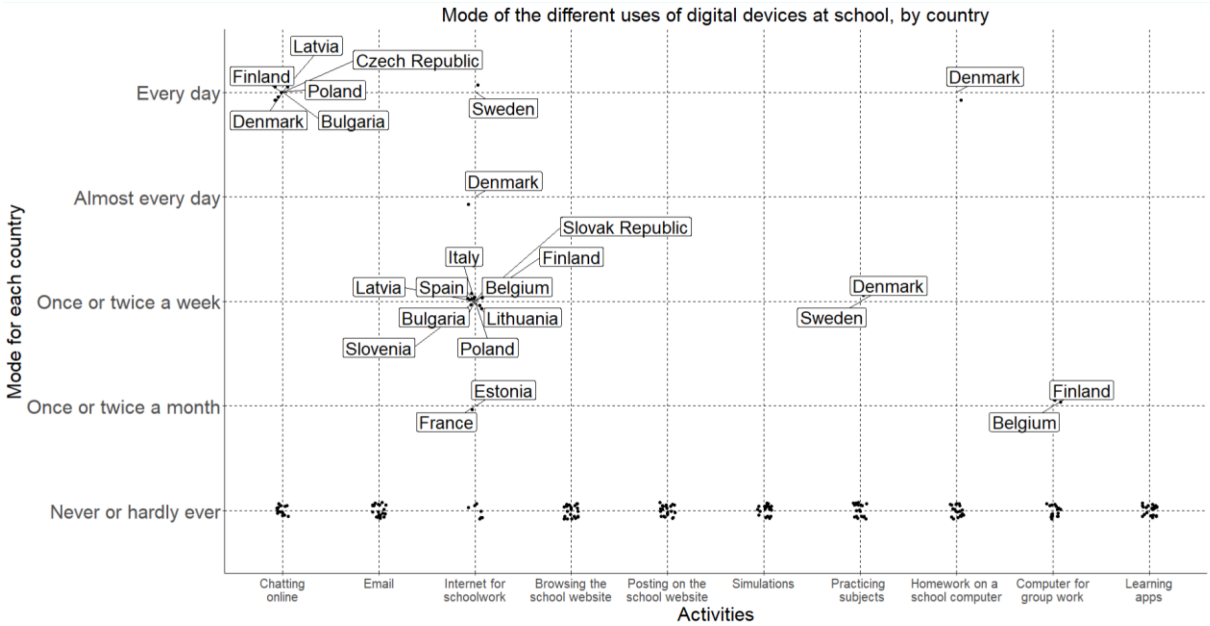


**Figure 12.** Mode of the frequency of digital device activities by country

Variables used: Country, Chatting_online, Email, Internet_schoolwork, Browsing_school_website, Posting_school_website, Simulations, Practicing_and_drilling, Homework_school_computer, Computer_group_work, Learning_apps.

Looking at the big picture, it is evident that the majority of the questions have a mode of *Never or hardly ever*. This observation, combined with the previous plots, suggests that the adoption of technologies in educational systems is still in its early stages. Therefore, it may be premature to conclude whether certain technologies, such as simulations which are the most advanced ones, can enhance students' academic performance.

There are two exceptions to this trend, represented by the variables "Chatting online" and "Browsing the Internet for schoolwork". In these cases, a reasonable number of countries have a mode that differs from *Never or hardly ever*.

In particular, for the former variable, six countries have a mode of *Every day*: Bulgaria, Latvia, Czech Republic, Poland, Finland, and Denmark. After analyzing the heatmap illustrated in Figure 5, it is evident that some of these countries also rank among the poorest-performing countries when compared to the ones in their respective macro-regions. More specifically, Latvia is one of the worst-performing countries in the Northern Europe region, Czech Republic is one of the worst-performing countries in the Central Europe region, and Bulgaria is one of the worst-performing countries in the whole dataset.

Given the nature of the activity "Chatting online at school", it can be viewed as a potential distraction from lessons and schoolwork, especially when the amount of time spent on it per day becomes significant.

On the other hand, for the variable "Browsing the Internet for schoolwork", the majority of countries have a mode which differs from *Never or hardly ever*. In particular, two nations have a mode that represents a higher frequency of usage than *Once or twice a week*: Denmark and Sweden.

There are only few other activities where some countries have a mode which differs from *Never or hardly ever*, namely "Practicing and drilling, such as for foreign language learning or

mathematics", "Doing homework on a school computer", and "Using school computers for group work and communication with other students". In these cases, the majority of countries with a mode different than *Never or hardly ever* are from Northern Europe, with Belgium being the only exception.
Interestingly, Estonia is one of the top-performing countries overall, but when it comes to these activities, the mode of students responses is almost always *Never or hardly ever*.

Furthermore, the time utilization of the Internet at school varies across different countries. The results are presented in Figure 13. It illustrates the student response distribution regarding the question "During a typical weekday, for how long do you use the Internet at school?".
In this study, the countries have been divided into macro-regions, following the same classification as Figures 7, 8 and 9: Central Europe, Northern Europe, South-Eastern Europe, and South-Western Europe.
Unlike the previous variables, this one is not divided by subject. The question seeks a more general answer, without making such distinctions.

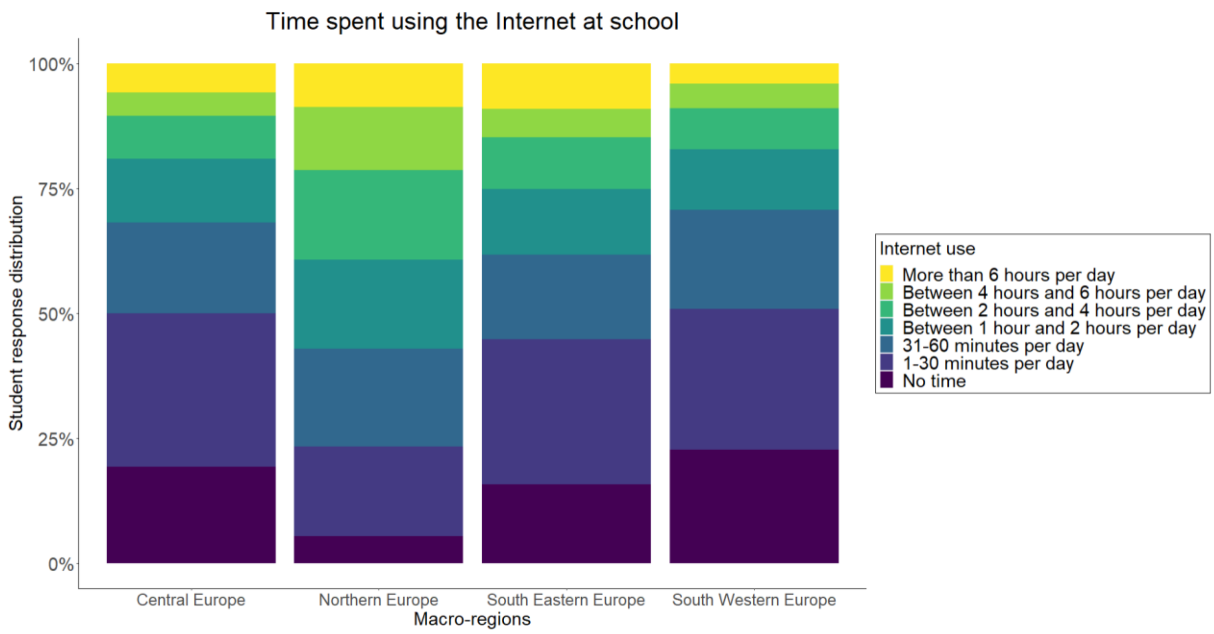


**Figure 13.** Stacked column chart of time spent using the Internet at school by macro-region. Variables used: Country, Time_internet.

The distribution of different Internet usage levels in Central Europe, South-Eastern Europe, and South-Western Europe is quite similar: approximately 50% of students reported either never using the Internet during a typical weekday or using it for only 1 to 30 minutes per day. The remaining students are distributed across the other usage levels, which include *31-60 minutes per day*, *Between 1 hour and 2 hours per day*, *Between 4 hours and 6 hours per day*, and *More than 6 hours per day*.
Northern-Europe stands out from the other macro-regions, with a lower percentage of students reporting no Internet use during a typical weekday. Over 30% of students in this region reported using the Internet for 2 hours or more, which is significantly higher than the other macro-regions.

These results are consistent with Figure 11, as countries with the highest use of digital devices also tend to have higher Internet usage.

### 2.3.5 Digital Devices Users

In addition to the amount of time spent on digital devices at school and the activities performed with the latter, the specific user of digital devices in class (i.e. students, teachers, both) may also have an impact on students' performances.

The frequency of student responses to the question "Within the last month, has a digital device been used for learning or teaching during lessons in the following subjects?" is displayed in Figure 14 . The *No* alternative indicates cases where digital devices were not used in the subject during the last month.
The chart is divided into four answer choices, each containing three columns that represent the subjects of reading, mathematics, and science.

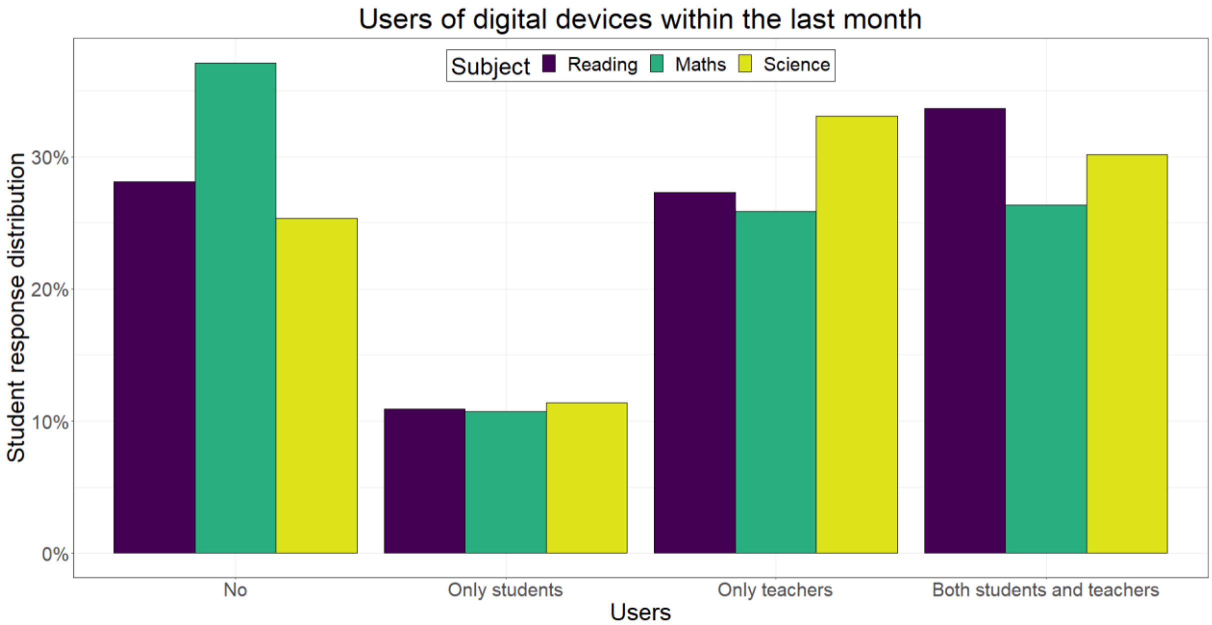


**Figure 14.** Clustered column chart of the student response distribution regarding the specific users of digital devices.
Variables used: Users_digital_devices_reading, Users_digital_devices_math, Users_digital_devices_science.

It is immediately evident that a similar percentage of students, roughly 30%, indicated that within the last month, either solely the teachers used digital devices at school, or both students and instructors employed them, or neither party utilized them.
The remaining 10% of students reported they were the sole users of digital devices at school and that their teachers did not employ them.
When comparing the different subjects, it is noticeable that a significantly higher percentage of students is unable to use digital devices during math lessons, in comparison to the other two

subjects. Consequently, the proportion of students reporting that only teachers or both students and teachers utilized digital devices during math lessons in the past month is lower than that of the other two subjects.
In contrast, when it comes to the *Only students* alternative, instead, the percentages among the three variables are quite similar, all hovering around 10%.
Lastly, when comparing reading with science, comparable percentages can be observed. However, it is worth noting that during science lessons, a higher percentage of students report that only teachers use digital devices, while during reading lessons, a higher percentage of students report that both students and teachers use digital devices.

### 2.3.6 Relationship Between Schools Economic Condition and Digital Device Usage

Given the high cost of digital devices, it seems reasonable to assume that schools and countries with a stronger economic condition have a greater abundance of such devices. Students in these educational institutions would thereby be granted more time to use digital devices.

The following violin plot aims to confirm the relationship between a school's economic status and the time its students spend using digital devices. The analysis is carried out by distinguishing between macro-regions to determine if the relationship holds true in some regions and not in others. The horizontal axis displays this distinction, while the vertical axis represents the school ESCS, a variable constructed to explain the average economic, social, and cultural status of each school. For each macro-region there are four violin plots representing the possible answers to the question "In a typical school week, how much time do you spend using digital devices during classroom lessons?".
While this plot focuses on digital device usage during reading lessons, the plots for the other two subjects, mathematics and science, are nearly identical. Therefore, to avoid redundancy, they are not displayed.

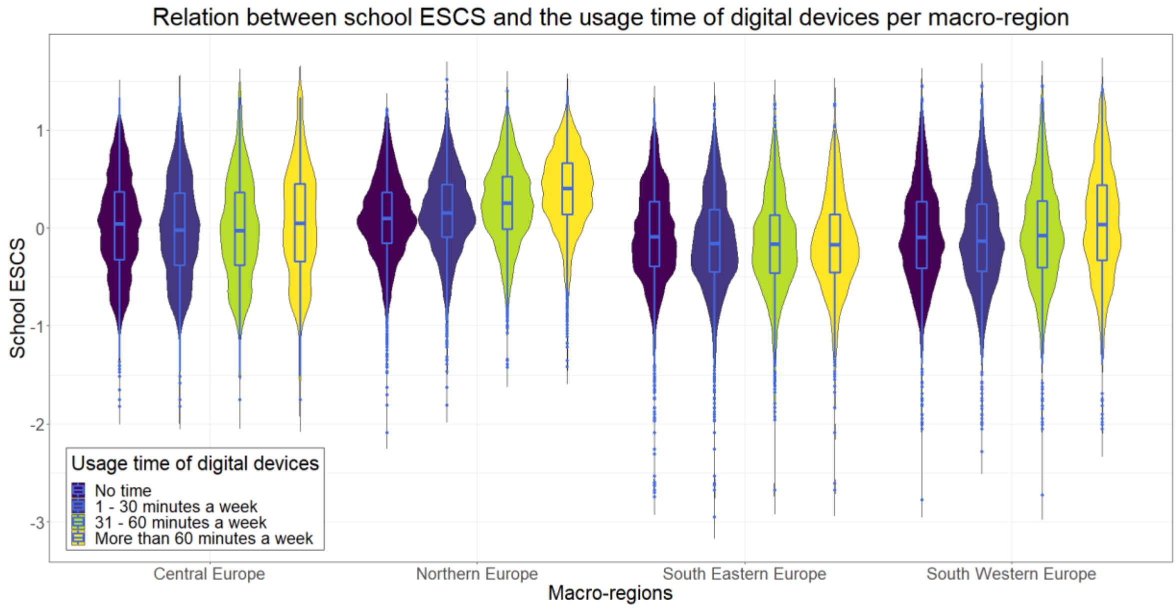


**Figure 15.** Violin plot showing the relationship between the school ESCS and the usage time of digital devices by macro-region

Variables used: ESCS_school, Time_digital_devices_reading.

Analyzing Central Europe and South Western Europe, it appears that a higher school ESCS does not necessarily correlate with an increased usage time of digital devices. The only noticeable increase is observed in the highest usage level, which is the only one indicating a considerable amount of time spent on digital devices per week.

Northern Europe is the only region where a clear trend is evident. A higher economic, social, and cultural status of the school is associated with a higher usage level of digital devices at school. Policy-makers must monitor the phenomenon closely, to avoid that in-equality issues arise in the long run.

On the other hand, South Eastern Europe exhibits a slight decreasing trend.

### 2.3.7 Relationship Between Digital Devices Use and Students' Performance

After having obtained a general overview of the students' responses to questions about the use of digital devices at school, the next step focuses on identifying potential insights into the relationship between the use of digital devices and students' academic performance, through a series of descriptive analyses.

The first analysis investigates the relationship between the amount of digital device usage in a typical school week and students' test performance.

Two heatmaps are then presented. The first one illustrates the association between students' achievement and the interaction between Internet usage time, and the specific user of digital devices in class (i.e. students, teachers, both). The second heatmap focuses on the interaction between the frequency of two activities that can be performed using digital devices: playing simulations and doing homework on a school computer.

Lastly, two boxplot figures are presented to examine the relationship between students' performance and digital device usage. One boxplot focuses on the frequency of browsing the Internet for schoolwork, while the other examines the frequency of using learning apps and learning websites.

The first analysis is presented in Figure 16, which is divided into three categories, each corresponding to one of the three subjects under consideration, while the score associated with each subject is indicated on the vertical axis.
The data are presented using four boxplots per subject, each representing a different range of digital device usage. The ranges include students who experienced no usage of digital devices, those who used them for 1 to 30 minutes a week, those who used them for 31 to 60 minutes a week, and those who used them for more than 60 minutes per week.

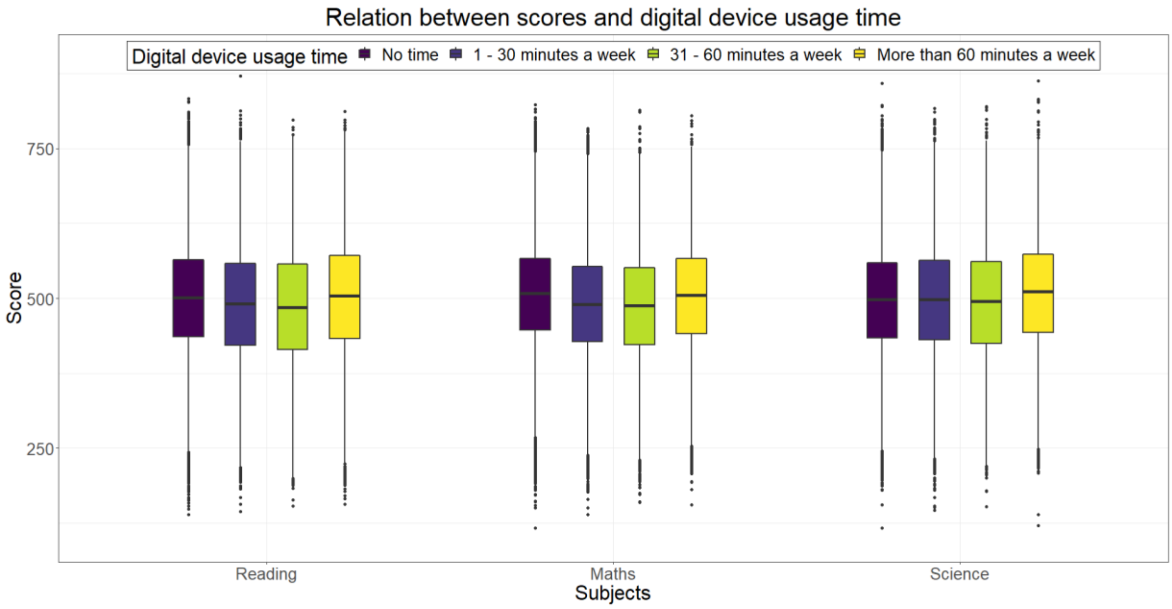


**Figure 16.** Boxplot showing the relationship between students' academic performance and digital device usage time by subject
Variables used: Reading_score, Math_score, Science_score, Time_digital_devices_reading, Time_digital_devices_math, Time_digital_devices_science.

Looking at the big picture, minor differences appear between the different levels of digital device usage. A similar trend is observed in both reading and mathematics. A lack of digital device usage seems to be associated with slightly higher performance compared to the *1 – 30 minutes a week* and *31 – 60 minutes a week* usage levels. Conversely, a significant improvement in performance is observed when usage exceeds 60 minutes per week, outperforming all other alternatives.
As previously mentioned in the description of Figure 10, it is worth noting that considering a time interval of one week, a usage of up to 30 or 60 minutes for digital devices may be regarded as negligible. Therefore, any minor decrease in performance may not be worth to be analyzed. On the other hand, when students are given sufficient time to utilize digital devices, they become familiar with them, overcoming any learning barriers, consequently reaping the

potential benefits. Possibly due to these reasons, a higher usage time of digital devices is associated with improved academic performance among students.
In contrast to reading and mathematics, there is a noticeable difference in the trend observed for science. Specifically, a decrease in performance when transitioning from no usage of digital devices to usage of up to 60 minutes per week is not observed. As a matter of fact, the first three boxplots for the science category appear to be relatively constant in height. However, as seen in the other two subjects, there is a sudden increase in performance for the usage alternative *More than 60 minutes a week*.
The difference between science and the other subjects can be explained by the greater usefulness of using digital devices for visualizing abstract and complex scientific concepts.

