The Relationship between Information and Communication Technology and Academic Achievement in Mathematics and Science in PISA 2015

by

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Abstract

Information and Communication Technology (ICT) is present in many classrooms around the world but its effect on student learning is not fully understood. This research investigates the relationship of ICT with the mathematics and science scales for 15-year-old students in 47 countries that participated in PISA 2015. First, a scoping literature review was conducted to ascertain which ICT factors supported or hindered mathematics and science achievement. Second, two main research questions were posed to explore the impact of students' countries on the relationships between ICT and academic achievement in mathematics and science: (1) *To what extent does ICT help or hinder students' mathematics and science learning in Bulgaria and Finland, respectively, two countries with different ICT profiles, when controlling for students' socio-economic status?* and *(2) Are the ICT, science, and mathematics variables measurement invariant across the countries participating in the PISA ICT questionnaire?* The first question was answered using structural equation modelling for both sample countries. The second question was answered using the Alignment method on 48 participating countries. Results indicated that (1) students' use and availability of ICT were negatively associated with mathematics and science scores, whereas their level of comfort in ICT was positively associated with academic scores; and (2) mathematics and science scales were measurement invariant across all countries, whereas the ICT scales were not. This research makes the following contributions: (1) it shows that comfort and confidence in ICT use is a more critical predictor of academic achievement than use and availability of ICT; (2) it reveals that cultural differences between countries limit the comparison of ICT scales for large groups; (3) it indicates that mathematics and science plausible values are comparable across many countries simultaneously; and (4) it presents the results of a scoping review of the association of ICT with mathematics and science scores in the PISA data.

Dedication

This thesis is dedicated to all those who have helped me learn and who have taught me that thinking critically and using rational thought are the key to understanding the world.

"Let us reason our solutions with agnosticism in all things, holding fast only to that which is demonstrably true… That which will not bend must break, and that which can be destroyed by truth should never be spared its demise."

-Lucien Greaves

"Somewhere, something incredible is waiting to be known."

-Carl Sagan

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Chapter 1: Introduction

Technology is ubiquitous in the digital 21st century, with more technology than ever being incorporated into education, from iPads in primary school mathematics classes (Hilton, 2018) to mobile phone use in graduate classes (Mueller, Wood, De Pasquale, & Cruikshank, 2012) and laptop use in all levels of education (Sung, Chang, & Liu, 2016). Nowadays, students have more access to technology in the classroom than ever before and, as a result, the educational landscape is changing (OECD, 2015; Johnson et al., 2014; Tang & Hew, 2017). However, pervasive technology does not always lead to enhanced academic achievement. Thus, the current research explores the ramifications of students' increased exposure to technology for their academic achievement. More specifically, the current work focuses on the relationship between students' Information and Communication Technology and their academic achievement in mathematics and science. This work is conducted within an international scope by examining these relationships across multiple countries.

1.1 Information and Communication Technology

Information and Communication Technology (ICT) represents digital technology that is used for sharing and storing digital information and communicating with others (OECD, 2003). Examples of ICT include computers, tablets, internet connection, USB memory storage, eBook readers, interactive whiteboards, smartphones, video games, chatrooms, digital media, and more. This definition emphasizes that ICT is not a synonym for technology, but rather it includes specific criteria. Although ICT and Information Technology (IT) are similar, IT does not include the important distinction of technology used for the purpose of communication and sharing (Murray, 2011; Daintith, 2009). ICT is defined by PISA as "the use of any equipment or software for processing or transmitting digital information that performs diverse general functions, whose options can be specified or programmed by its user" (OECD, 2005).

Skills in ICT are crucial for global citizens of the digital 21st century (Fraillon, Ainley, Schulz, Friedman & Gebhardt, 2014; ICT Council, 2016). The importance of a public versed in technology use has been known for some time (Castells & Blackwell, 1998). Both parents and teachers recognize this change and support the incorporation of ICT in school learning, as they believe it will improve learning and the students' chances to be employable (European Union, 2019a). As careers of all types continue to rely on ICT, it is important for people entering into the workforce to be proficient in the use of ICT (Bresnahan & Yin, 2017). The current employment environment reflects the need for technology-capable workers who will stay relevant in the digital 21st century (ICT Council, 2016; Yeganehfar, Zarei, Isfandyari-Mogghadam, & Famil-Rouhani, 2018; Cussó-Calabuig, Farran, & Bosch-Capblanch, 2018; Nordicity, 2017).

Many countries experience a need for a skilled ICT workforce, including Nigeria, Italy, South Africa, and Canada (Onwuagboke, Singh, & Fook, 2015; Lovaglio, Cesarini, Mercorio, & Mezzanzanica, 2018; Kirlidog, van der Vyver, Zeeman, & Coetzee, 2018; Nordicity, 2017). For example, in Canada, spending on ICT in Alberta schools will be increased by $37 million in the next six years to meet this need (Ceci, 2018). The technology-focused country of South Korea has placed a great importance on technology inclusion as a way of upgrading their labour markets in the near future (Kim, 2000). As a result of this demand, students in all countries are expected to have access to more ICT than ever before (OECD, 2015; Johnson et al., 2014; Tang & Hew, 2017). However, current ICT access is not consistent across countries (OECD, 2017a). For instance, one in five European students attends a school with access to high-speed Internet

(European Union, 2019a). Russia provides an example of a country with the potential to achieve more integrated ICT use (Dneprovskaya, Bayaskalanova, Ruposov, & Shevtsova, 2018). There is a great demand for ICT to be integrated into higher education. However, to date, there is a lack of governmental support and organization for this to happen. Moreover, Nordic countries such as Finland continue to have better access to technology and be Digital Frontrunners, whereas others like Bulgaria remain as Digital Challengers (European Union, 2019a, 2019b, 2019c; Ridao-Cano & Bodewig, 2018; Novak et al., 2018). Also, there seems to also be a link to academic achievement as Digital Frontrunner countries often have higher classroom achievement than Digital Challengers.

1.2 Mathematical Literacy

Mathematics constitutes one of the key domains of academic achievement, as an understanding of mathematics is imperative for all functioning members of society (National Mathematics Advisory Panel, 2008; OECD, 2017a). As this understanding starts during a child's formative years of education and as it is crucial for individuals when they prepare to enter adulthood, the Program for International Student Assessment (PISA) assesses 15-year-olds' mathematical literacy. PISA defines *mathematical literacy* as

> "... an individual's capacity to formulate, employ and interpret mathematics in a variety of contexts. It includes reasoning mathematically and using mathematical concepts, procedures, facts and tools to describe, explain and predict phenomena. It assists individuals to recognize the role that mathematics plays in the world and to make the well-founded judgements and decisions needed by constructive, engaged and reflective citizens." (OECD, 2013, 2017a).

Mathematics also constitutes the foundation to so many other essential skills, such as telling time, understanding distances, cooking, managing money, and problem solving. Mathematical literacy and skills are essential for well-adjusted individuals to productively contribute to society, as they are foundational for other areas of study, such as physics and engineering (OECD, 2017a, 2017b). Despite the importance of mathematical skills for all individuals, especially students, the mean mathematics scores of the majority of countries have not been increasing significantly in PISA, with only four countries previously above the global average continuing to improve (OECD, 2016b). Throughout half of the European Union, more than 20% of the 15-year-olds perform below the world average mathematics score (Ridao-Cano & Bodewig, 2018). Importantly, in European countries with less access to ICT such as Bulgaria or Romania, the percent of low performers increases to more than 33% when compared to the average country participating in the Organization for Economic Co-operation and Development (OECD). These comparisons are between-country comparisons. Contrasting mathematics scores of two countries with different ICT profiles yields results with limited applicability on a national scale; between-country comparisons allow making inferences about how different ICT "types" of countries are associated with achievement, but do not allow for inferences about how differences in ICT within the country are associated with individual achievement. Thus, understanding the relationship between the individual factors of ICT and mathematics scores within a country will be key for policymakers designing interventions and policies within each country. Such knowledge will allow targeted interventions for the specific needs of each country.

1.3 Science Literacy

Science literacy, defined as the reflective citizen's ability to interact with the issues and ideas of science (OECD, 2017b), is essential for evaluating claims made by others or for assessing evidence for those claims (van der Linden, Maibach, Cook, Leiserowitz, & Lewandowsky, 2017). In an era in which people are constantly bombarded with facts, opinions, and information, consumers of information need to be able to sort through the falsehoods to find the truth and avoid being taken advantage of by "flim-flam" (Randi, 1982). In the 21st-century digital landscape, ICT becomes an important tool in the process of discerning facts from fiction. Importantly, science literacy is the focus of PISA 2015, which constitutes a portion of the data for this research.

Unfortunately, there has been little change in science performance across OECD countries since 2006 (OECD, 2016a). Only six countries have increased their average science performance in the last four iterations of PISA. In 2015, 24 countries were measured as performing above the OECD science average. Seven countries were not significantly different from the OECD means, and the remaining 39 countries perform below the OECD average.

1.4 ICT and Academic Achievement

Empirical evidence from earlier research shows that more technology in schools does not necessarily translate into improved student grades (Bulut & Cutumisu, 2017; Cheung & Slavin 2013; De Witte & Rogge, 2014; Hu, Gong, Lai, & Leung, 2018). For example, studies have shown that increased technology availability in schools is associated with decreased academic achievement (Brown, 2018; Hu et al., 2018; Cheung & Slavin, 2013; De Witte & Rogge, 2014). Yet other researchers report various positive effects of ICT on students' mathematics and science scores (Petko, Cantieni, & Prasse, 2017; Meggiolaro, 2018). Moreover, others have reported no significant relationship between types of ICT and mathematics and science scores (Meng, Qiu, & Boyd-Wilson, 2018; Bulut & Cutumisu, 2017). A literature review on this topic uncovers the mixed and contradicting body of evidence that links ICT to academic achievement. Thus, an open question remains regarding the effect of increased ICT on academic achievement: *What aspects of ICT cause increases and decreases in academic achievement?*

1.5 PISA

The data used in this research was collected by the OECD in 2015, as part of their tri-annual Programme for International Student Assessment (OECD, PISA, n.d.). PISA is an assessment implemented by the Organization for Cooperation and Development (OECD) that collects data from 15-year-old students in countries around the world every three years (OECD, 2017b). The OECD "is an international organization that works to build better policies for better lives. [Their] goal is to shape policies that foster prosperity, equality, opportunity and well-being for all" (OECD, About, n.d.). Stakeholders include governments, policy makers, and citizens to tackle challenges in education, economics, and other areas. These international surveys collect a wide variety of data involving 15-year-old students and schools from 72 participating countries across the world (OECD, 2017a; 2017b). For this research, data from PISA's mathematics and science literacy tests will be employed, together with the *ICT Familiarity Questionnaire* (OECD, 2014a).

Despite the fact that the OECD participating groups are referred to as countries, some identify themselves as separate economies or states. Although some countries are considered lower performing or lower ranking on the PISA scale, PISA is a specific measure and countries cannot be reduced to their PISA rank.