The second descriptive analysis of this section is a heatmap representing the mean scores of students in the three subjects examined in this study, categorized by the time spent using the Internet, and the specific user of the digital device.
The first plot relates to the reading scores, the second concerns mathematics scores, and the third is related to the science scores.
The horizontal axis of all three heatmaps represents the students' responses to the question "Within the last month, has a digital device been used for learning or teaching during lessons in the following subjects?". In the case that digital devices have been used during class activities, the answers also indicate the specific user of the digital devices.
On the vertical axis, the students' responses to the question "During a typical weekday, for how long do you use the Internet at school?" are represented. They range from 0, indicating no use of the Internet during a typical weekday, to more than 6 hours.
Lastly, the mean scores for the three subjects are represented using different colors and rounded values in the heatmaps.

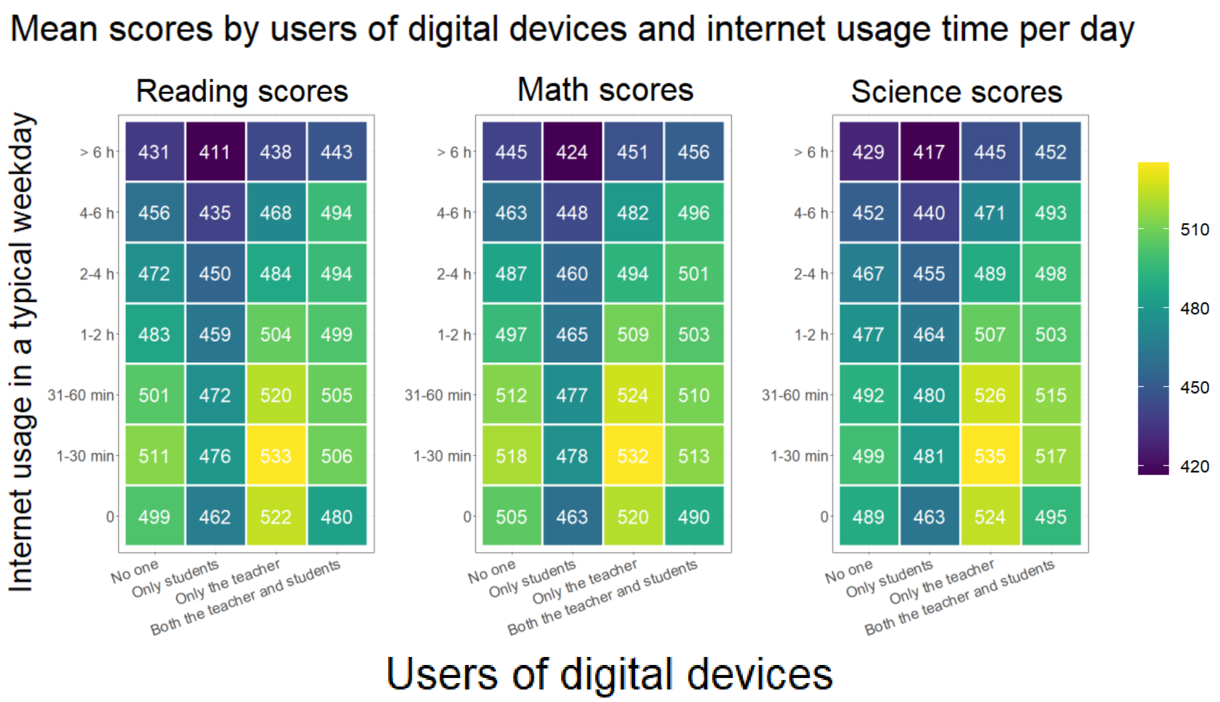


**Figure 17.** Heatmap showing the association between students' academic performances and the interaction between the Internet usage time and the specific user of digital devices. Variables used: Reading_score, Math_score, Science_score, Users_digital_devices_reading, Users_digital_devices_math, Users_digital_devices_science, Time_internet.

Considering the overall picture, the heatmaps reveal a consistent pattern of mean scores across all three subjects, indicating the strength of the conclusions.

By analysing the usage of Internet in terms of time, and keeping constant the digital device users, it is observed that the students' performance increases from a null use of the Internet to a moderate use of the latter *1-30 min* per day, for every subject. Beyond this point, increasing the use of the Internet at school results in a critical decrease in mean student performance, regardless of the user.

This behavior can be explained by the fact that using the Internet for schoolwork or to learn difficult concepts can be beneficial. However, when the use exceeds a certain threshold, it becomes a distraction and hinders academic progress. Moreover, it is unlikely that a student would use the Internet for academic purposes for extended periods of time, such as six hours a day. It is more probable that the student is browsing the Internet and engaging in non-school related activities, which can negatively impact the scholar's academic performance.

By focusing on the different alternatives of the horizontal axis and keeping the vertical axis constant, a peculiar pattern can be oberved. This behaviour is similar across the three subjects. One of the most significant patterns is that the average students performance is consistently at its lowest when only students use digital devices. Students in this category perform even worse than scholars that do not use digital devices at all in class.

A possible explanation is that students may become distracted when using digital devices without proper supervision from professors. Additionally, it is possible that students lack the necessary skills to effectively utilize digital devices for learning purposes.

Furthermore, in each subject under consideration, if the Internet usage is limited to two hours or less, the highest average student performances are observed when only the teacher uses digital devices. However, if Internet usage exceeds two hours, the best performances are associated with the case in which both the teacher and students use digital devices together.
Certainly, when only the teacher uses digital devices, ICTs are less likely to pose a distraction since the teacher has control over their usage and can provide guidance to their students. On the other hand, For high levels of Internet usage, there are several ways to explain the better student performance in case both the teacher and students use digital devices together.
Firstly, when both parties use digital devices, they can collaborate more effectively and engage in interactive learning activities, which can lead to better student performance. Additionally, students may be more motivated to learn when they are actively involved in the learning process.
Keeping the focus on the scenario where both the teacher and students use digital devices together, it is evident that its position in comparison with the other levels varies significantly with the increase of Internet usage. In particular, when Internet usage is low (ranging from 0 to 30 minutes for reading lessons and 0 to 60 minutes for mathematics lessons), performances are only better than the case where only students use digital devices. However, this is not the case for science, since even at these levels of Internet usage, the considered scenario is only surpassed by the scenario where only the teacher uses digital devices. In the other two subjects, until two hours of Internet usage, the scenario where both the teacher and students use digital devices shows the second-best performances, similar to the science case. Finally, as previously mentioned, when Internet usage exceeds two hours per day, this scenario becomes the best one.
This behaviour can be explained by the previous observations. When Internet usage is low, it may be better for teachers to maintain control, or even prohibit the use of digital devices to prevent possible distractions for students. At medium levels of Internet usage, the scenario where both the teacher and students use digital devices together is more effective than not using digital devices at all. Lastly, when Internet usage is at its peak, students must be monitored to ensure they use use the digital devices for learning purposes instead of getting distracted by browsing the Internet.
The observed difference in trend during science lessons can be explained by the fact that digital devices are essential in science to visualize and comprehend complex concepts. Therefore, the scenario where nobody uses digital devices is penalized, and the scenario where both teachers and students use digital devices immediately outperforms it.
Although it is being analyzed within the context of other scenarios, it is worth briefly describing the scenario where nobody uses digital devices. In reading and mathematics lessons, when paired with low Internet usage, this scenario is surprisingly more effective than the scenarios where only students use digital devices or where both teachers and students use them together. However, beyond a certain threshold (30 minutes for reading lessons and 1 hour for mathematics lessons), this scenario is only better than the scenario where only students use digital devices. On the other hand, during science lessons, not using digital devices is always less effective than the scenario where where both teachers and students use digital devices.
As previously explained, when Internet usage is low, a traditional teaching approach without digital devices may be more effective in preventing distractions. However, as Internet usage

time increases, it is better to have students use digital devices to prevent them from getting distracted.

A similar plot is used to show the possible correlations between various activities performed using digital devices and the average student academic performance in the subjects under examination.
The dataset includes ten activities the students were asked about, with the question "How often do you use digital devices for the following activities at school?". However, since chapter 4.1 highlights the activities that are more significant for each subject, the following plots will only show the relationship between these activities and the students' academic performance.
In particular, the following heatmap displays the frequency with which students use digital devices for playing simulations on the vertical axis and the frequency with which scholars do homework on a school computer on the horizontal axis. These two activities are identified as being among the most significant in explaining the academic performance of the students, out of the ten activities present in the dataset. Similar to the previous heatmaps, the mean scores for the three subjects are represented using different colors and rounded values.

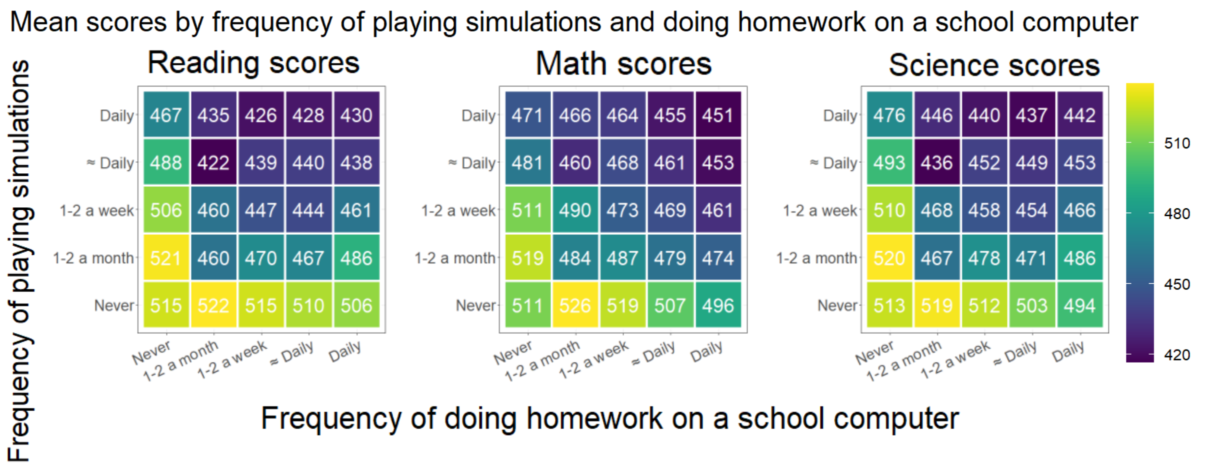


**Figure 18.** Heatmap showing the association between students' academic performances and the interaction between the frequency of playing simulations and the frequency of doing homework on a school computer.
Variables used: Reading_score, Math_score, Science_score, Simulations, Homework_school_computer.

Beginning the analysis by examining the variation in the frequency of playing simulations, it is evident that, across all three subjects, an increase in the use of digital devices for playing simulations, results in a decrease in the mean academic performance of the students. There is an exception when the frequency of doing homework on a school computer is *Never*. In this case, an increase in the frequency of playing simulations from zero to once or twice a month results in an improvement in scholars' academic performance.
There are other few minor exceptions, displaying a modest improvement or an unchanged average, when the frequency of doing homework on a school computer is once or twice a month and the frequency of playing simulations increases from once or twice a month to once or twice

a week, for reading and mathematics. However, the variation in these cases is negligible and not significant enough to warrant further analysis.
A possible explanation for the overall decrease in academic performances could be that excessive use of simulations may lead to distraction among students. It is worth noting that, since the dataset used in this analysis is from 2018, a time when simulations were less advanced, poorly designed simulations may have contributed to the distraction of the students. It would be interesting to repeat this analysis with a new dataset that includes immersive digital worlds where students can explore and learn new concepts in a more engaging manner.
On the other hand, a limited usage of simulations, such as once or twice a month, can still provide benefits by reinforcing concepts learnt during lessons. This is only the case if no other distractions are present, as indicated in the graph by the frequency of doing homework on a school computer being *Never*.
Comparing now the different alternatives of frequency of doing homework on a school computer and analysing the bottom row for all three subjects, a similar pattern to the previous variable can be observed. Specifically, if the frequency of playing simulations is *Never*, an increase in the frequency of doing homework on a school computer from zero to once or twice a month results in an improvement in academic performance.
However, apart from this row, this variable does not exhibit a consistent decrease in academic performance as the frequency of usage increases. In fact, a decrease is regularly observed when transitioning from *Never* to once or twice a month, but subsequent moderate fluctuations in either direction can be observed.
It is evident, though, that a complete absence of homework done on a school computer is associated with higher academic performance, apart for the previously noted exception.
One potential explanation could be that students are not used to work on school computers, lack the necessary skills, or find it distracting. However, if students use school computers for homework in moderation, it could be that they are taking advantage of the resources available to them. School computers may have software or programs that students do not have access to at home, which could support their learning and understanding of the subject. Additionally, school computers may provide a more focused environment for completing assignments, which could lead to better performance.
Analysing the two variables together, by moving diagonally in the heatmap, it is evident that in the vast majority of cases, academic performance decreases as the frequency of the two activities increases. The optimal combination appears to be when one activity is never performed, and the other is performed once or twice a month. However, it should be noted that when the frequency of both variables is once or twice a month, academic performance is significantly worse than the previously described scenario.
This trend can be attributed to the fact that using various digital devices simultaneously for different purposes can lead to distractions. Therefore, a very moderate usage of digital devices may be better for academic achivement.

The last activity on the list of ten, which is crucial in explaining students' academic scores across all three subjects is "Browsing the Internet for schoolwork".

The boxplot below displays the relationship between reading test scores, represented on the vertical axis, and the frequency with which students use the Internet to browse for schoolwork. The boxplots are grouped by macro-region.
This variable is found to be significant for all three subjects, with a consistent correlation to students' test scores. To avoid redundancy, a single plot is presented. The results can then be then extended to both mathematics and science.

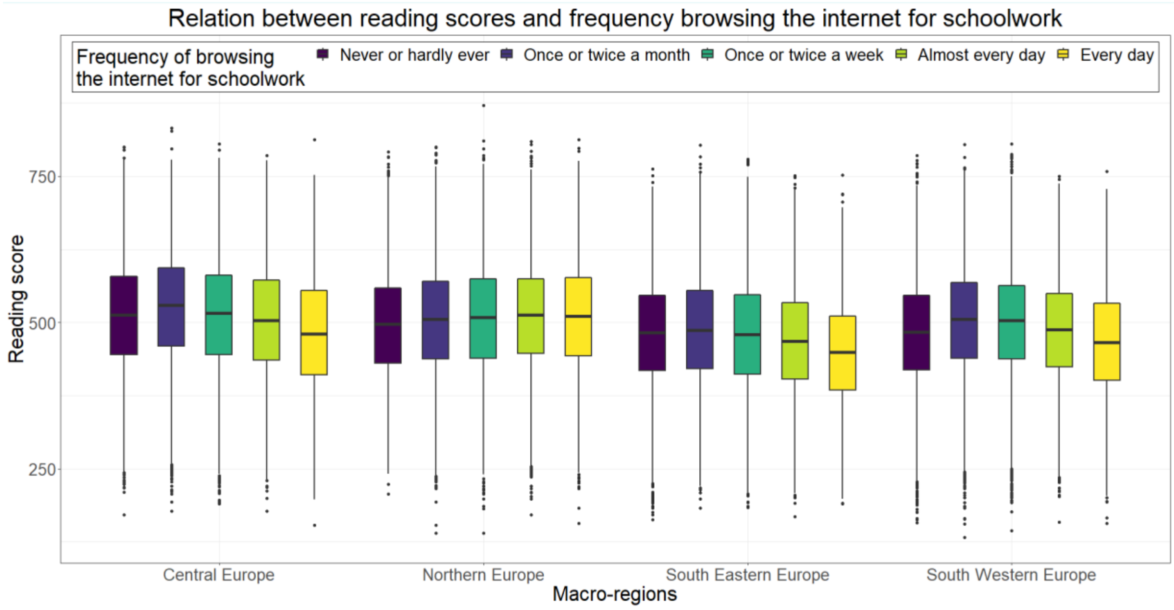


**Figure 19.** Boxplot showing the relationship between students' academic performance and the frequency of browsing the Internet for schoolwork
Variables used: Reading_score, Math_score, Science_score, Internet_schoolwork.

Similarly to the previous heatmaps, this activity reveals a comparable trend in Central Europe, South Eastern Europe, and South Western Europe. Specifically, the student performance increases as the usage frequency progresses from a null usage to a moderate usage, corresponding to a maximum of two times a month. However, a further escalation in frequency leads to a consistent decline in students' performance.
A distinct behavior emerges in Northern Europe. Here, increasing the Internet use from a null level to higher levels results in an improvement in students' academic performance.
As the variable "Frequency of browsing the Internet for schoolwork" is somewhat comparable to the "Internet usage in a typical weekday" analyzed in Figure 17, it may be plausible that the explanation for the observed decrease in academic performance with an increase in Internet usage may be the same. Specifically, when the time spent on the Internet exceeds a certain threshold, it may act as a distraction and impede academic progress.

Up to this point, each of the variables that will be later recognized in chapter 4.1 as the most significant ones for explaining academic performance have been analyzed, with the exception of one: the frequency of using learning apps or learning websites at school. This variable is identified as being particularly important only for explaining mathematics scores, and therefore solely the relationship between the latter two variables will be analyzed.

The following plot displays mathematics scores on the vertical axis, while the horizontal axis distinguishes between macro-regions. Within each of these distinctions, the performance related to each level of the frequency of the aforementioned activity will be displayed.

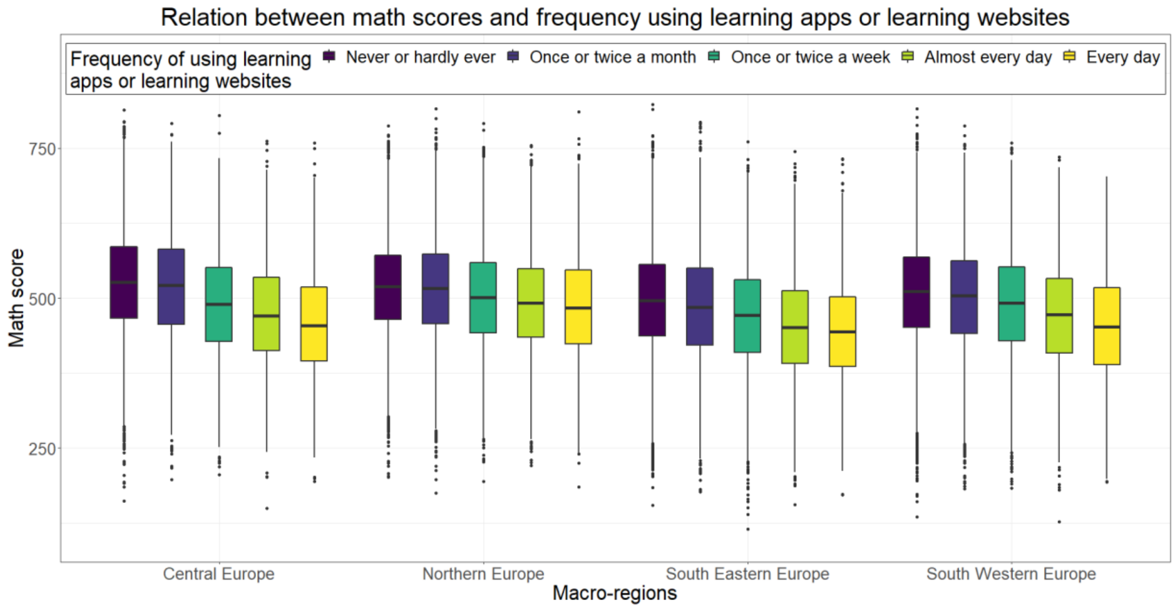


**Figure 20.** Boxplot showing the relationship between students' academic performance and the frequency of using learning apps or learning websites.
Variables used: Reading_score, Math_score, Science_score, Learning_apps.

The activity in question exhibits similar patterns to the ones previously analyzed, though with a noticeable difference: there is no clear increase in academic performance when transitioning from null usage to moderate usage. Specifically, across all four macro-regions a higher frequency of using learning apps or learning websites appears to be associated with lower academic performance. This behavior is particularly noticeable in three of the four macro-regions: Central Europe, South Eastern Europe, and South Western Europe. A milder trend is observed in Northern Europe.
A plausible explanation for this phenomenon could be represented by the learning barriers that students face when dealing with new apps and websites. These barriers may cause students to focus more on the details of the software and how to overcome its challenges, rather than on learning and understanding new concepts.

# 3. Methodology

In the following section the aim is to present the methodological approach and the tools adopted throughout the study. The chapter is divided into three sub-chapters:

First, a description of the theory behind the variable selection procedure used to subset the ICT variables in the dataset is presented. This is foundational for understanding the reasonings behind the choice of the number of variables to include in the models. Furthermore, the chapter provides additional explanations on why it is necessary to reduce the number of variables to include in the models before performing any statistical analyses.

Second, an overview of the theory behind linear mixed models and a description of how they are implemented throughout the research is presented. The goal is to provide the reader with a general understanding of one of the main statistical tools used throughout the research. Throughout the paragraph, greater details on why LMMs are appropriate for the PISA dataset, and a description of the LMMs carried out throughout the study are presented.

Finally, an outline of the overall functioning of regression trees with random effects is provided. The aim of the paragraph is to describe the second main statistical tool used throughout the study. Details on why regression trees with random effects are suitable for the dataset under analysis, and a description of the regression trees created throughout the research are also presented.

## 3.1 Variable Selection Methodology

This paragraph provides a complete elaboration of the variable selection process adopted throughout the research, including a detailed description of the criteria used to select the variables.

After carefully reviewing the original PISA dataset, a rigorous selection process was conducted to determine the variables to be included in the analyses. This process was supported by an extensive review of the literature, resulted in the list of variables presented in Table 1. Each variable was chosen based on its potential to influence students' academic performance, ensuring a comprehensive and relevant set of predictors.

This study focuses on the use of ICTs at school and includes a range of variables related to the topic. Specifically, two variables describe the amount of time that digital devices are used during lessons, one variable identifies the specific user of the ICTs, and ten variables describe the activities that students perform with digital devices at school. These activities include: *Chatting_online*, *Email*, *Internet_schoolwork*, *Browsing_school_website*,

*Posting_school_website, Simulations, Practicing_and_drilling, Homework_school_computer, Computer_group_work*, and *Learning_apps*.
Some activities, such as *Internet_schoolwork* and *Simulations*, are specifically designed to enhance students' academic performance by leveraging the benefits of using digital devices during class activities. Others, such as *Chatting_online* and *Email*, are more general activities that do not necessarily impact students' academic performance, since students may use digital devices to perform these activities when they are not supervised by teachers.
Furthermore, given that a student who reports a high frequency of use of digital devices on some of these activities is likely to report a high frequency of digital device use also on other activities, there is a risk of multicollinearity in the statistical analyses. This means that the variables may be highly correlated, potentially leading to inaccurate results.

To identify the activities that may have the most significant impact on students' academic performance and reduce the number of potentially correlated predictors, a variable selection process is necessary.
Random forest, a machine learning algorithm that combines multiple decision trees to make more accurate predictions, is used for the variable selection purpose.
This algorithm is chosen for variable selection due to its robustness in handling noisy and highly variable data, as well as high-dimensional data and missing values. The robustness is achieved through the construction of a large number of random trees, each trained on a random subset of the data and a random subset of the predictor variables. By combining the predictions of all the trees, the algorithm is able to reduce the variance in its forecasts and the overfitting of data.
In this study, random forest is used for its ability to estimate the importance of each predictor in explaining the response variable. It allows to identify the most relevant variables among the ones describing the class activities that students perform with digital devices. The algorithm under consideration computes the variable importance as a measure based on the decrease in model accuracy when the values of a specific predictor are permuted, while holding the values of all other variables constant. By repeating this process for each predictor, the importance of each variable can be computed.

## 3.2 Linear Mixed Models Methodology

After having selected the variables to be included in the model, linear mixed models were performed to analyze the data. In the following paragraph, a brief explanation of the theory behind linear mixed models (i.e. LMM) and a description of how the models are used throughout the study is presented. The aim of the chapter is to provide the reader with a general understanding of the overall functioning of LMMs, an explanation to why these tools are valuable for the following research, and an overview of how these statistical methods are applied to the PISA dataset.
Linear mixed models, also known as multilevel models, are an extension of classical linear models. Unlike classical linear models which only include fixed effects, LMMs allow to estimate the impact of both fixed effects and random effects on the independent variable of a

regression. These models are appropriate in all the cases in which the observations of a dataset display a clear hierarchical structure. For instance, a dataset providing patient level data, together with information concerning the doctor that the patient is being treated by, is a clear example of a hierarchical dataset. This is because the different patients in the dataset can be grouped together according to their doctor. The typical formula of the LMMs carried out throughout the research is presented below:

$$y_{ikj} = \beta_0 + \beta x_{ikj} + b_j + u_{kj} + \varepsilon_{ikj}$$

$i = 1, \ldots, n_{kj}$ represent the students nested in a school $kj$ that in turn are nested in a country $j$
$\varepsilon_{ikj}$ represent the error terms in the model
$b_j$ represent the country specific random effects
$u_{kj}$ represent the school specific random effects
$x_{ikj}$ represent the student and school covariates
$\beta$ represent the regression coefficients
$\beta_0$ represents the general intercept

The fixed effects of a LMM refer to the impacts that the covariates of an observation have on the response variable, independently of the group (i.e. hierarchy) the observation belongs to. They represent the average impact that the covariates of a LMM have on the response variable, and they are not observation specific. For example, a researcher may be interested in studying the effect that a drug has on a patient's recovery time independently of the doctor the patient is being treated by. The effect that the drug has on a patient's recovery time is thereby "fixed" for every observation in the dataset.
On the other hand, the random effects are observation specific. This means that the impact that the random effects of a LMM have on the response variable differs according to the observations they refer to. For instance, in addition to the fixed effect that a drug has on a patient's recovery time, a researcher may want to study if the drug's effect changes according to the doctor that administers the drug to the patient. This additional information is captured by introducing a random effect describing the doctor administering the drug to the patient. Since all the patients treated by different doctors have a different effect of the drug on their recovery time, the effect is subject specific.
The random effects allow to capture the correlation among the observations in each hierarchy (e.g. all the patients treated by the same doctor), which in turn reduces the chance of the residuals of the regression of being heteroscedastic and multicollinear.
To further clarify the functioning of LMMs, a description of the models that are adopted in the following research is presented hereafter.

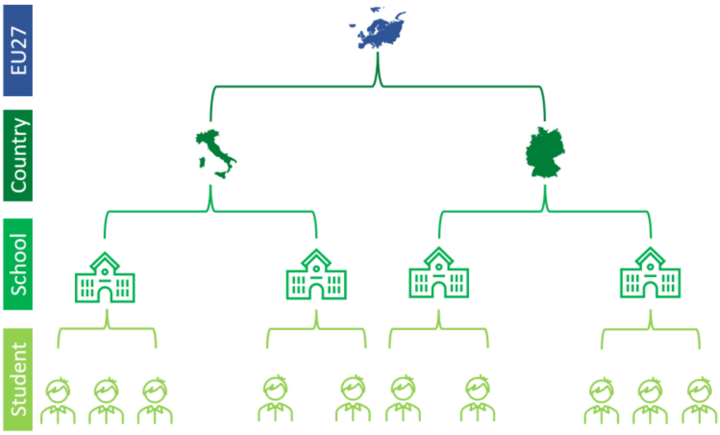


**Figure 21.** Hierarchy of the Linear Mixed Models.

As shown in Figure 21, the data in the PISA 2018 dataset clearly displays a hierarchical nature. This is because the students in the dataset can be grouped by the school they are attending and subsequently by the country in which they are studying. For this reason, two-level linear mixed models are performed.

Linear mixed models are preferred to classical linear models since they allow to model the correlations among the test scores of students attending the same school, and for the correlations in the test scores of scholars studying in the same country.

One may argue that using two levels of hierarchy may seem excessive. They may sustain that a single, country specific, hierarchical level may be sufficient to account for the differences in students test scores.

However, the choice of adding a second hierarchical level to the LMMs, referring to the school the student is attending, is supported by Figure 22. As shown in the right hand side of the graph, in some countries the variation in the students test scores between schools is comparable to the variation in the students test scores within schools. This means that in specific nations, students test scores may vary significantly according to the schools the students are attending. It is thereby important to add a school specific hierarchical level in the LMMs.

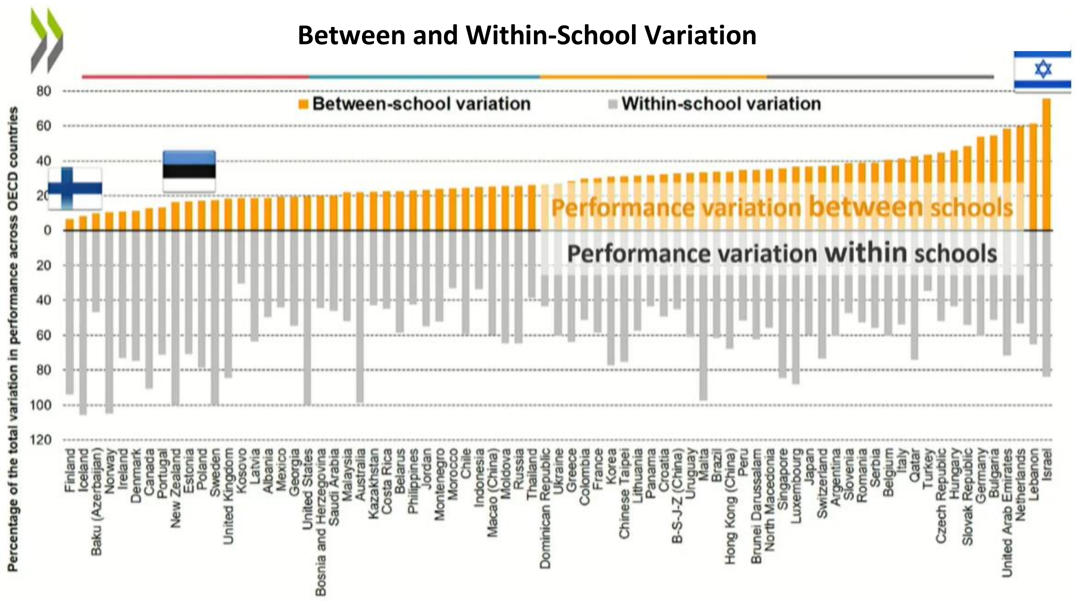


**Figure 22.** Variation of reading performance between and within schools.
Source: EduSkills OECD YouTube channel.
Video: OECD PISA 2018 Results International Launch.

Throughout the study, three linear mixed models are performed. Each model refers to one specific subject among reading, mathematics or science. The aim of the three models (i.e. M1, M2 and M3), is to unveil the impacts that the different explanatory variables in the dataset have on the students' reading, mathematics and science test scores respectively. The equations of the models are presented hereafter:

$$\begin{aligned}\boldsymbol{M1}.\, Reading\_score = {} & Intercept + ESCS + ESCS\_school + Time\_digital\_devices\_reading + Users\_digital\_devices\_reading \\ & + Simulations + Time\_internet + Homework\_school\_computer + Internet\_schoolwork \\ & + Enjoyment\_digital\_devices + Outsider + Gender + Read\_if\_have\_to + Teacher\_assistance \\ & + Persistence + Parent\_assistance + Age\_at\_immigration + School\_competition + Student\_seletion \\ & + Grade\_repetition + Reading\_not\_studied + random\_school\_intercept + random\_country\_intercept \\ & + residuals\end{aligned}$$

$$\begin{aligned}\boldsymbol{M2}.\; Math\_score = {} & Intercept + ESCS + ESCS\_school + Time\_digital\_devices\_math + Users\_digital\_devices\_math \\ & + Time\_internet + Simulations + Homework\_school\_computer + Internet\_schoolwork \\ & + Learning\_apps + Enjoyment\_digital\_devices + Outsider + Gender + Read\_if\_have\_to \\ & + Teacher\_assistance + Persistence + Parent\_assistance + Age\_at\_immigration \\ & + School\_competition + Student\_selection + Grade\_repetition + Math\_not\_studied \\ & + random\_school\_intercept + random\_country\_intercept + residuals\end{aligned}$$

$$\textbf{M3}. Science\_score = Intercept + ESCS + ESCS\_school + Time\_digital\_devices\_science + Users\_digital\_devices\_science + Time\_internet + Simulations + Homework\_school\_computer + Internet\_schoolwork + Enjoyment\_digital\_devices + Outsider + Gender + Read\_if\_have\_to + Teacher\_assistance + Persistence + Paret\_assistance + Age\_at\_immigration + School\_competition + Student\_selection + Gade\_repetition + Science\_not\_studied + random\_school\_intercept + random\_country\_intercept + residuals$$

In all the three LMMs, the independent variables can be grouped into two macro-categories, hereafter referred to as: fixed effects and random effects.

On one hand, the variables included as fixed effects can be further grouped into three subcategories according to the domain they refer to.
First, the fixed effects include school specific variables. These variables describe the school's socio-economic status, the number of schools it competes with, and an indication on whether the school applies a selection procedure for admitting its students.
Second, the fixed effects include student specific variables. These variables comprise students socio-demographic information like their gender, socio-economic status and age at immigration. They also describe the students attitudes towards learning, such as the scholars resourcefulness and persistence in completing school tasks. Additional insights are then provided on whether the scholars have ever repeated a grade or whether they feel like outsiders in class. Lastly, details are provided on the amount of teacher and parental assistance the scholars receive while performing school tasks.
Third the fixed effects include ICT specific variables. These variables describe the amount of time that the Internet and digital devices are used at school during class activities. Additionally, they provide details on the activities that digital devices are used for in class, and insights on who adopts the digital devices during school lectures. Finally, information on whether the students enjoy using digital devices is also provided. Further details on the variables used in the linear mixed models are available in chapter 2.2.
The analyses of the fixed effects aims at assessing the impacts that ICTs have on students' test scores in reading, mathematics and science while controlling for the school and student specific variables. Since they are fixed effects, they are not observation specific. This means that the impact that these variables have on the students test scores in reading, mathematics and science is independent of the school and country the students are studying in.

On the other hand, the linear mixed models include two random effects: a school specific random intercept and a country specific random intercept. These effects are observation specific. This means that for every school and for every nation in the dataset, a tailored intercept is calculated. This allows to create a model for every possible school-country combination in the data. In order to do so, the model assumes correlation among the test scores of students attending the same school and dependence in the test score of scholars studying in the same country.
The analyses of the random intercepts aims at unveiling the differences in the test scores of students attending different schools and countries.

## 3.3 Regression Trees with Random Effects Methodology

Finally, the last statistical tool used throughout the study is the hierarchical regression tree. This technique was chosen for several reasons.
Firstly, as a non-parametric model, it can handle complex relationships between the dependent and the explanatory variables. This means that it can capture relationships that may be difficult to identify with linear mixed models.
As the two models use different approaches to find relationships between variables, a similarity in their results would provide strong evidence of the findings from the LMM.
Secondly, the dataset is organized into three different layers: students, schools, and countries. Hierarchical regression trees preserve this hierarchy while analyzing the impact of the explanatory variables on the dependent variable. Similarly to linear mixed models, random effects are implemented to account for the variability within each layer that is not explained by the fixed effects.
Thirdly, this technique has the advantage of being able to handle missing values, which is not possible with the previous model, LMM. This results in an increase in the number of observations to include in the models. Therefore, if the same findings are replicated in both models, it provides strong evidence of the validity of the LMM findings.
Lastly, the visual representation provided by the regression trees is a valuable tool for interpreting the results.
When the decision tree diagram is plotted, it displays different paths, each representing a unique combination of predictor variables associated with a specific value of the dependent variable. At the bottom of these paths, there are nodes that represent a subset of the data sharing a common set of predictor variables and a unique value of the dependent variable.

To gain insights into how the students' academic performance in the three subjects under consideration varies with different combinations of the predictor variables, three hierarchical regression trees are performed.
The first tree has *Reading_score* as dependent variable, the second one focuses on students' *Math_score*, and the third one on scholars' *Science_score*.

To gain insights into the variables included in each regression tree, the following three lists are presented.

$$\begin{aligned}\boldsymbol{M4}.\,Reading\_score \sim\ & ESCS + ESCS\_school + Time\_digital\_devices\_reading + Users\_digital\_devices\_reading \\ & + Simulations + Time\_internet + Homework\_school\_computer + Internet\_schoolwork \\ & + Enjoyment\_digital\_devices + Outsider + Gender + Read\_if\_have\_to + Teacher\_assistance \\ & + Persistence + Parent\_assistance + Age\_at\_immigration + School\_competition + Student\_seletion \\ & + Grade\_repetition + Reading\_not\_studied + random\_school\_intercept + random\_country\_intercept\end{aligned}$$

$$\boldsymbol{M5}.\ Math\_score \sim ESCS + ESCS\_school + Time\_digital\_devices\_math + Users\_digital\_devices\_math + Time\_internet \\ + Simulations + Homework\_school\_computer + Internet\_schoolwork + Learning\_apps \\ + Enjoyment\_digital\_devices + Outsider + Gender + Read\_if\_have\_to + Teacher\_assistance \\ + Persistence + Parent\_assistance + Age\_at\_immigration + School\_competition + Student\_selection \\ + Grade\_repetition + Math\_not\_studied + random\_school\_intercept + random\_country\_intercept$$

$$\boldsymbol{M6}.Science\_score \sim ESCS + ESCS\_school + Time\_digital\_devices\_science + Users\_digital\_devices\_science \\ + Time\_internet + Simulations + Homework\_school\_computer + Internet\_schoolwork \\ + Enjoyment\_digital\_devices + Outsider + Gender + Read\_if\_have\_to + Teacher\_assistance \\ + Persistence + Paret\_assistance + Age\_at\_immigration + School\_competition + Student\_selection \\ + Gade\_repetition + Science\_not\_studied + random\_school\_intercept + random\_country\_intercept$$

It is worth noting that random intercepts are implemented in each model to account for the variability within each school and country.
In order to prevent overfitting and ensure a reasonable number of splits, each algorithm is executed with a fixed minimum reduction in the sum of squared errors (i.e. SSE) required to justify further node splitting of 0.003. This means that if the SSE reduction falls below this threshold, the node is not split and becomes a terminal node. Conversely, if the SSE reduction exceeds or equals 0.003, the algorithm proceeds with the node splitting.

# 4. Results

In the following section the aim is to highlight the results of the statistical analyses conducted on the PISA 2018 dataset. The objective is to unveil the impacts that Information and Communication Technologies have on students' reading, mathematics and science test scores. The chapter is divided into three sections:

First, the results of the variable selection procedure are presented. The objective is to provide insights on the main ICT variables related to the students' academic performance. Answers to the following questions are provided:

*Which ICT variables are strongly associated to students' reading test scores?*
*Which ICT variables are strongly associated to students' mathematics test scores?*
*Which ICT variables are strongly associated to students' science test scores?*

Second, the results of the linear mixed models are presented. The objective is to provide educators and decision makers with valuable insights on the main determinants of students' academic results. The paragraph aims at addressing the following inquiries:

*What is the overall impact of ICTs on students' test scores?*
*Who among teachers and students should use ICTs during class activities?*
*In what learning activities are ICTs most effective?*
*What insights can be drawn from the random effects of the linear mixed models?*
*Do the linear mixed models respect the modelling assumptions?*

Finally, the results of the regression trees with random effects are presented. The aim of the paragraph is to provide the results and to present the policy-making implications that can be inferred by applying these tools to the PISA dataset. Examples of the questions addressed throughout the subchapter are presented hereafter:

*What are the main insights that can be inferred by analyzing the results of these techniques?*
*What are the variables that most significantly influence students' academic performance? Are they related to the use of ICTs at school?*
*What conclusions can be drawn from the random effects of these models?*

## 4.1 Variable Selection Results

To identify the variables that are relevant for explaining students' academic performance, three random forest algorithms are executed. Separate algorithms are run for reading, mathematics, and science since each subject may have different relevant variables.
To summarize the results, a plot is generated to illustrate the importance of each variable.
The horizontal axis shows the increase in mean squared error that would result from permuting the values of the corresponding predictor variable, while holding the values of all the other variables constant.

The vertical axis shows the ten activities arranged in descending order of importance. The activity that causes the highest increase in mean squared error when its values are permuted is considered the most important, while the one that causes the lowest increase in mean squared error is the least important.

Presented below are three variable importance plots, with the first plot being associated with reading, the second with mathematics, and the third with science.

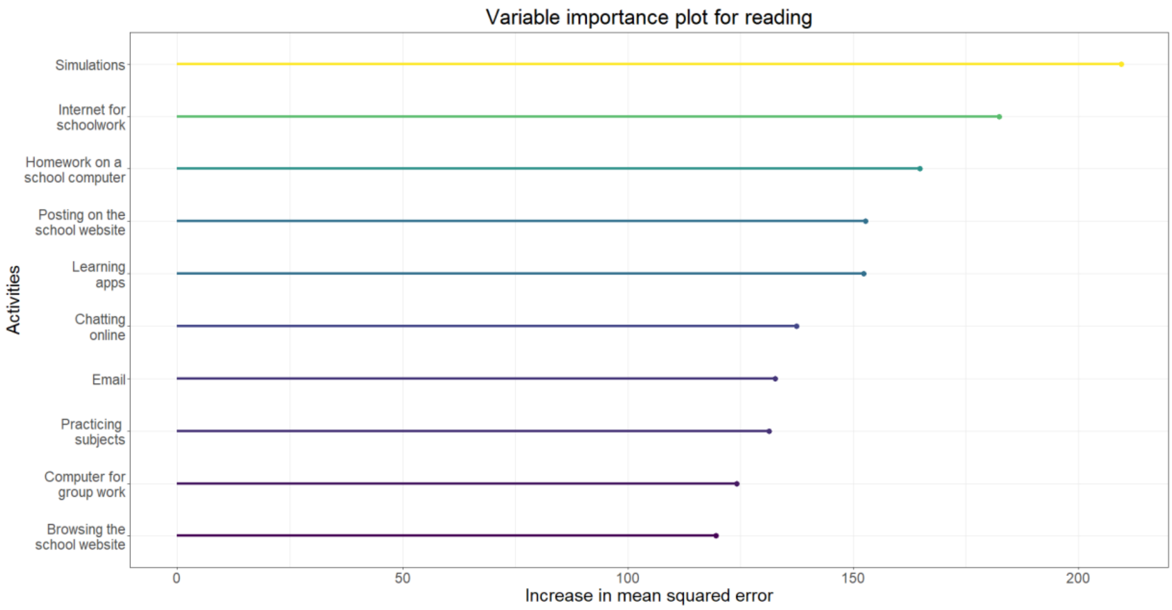


**Figure 23.** Variable importance plot for reading.

Variables used: Reading_score, Chatting_online, Email, Internet_schoolwork, Browsing_school_website, Posting_school_website, Simulations, Practicing_and_drilling, Homework_school_computer, Computer_group_work, Learning_apps.