1.6 Research Questions

The purpose of this research is to explore the association of ICT with mathematics and science academic achievement for students from different countries in terms of digital proficiency. This research explores the association of ICT factors (ICT availability, ICT comfort, and ICT use) with mathematics and science scores of students from around the globe who participated in the ICT questionnaire. The main research questions posed in this study are the following:

- *To what extent does ICT help or hinder students' mathematics and science learning in Bulgaria and Finland, respectively, two countries with different ICT profiles, when controlling for students' socio-economic status? Specifically, is more access to ICT associated with worse mathematics and science performance in each country?*
- *Are the ICT, science, and mathematics variables measurement invariant across the countries participating in the PISA ICT questionnaire?*

Structural Equation Modelling (SEM) and the Alignment method (Asparouhov & Muthén, 2014) will be used to answer the first and second research questions, respectively. To do this, the present study examines how ICT is related to academic achievement in different countries because students live in a global community and instructors wish to prepare all students to be competitive internationally in a digital world. This research is important if the goal is to increase students' academic achievement worldwide. It is crucial to uncover the helpful nature of ICT so that teachers can use these to uplift learning through technology. Given the global setting of technology, it is also important to know whether these relationships differ based on a student's country. With ICT as a tool in classrooms, it is hoped that mathematical, scientific, and digital literacy, as well as computational and critical thinking will improve. Regardless of the results of this research, technology will continue to advance and become more incorporated in our lives. Thus, this research aims to inform teachers and policy makers on how ICT can aid students' academic performance.

1.7 Chapter Summary

This chapter explores the concept of ICT, its pervasiveness in today's global digital society, and its relationship with mathematics and science achievement. It outlines the main research questions that explore the impact of ICT inside and outside the classroom on students' academic achievement in mathematics and science, while considering the students' socio-economic status and countries.

Chapter 2: Theoretical Framework

This research draws on several theoretical frameworks to conceptualize the relationship between ICT and the academic scores in mathematics and science of students from different countries. Cultural constructivism puts into perspective the cultural environments of different countries and how they might influence the technology available to students and the results of these relationships (Cole & Wertsch, 1996; Cobern, 1993). This, in turn, may change the way students create knowledge that helps them to succeed in school. Novak et al. (2018) describe the differences between countries who are Digital Challengers and Digital Frontrunners and how they connect to students' Science Technology, Engineering, and Mathematics (STEM) learning. Self-Determination Theory (SDT) proposes an explanation of the motivation and drive behind learning and mastering a skill (Ryan & Deci, 2000). Finally, the Digital Natives narrative is introduced to frame the generation that constitutes the focus of this research (Prensky, 2001).

2.1 Cultural Constructivism

As students' countries play an important role in this research, cultural constructivism informs the current approach. A key comparison in this study is how the relationship between academic scores and ICT differs depending on the student's country. As seen in cultural constructivism, which stems from the Piagetian (1952) constructivist learning theory, the societal and cultural environment can dictate the learning that occurs for those individuals (Cole & Wertsch, 1996; Cobern, 1993). For instance, knowledge creation and learning may unfold differently as they are deeply influenced by learners' cultural surround. In this theory, children learn through their active construction of knowledge. This can be implemented into the current research because students use ICT that is available to them, in their environment, to create the knowledge they need for their mathematics and science classes. This directly relates to the availability of ICT devices to students in PISA's *ICT Familiarity Questionnaire* (OECD, 2014a). These subscales provide an insight into the technology in these students' environment. Also, in Vygotsky's social development theory (1978), learning is a social process that occurs through interactions with others. A key aspect of ICT is its use for communication and connecting people around the world.

2.2 Digital Frontrunners and Challengers

When examining different countries, distinctions can be made between a country's wealth, education quality, available technology, and technology culture. For example, the number of computers available to students varies greatly from less than five students per computer in some countries to over 40 students per computer in others in the early 2000s (Law, Pelgrum, & Plomp, 2008). In the context of technological innovations and advancements, countries can be split into two categories, Digital Challengers and Digital Frontrunners (Novak et al., 2018). Digital Challengers generally have less advanced technology standards than the average country, which means that they display a higher growth potential. According to Novak et al. (2018), Bulgaria, Croatia, the Czech Republic, Hungary, Latvia, Lithuania, Poland, Romania, Slovakia, and Slovenia are examples of European Digital Challengers. On the other end of the scale, more technologically-advanced countries that display a high digitization rate would be considered Digital Frontrunners. These are European countries like Belgium, Denmark, Estonia, Finland, Ireland, Luxembourg, the Netherlands, Norway, and Sweden. Novak et al. (2018) discuss an important connection between STEM learners and a country's status as Frontrunner or Challenger. The authors explain the need for STEM learners to transform a country from a Digital Challenger to a Digital Frontrunner. This supports the present research that investigates the important association of mathematics and science education with ICT within the context of different countries. The results from this research can inform practice in classrooms across the globe. If the proper ICT components that promote mathematics and science education can be parsed out, schools could improve the use of ICT to support learning. As a result, this transformation could turn a Digital Challenger country into a Digital Frontrunner. According to Novak et al. (2018), this would increase a country's GDP, reduce unemployment, and shorten work weeks for a better quality of life.

2.3 Self-Determination Theory

Self-Determination Theory (SDT) posits that an individual's learning is driven by self-motivation and determination. Specifically, the learner exerts effort to obtain a positive outcome (Ryan & Deci, 2000). SDT underlies some of the measurements around students' ICT involvement. There are three basic psychological needs that are tied to SDT: competence, autonomy, and relatedness. These are reflected closely in the *ICT Familiarity Questionnaire* (OECD, 2014a) from PISA 2015, which includes questions that assess a student's perceived competence and autonomy surrounding ICT use, as well as ICT as a social topic. Competence reflects a student's level of mastery and control over outcomes when using ICT. Autonomy constitutes the student's desire to make their own choices when using ICT. Relatedness is the drive to connect and communicate with others. In the PISA 2015 *ICT Familiarity Questionnaire*

(OECD, 2014a), competence is measured by the COMPICT (IC014) subscale. Students' self-reported autonomy around the use of ICT is measured by the AUTICT (IC015) subscale. Relatedness is measured by the SOIAICT (IC016) subscale. The subscales in the *ICT Familiarity Questionnaire* are detailed in PISA's reports (OECD, 2014a; 2017). When these needs are fulfilled, they increase an individual's self-motivation. According to SDT, people view their actions as self-determined and, when they perform well, this enhances their feelings of autonomy. Positive social interactions, competence, and autonomy are conducive to increasing intrinsic motivations. With high intrinsic motivation, students will be self-driven to challenge themselves with using technology, which creates the conditions where learning is more likely to occur (Hamari et al., 2016; Hung, Sun, & Yu, 2015). Like the other theories discussed, SDT also explains that a person's motivation and achievement is influenced by their environment. Optimal development and mastering skills can only occur if the individual learns in a nurturing environment that supports growth (Ryan & Deci, 2000). This can be tied to Digital Frontrunners and Challengers because students who master technology may also learn better when using technology, given that they were raised in an environment where ICT is abundant and easily integrated into their lives. Conversely, in a Digital Challenger country, fewer connections with ICT during development may lead to suboptimal performance with ICT when attempting to learn using ICT later in life.

2.4 Digital Natives

Finally, as discussed in Prensky's (2001) seminal paper on digital natives, a large shift occurred in the late 20th century on how students need to be taught. Individuals born after the 1980s (depending on the country) had the opportunity to grow up in the digital age and are referred to as digital natives rather than digital immigrants (Palfrey & Gasser, 2011; Prensky

2001). This shift sparked a change in how students are taught, which is still being tested and investigated by researchers and educators, reflected in the vast amount of current literature on teaching styles and on incorporating technology meaningfully to enhance education. However, the relationship between academic achievement and ICT is not as straightforward as "more equals better." Recently, digital immigrants are starting to be replaced by digital natives as educators in classrooms (Hudgins & Anderson, 2015). It is likely that this process will change the way ICT is implemented in classrooms since teachers who are digital natives would have higher competence around ICT (Lund, Furberg, Bakken, & Engelien, 2014; Cox & Marshal, 2008). Even though ICT is available, it does not mean that teachers will include it in their lessons if they are not comfortable using it (Empirica, 2006; Ravitz, Wong, & Becker, 1998). Prensky (2001) posed the question of how to use computers and calculators in a mathematics class rather than whether computers should be simply used. This question is extrapolated to form the base research question of this study: *What aspects of ICT are important for improving students' academic achievement?*

2.5 Chapter Summary

This chapter outlines the various theoretical frameworks that were assembled to provide a context for the present research. Cultural Constructivism, Self-Determination, Digital Natives and Immigrants, as well as Digital Frontrunners and Challengers provide a theoretical background that justifies this research. Growing up in a country that may or may not be technologically advanced and being born before or after the technology boom or at the turn of the century are two factors that can drive an individual's later interaction with technology. Therefore, these factors have the potential to affect individuals' education. A student's self-motivation and drive to create knowledge is also dependent on the environment or country.

Chapter 3: Literature Review

3.1 Literature Review Methods

A scoping review represents an exploratory method that maps systematically the literature on a topic, by identifying key concepts, theories, and sources of evidence, as well as by addressing broader research topics where many different study designs might be applicable. Rather than exhaustively researching a topic, this type of review explores "the extent, range, and nature of research activity in a topic area" (Pham et al., 2014). A five-stage searching and selecting method was employed to conduct this review (Arksey & O'Malley, 2005) that includes: 1) identifying the research questions; 2) identifying relevant studies; 3) selecting studies; 4) charting the data; and 5) collating, summarizing, and reporting the results. This allowed us to compare and contrast theoretical frameworks, methods and analyses, and results. The purpose of this review is not an extensive and comprehensive representation of all research on the topic. Instead, it facilitates an understanding of the variety of findings when examining the association of ICT with academic achievement in mathematics and science using PISA data. The main research question guiding this review is the following: *Does students' involvement with ICT as measured by PISA have a positive, negative, or no effect on 15-year-old students' mathematics and science scores?*

To locate studies for this review, a search was conducted in Google Scholar, PsycINFO, and Education Resources Information Center (ERIC). The key search terms are included in *Appendix B*. Publication alerts were set up with similar keywords to retrieve new studies relative to these topics. A snowball approach was used to probe journals for other useful studies and citations. The inclusion criteria narrowed the search to secondary research that was conducted with PISA data from any iteration between 2000 and 2015. The studies had to use items or subscales from the *ICT Familiarity Questionnaire* as predictor variables and either plausible mathematics or science values, or both, as outcome variables. Studies that did not conduct quantitative statistics on numerical data provided by PISA were not included.

The query in ERIC returned 30 articles, of which six were used. This search in PsycINFO provided three useful articles after removing duplicates. The remainder of the articles were found in Google Scholar and through the snowball method. Google Scholar returned 612 results which were reduced to 586 when the date was limited to 2000, the year when the PISA assessment commenced. Table 1 shows all 22 articles that were included in the literature review. Table 2 is split into positive, negative, and null results to help visualize the spread of the results found, while Table 3 demonstrates what PISA iterations were used.

3.2 Description of Studies Used

Researchers have employed a wide range of methods and angles to examine the relation between ICT and students' achievement. Table 5 includes a list of statistical methods used by the 22 studies. For instance, Petko et al. (2017) used multiple linear regression (MLR) to examine the relationship between ICT and mathematics and science scores for 39 of the participating countries in the 2012 PISA database. Hu et al. (2018) uncovered details about the ICT relationship with mathematics and science scores at an average OECD level with 44 countries using hierarchical linear modelling (HLM) in PISA 2015. Meng et al. (2018) analyzed Chinese and German ICT data from PISA 2015 with structural equation modelling. Meggiolaro (2018) used PISA 2012 data to explore the intersection of ICT and mathematics in Italian students using multilevel models, while Gamazo, Martínez-Abad, Olmos-Migueláñez, and Rodríguez-Conde (2018) used the same method and logistic regression to analyze the PISA 2015 data for Spanish students. Using Exploratory Factor Analysis (EFA) and HLM on the PISA 2006 data, Luu and