The analysis of the above plot clearly indicates that *Simulations* is the most important predictor. Therefore, this variable will be included in the statistical analyses related to reading in the following chapters.

Additionally, *Internet_schoolwork* and *Homework_school_computer* are also crucial variables to be included in the following analyses. The choice of these activities is strengthened by the fact that they may be performed with the intention of improving students' academic performance.

A noticeable decrease in the mean squared error is instead observed when transitioning from "Homework on a school computer" to "Posting on the school website".

For this reason, it was decided to include only the first three variables in the statistical methods related to reading.

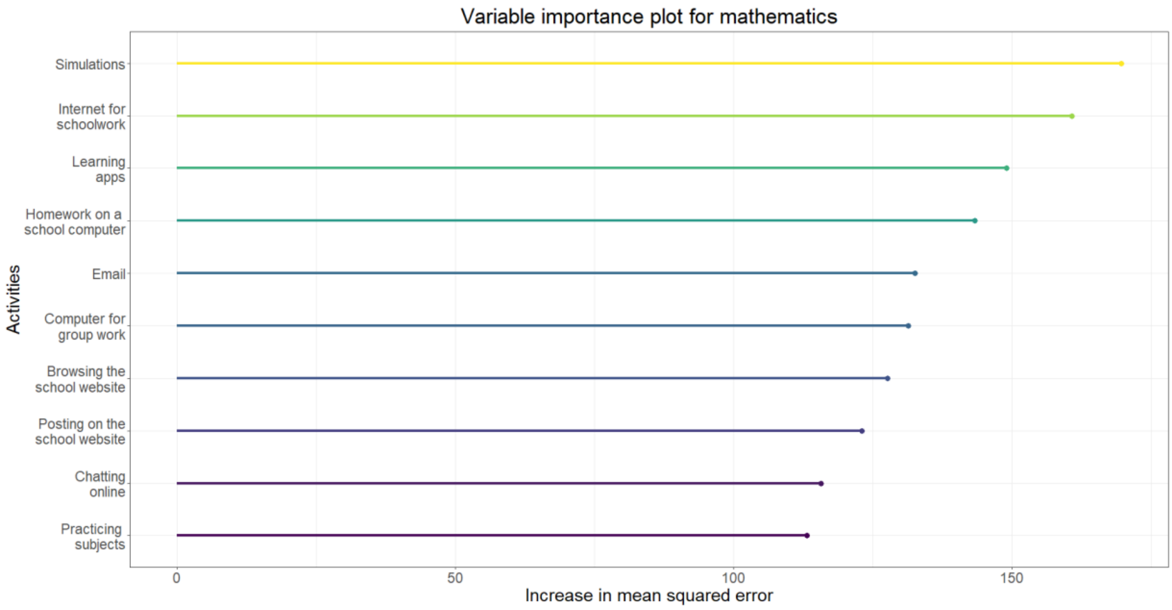


**Figure 24.** Variable importance plot for mathematics.

Variables used: Math_score, Chatting_online, Email, Internet_schoolwork, Browsing_school_website, Posting_school_website, Simulations, Practicing_and_drilling, Homework_school_computer, Computer_group_work, Learning_apps.

In the case of mathematics, four variables have been considered: *Simulations*, *Internet_schoolwork*, *Learning_apps*, and *Homework_school_computer*.
An evident decrease in the mean squared error is observed after including these four activities.

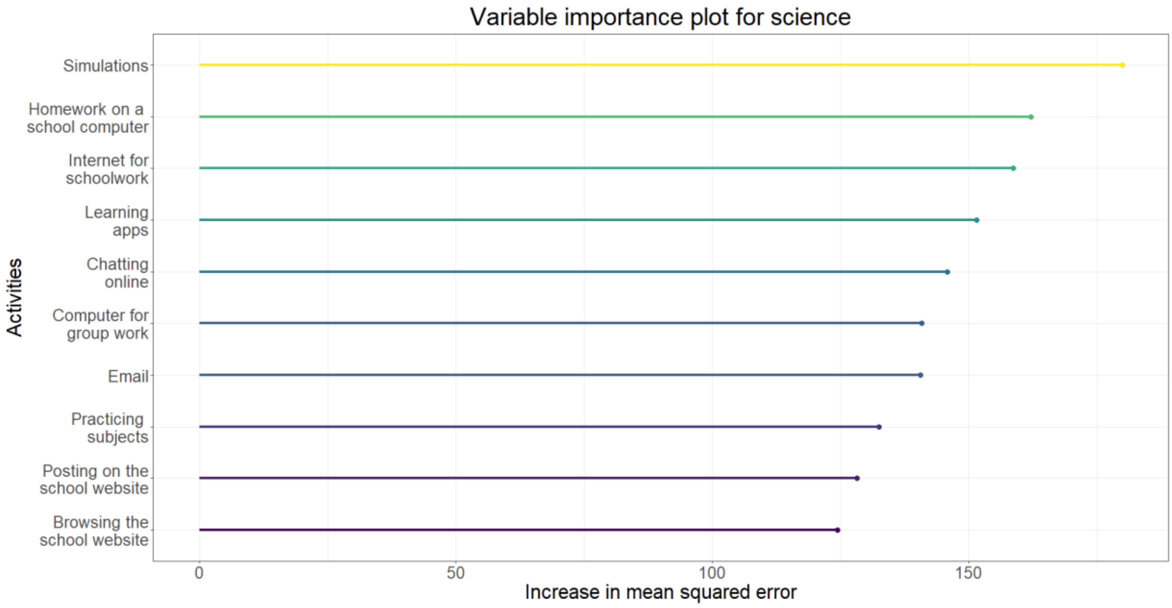


**Figure 25.** Variable importance plot for science.

Variables used: Science_score, Chatting_online, Email, Internet_schoolwork, Browsing_school_website, Posting_school_website, Simulations, Practicing_and_drilling, Homework_school_computer, Computer_group_work, Learning_apps.

Lastly, in relation to the science plot, the first three variables have been selected to be included in the statistical techniques of the following chapters: *Simulations*, *Homework_school_computer*, and *Internet_schoolwork*. It is worth noting that the list of the activities performed with digital devices for science is identical to the one chosen for reading, which allows a better comparison between the models built on the two subjects.

The results presented earlier are obtained by implementing the random forest algorithm with 500 trees. It is important to highlight that plotting the out-of-bag error against the number of trees revealed a decrease in error until the inclusion of 200 trees. Beyond 200 trees, the error level remained constant. The results of the random forest are thereby considered statistically robust.

## 4.2 Linear Mixed Models Results

### 4.2.1 Results

Subsequently, an analysis on the regression coefficients of the ICT variables in the dataset is presented. The aim of the paragraph is to provide educators with interesting insights on the impacts that Information and Communication Technologies have on students' test scores. Once again, it is worth noting that all the discussed conclusions are not of causal nature.

The results for the reading, mathematics, and science models are presented in Figure 26, 27, and 28. The vertical axis in each figure lists all the independent variables included in the respective models. First, the ICT variables are presented. Subsequently, all the variables used to control for confounding factors are described.
In the columns of the corresponding figures, the point estimate of each coefficient, together with its 95% confidence interval are then reported.

It is worth noting that the fixed intercepts are not displayed in the figures provided below. This is due to their significantly higher scale, which would negatively impact the visual representation. Nonetheless, the intercept values for the reading, mathematics, and science models are as follows: 466.49 (with a standard error of 4.46), 461.09 (with a standard error of 4.2), and 457.09 (with a standard error of 4.61).

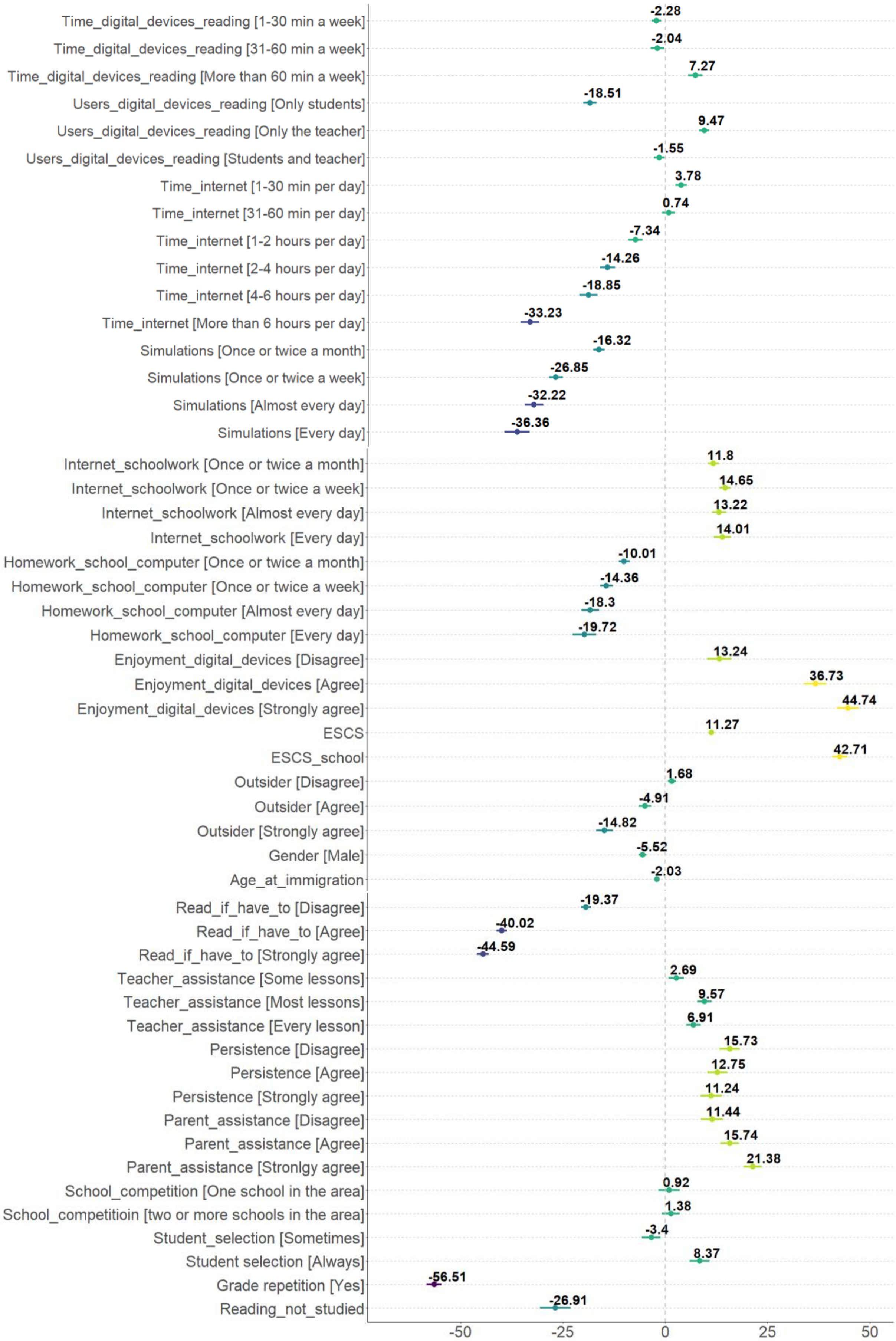


**Figure 26.** Confidence intervals for the coefficients of the reading model

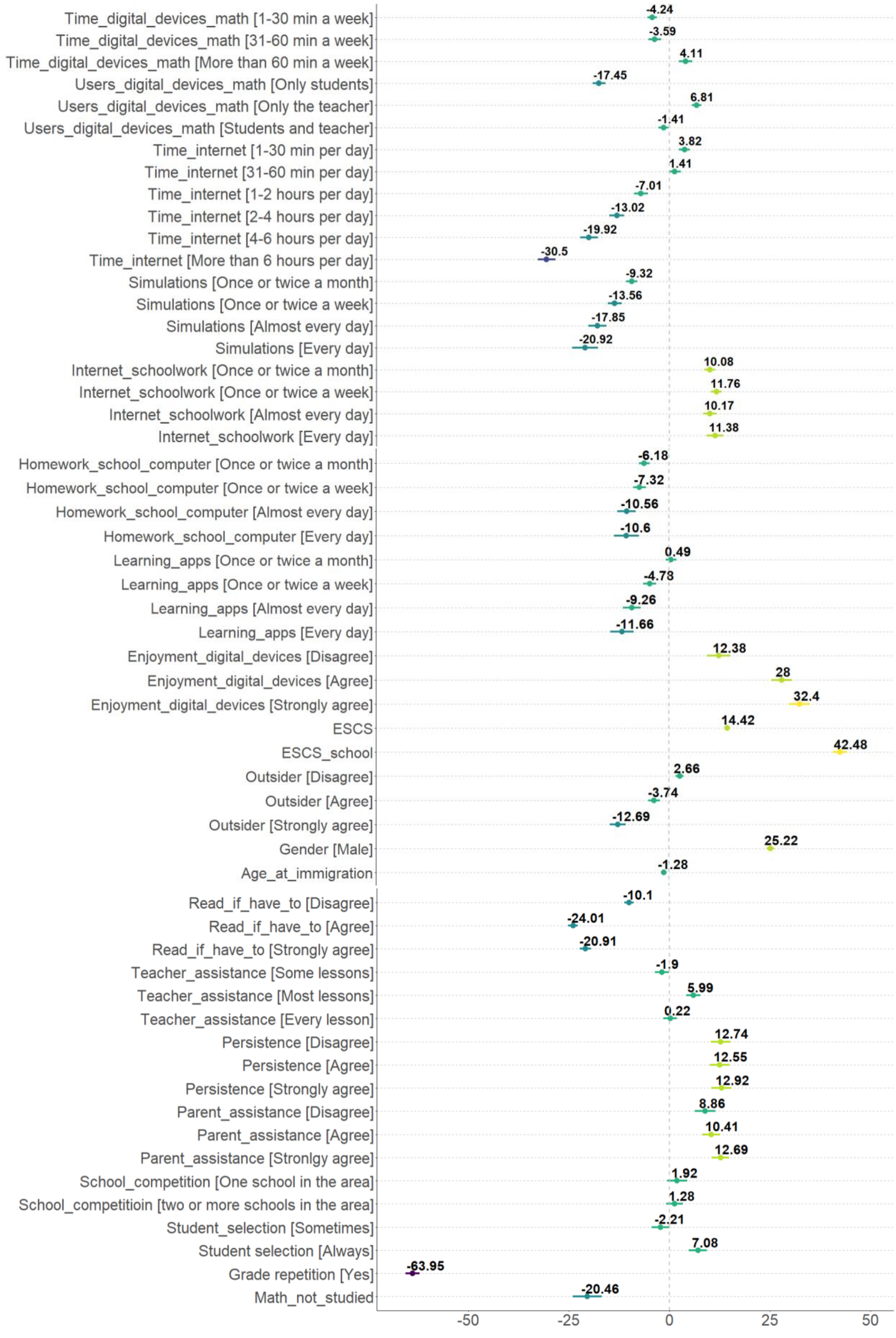


**Figure 27.** Confidence intervals for the coefficients of the mathematics model

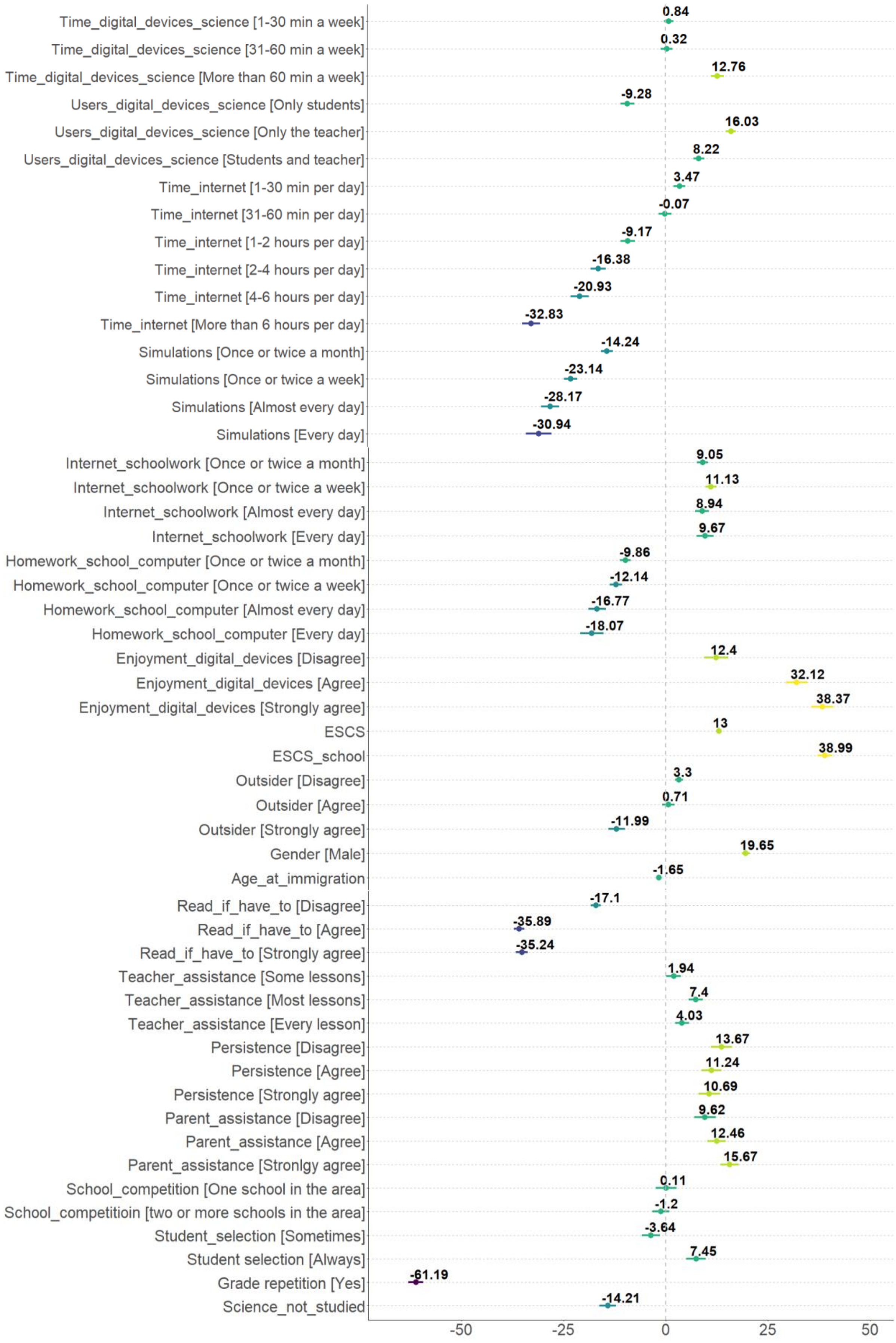

**Figure 28.** Confidence intervals for the coefficients of the science model

After reviewing the three models, it becomes clear that the variables have a consistent impact on the dependent variable. When a coefficient is positive in one model, it is highly likely that it is positive in the other two models as well. Similarly, negative coefficients are consistent across all models.
Additionally, the width of each confidence interval indicates that the coefficients have been estimated with reasonable precision. This could be attributed, in part, to the considerable number of observations in each model.

The first inquiry intends to unveil if students' attitude towards digital devices has an effect on their academic achievements. More precisely, the following question is addressed:

*"Do students that enjoy using digital devices achieve better test scores than scholars that do not enjoy using these technologies?"*

In all three subjects, the results display that the more students enjoy using digital devices, the higher their test scores tend to be. This in an interesting insight from a policy making perspective, as it highlights that students' perception towards technology is as important as the technology itself. In order for schools to fully exploit the advantages of the technological transition occurring in educational institutions, educators must assure that the actors involved in the process are fully committed to it. Educators must try to unveil why certain students perceive digital devices negatively, in order to correct these misperceptions and allow scholars to fully exploit the benefits that the technologies provide to their academic performance.

Second, the results show that using digital devices at school has a positive impact on students' test scores only if they are used for more than 60 minutes a week. The highest benefit of using digital devices at school is associated to science. This is because in the latter subject the technologies may be used to communicate abstract concepts to students. Adopting technologies less than 60 minutes per week instead, has a null or negative effect on students' test scores, depending on the subject under analysis and on the amount of time the students use digital devices at school. The result is reasonable considering that the question refers to a weekly technology usage. If digital devices are not even used for one hour per week, it is hard to imagine the benefits that these technologies may bring. An example is provided hereafter to clarify the concept.
If teachers use digital devices less than 60 minutes per week, it is unlikely that they master the technologies. In the moment they need to use the digital devices, it is probable that they encounter technical difficulties or lose time in preparing the class assignments due to their lack of experience with the technologies. The benefits of using the digital devices are therefore overcome by the negative effects brought by the loss in valuable lecture time.
On the other hand, if teachers use digital devices frequently, the loss in time for setting up the digital devices during lectures becomes negligible, and students fully benefit from using digital devices in class. As highlighted in the literature review, the use of technologies in schools stimulates students' motivation towards learning, increases student engagement and promotes active participation in class. In addition, thanks to the many possibilities that are facilitated by digital devices, teachers may tailor lectures and teaching methods according to their students' characteristics. Lastly, by using technologies frequently, teachers remain updated on the latest

and most effective ways of using digital devices for enhancing their students' academic performance.
All these insights are valuable from a policy making perspective. Policy makers must try to unveil the reasons behind the scarce use of digital devices in certain educational institutions to avoid that students in these schools lag behind in terms of academic preparation.
In case the low use of digital devices in certain schools is associated to the lack of economic resources to buy these technologies, policy makers must find ways to provide grants to these schools. Students must always be provided approximately the same quality of education, independently of the socio-economic conditions of the schools they are attending.
If instead digital devices are scarcely used in schools because teachers lack the necessary skills to adopt the technologies, the schools in which these educators are teaching must undergo a deep organizational change. Using ICTs in educational institutions does not simply mean providing teachers with advanced technologies. It requires a change in traditional educational systems. Teachers must be taught how to use these technologies, how these digital devices can be used to improve their students' academic performance, and more. Schools must also update their educational bodies and the skills that they teach, in order for ICTs to be effective in enhancing students' test scores.

Third, the results allow to assess if students' test scores vary according to the specific user of the digital devices at school. Namely, an answer to the following question is provided:

*Is it better that students or teachers use digital devices at school?*

In all the three subjects under analysis, the students that report that only their teachers use digital devices during lectures significantly outperform scholars that report that nobody (neither students nor teachers) use digital devices during their lectures. Once again, the highest increase in students' performance is achieved in science.
On the contrary, when only the students use digital devices during lectures, their test scores are inferior to the ones of the scholars that report that nobody uses technologies during their lectures. These students perform particularly poorly in reading and mathematics.
The results are reasonable considering that the students assessed by the PISA 2018 questionnaires are 15 years-old. More precisely, the negative effects of having students autonomously use digital devices are twofold:
On one hand, the technologies may be a distraction for the students. Imagine a scenario in which a reading teacher asks students to autonomously use a computer for performing an academic task. If students are not disciplined enough, they may use the computer for browsing the Internet, playing computer games and more. In turn, this results in wasting potentially valuable hours of lectures.
On the other hand, students may not have the necessary skills to autonomously use digital devices. This is not necessarily limited to students' technical skills with these technologies. As highlighted by cognitive load theory, in order for students to autonomously complete a task effectively, they must have sufficient knowledge on the subject. Imagine for instance a circumstance in which a reading teacher asks students to write an essay on a subject they have never heard about. In this case, the lack of previous knowledge on the matter may result in students getting lost in the myriad of information that they can access by using the digital

devices. Instead of being a supportive instrument, the digital devices may "paralyze" students with their abundance of information.
For these reasons, it is best that teachers use digital devices during class activities. Naturally one may wonder:

*How about if students and teachers use digital devices together?*

The results highlight that in the latter case, using digital devices improves students' test scores only in science (compared to the case in which digital devices are not used all).
All these insights are useful from a policy making perspective. They provide a guideline on which new teaching practices may potentially be successful, according to the users of the digital devices that the methodologies focus on. This does not mean that all the teaching approaches that are centered around students using digital devices should be discarded. Policy makers must understand the reasons behind the current ineffectiveness of students autonomously using digital devices at school, in order to improve their efficacy in using the digital devices in the future.

Fourth, the results describe the impacts that the use of the Internet at school has on students' test scores.
The findings emphasize that in all three subjects, students that report using the Internet for schoolwork significantly outperform those that do not. What matters is that students use the Internet, irrespectively of the frequency of usage. If students use the Internet daily, weekly, or monthly, the increase in their test scores is approximately constant. The most substantial increase in students' academic performance is reported in reading.
Additionally, the results highlight that assuming a daily use of the Internet at school, it is important not to exceed in the time spent using this technology. While using the Internet up to 30 minutes per day increases students' average test scores, exceeding this limit significantly damages students' academic results. The more students overcome the 30 minute threshold, the lower their test scores tend to be. This result is reasonable considering that the Internet is often considered as a complementary technology. During lectures, teachers may use the Internet to show students multimedia content to explain abstract concepts. For schoolwork, scholars may use the Internet to browse additional information on unclear topics. However, if students start using the Internet at school for many hours a day, it is likely that they get distracted by it. They may use the Internet for non-academic related activities when they are not supervised by teachers. Additionally, in the upcoming years, students may use the Internet to ask AI technologies to perform their schoolwork. This may impede scholars from learning specific skills, that they then would not know how to apply during tests that prohibit the use of the Internet.
These insights are valuable from a policy-making perspective. They highlight that to date, the Internet is perceived as a complementary technology. To summarize the insights in one phrase: *using the Internet in moderation is key*.

Lastly, the results emphasize the different impacts that the activities performed with digital devices have on students' test scores. In all the three subjects under analysis, the effects of using digital devices for conducting simulation activities, and for doing homework on a school

computer are examined. Additionally, in mathematics, the impacts of using learning apps on scholars' test scores is also assessed.
The results yield that using digital devices for the aforementioned activities has a negative impact on students' test scores in all three subjects. More precisely, the more frequently students use the digital devices for the above mentioned activities, the worst their test scores tend to be. The possible explanations are twofold:
First, the reader must always keep in mind that PISA administers the questionnaires to 15 year-old students. Often, scholars in this age range do not have the necessary maturity to autonomously use digital devices effectively. If left unsupervised, students may exploit the digital devices to perform non-academic tasks, such as chatting online with other classmates. Therefore, the problem may stand in the users of the digital devices rather than in the technology itself.
Second, the reader must also recall that ICTs have only recently been introduced in educational institutions. Hence, comparing traditional pedagogical methodologies that have been adopted for centuries, with recent ICT-enabled teaching practices may be overly simplistic. As highlighted in the literature review, the majority of schools to date are only at the beginning of the technological transition. The transition requires time, effort and a deep change in schools' organizational structures. Therefore, the negative impacts of using digital devices for simulations, or for doing homework on school computers may be caused by the lack of experience that the students and teachers of these educational institutions have in using the digital devices. In fact, by combining the regression coefficients of Figures 26, 27, and 28 with the results of Figure 12, it is clear that the only activity that currently has a positive impact on students' test scores (i.e. Internet for schoolwork) is also the only one that is currently being widely performed in schools. It is therefore likely that students and teachers have mastered the techniques to effectively use digital devices for this activity. For all the other activities instead, teachers and students may lack the necessary skills to use the technologies effectively. Only when students and teachers will have the necessary skills to use technologies effectively will the true impact of using ICTs for the above mentioned activities emerge.
Between using digital devices for simulation activities, and adopting digital devices for performing homework on school computers, the first activity has a bigger negative impact on students' test scores. This is reasonable considering that in 2018, the activity had only recently been introduced in schools. The simulations that were used in 2018 are in fact very different than the ones that students are accustomed to today.
In addition, both activities have a high negative impact on students' test scores in reading. This is also coherent to the literature, as it was previously highlighted that reading in digital formats may reduce the pleasure that students perceive while reading books in paper format.
Lastly, in mathematics, using learning apps at school has a similar negative impact on students' test scores to using digital devices at school for homework.

In summary, although the aforementioned analyses highlight that using digital devices in certain academic activities may have a negative impact on students' test scores, policy makers must not limit their decision on whether to invest or not in these technologies on the mere analysis of students grades. Students' test scores are only one of the consequences of adopting ICTs in schools. Policy makers must also assess the impacts that these technologies have on students' learning process as a whole, such as the influence that these devices have on scholars' motivation, enjoyment, attitude towards learning, and more.

Shifting the focus to the variables included to control for potential confounding factors, it is necessary to assess whether the point estimates for the coefficients and their confidence intervals are aligned with the existing literature. This is a crucial step to evaluate whether the model is behaving as expected and to assess if the results are reliable.

Firstly, regarding the economic, social and cultural status of the family, it is evident that it exerts a positive and statistically significant effect on students' scores. The point estimate for the coefficient related to this variable is quite consistent across all three models, with a slightly greater value in the mathematics model. As previously discussed in chapter 1.1, there are several possible explanations for this, including parents with higher incomes who can provide greater access to educational resources for their children, families with higher social capital who can offer valuable role models and create supportive networks for their kids, and parents with higher levels of education who are more likely to make significant investments in the education of their children.
Consequently, the findings of the three linear mixed models are in line with the existing literature, indicating that students' academic achievement, on average, increases as their family's *ESCS* rises.

Moving on to the concept of economic, social and cultural status of schools, it can be observed that the coefficient is positive and statistically significant, indicating that students who attend schools with higher *ESCS*, perform better on average than students who attend schools with lower *ESCS*.
This result supports the statements made in chapter 1.1, where it was mentioned that schools with different economic and social conditions could potentially show dissimilarities in the teaching materials, the teachers' years of experience, and the teacher-student ratio.
Notably, the coefficient associated with the *ESCS* of the school has a significantly higher magnitude when compared with the *ESCS* related to each specific family. It may lead to the assumption that the average economic, social and cultural status of a school has a greater impact on students' academic achievement than the *ESCS* related to the specific family. However, it is important to consider that although the variables *ESCS* and *ESCS_school* have similar averages (around -0.03), they have considerably different standard deviations. Specifically, the former has a standard deviation of around 0.95, while the latter has a standard deviation of around 0.53. Therefore, when assessing the influence of the two variables in the regression model, the multiplication of a student's variable value with the corresponding coefficient shows that the coefficient *ESCS_school* is associated with values that tend to have a lower absolute magnitude. This leads to a comparable impact between the two variables under consideration.

The next regressor to be analyzed is the *Outsider* variable, which aims to measure the extent to which students feel like outsiders in their school. Agreeing with the statement "I feel like an outsider (or left out of things) at school", may impact students' motivation, leading to a negative effect on their academic performance.

In all three models, the reference level is *Strongly disagree*, therefore it is reasonable to expect a negative trend transitioning from *Strongly disagree* to the alternatives *Disagree*, *Agree*, and *Strongly agree*.
Interestingly, a slightly positive effect is observed in the *Disagree* alternative compared to the reference level. One potential explanation for this is that there may not be a clear separation between students who *Strongly disagree* and those who *Disagree* with the statement.
Conversely, as expected, it is evident that students who reported *Agree* or *Strongly agree* performed worse on average.
In the model for science, there is an exception where a slightly positive but non-significant effect is observed for the *Agree* alternative, indicating that student performance may not be affected if they report *Agree* compared to the reference level *Strongly disagree*.
However, a large negative coefficient is associated with the *Strongly agree* alternative, indicating a clear separation between students who completely feel like outsiders and those who do not.

Shifting the attention to gender differences, a clear difference between the models is observed. Coherently with the existing literature, females exhibit superior performance on average in reading when compared to their male counterparts. Conversely, males tend to outperform females on average in mathematics and science.

The variable *Age_at_immigration* exhibits a comparable coefficient in all three models, which is negative and statistically significant. This indicates that a students' academic performance declines with an increase in the number of years spent in a foreign country before taking the test. This finding is consistent with the information presented in chapter 1.1, where it was discussed that students who spend fewer years in the country where the test is taken may not have adequate time to learn the new language and develop the skills required for performing tests in the country.

When analyzing the variable *Read_if_have_to*, the reference level of *Strongly disagree* is utilized. Since this variable may control for students' ability to concentrate on reading, it is expected that if a student agrees with the statement "I read only if I have to", their academic performance will be lower compared to a student who disagrees with it.
In line with the aforementioned explanation, the coefficients displayed in Figure 26, 27, and 28 regarding the variable *Read_if_have_to* are all negative and significant. Specifically, in the reading model there is a decreasing trend, with a coefficient of -44.59 for students who *Strongly agree* with the statement. In the other two models, a decreasing trend is observed when transitioning from *Strongly disagree* to *Agree*. However, the alternative *Strongly agree* shows a slightly higher coefficient than the alternative *Agree*. This effect could be attributed to the difficulty in distinguishing between students who *Agree* with the statement and who *Strongly agree* with it. A similar challenge was also noted when describing the coefficients of the variable *Outsider*.

In terms of the variable *Teacher_assistance*, a similar trend is observable in both the reading and science models. Specifically, students who reported receiving assistance from their teachers during the majority of lessons tend to perform the best academically. In comparison to the reference level, represented by students who do not receive assistance from their teachers,

students who receive help during some lessons exhibit better performance. However, they are still outperformed on average by scholars who receive help during every lesson.
In the mathematics model, it can be observed that students generally perform better if they receive help from teachers during most lessons. However, if they receive help during only some lessons, there is a slightly negative impact on the dependent variable, with a confidence interval that is very close to 0. On the other hand, when students receive help during every lesson, the effect is highly non-significant, as the estimated coefficient is 0.22, but the confidence interval includes the value 0.
These findings are in line with expectations, as teacher assistance may often result in higher academic performance by enabling students to better understand difficult concepts. Moreover, teachers can also provide valuable feedback on students' work to help them identify areas for improvement, and provide support during lessons to increase their engagement in the learning process.
Conversely, if teachers provide help to students during every lesson, it can lead to a situation where students become overly dependent on teachers, and they may not develop the necessary skills and confidence required to solve problems independently. This can result in lower academic performance, as students may struggle when they are not able to receive immediate help from their teachers. Moreover, spending excessive time in teacher-assisted activities can reduce opportunities for students to learn crucial skills such as problem-solving and critical thinking. These potential reasons may account for the lower coefficient associated with the *Every lesson* alternative when compared to the *Most lessons* alternative.
All coefficients are consistent with the aforementioned explanations, except for the one obtained in the mathematics model, where students who receive help from teachers during some lessons show a slight decrease in academic performance. It is worth noting that mathematics is a subject that requires a lot of practice and repetition in order to master concepts and develop problem-solving skills, and it requires a thorough understanding of fundamental concepts before moving on to more complex topics. When teachers provide help during only some lessons, students may miss critical foundational concepts that are necessary for success in later lessons. As a result, this could lead to lower academic performance in the long run, as students may struggle to keep up with more advanced topics.

Shifting the attention to the *Persistence* variable, the students' level of agreement with the statement "Once I start a task, I persist until it is finished" is analyzed. Given that the reference level is *Strongly disagree*, it is reasonable to expect that students who did not report *Strongly disagree* would have achieved higher performances. This is because maintaining effort, focus, and determination over time is likely to yield better results.
Consistently with this statement, all three models exhibit a substantially positive impact of *Persistence* coefficients on performances, regardless of the level selected, provided that the student did not report *Strongly disagree*.

A consistent trend can be observed with respect to the *Parent_assistance* variable. Specifically, students' performances are on average higher as their level of agreement with the statement "My parents support my educational efforts and achievements" increases.
As previously discussed in chapter 2.2, students may benefit from greater family resources such as books, technologies, time, attention, and advice. Although practical support may be deemed the most crucial type of support provided by parents, emotional support also plays a vital role.

When students feel valued, loved, and supported by their parents, they are more likely to develop a positive attitude towards school and learning.

The confidence intervals related to the *School_competition* variable consistently include 0, suggesting that the presence of one, two, or more schools in the same geographic area may not influence students' academic performances.

The inclusion of the *Student_selection* variable aimed to mitigate the bias that may arise from schools admitting only those students who have passed a specific test. As a result, it is reasonable to expect that students enrolled in such schools would exhibit higher test scores on average.
Consistent with this statement, it can be observed that schools that persistently administer admission tests have students who perform better on average, as highlighted by the positive and highly significant coefficient associated with the *Always* alternative across all three models.
Unexpectedly, the *Sometimes* alternative has a negative coefficient. The reasons behind why schools administer tests for admission only on certain occasions are not evident from the available dataset, making it difficult to infer a possible explanation for the negative coefficient. A school may choose to administer admission tests selectively in certain years due to capacity management concerns. For instance, if a school forecasts a high demand for enrollment but has limited available space in a given year, an admission test becomes necessary. Conversely, if the expected number of students is lower than the available places, there is no need to conduct an admission test during that particular year.
It is worth noting that an inconsistent use of admission tests in schools may create various challenges and difficulties for students and parents. For instance, students who obtain admission to a school through a test may experience a sense of inequality compared to those who gained admission without undergoing such testing.

As expected, the last two variables in each model exhibit a negative coefficient that is statistically significant and has a high magnitude.
Firstly, the *Grade_repetition* variable identifies students who have repeated a grade at least once during their academic journey. This variable's negative coefficient can be attributed to several reasons, such as severe difficulties in understanding academic concepts or mastering certain skills, which lead to the need to repeat a grade. This experience can signal academic struggles and may continue to impact the student's performance in the future. Moreover, repeating a grade may result in a loss of motivation, disengagement, and lower confidence that scholars have in themselves, making it difficult for students to fit in with their new peers.

Lastly, by analyzing the dummy variables Re*ading_not_studied*, *Math_not_studied*, and *Science_not_studied*, it becomes evident that if a student did not study a specific subject, their average performance is lower than the performance of students who did study that subject. It is clear that students who have studied a subject have acquired the necessary knowledge and skills needed to answer questions accurately. On the other hand, students who have not studied a subject did not have the opportunity to acquire such knowledge and develop those skills.

In conclusion, an analysis of the random effects of the linear mixed models is provided hereafter. Despite the models are created to have both a country specific and school specific random intercept, the latter is excluded from the below analysis. Comparing school specific random intercepts is in fact considered to be excessive given the more than 5000 educational institutions in the dataset. This does not mean that school specific random intercepts are not important. They are still used to model the correlations among the test scores of students attending the same schools, allowing to reduce multicollinearity effects in the coefficients of the models. These random effects are simply not used for explanatory purposes in the study.

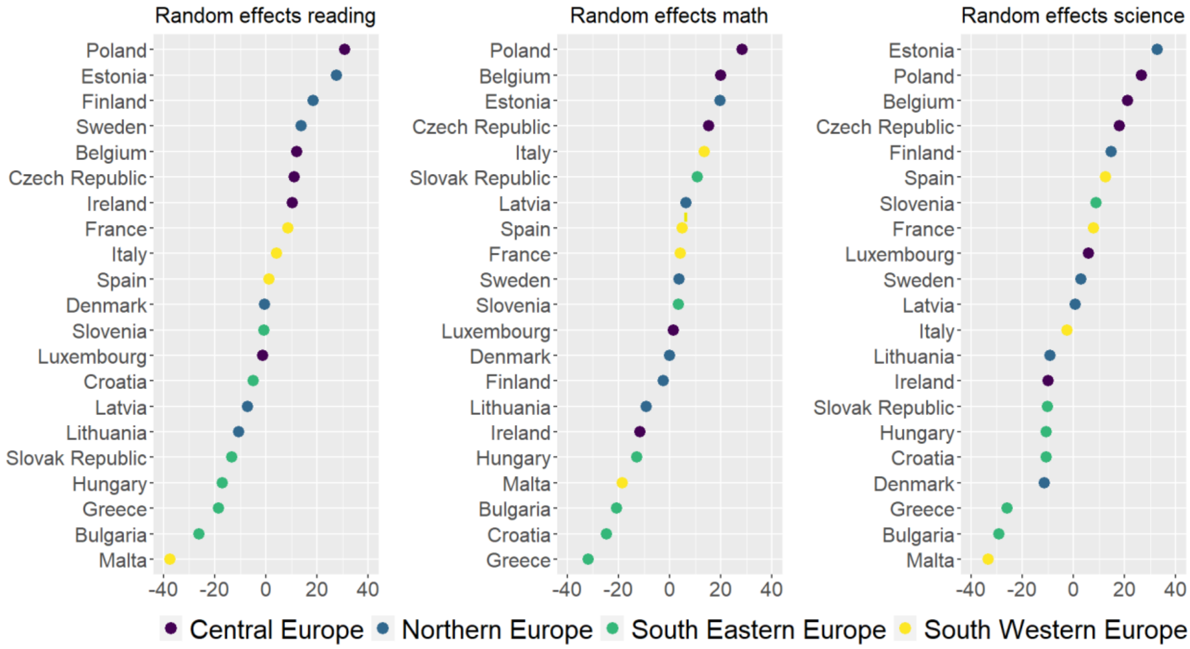


**Figure 29.** Random effects of the Linear Mixed Models

On the other hand, Figure 29 displays the country specific random effects of all three models. The entity of the random effects are net of the variability in the students' test scores that is explained by the covariates in the models. This means that for each country, the random effects allow to capture the additional variability in students' test scores that is attributable to potential omitted variables in the dataset. The larger each nations' random effects are in the plots, the bigger the impacts these omitted variables have on the students' test scores.

Figure 29 confirms the results of the descriptive statistics. Students' in Northern and Central Europe are among the top achievers in the PISA 2018 assessments in all three subjects. Particularly strong results are achieved by their scholars in reading.

On the contrary, students from South Eastern Europe are consistently among the least performing scholars in all the three assessments. Exceptionally negative performances are also delivered by pupils in Malta.

What the random effects add to the descriptive statistics though, is that the remarkably positive or negative achievements of the students in the aforementioned macro-regions cannot simply be attributable to the control variables and the ICT variables used in the LMMs. Students' academic results are not simply influenced by the scholars' personal traits, the characteristics of the schools they study in, or the amount of technologies they use during class activities. There is a multitude of other aspects that influence students' academic achievements that the random effects indirectly allow to capture. The random effects portray the impacts that all these omitted variables combined have on students' test scores, without specifying what these variables may be. In order to discover what these variables are, additional models would need to be performed.