Freeman (2011) compared ICT and science scores of Canadian and Australian students. Bulut and Cutumisu (2018) employed structural equation modelling to examine the use and availability of ICT for Turkish and Finnish students in the PISA 2012 data. Skryabin, Zhang, Liu, and Zhang (2015) reviewed data from 39 countries PISA 2012 as well as other large international databases using HLM to explore the links between ICT and mathematics and science scores. Tan and Hew (2018) used HLM to study the impact of ICT on mathematics scores in PISA 2012 for students in seven Confucian heritage cultures (CHC): Hong Kong, Japan, Korea, Macau, Shanghai, Singapore, and Taipei. Using the first iteration of PISA in 2000, Papanastasiou, Zembylas, and Vrasidas (2003) implemented regression models to examine the relationship between computer use and availability in students from the United States of America. Koğar (2019) reported findings linking mathematics and science scores with ICT using the Chi-squared automatic interaction detection method on 35 OECD countries from PISA 2015. Zhang and Liu (2016) examined PISA data at the OECD level from 2000 to 2012 and reported the connections between ICT and academic achievement using HLM. The Reboot Foundation used more broad measures of general computer use and computers per student from PISA 2003 to 2015 using correlational methods. Other researchers used data mining techniques to uncover patterns in PISA 2015 data (Martínez-Abad, Gamazo, & Rodríguez-Conde, 2018). Juhaňák, Zounek, Záleská, Bárta, and Vlčková (2018) employed multilevel modelling and included gender as a control variable later in their analysis to examine ICT with mathematics and science scores of students in the PISA 2015 database from the Czech Republic. As part of a large-scale study, Rodrigues and Biagi (2017) examined the relationship between low, medium, and high intensity use of ICT and mathematics and science for 25 European countries in PISA 2015 using multiple linear regression. Agasisti, Gil-Izquierdo, and Han (2017) examined the effects of ICT use at home for school work on 12

European countries from PISA 2012 using propensity score matching and instrumental variables. Özberk, Kabasakal, and Öztürk, (2017) examined Turkish students from PISA 2012 using two-level hierarchical linear modelling. Delen and Bulut (2011) examined the PISA 2009 science and mathematics scores with ICT availability of Turkish students using hierarchical linear modelling. Using multiple models of Spanish students' ICT data from PISA 2009, Fuentes and Gutiérrez (2012) inspected the effects on their and mathematics and science scores. Su (2017) used PISA 2015 data to explore the effects of ICT on mathematics performance for Chinese and Korean students. The researcher used a variety of methods, such as the International Association for the Evaluation of Educational Achievement (IEA) international database analyzer, t-tests, and path analysis models. Kubiatko and Vlckova (2010) examined Czech students from PISA 2006 using ANOVAs (Analysis of Variance) and post hoc pairwise comparisons to investigate the relationship between ICT and science scores.

3.3 ICT Use at School (USESCH)

Mathematics

Positive Relations. Meggiolaro (2018) found that Italian students' mathematics scores were positively correlated with several ICT use factors in the PISA 2012 data, regardless of whether they take place in their home or school. The strongest correlation occurred with moderate rather than extreme use of ICT. Examples of ICT-use factors at school that were positively associated with higher mathematics scores were gaming, problem solving, knowledge creating, and retrieving, organizing, and managing information. Similarly, the Reboot Foundation (2019) reported that moderate ICT users in classes achieved higher scores in the PISA 2015 data than their peers who use technology heavily. Interestingly, students with the highest reported ICT use at school, although outperformed by students reporting moderate ICT use, achieved higher scores than students who did not use ICT at all. Koğar (2019) uncovered a positive relationship between use of ICT devices while at school and mathematics scores in the PISA 2015 data. Conversely, Rodrigues and Biagi (2017) found that low-intensity users of ICT at school in European countries in PISA 2015 had higher scores than other levels of users.

Negative Relations. Intensity of computer use at school in mathematics lessons and some related mathematics activities were negatively associated with mathematics scores for Italian students in the PISA 2012 data (Meggiolaro, 2018). In 2009 and 2015, Spanish students performed worse in academics when they used more ICT in school (Fuentes & Gutiérrez, 2012; Gamazo et al., 2018; Martínez-Abad et al., 2018). Hu et al. (2018) analyzed 44 OECD countries from PISA 2015 and found that, on average, students would drop nearly ten points in mathematics with an increase of one standard deviation of ICT use at school. Petko et al. (2017) and Skryabin et al. (2015) replicated these results with the same PISA 2012 data. Bulut and Cutumisu (2018) examined Finnish and Turkish students from PISA 2012 and also found a negative relationship between ICT use at school and mathematics scores. Juhaňák et al. (2018) found that Czech students who accessed the Internet for more than one hour per day at school showed lower academic achievement in PISA 2015. On average, for European countries, mid-ICT and high-ICT users held a negative relationship between ICT use at school and mathematics scores in PISA 2015 (Rodrigues & Biagi, 2017). Su (2017) found that both Chinese and Korean students from PISA 2015 had a negative relationship between mathematics scores and ICT use at school. However, the students' USESCH score did positively predict their self-perceived competence.

No Relations. Although the literature revealed some associations between ICT and mathematics, there were also instances in which no associations were found. For instance, Tan and Hew (2018) found no significant relationship between the use of ICT devices at school and mathematics scores in the PISA 2012 data. In PISA 2015, researchers found that the use of ICT by Czech students in school (USESCH) is uncorrelated with their mathematics performance (Juhaňák et al., 2018). However, when the interaction with school type (state funded, church funded, or private) is considered, the relationship with mathematics scores becomes significant and is stronger.

<u>*Science*</u>

Positive Relations. Using computers in Australian schools was positively associated with science scores in the PISA 2006 data (Luu & Freeman, 2011). For Canadians, browsing the Internet at school or at home was also positively linked to higher science scores. European students who use low levels of ICT in schools also tend to perform better in science in PISA 2015 (Rodrigues & Biagi, 2017).