As highlighted in Table 2, it is extremely important to include the random effects in the LMMs. Combining the country and the school specific random effects allows to explain approximately 40% of the residual variance in all of the three models.
Finally, Table 2 also highlights that the conditional $R^2$ of all three models lies between 42% and 46%. Although the reader may be skeptical about the values of the conditional $R^2$, since achieving an $R^2$ above 50% is extremely rare in social sciences, all the models are considered to be statistically robust. The values of the conditional $R^2$ are also a minor problem considering that the models are not used for prediction. They simply aim at analyzing the effects that the explanatory variables in the dataset have on the dependent variable.

| *Index (%)* | *M1(reading)* | *M2(mathematics)* | *M3(science)* |
|---|---|---|---|
| *Country PVRE* | 15,71 | 15,39 | 16,58 |
| *School PVRE* | 21,38 | 21,47 | 21,24 |
| *Total PVRE* | 37,09 | 36,86 | 37,82 |
| *Conditional $R^2$* | 45,56 | 42,50 | 43,24 |

**Table 2.** PVRE and Conditional $R^2$ of the Linear Mixed Models

### 4.2.2 Assumptions

Before examining the normality and homoscedasticity assumptions on the residuals of the models, it is important to briefly discuss two potential issues that may arise when running regression models.
Firstly, it is worth noting that the inclusion of a large number of variables in each linear mixed model may result in a low ratio between the number of observations and the number of parameters to be estimated.
This might be problematic as it can lead to overfitting of the model, which can compromise the reliability and generalizability of the results.
Secondly, multicollinearity can also raise a challenge. For instance, if a student reports a high frequency or usage time in one specific question regarding digital devices, it is likely that they will exhibit similar patterns in response to other questions related to digital devices.
This can lead to high levels of correlation among the explanatory variables, which can make it difficult to distinguish the unique effects of each variable on the outcome.

To address the first potential issue, the upcoming part will present the ratios between the number of observations and the number of parameters estimated in each model.

The number of observations in each of the models differs since each subject has a different amount of missing values.
Specifically, the reading model has 99248 observations, the mathematics model has 96998 observations, and the science model has 98209 observations.
The number of parameters that need to be estimated also varies depending on the model considered, since the number of independent variables included in each model depends on the results of the variable selection process that was performed using the random forest algorithm. The list of parameters that must be estimated includes the fixed intercept, the coefficients of the independent variables, the variance of the schools' random intercepts, the variance of the countries' random intercepts, and the variance of the residuals.
For the reading and science models, the same number of independent variables leads to the same number of coefficients to be estimated: 52. In the mathematics model, an additional variable called *Learning_apps* has been included. Since this variable has five levels and one is used as the reference level, the number of coefficients to be estimated in this case is 56.

Based on the numbers provided above, the following ratios between the number of observations and the number of parameters to be estimated were computed:

$$\textit{Ratio for the reading model} = \frac{99248}{1+52+1+1+1} = 1772.3$$

$$\textit{Ratio for the math model} = \frac{96998}{1+56+1+1+1} = 1616.6$$

$$\textit{Ratio for the science model} = \frac{98209}{1+52+1+1+1} = 1753.7$$

The remarkably high value of each ratio suggests that the parameter estimation is unlikely to generate any significant issues.

After confirming that the first concern did not present any significant issues, the upcoming part will explore the second potential problem: multicollinearity.
Multicollinearity is a well-known issue in regression models, as it can lead to unstable parameter estimates. As mentioned earlier, a potential issue in this study is related to students reporting similar responses to the questions about digital devices.
Despite the difficulty in overcoming this problem, there are two main reasons why multicollinearity issues may not arise.
First, each dataset contains a considerable amount of data, which reduces the variance in the estimated coefficients and increases their precision.
Second, the use of random effects can also help in addressing the issue of multicollinearity. They can capture the correlation among students within the same school and country. Random effects allow to separate the variation in the test scores of students that is due to scholars' individual characteristics, from the variation in students' test scores that is associated to the school or country they belong to. Consequently, the use of random effects can lead to a more accurate estimation of the coefficients.

In conclusion, the potential issue of multicollinearity should not be ignored, but the aforementioned factors support a correct interpretation of the results obtained from the three models.

One final step to ensure the accuracy of the interpretation of the three models is to examine the normality of both residuals and random effects, as well as the homoscedasticity of the former. To assess the normality of the residuals, a Q-Q plot is employed, which displays the quantiles of the residuals on the vertical axis and the quantiles of the normal distribution on the horizontal axis.
Figure 30 analyzes in sequence the normality of the residuals for the reading, mathematics, and science models.

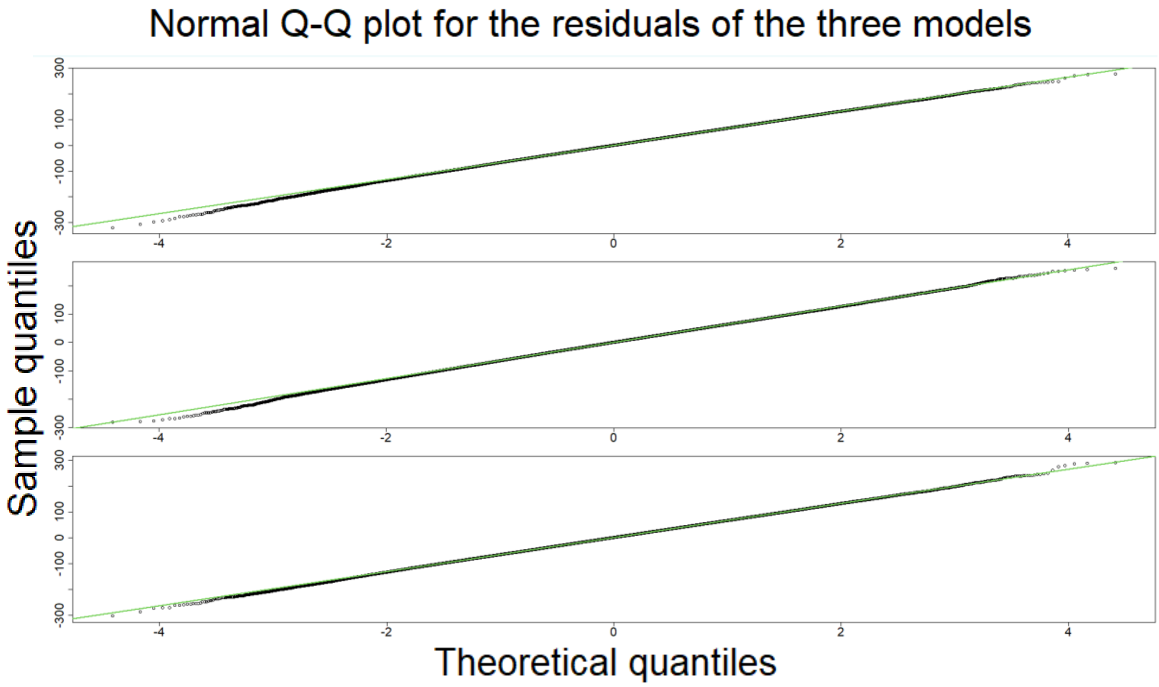


**Figure 30**. Q-Q plot for the residuals of the reading, mathematics, and science models.

Each plot shows a strong correspondence between the sample quantiles and the theoretical quantiles of a normal distribution. Although the residuals of the reading model exhibit a slight deviation from the quantiles of the normal distribution in one end of the plot, overall they appear to follow a normal distribution. These plots provide support for the normality assumption of the residuals of all three models.

To assess the normality of the random intercepts, similar plots to those of the aforementioned residuals are employed.
Figure 31 analyses the normality of the random intercepts for each country in the reading, mathematics, and science models respectively.

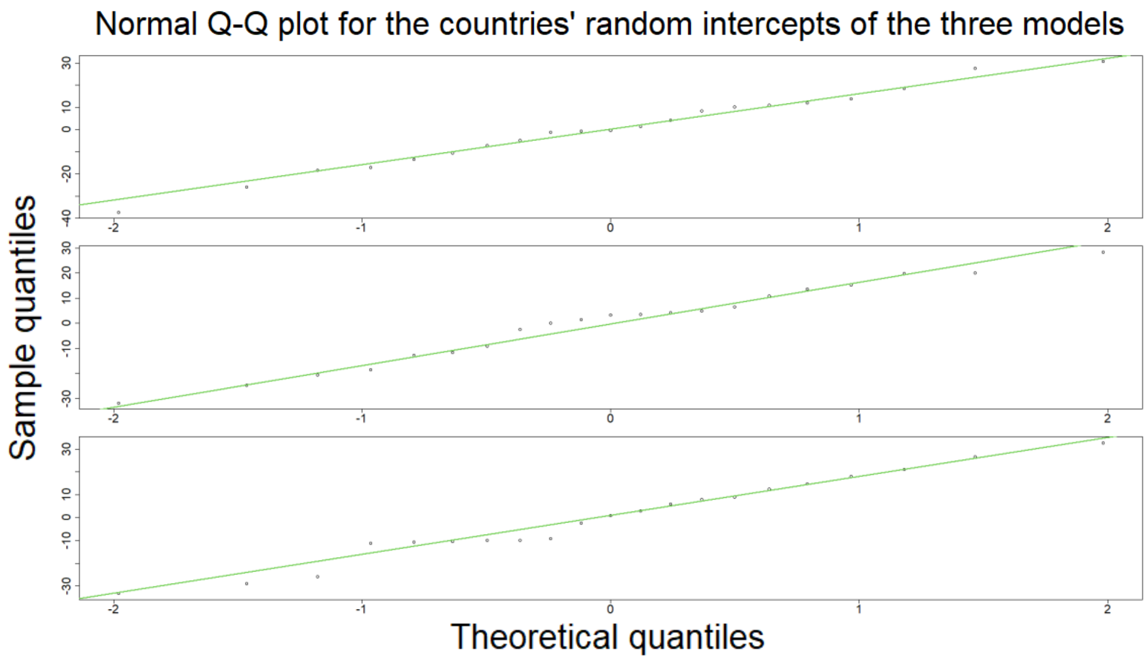


**Figure 31**. Q-Q plot for the countries' random intercepts of the reading, mathematics, and science models.

There is evidence to suggest the normality of the random intercepts for each country.
A check for the normality of the random intercepts for each school is also necessary.
Figure 32 analyses the normality of the random intercepts for each school in the reading, mathematics, and science model respectively.

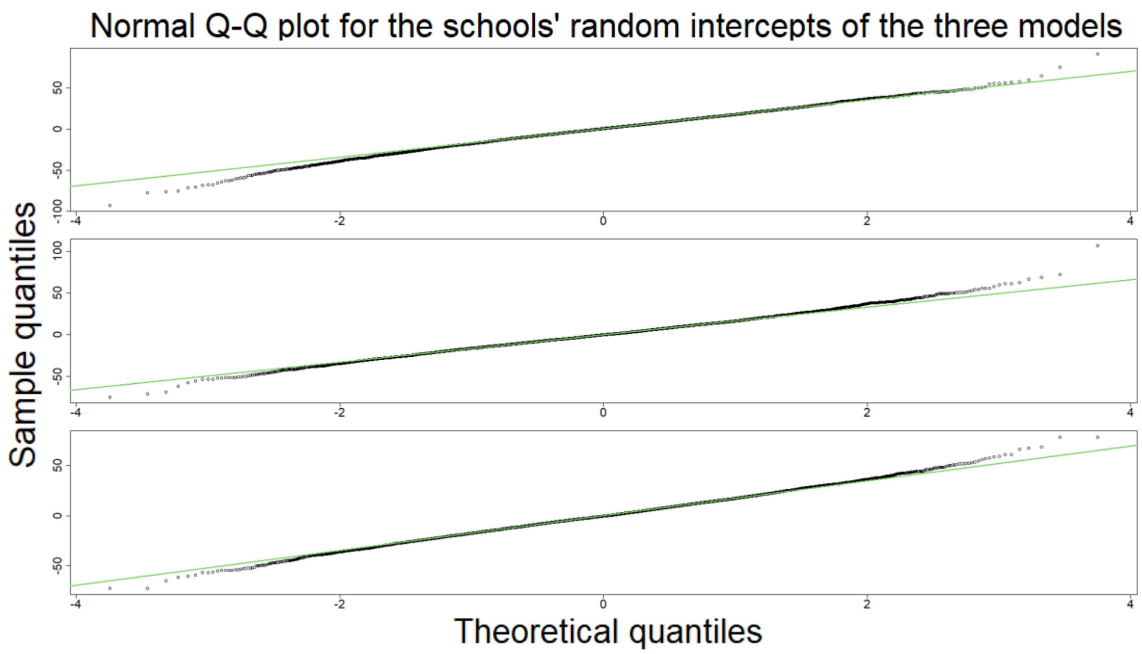


**Figure 32**. Q-Q plot for the schools' random intercepts of the reading, mathematics, and science models.

Except for a deviation in the reading model, similar to the one observed in the analysis of the normality of the residuals, the distribution of the random intercepts for each school appears to be normal.

Next, to examine the homoscedasticity assumption, a plot was created to visualize the relationship between standardized residuals and fitted values, with the aim of assessing whether the variance of the residuals is distributed uniformly across different fitted values.
Figure 33, 34, and 35 display the standardized residuals distribution in relation to fitted values for the reading, mathematics, and science models, respectively.


**Figure 33**. Standardized residuals vs fitted values for the reading model.

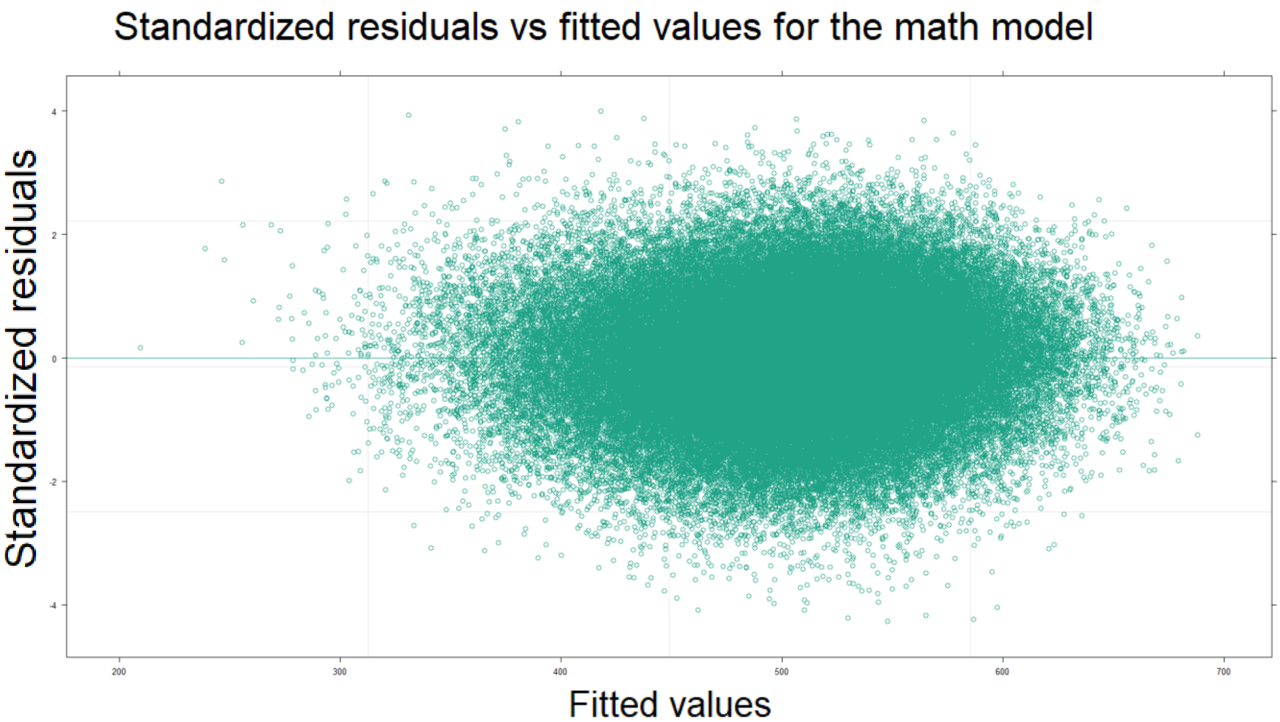


**Figure 34**. Standardized residuals vs fitted values for the mathematics model.

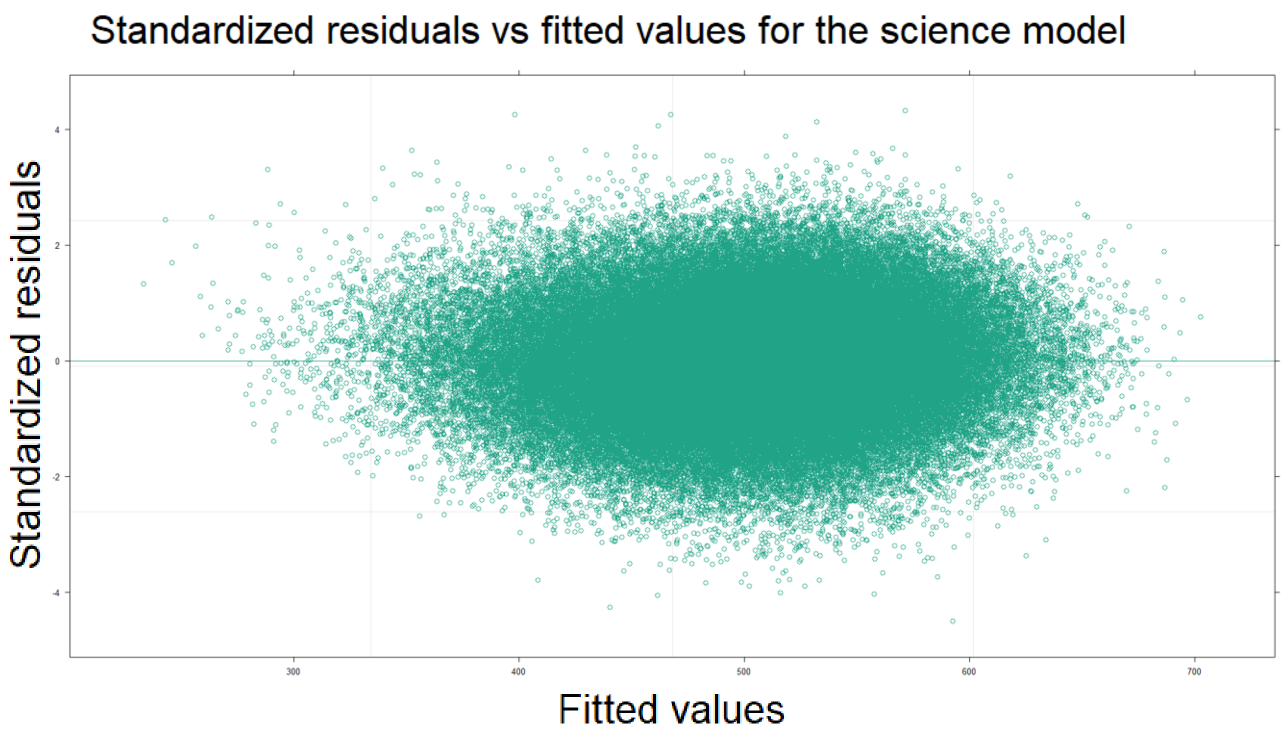


**Figure 35**. Standardized residuals vs fitted values for the science model.

The distribution of the standardized residuals with respect to the fitted values appears to be consistent among the three models, as indicated by the evenly dispersed residual cloud.
However, an observable pattern emerges when transitioning from low to medium-low, or from medium-high to high fitted values.
These trends may be attributed to the fact that a significant number of students scored near the average score of 500, with fewer students scoring very high or very low. This is because PISA standardizes the test scores to have mean of 500 and standard deviation of 100.
Apart from these marginal trends, the residual cloud maintains a constant variance around the different levels of fitted value.

In order to gain a more comprehensive understanding of the distribution of the residual variance, it is worth assessing its variation across different countries.
Boxplots provide a powerful visualization tool for analyzing the variance of the residuals within each country, by examining the interquartile range and the range between the highest and lowest residuals per country.
Figure 36, 37, and 38 present the boxplots of the residuals for each country in the reading, mathematics, and science model, respectively.

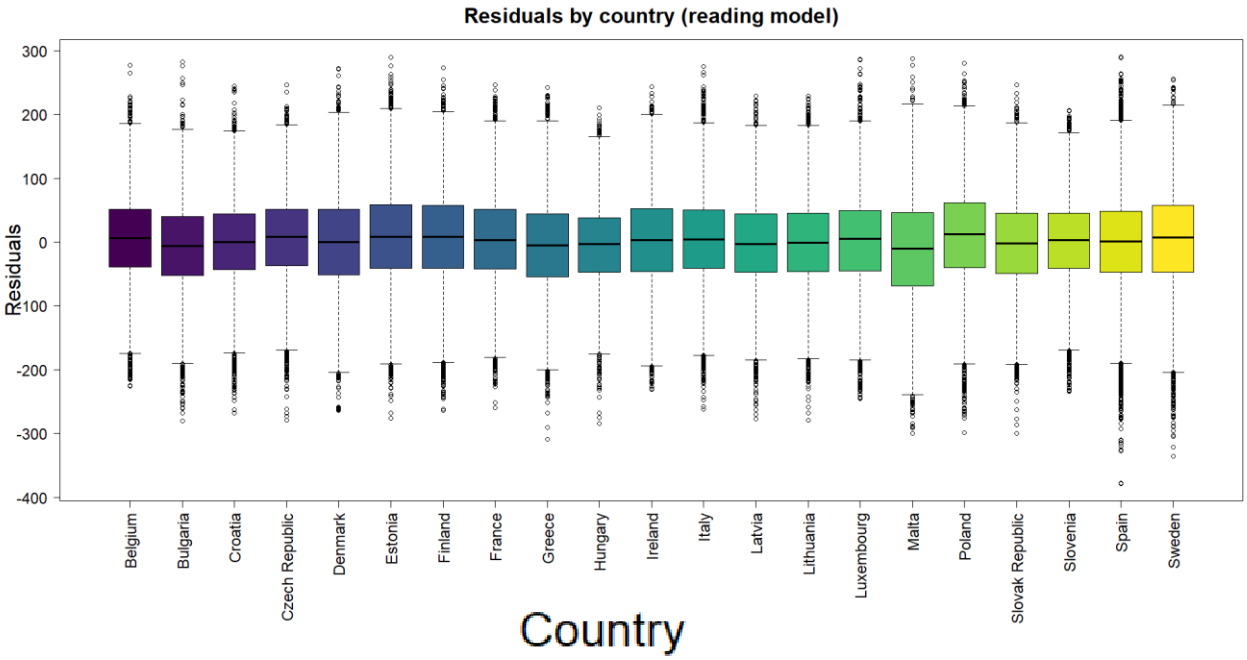


**Figure 36**. Boxplot of residuals by country for the reading model.

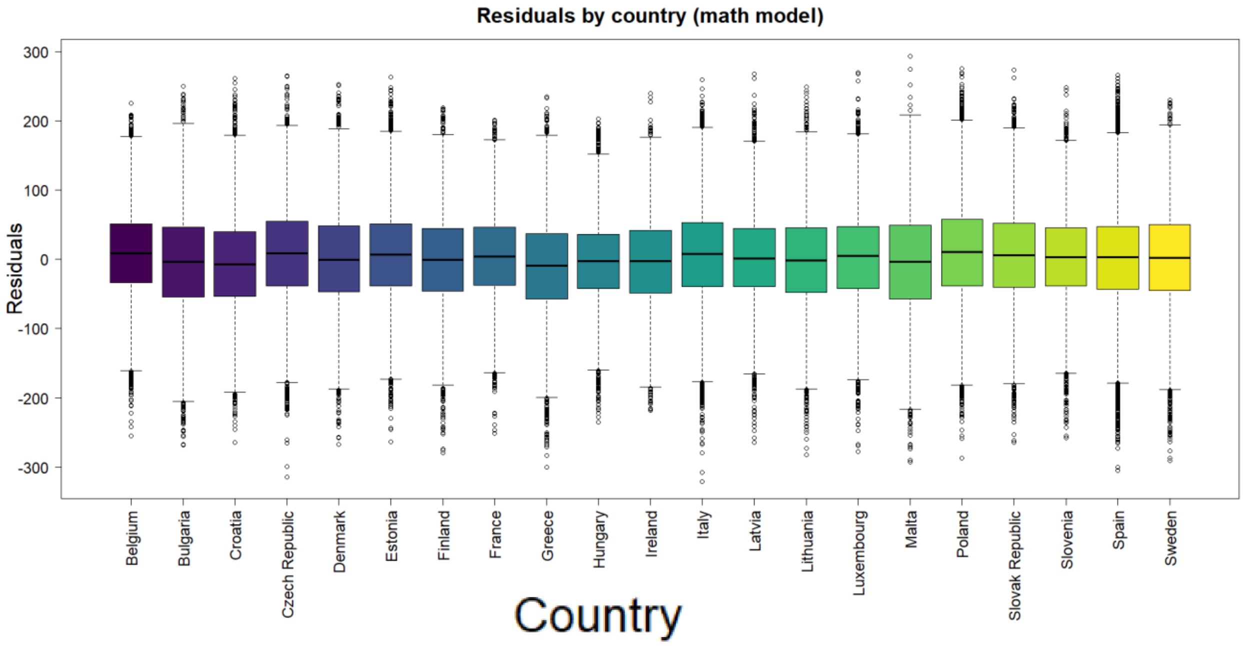


**Figure 37**. Boxplot of residuals by country for the mathematics model.

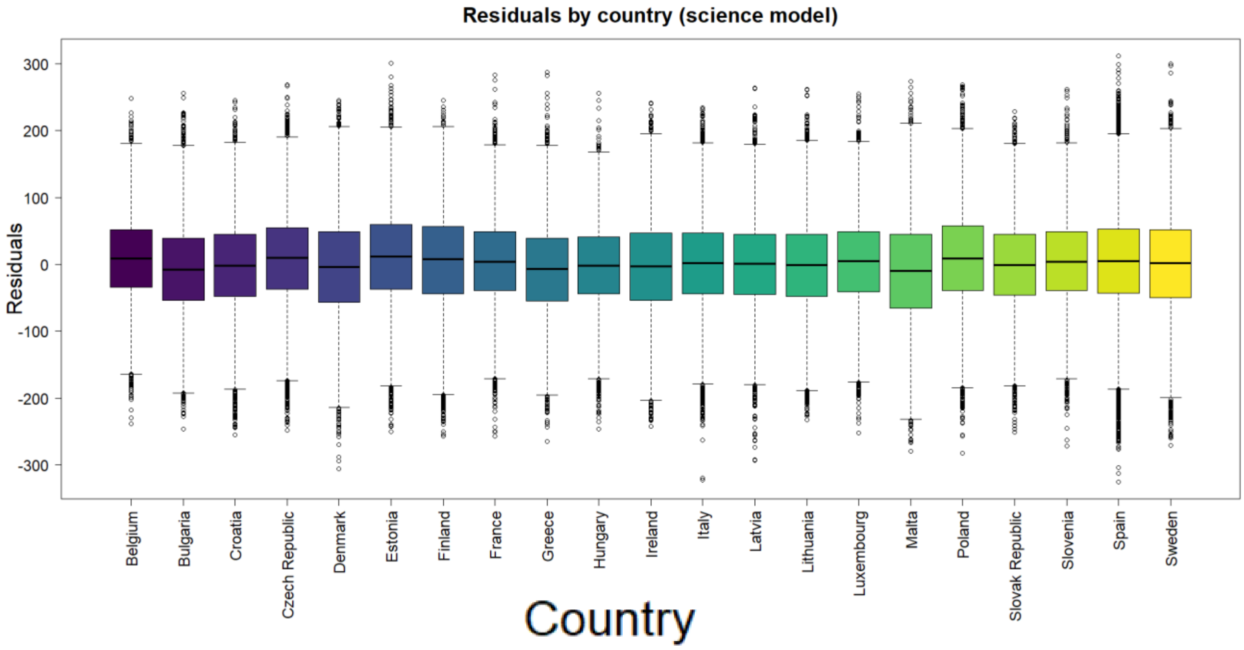


**Figure 38**. Boxplot of residuals by country for the science model.

The residual variance across countries appears to be highly consistent in all three models. While some countries, such as Slovak Republic and Hungary, display a slightly lower variability, others, such as Malta, appear to have a higher variability. Nonetheless, the overall differences among the residuals across countries are relatively minor.

In conclusion, it can be confidently stated that the assumptions of all three linear mixed models hold, and therefore the findings presented in section 4.2.1 can be considered reliable.

## 4.3 Regression Trees with Random Effects Results

The methodological approach described in the previous paragraph is applied to each of the three hierarchical regression trees presented below.
The first tree presented examines *Reading_score* as the dependent variable, followed by the *Math_score* tree, and in conclusion the *Science_score* tree is presented.

Each plot displays a set of exclusive paths, each leading to a group of students who share a common score in the PISA standardized test. When a path encounters a numerical variable, such as *ESCS*, the subset splits into students with values lower than the displayed one (following the left path) and those with values higher than the displayed one (following the right path).
Conversely, when a path comes across a categorical variable, the distinction is based on the levels of the variable. In this case, the plot displays some alternatives on the left and some on the right. Students who reported an answer that is included in the choices on the left will belong to the subset that will follow the left path, while students who reported an answer that falls under the alternatives on the right, will follow the right path.

At the bottom of each plot, the leaf nodes are displayed, indicating the end of each path. Each leaf node includes the students who followed that specific path and are grouped based on their shared score.
Despite being grouped together, the students belonging to these groups exhibited different scores in the PISA standardized test. Although the tree structure has the potential to further expand, aiming to predict individual student scores with enhanced precision, the tree is pruned at a certain level to avoid overfitting.
Therefore, these algorithms are conducted to highlight the variables that significantly impact students' scores, and to validate the findings obtained via linear mixed models.

The numbers displayed in each leaf node represent the potential score for the group of students that belong to that corresponding node. Lastly, the percentage below each leaf node indicates the percentage of students in the entire dataset that falls into that specific leaf node.

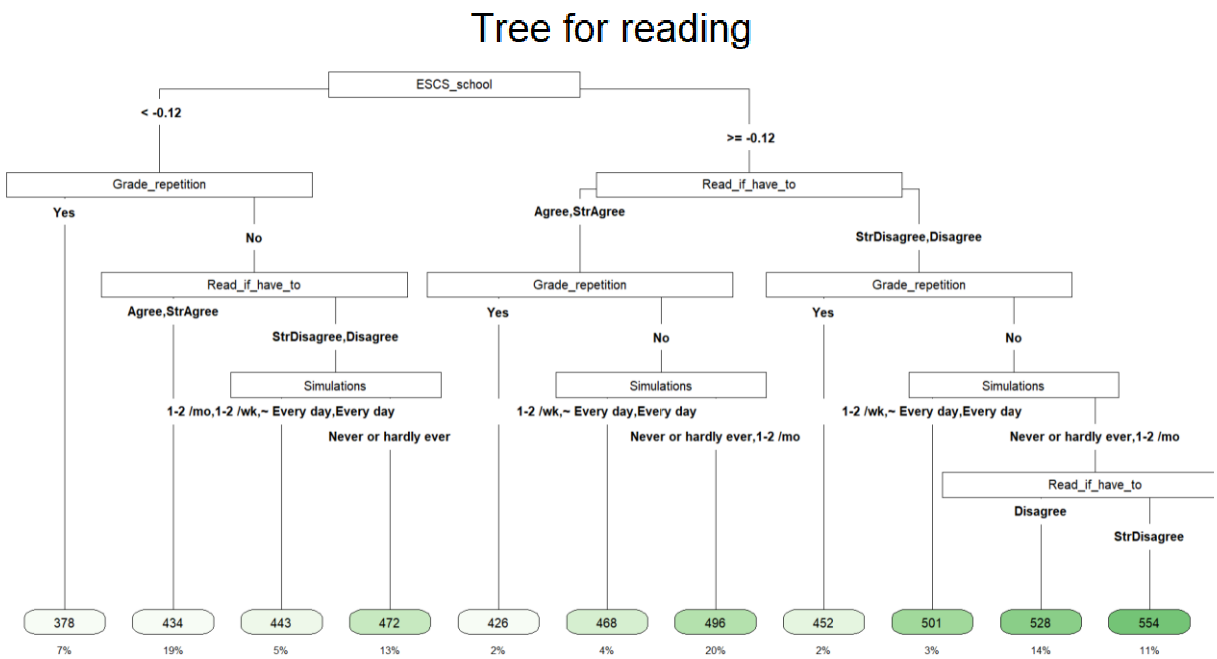


**Figure 39**. Decision tree diagram for reading

The hierarchical regression tree for reading identifies eleven distinct groups of students, represented as leaf nodes. These groups are determined using only four key variables, which are significant in explaining the students' test scores: *ESCS_school, Grade_repetition, Read_if_have_to, and Simulations.*

*ESCS_school* is the initial variable that divides the dataset into two exclusive subsets. Students reporting a school economic, social and cultural status value lower than -0.12, score lower on average compared to those reporting a higher value.
Subsequently, each path of the hierarchical regression tree presents a unique set of variables that divides the dataset.

From a general overview of the plot, it is evident that whenever *Grade_repetition* is used to create a fork in the path, students who report *Yes* have a lower score than those who answer *No*. This variable appears three times in the tree, on both the left and right sides of the tree, and serves to divide the students who repeated a grade from those who did not repeat it.

The variable *Read_if_have_to* also creates distinctions in the observations three times.
The first two times, it creates a division between students who *Agree* or S*trongly agree* to the statement "I read only if I have to" and those who *Disagree* and *Strongly disagree*. Students who report that they read even if they are not obliged, namely those who answer *Disagree* and S*trongly disagree*, tend to perform better in academic contexts. Conversely, those who read only when they have to, tend to have lower performances.
The third time that *Read_if_have_to* is used, visible in the bottom-right of Figure 39, the distinction is different from the previous two. This is due to the fact that the path under consideration already comes from a previous distinction between students who A*gree* or *Strongly agree* and students who *Disagree* or *Strongly disagree*.
Specifically, the considered path is the one including only students who *Disagree* or *Strongly disagree* to the statement "I read only if I have to". Therefore, the distinction is made between students who *Disagree*, who will be part of the group on the left, and those who S*trongly disagree*, who will belong to the group on the right.
It is clear from this last case that students who *Strongly disagree* have a higher academic performance than those who simply *Disagree*.

Among the variables displayed, *Simulations* is the last one that creates significant divisions in the dataset, appearing in three different paths. It presents a consistent pattern: when students report a higher usage of simulations during lessons, they tend to have a lower academic performance, while those who report lower usage tend to have higher academic performances.

These results are consistent with the findings obtained from the linear mixed models.
Specifically, the LMM revealed a positive and significant coefficient for the economic, social and cultural status of the school. Similarly, the hierarchical regression tree attributes a higher academic performance to students who attend a school with a higher ESCS.
Secondly, the linear mixed model found a low and significant coefficient for students who repeated a grade in their academic path. Similarly, as displayed in Figure 39, students who answered *Yes* to the question "Have you ever repeated a grade?" are placed in groups with lower scores in the regression tree.
Thirdly, the LMM reveals a clear pattern for the *Read_if_have_to* variable. Specifically, the extent to which the student agrees with the statement "I read only if I have to" shows a negative impact on their academic performance. This is evident from the LMM's, where scholars' performance decreases as students' agreement to the statement "I read only if I have to" increases. Similarly, the hierarchical tree indicates that students who *Disagree* or *Strongly disagree* tend to perform better than those who *Agree* or *Strongly agree* to the aforementioned statement.
Moreover, when *Disagree* and *Strongly disagree* are compared, the latter group performs the best. These findings are aligned to the results obtained in the linear mixed models, since the alternative *Disagree* has a significant and negative coefficient, while *Strongly disagree* is used as the reference level.

Lastly, the variable *Simulations* is also consistent in both models. Specifically, the LMM reveals a decreasing trend in students' academic scores as the frequency of playing simulations during lessons increases. Coherently, the hierarchical tree indicates that students who use simulations less frequently tend to achieve higher academic performances than those who use them more often.

After having analyzed the hierarchical regression tree results for reading, the subsequent step is to examine whether there are any variations in the model for mathematics.
The upcoming plot's interpretation is quite similar to that of Figure 39, although there may be deviations in the importance of the variables.

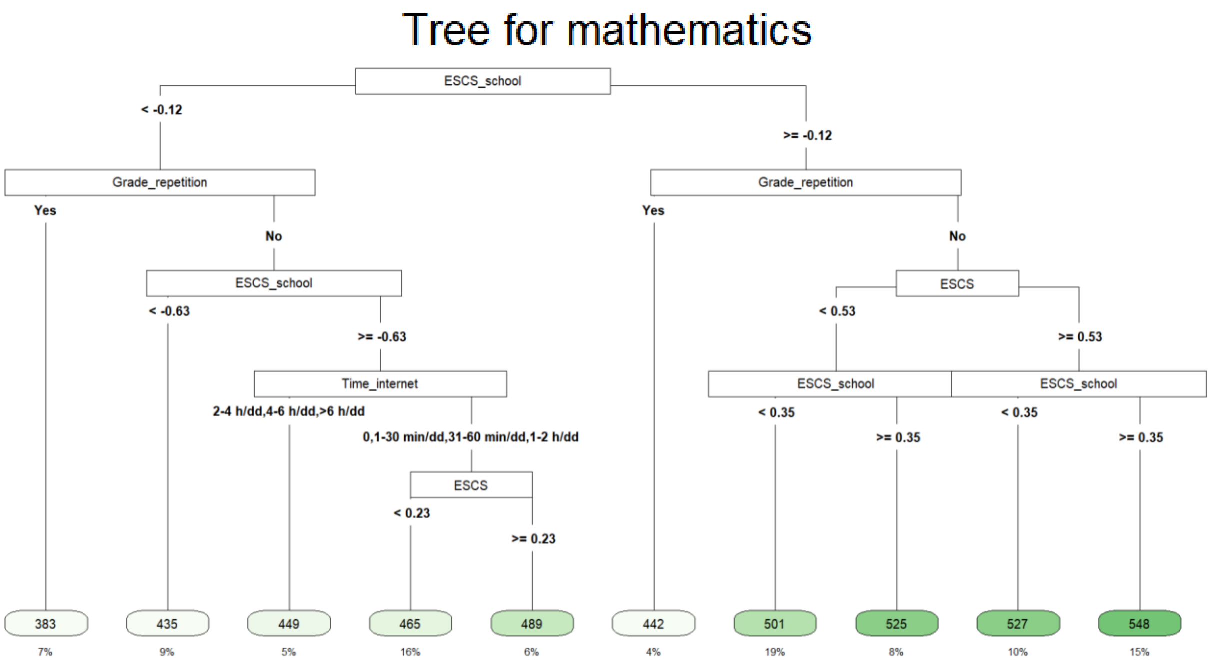


**Figure 40**. Decision tree diagram for mathematics

From a general view, it is evident that the primary variable that divides the dataset into two subsets is the same as in the previous plot: *ESCS_school*. Similarly, the threshold value for this variable is again -0.12. Specifically, students who reported an *ESCS_school* below -0.12 tend to have lower academic performances compared to those in the opposite group.

This time, the variable that splits each of the two initial groups into four is the same for both paths. The variable in consideration, *Grade_repetition*, shows that students who repeated a grade at least once tend to have a lower academic performance than those that do not. It follows the same pattern as in the model for reading.

In the hierarchical regression tree for mathematics, the economic, social and cultural status of the school is found to have a significant impact on the dataset, not only at the top of the tree but also in the middle of the paths.
Specifically, on the left-hand side of the plot, *ESCS_school* differentiates between students who attend schools with a very poor status and those who attend schools with a medium-low status.

On the other hand, on the right-hand side of the plot the variable focuses on distinguishing schools with a very high status from those with a medium-high status.

In addition to the school status, the economic, social and cultural status of students' families also plays a significant role on students' test scores in this model. Specifically, it distinguishes families with a higher status, which contribute to increasing their children's academic scores, from those with a lower status, resulting in lower academic performance for their children. This finding is consistent with the results obtained from linear mixed models, which showed a positive and statistically significant coefficient for this variable. This suggests that students from families with a higher *ESCS* tend to perform better on average.

The mathematics model shows a variable not included in the reading model: *Time_internet*. This variable splits students into two groups based on their daily Internet usage. Specifically, those using the Internet for at least two hours per day, fall into the lower performance group. This result is also consistent with the findings of LMM, which indicate that students who use the Internet for very short periods (maximum sixty minutes) tend to perform slightly better than students that use the Internet for large amounts of time. Therefore, it is generally appropriate to distinguish between students with low and high Internet usage.

Lastly, the plot of the hierarchical regression tree for science is presented.

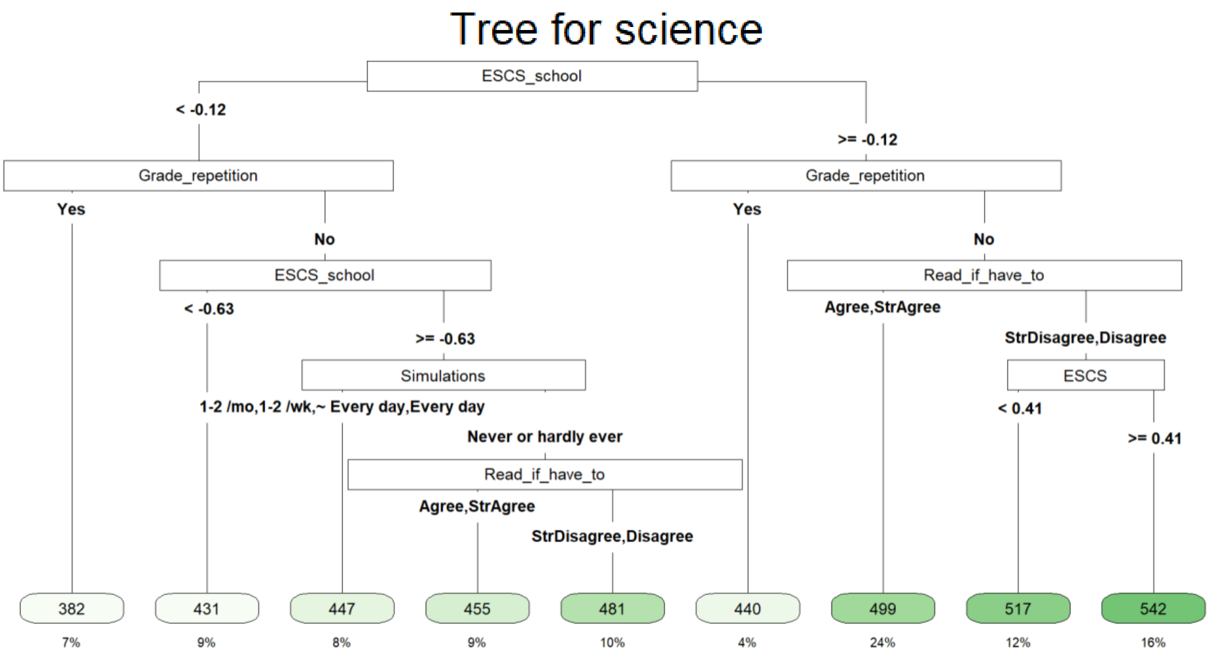


**Figure 41**. Decision tree diagram for science.

The hierarchical regression tree for science initially follows a similar pattern to the one observed in mathematics: the *ESCS_school* variable divides the dataset into two groups, which are subsequently divided into four groups by the *Grade_repetition* variable.