Negative Relations. Hu et al. (2018), Petko et al. (2017), Bulut and Cutumisu (2018), and Skryabin et al. (2015) found a negative relationship between ICT use at school and science scores using PISA 2012 and 2015 data. Luu and Freeman (2011) examined the link between ICT and science performance for Canada and Australia using the PISA 2006 data and found that most facets of ICT use, other than browsing the Internet, were negatively associated with science scores. Gamazo et al. (2018) reported a negative relationship for Spanish students in 2015. Very high frequencies of ICT use were associated with worse science scores than medium use for both Canadian and Australian students (Luu & Freeman, 2011). The academic scores of students who spend more than one hour a day at school on the Internet suffer (Juhaňák et al., 2018). Similar to the mathematics results, European students in PISA 2015 performed worse in science when they used ICT from medium to high levels (Rodrigues & Biagi, 2017). Spanish students in PISA 2009 and 2015 with more ICT use performed worse than their peers on mathematics (Fuentes & Gutiérrez, 2012; Martínez-Abad et al., 2018).

No Relations. Luu and Freeman (2011) discussed several mixed results, but specific ICT use at school was not associated with science scores for Canadian students in the PISA 2006 data. In PISA 2015, researchers found that the use of ICT by Czech students in school was not correlated with their science performance (Juhaňák et al., 2018). However, as in the case of mathematics, when the interaction of school type is included, the relationship becomes significant.

3.4 ICT Use at Home for Schoolwork (HOMESCH)

<u>*Mathematics*</u>

Positive Relations. Same as for the ICT use at school, Meggiolaro (2018) found a positive relationship between mathematics scores and ICT, when ICT was used at home for academic purposes in PISA 2012. Opposite to their previous findings, Petko et al. (2017) found a positive relationship between ICT use at home for schoolwork and mathematics scores. Tan and Hew (2018) also uncovered a positive relationship between ICT use at home for schoolwork and mathematics scores in PISA 2012. Rodrigues and Biagi (2017) reported a positive relationship between mathematics and ICT use at home for schoolwork but only for European students who used relatively low ICT in PISA 2015.

Negative Relations. Skryabin et al. (2015) found a significant negative relationship between students who use ICT at home for school related purposes and lower mathematics scores in the PISA 2012 data. Medium and high users of ICT in Europe also had lower mathematics scores in PISA 2015 (Rodrigues & Biagi, 2017). Agasisti et al. (2017) also found a relationship for European students. In fact, this relationship was slightly stronger for students with higher SES. Spanish students in PISA 2015 also show a negative relationship between mathematics and HOMESCH (Martínez-Abad et al., 2018). When examining Chinese and Korean students' mathematics scores from PISA 2015, Su (2017) reported that HOMESCH acted as a negative predictor for China, but was not significant for Korea. Also, HOMESCH acted as a positive predictor for a students' self-perceived competence towards ICT in China, but once again, was not significant in Korea.

No Relations. Hu et al. (2018) found no significant relationship between mathematics and ICT use at home in PISA 2015. Other researchers found no significant relationship between ICT use at home for academics and mathematics scores for Finnish and Turkish students in PISA 2012 (Bulut & Cutumisu, 2018) and for Czech students in PISA 2015 (Juhaňák et al., 2018).

<u>*Science*</u>

Positive Relations. Petko et al. (2017) observed a positive relationship only for the top-performing countries in the PISA 2012 data. Same as for mathematics, European students who use low amounts of ICT achieved higher science scores in PISA 2015 (Rodrigues & Biagi, 2017).

Negative Relations. All countries that were not top performing exhibited a negative relationships for ICT use at home for schoolwork and science scores in the PISA 2012 data (Petko et al., 2017). Hu et al. (2018) as well as Skryabin et al. (2015) established a negative relationship between ICT use at home for school work and science achievement at the OECD level in the PISA 2015 and PISA 2012 data, respectively. This negative relationship was also found in Australia in 2012 and the Czech Republic in 2015 (Luu and Freeman, 2011; Juhaňák et al., 2018). In Europe, medium and high users of ICT performed worse on science assessments than low users of ICT (Rodrigues & Biagi, 2017). Agasisti et al. (2017) also found this relationship with European students. The effect was slightly stronger for students with higher socio-economic status (SES). Spanish students in 2015 also had a negative relationship between science scores and HOMESCH (Martínez-Abad et al., 2018).

No Relations. The results for science and academic ICT use at home were not significant for Canadian students in 2006 as well as for Finnish and Turkish students in 2012 (Bulut & Cutumisu, 2018; Luu & Freeman, 2011).

3.5 ICT Use at Home for Entertainment (ENTUSE)

<u>Mathematics</u>

Positive Relations. When ICT devices are used at home for entertainment rather than for schoolwork, some researchers report different relationships with academic scores. Students from both Italy and Turkey were found to perform better in mathematics with more ICT use at home for entertainment in the PISA 2012 data (Bulut & Cutumisu, 2018; Meggiolaro, 2018). Italian students who used ICT for gaming also had higher mathematics scores in the PISA 2012 data. For Turkish students, ENTUSE was connected to higher mathematics scores in the PISA 2012 data (Bulut & Cutumisu, 2018; Özberk et al., 2017). Petko et al. (2017) discovered that students in countries with high mathematics scores reported lower levels of ENTUSE in the PISA 2012 data. Low European users of ICT for entertainment showed higher mathematics scores compared to other users (Rodrigues & Biagi, 2017). Like for the USESCH variable, Su (2017) reported ENTUSE as a positive predictor for mathematics scores for Chinese and Korean students from PISA 2015. ENTUSE also acted as a positive predictor for a students' sense of self competence around ICT.

Negative Relations. In contrast to Turkish students, Finnish students' mathematics scores seemed to suffer with higher levels of ENTUSE in the PISA 2012 data (Bulut & Cutumisu, 2018). These results are reflected by Petko et al. (2017) and Skryabin et al. (2015) who noticed that high levels of ENTUSE were detrimental for countries with higher mathematics scores. Students who used the Internet for fewer than 30 minutes or more than 6 hours per day at home performed worse than students who accessed the Internet between 31 minutes and 6 hours per day (Juhaňák et al., 2018). European students who were high users of ICT showed a negative relationship with mathematics (Rodrigues & Biagi, 2017). In PISA 2009 and 2015, Spanish students with higher measures of ENTUSE performed worse on the mathematics assessment (Fuentes & Gutiérrez, 2012; Martínez-Abad et al., 2018).