In addition to the previously mentioned variables, three further predictors play a significant role in dividing the students into subgroups: *ESCS*, *Read_if_have_to*, and *Simultations*.

Among these, *ESCS* only has an impact on the right-hand side of the tree, where it divides students belonging to a family with a very high economic, social and cultural status from the rest of the students. The impact of this variable on students' test scores is analogous to the one of the other trees.

Instead, the *Simulations* variable plays a role in the left-hand side of the tree, where it splits the observations based on the reported frequency of playing simulations. Specifically, students who reported playing simulations with null frequency, are separated into a distinct group. On the other hand, those who reported playing simulations at least once a month, are grouped together and are associated with a lower academic performance.

Lastly, the variable *Read_if_have_to* is involved in multiple paths in the tree. It distinguished students who *Disagree* or *Strongly disagree* to the statement "I read only if I have to" from those who *Agree* or *Strongly agree*.
The former group tends to have a higher academic performance, while the latter group tends to have a lower academic performance.

The consistency between the interpretation of these variables and the outcomes of the linear mixed models highlights their validity.

After having examined the significance of each covariate in explaining the students' academic results, in Figure 42 the country specific random effects of all three regression trees are presented. The results are coherent with those previously presented in Figure 29. Namely, the highest random effects are attributed to countries that belong to the Central Europe macro-region, while the smallest random effects are assigned to the nations that are part of the South Eastern Europe macro-region. This means that on average, net of the ICT variables and the control variables in the dataset, there are additional explanatory factors that describe the relatively strong and relatively weak academic performance of students in Central Europe and South Eastern Europe respectively.
Additionally, comparing Figure 29 to Figure 42 a slight difference emerges. Figure 42 includes countries that are not present in Figure 29 such as Portugal, Germany, Austria, Netherlands and Romania. This is because unlike in the linear mixed models, the regression trees with random effects do not automatically eliminate the rows in the dataset that have missing values. Consequently, the regression trees are created on a higher number of observations, allowing for a greater robustness in their results.

Once again, it is worth noting that the school specific random effects are not plotted below due to their high number. Comparing thousands of parameters without even knowing the characteristics of the schools they are representing is in fact irrelevant from an explanatory purpose.

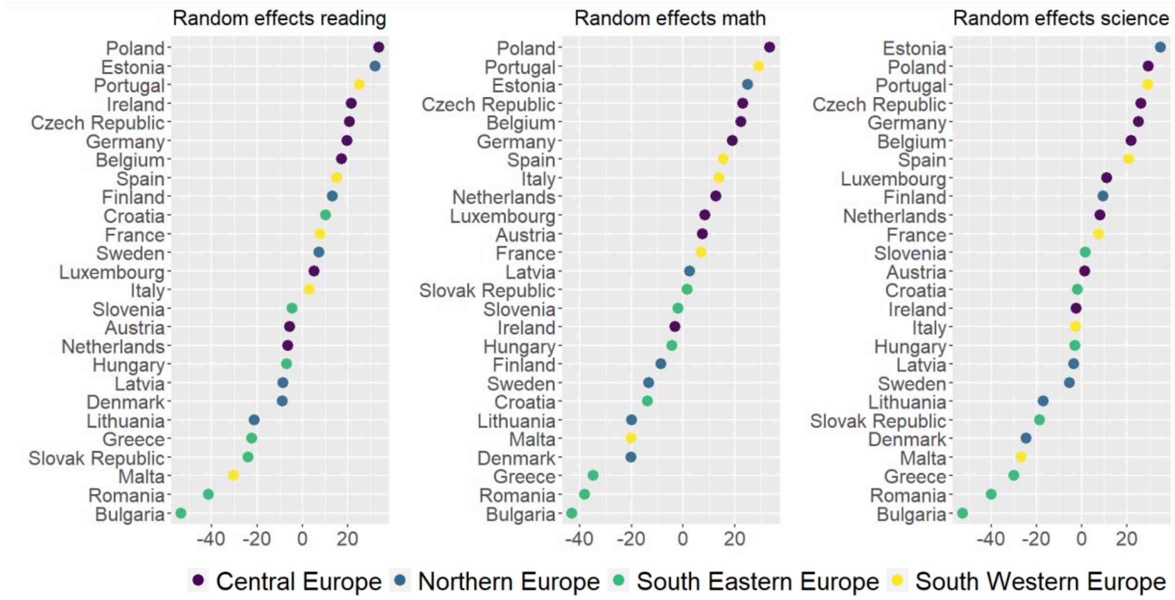


**Figure 42.** Random Effects of the Regression Trees

Lastly Table 3 highlights the importance of including the random effects in the regression trees. Combining the country specific and the school specific random intercepts allows in fact to assign between 43% and 46% of the residual variance in students' test scores, to the school and the country the scholars' are studying in. If these effects had not been included in the three models, this residual variance would have been assigned to the error terms in the models.

| *Index (%)* | *Tree(reading)* | *Tree(mathematics)* | *Tree(science)* |
|---|---|---|---|
| *Country PVRE* | 16,42 | 16,97 | 17,31 |
| *School PVRE* | 29,27 | 26,27 | 27,41 |
| *Total PVRE* | 45,69 | 43,24 | 44,72 |

**Table 3.** PVRE of the Regression Trees

# 5. Conclusion

## 5.1 Concluding Insights, Managerial, and Policy-Making Implications

In conclusion, the following study has examined the impacts that Information and Communication Technologies have had on 15 year-old European students in the PISA 2018 assessment cycle. Three methodological approaches are combined: descriptive statistics, linear mixed models, and regression trees with random effects. A brief summary of the most relevant insights, and of the main policy-making implications unveiled throughout the research are presented hereafter:

First, the study depicts that in 2018, digital devices are widely not adopted in schools. Approximately 30% of students report never using digital devices monthly. Of the remaining 70% of scholars, 60% state that they do not even use these technologies on a weekly basis. These results, combined with the ones of Livingstone (2012), highlight that in the majority of EU27 nations, educational institutions are still at the beginning of the digital transformation.

Understanding the reasons behind the current scarce adoption of ICTs at school is fundamental for policy makers. The possible explanations are twofold:

On one hand, schools may lack in ICT infrastructure (Balanskat et.al, 2006), and not have the necessary funds to invest in these technologies. In this case, policy-makers must find ways to provide grants to the schools that lack the necessary resources to invest in ICTs. Students must be provided the same quality of education, independently of the socio-economic status of the educational institutions they are attending.

On the other hand, teachers may lack the necessary skills to adopt these technologies during class activities, as highlighted by Ikeda (2020). Teachers that lack digital teaching experiences may continue to use traditional pedagogical approaches despite having ICTs readily available in their classes. This scenario highlights that in order for ICTs to be used during school activities, educational institutions must undergo a deep organizational change. Teachers and students must be taught the necessary skills to use the technologies effectively, and must be shown the advantages of using these technologies for their class activities. This is necessary for the latter to be fully engaged in their schools' digital transformation. The linear mixed models highlight that scholars that enjoy using digital devices perform significantly better in the PISA assessments than those who do not. Educators must therefore try to unveil why certain students negatively perceive digital devices, in order to increase the students favorability towards these technologies, and allow these scholars to fully exploit the benefits that ICTs have on their academic performance.

The models also highlight that not only is it important to use digital devices. It is equally essential to use them for more than 60 minutes per week. In fact, if educators do not even use digital devices one hour per week, it is unlikely that they master the necessary skills to use the technologies effectively. In the moment they need to use the devices for class activities, it is probable that the loss in lecture time attributable to setting up the digital devices overcomes the actual benefit of using the technologies. Instead, when teachers use digital devices frequently, they master the necessary skills to use these devices efficiently and effectively. The benefits of using digital devices in class are manyfold. To name a few, technologies may increase students engagement and attitude towards learning activities (Kulik, 1994), promote students' active participation in class, and allow students to visualize abstract concepts during lessons (Bindu, 2016). This is especially true in subjects like science, where being able to represent complicated models significantly improves students' learning outcomes. Additionally, teachers may use ICTs to tailor their lesson according to their students' needs.

Second, the research illustrates that using the Internet at school has a positive impact on students' test scores. The highest benefit is achieved in reading. Independently on whether the Internet is used on a daily, weekly or monthly basis, classes that use the Internet at school significantly outperform those that do not. What matters is that the technology is not used excessively. The linear mixed models identify an ideal threshold of thirty minutes per day. If the Internet is used at school for less than thirty minutes per day, an increase in students' test scores is observed. This is because the Internet is a complementary technology. Teachers may use it to show videos, images and other multimedia contents to their scholars to explain abstract concepts (Drigas et.al 2016) . Students may use it to browse material on unclear topics. On the contrary, when the latter technology is used for more than thirty minutes per day, it has a negative impact on students' test scores. The more the limit is exceeded, the bigger the negative impact on students' test scores observed. When the Internet is used excessively (e.g. 4 or 5 hours per day) it may become a distraction for both teachers and students. Scholars may use it to chat with their peers, browse non-academic related content, and more. Agasisti et. al (2020), also observed that ICTs may be a source of distraction for students.

Third, the study examines who are the main users of digital devices during class activities. The research depicts that when digital devices are used in class, in 30% of cases only teachers are allowed to use the devices, in 30% of cases the teachers and students use the digital devices together, and lastly in 10% of cases students are left to autonomously use these technologies. In order to understand if schools are focusing on the right users of digital devices during class activities, these insights need to be compared to the linear mixed models.
The linear mixed models highlight that the students that report that only their teachers are allowed to use digital devices during class activities significantly outperform the scholars of the classes in which digital devices are not used at all. Particularly positive achievements are observed in science. On the contrary, scholars that report autonomously using digital devices in class activities underperform compared to the students of the classes in which digital devices are not used at all. These students perform poorly mainly in reading and mathematics. These results are reasonable considering that the students analyzed in the PISA 2018 assessment cycles are 15 years-old. The explanations are twofold:
First, if students use these digital devices unsupervised during class activities, they may use the technologies for non-academic purposes when teachers are not looking (Vahedi et.al 2021). For

example, they may use the digital devices for playing computer games, browsing the Internet for leisure, and more.
Second, students may not have the necessary skills to autonomously use these digital devices. This does not refer to students' technical skills. As stated by cognitive load theory, for students to independently perform a task effectively, they need to have prior knowledge on the subject (Kirschner, 2006). Otherwise, they may get lost in the myriad of information they can access through the digital devices. Students may not be able to recognize true information from the misleading misinformation accessible through the digital devices. Therefore, rather than helping students, the abundance of information that scholars can access through digital devices may confuse them, and hamper their academic progress. When students do not have prior knowledge on a subject, they need to be guided by teachers.
All these insights are useful for educators and policy makers as they provide a guideline for which teaching approaches may be successful in improving students' academic performances. For example, they highlight that technology based teaching approaches that focus on teachers using digital devices in class may be more successful than teaching approaches that are centered on students using the digital devices autonomously. This does not mean however that all the teaching approaches thar are centered on students using digital devices independently should be abandoned. Policy makers must understand the reasons behind the current ineffectiveness of these approaches, in order to improve them in the future.
Lastly, the linear mixed models highlight that the teaching approaches that are centered around students and teachers using digital devices together are effective only in science.

Fourth, the research examines which EU27 nations are widely adopting ICTs in their school activities. According to the study, the nations that are part of the Northern Europe macro-region are currently the main adopters of Information and Communication Technologies at school. This result is particularly interesting considering that these nations are among the top performing countries in the PISA dataset. However it would be overly simplistic to attribute these nations' exceptional student performance only to the extensive use of digital technologies at school. The reasons are twofold:
First, the random intercepts of these nations in the linear mixed models are among the ones with the highest absolute value. This means that other than the variables describing the use of ICTs in the schools of these nations, there are several other factors explaining the exceptional student performance in these countries. Examples of these variables are the students' and schools' socio-economic status (Hanushek 1979) , the variables describing the students' attitudes toward learning, and the variables unfolding if the students have ever repeated a grade in their academic career. Additionally, there may be omitted variables in the study that have not been accounted for in the models.
Second, the nations that are part of the Central Europe macro-region, which are also among the top performing countries in the dataset, currently are not extensively using ICTs at school. This further strengthens the assumption that the exceptional student performance of scholars in Northern Europe cannot simply be attributed to the use of ICTs at school.

Keeping the focus on the comparison between the academic performance of students across macro-regions, the study highlighted that the most performing nations in the dataset belong to the Northern Europe and Central Europe macro-regions. On the contrary, the nations belonging to the South Eastern Europe macro-region are the least performing. These insights are also valuable for policy makers. The reasons are threefold:

First, policy makers must understand why the scholars in the nations of the South Eastern Europe macro-region are performing worse than average. Otherwise, students in these macro-regions may be perceived as less skilled on the labor market. Not only would these students be granted an inferior quality of education throughout their studies. In the long run, they may also have lower wages (Currie et.al 1999), and have greater difficulties in moving to more performing countries. This may create a negative cycle, leading to an increase in school dropout rates, illiteracy, and more.

Second, policy makers must try to unveil the reasons behind the exceptional performance of students in the Northern Europe and Central Europe macro-regions. This may be used for internal benchmarks. Denmark is an example. In Science, Denmark is performing worse compared to its neighbors in the Northern Europe macro-region. Compared to nations that are part of different macro-regions, Denmark most likely has a similar socio-economic condition, and a similar pedagogical mindsets to the ones of its strong performing neighboring countries. Policy makers must therefore understand what Denmark is doing differently than its neighbors, in order to replicate their well-functioning teaching practices to its own educational system, and improve its students' performance in the future.

Adopting the same approach to nations that are part of different macro-regions is instead risky. Nations part of different macro-regions may significantly differ in terms of socio-economic conditions, and teaching approaches. Simply replicating a well-functioning teaching approach of the nations of the Northern or Central Europe macro-regions to the less-performing nations of the South Eastern Europe macro-region, without performing any adjustments may be overly simplistic. Policy makers must always remember that there is no "one size fits all" solution (Pratt, 2002).

Third policy makers from top performing nations may also learn from the ones of less performing countries. Consider the Northern Europe and South Western Europe macro-regions. Despite students in Northern Europe perform better than scholars in South Western Europe, the variability of the performance of the students in the former is much higher than the one of the latter. This means that educators in South Western Europe are more capable of assuring a homogenous quality of education among their nations. In Northern Europe instead, inequality concerns may arise in the long run if the issue is not addressed carefully.

Finally, the research highlights the activities for which digital devices are currently being used the most in schools. Among all the activities, students in the majority of EU27 nations are only widely adopting ICTs for using the Internet for schoolwork, and chatting online. Additionally, students from the Northern Europe macro-region are also using them for practicing subjects, doing homework on a school computer, and using computers for groupwork activities. For all the other activities instead, the majority of students in the EU27 nations are currently not using

ICTs. Once again, this highlights that the majority of the schools in the EU27 countries are still at the beginning of the digital transformation (Livingstone, 2012).
Additionally, the linear mixed models aimed at unveiling the impacts that using digital devices for simulation activities, doing homework on a school computers, and using learning apps at school have had on students test scores. The result highlighted that using ICTs in class for the aforementioned activities currently has a negative impact on students' performance compared to not using them at all. The more scholars spend time using digital devices for the above-mentioned activities, the lower their test scores tend to be. The reasons may be twofold:
First, as mentioned previously, the PISA 2018 questionnaires are administered to 15 year-old students. If scholars are left unsupervised, they may use the digital devices for non- academic related activities when the teachers are not closely monitoring them (Vahedi et.al 2021). If this is the case, rather than enhancing students' academic performance, these activities may distract students during their academic tasks and decrease the time they spend studying.
Second, ICTs have only recently been introduced in teaching practices. The majority of schools are still at the beginning of the digital transformation (Youssef and Dahmani, 2008). The latter is a process that requires time, effort, and a deep change in educational institutions' organizational structures. Shifting towards ICT-based teaching practices does not simply mean providing teachers with advanced technologies. Teachers need to be taught the necessary skills to use these technologies, and how to use the digital devices to enhance their students' academic achievements. Therefore, comparing traditional and well consolidated pedagogical approaches to recently introduced ICT-enabled forms of education may be overly simplistic. The reasons behind the current ineffectiveness of using digital technologies for the aforementioned activities may be related to the lack of experience that teachers have in using these technologies rather than in the technologies themselves. In fact, the only activity that currently has a positive impact on students' test scores is using the Internet for schoolwork. This is also the only activity in which the majority of EU27 nations are currently using ICTs in school. Therefore, it is likely that the students and teachers of these nations have acquired the necessary skills to use ICTs for the latter activity.
Finally, between using digital devices for simulation activities, and adopting digital devices for performing homework on school computers, the first activity has a bigger negative impact on students' test scores. This is reasonable considering that in 2018, the activity had only recently been introduced in schools. The simulations that were used in 2018 are in fact very different than the ones that students are accustomed to today. Furthermore, in both activities, the highest negative impact is observed in reading. This is because reading in digital formats may reduce the pleasure the students perceive while reading books, compared to traditional paper formats (Ikeda and Rech, 2022).

## 5.2 Limitations

While this study offers valuable insights into the relationship between ICTs usage and academic performance, it is important to acknowledge its limitations.

Firstly, the external validity of the findings may be subject to certain shortcomings. The study focuses specifically on a particular age group, namely 15-year-old students, and caution must be employed when generalizing the results to other age groups or educational contexts. Additionally, although the study includes a diverse range of European countries (27 in total), it is important to recognize that the findings may not be directly applicable to other geographical regions.

Secondly, the study relies on self-reported data obtained through surveys and questionnaires, which introduces potential limitations related to response bias and inaccuracies in reporting. Moreover, the reliance on self-reported data assumes that participants accurately remember and report their experiences, attitudes, and behaviors. This potentially leads to errors and inconsistencies. These factors can impact the reliability and validity of the data, raising concerns about the accuracy and generalizability of the findings.

Lastly, it is worth noting that this study analyses the relationship between ICTs usage in schools, and students' academic performances based on data from 2018. As technology rapidly evolves, the tools and platforms utilized during the period of investigation may not be directly comparable to those currently in use. For instance, the simulations examined in this study may exhibit a huge disparity when compared to the advanced simulations employed in subsequent years. Specifically, the following years witnessed the emergence of simulations that allow students to immerse themselves within a comprehensive digital environment, fostering active engagement and interaction with every constituent element. Conversely, the simulations examined in this study may not fully capture the immersive and interactive experiences made possible by the latest advancements in technology. Therefore, it is important to recognize that the conclusions drawn from this study are specific to the technologies employed in 2018 and may not fully capture the current landscape.

In conclusion, the study provides valuable insights, but careful consideration and interpretation of the results should be exercised.

## 5.3 Future Developments

In conclusion, in the following paragraph possible future research topics that can complement the above presented study are presented.

First, as highlighted in the literature review, Information and Communication Technologies may have several impacts on students' academic development. Simply examining the effects that ICTs have had on students' test scores may be overly simplistic. These technologies may increase students attitude, engagement and motivation towards learning, improve students' teamwork skills, and promote active participation in class. Researchers may want to use proxies of the aforementioned variables as dependent variables in future statistical models, to examine how ICTs influence the latter. Possible research questions are presented hereafter:

*Does using ICTs in class activities affect students attitude towards learning? How?*

*Does using ICTs in class activities improve students teamworking skills? How?*

*Does using ICTs in class activities increase students' active participation in class? How?*

Second, researchers may conduct a longitudinal analysis. The following study has focused on assessing the impacts that ICTs have had on students test scores in 2018. However, it is likely that the role that technologies have played in educational institutions in the last decades has significantly changed. It may be interesting to examine whether the impact that ICTs have had on students' academic achievements has been increasing or decreasing in time. Sample questions are provided below:

*Have the impacts of ICTs on students' academic achievements changed since their first adoption in educational institutions?*

*Are educational institutions improving in how they use ICTs in class activities?*

Third, the following study may be extended to include further subjects other than reading, science and mathematics. Additionally, researchers may be interested in assessing which specific technology has had the highest impact on student' academic performance. The following issues may be addressed:

*Which specific technology has had the most significant impact on students' test scores?*

*Do the results of the above presented study hold even for non-European nations?*

*What is the impact that ICTs have had on subjects other than reading, mathematics and science?*

Lastly, policy makers may be interested in extending the following research to include nations that are not part of EU27 countries. The effects of ICTs on students reading, mathematics and science test scores may significantly differ in continents like Asia, Africa and America. Additionally, researchers may be interested in examining the effects that ICTs have on students from different age groups than the ones examined by the PISA 2018 assessment cycle. Possible research questions are provided hereafter:

*Do ICTs have a comparable impact on students test scores in all nations?*

*Does the impact that digital devices have on learners academic achievements vary according to the scholars age?*

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