No Relations. At the OECD level, Hu et al. (2018) again found no significant relationship for mathematics scores and ICT use outside of school, even for entertainment. Similarly, Juhaňák et al. (2018) reported no relationship between the mathematics scores of Czech students and use of ICT for entertainment. Finally, European students with mid-frequency ICT use did not have a significant relationship with mathematics (Rodrigues & Biagi, 2017).

<u>Science</u>

Positive Relations. Bulut and Cutumisu (2018) found a positive relationship for Turkey in the PISA 2012 data for both science and mathematics with ENTUSE. Hu et al. (2018) discovered a positive relationship between science scores and ENTUSE. Again, low-intensity users of ICT showed higher science scores than their peers (Rodrigues & Biagi, 2017).

Negative Relations. Bulut and Cutumisu (2018) found a negative relationship between ENTUSE and science scores for Finnish students. Petko et al. (2017) revealed a significant negative relationship for science scores and ENTUSE at the OECD level. Using earlier data from 2006, Luu and Freeman (2011) discovered that frequent ICT use for entertainment or school work was negatively associated with students' science scores in Canada, with the exception of browsing the Internet. Czech students who use the Internet for fewer than 30 minutes or more than 6 hours per day at home achieved lower science scores than students who use the Internet between 31 minutes and 6 hours a day (Juhaňák et al., 2018). Similar to before, in Europe, high-intensity users of ICT performed worse on science assessments in PISA 2015 (Rodrigues & Biagi, 2017). In PISA 2009 and 2015, Spanish students with higher measures of ENTUSE performed worse on the science assessment (Fuentes & Gutiérrez, 2012; Martínez-Abad et al., 2018).

No Relations. Skryabin et al. (2015) found no significant relationship between students' science scores and their use of ICT for entertainment outside of school in the PISA 2012 data. Juhaňák et al. (2018) replicated these results when examining the Czech Republic in the same database. Medium users of ICT in Europe did not have a significant relationship with science scores (Rodrigues & Biagi, 2017).

3.6 ICT Availability at School (ICTSCH)

Mathematics

Positive Relations. Limited research revealed that availability of different ICT devices at school was associated with higher mathematics scores. This was only the case for Turkish students in PISA 2012 and Spanish students in PISA 2009 (Bulut & Cutumisu, 2018; Fuentes & Gutiérrez, 2012).

Negative Relations. In contrast to the results found for Turkey, ICTSCH was associated with lower scores in Finland in PISA 2012 (Bulut & Cutumisu, 2018). Koğar (2019) reported a negative relationship between ICT use at school and mathematics scores at the OECD level in the PISA 2015 data. The author highlighted eBook reading devices as the strongest negative predictor of scores. Overall, the Reboot Foundation (2019) found negative associations between

ICTSCH and their PISA mathematics scores. Martínez-Abad et al. (2018) found negative results for the number of ICT devices at home and mathematics scores.

No Relations. Hu et al. (2018) uncovered no significant relationship between availability at school and mathematics scores at the average OECD level in PISA 2015. Tan and Hew (2018) also found no relationship between ICTSCH and mathematics scores in PISA 2012. The mathematics scores of Czech students in 2015 were not significantly correlated with ICTSCH (Juhaňák et al., 2018). A higher ratio of computers to students did not have a significant effect on mathematics scores (Reboot Foundation, 2019).

<u>Science</u>

Positive Relations. Similar to results for mathematics, Turkish students from PISA 2012 and Spanish students from PISA 2009 also achieved increased science scores with higher ICTSCH (Bulut & Cutumisu, 2018; Fuentes & Gutiérrez, 2012).

Negative Relations. Koğar (2019) reported a negative relationship between available ICT devices and science scores in PISA 2015. As in the case of mathematics, eBook readers were the culprit associated with lowest science scores. Similar to the results for mathematics, the Reboot Foundation (2019) found a small negative correlation between the availability of computers in schools and science scores. Spanish students' science scores were lower when they had more ICT devices available to them at school (Martínez-Abad et al., 2018).

No Relations. Analyses of the data from Czech, Finnish, and American students revealed a non-significant relationship between science scores and ICTSCH in PISA 2015, 2012, and 2000, respectively (Bulut & Cutumisu, 2018; Juhaňák et al., 2018; Papanastasiou et al., 2003). Similarly, the relation between the science score and ICTSCH was, on average, non-significant for 44 countries who participated in PISA 2015 (Hu et al., 2018). The specific ratio of students to computers did not significantly predict science scores (Reboot Foundation, 2019).

3.7 ICT Availability at Home (ICTHOME)

Mathematics

Bulut and Cutumisu (2018) found a positive relation between mathematics and ICTHOME for Turkish students in PISA 2012. Also using Turkish data, but from PISA 2009, Delen and Bulut (2011) found a positive correlation between ICTHOME and mathematics scores. Similarly, Fuentes and Gutiérrez (2012) also found a positive relationship while analyzing Spanish students from PISA 2009.

Negative Relations. Hu et al. (2018) reported a negative relationship between students' ICTHOME and both mathematics and science scores at the OECD level in PISA 2015. Tan and Hew (2018) also found a negative relationship in a sample of students from Asian countries with Confucian heritage cultures in PISA 2012. At a single country level, Spanish students held negative relationships for higher ICTHOME and mathematics scores from PISA 2015 (Martínez-Abad et al., 2018).

No Relation. Research revealed a null relationship between mathematics and ICT availability for Finnish and Czech students in PISA 2012 and 2015, respectively (Bulut & Cutumisu, 2018; Juhaňák et al., 2018).

Science

Positive Relations. An increase in ICTHOME was associated with an increase in science scores for Turkish students in PISA 2009 and 2012 (Delen & Bulut, 2011; Bulut & Cutumisu, 2018). Papanastasiou et al. (2003) found a positive relationship between the number of ICT devices at home and science scores for American students in PISA 2000. Fuentes & Gutiérrez (2012) also found a positive relationship while analyzing Spanish students from PISA 2009.

Negative Relations. As before, Hu et al. (2018) and Juhaňák et al. (2018) found a negative link between ICTHOME and academic scores in PISA 2015. Similarly, Spanish students held negative relationships for higher ICTHOME and mathematics scores in PISA 2015 (Martínez-Abad et al., 2018).

No Relations. No association was found between Finnish students' science scores and ICTHOME in PISA 2012 (Bulut & Cutumisu, 2018).

3.8 ICT Interest (INTICT)

Mathematics

Positive Relations. Meng et al. (2018) used ICT interest among other personal ICT perceptions in Chinese and German students who participated in PISA 2015. They found that student interest in ICT was a positive predictor of mathematics and science scores only for Chinese students. Hu et al. (2018) report an overall positive relationship between ICT interest and mathematics and science scores. An interest in the Internet as a tool was positively associated with mathematics scores at the OECD level in PISA 2015 (Koğar, 2019). Finally, positive relations between INTICT and mathematics were found for Spanish students in PISA 2015 (Martínez-Abad et al., 2018).

Negative Relations. Research revealed a negative relationship between mathematics scores and INTICT for German students in PISA 2015 (Meng et al., 2018).

No Relations. Although initially INTICT was not a significant factor for mathematics in a PISA 2015 study sampling Czech students, researchers found that, in some cases, gender significantly moderated the relation between ICT interest and mathematics (Juhaňák et al., 2018). Boys who showed higher interest in ICT had higher scores while girls who showed high interest in ICT had lower scores. This effect is, however, stronger for boys than it is for girls.

<u>*Science*</u>

Positive Relations. Hu et al. (2018) found an overall positive link between INTICT and science scores for 44 countries in PISA 2015. Meng et al. (2018) replicated this relationship for China within the same dataset. Finally, positive relations between INTICT and science were found for Spanish students in PISA 2015 (Martínez-Abad et al., 2018).

Negative Relations. German students who participated in PISA 2015 showed lower science scores as INTICT increased (Meng et al., 2018).

No Relations. Juhaňák et al. (2018) reported no relationship while examining the science scores and INTICT from Czech Republic in 2015. The interaction of interest and gender for science scores was not significant among Czech students.

3.9 ICT Competence (COMPICT)

<u>*Mathematics*</u>

Positive Relations. Similar to the results for ICT interest, COMPICT was found to be a positive predictor of mathematics scores in PISA 2015 (Hu et al., 2018). Zhang and Liu (2016) reported that confidence in Internet tasks was generally a positive predictor of higher mathematics and science scores from 2003 to 2009. Higher mathematics scores were also associated with more confidence in high-level ICT tasks in 2006 and 2009, but not in 2003. Comfort using unfamiliar ICT devices was a positive predictor of high mathematics scores in PISA 2015 (Koğar, 2019). Finally, positive relations between COMPICT and mathematics were found for Spanish students in PISA 2015 (Martínez-Abad et al., 2018). Using data from PISA

2009, Fuentes and Gutiérrez (2012) found a positive relationship between the attitudes towards ICT and ICT skill variables and mathematics scores for Spanish students.

Negative Relations. Meng et al. (2018) found a negative relationship between COMPICT and mathematics scores for Chinese students in PISA 2015.

No Relations. A null relationship was uncovered for German students' mathematics scores and COMPICT in PISA 2015 (Meng et al., 2018). There was no relation between COMPICT and academic achievement in a PISA 2015 study with Czech students (Juhaňák et al., 2018).

<u>Science</u>

Positive Relations. Confidence in high-level ICT tasks was associated with higher science scores in PISA 2009 (Zhang & Liu, 2016). According to Luu and Freeman (2011), more confidence in basic ICT skills and in presentation software was correlated with higher science scores in Canada and Australia in PISA 2012. Papanastasiou et al. (2003) found higher science scores in American students who were comfortable using word processing software to write papers in PISA 2000. Finally, positive relations between COMPICT and science were found for Spanish students in PISA 2015 (Martínez-Abad et al., 2018). Fuentes and Gutiérrez (2012) found a positive relationship between attitudes towards ICT and ICT skill with mathematics scores for Spanish students from PISA 2009.

Negative Relations. Meng et al. (2018) again found a negative relationship between COMPICT and science scores for Chinese students in PISA 2015.

No Relations. For German students, COMPICT did not predict science scores in PISA 2015 (Meng et al., 2018). In American students who participated in PISA 2000, comfort with general computer use and taking tests on the computer was not associated with science scores

(Papanastasiou et al., 2003). Similar to mathematics, the science score for Czech students in 2015 showed a non-significant relationship with COMPICT, after the inclusion of the gender interaction (Juhaňák et al., 2018).

3.10 ICT Autonomy (AUTICT)

Mathematics

Positive Relations. Both Hu et al. (2018) and Meng et al. (2018) found positive associations between AUTICT and their mathematics scores in PISA 2015. Another study found a significantly positive relationship in PISA 2015 between student performance and AUTICT for Czech students (Juhaňák et al., 2018). Spanish students held the same relationship in PISA 2015 (Gamazo et al., 2018; Martínez-Abad et al., 2018).

Negative or No Relations. The literature search did not yield any studies with negative or no relations between AUTICT and mathematics.

Science

Positive Relations. A positive relation was also found between science scores and AUTICT by Hu et al. (2018), Meng et al. (2018), and Juhaňák et al. (2018) for Czech students in PISA 2015. The same relationship was also found for Spanish students in PISA 2015 (Gamazo et al., 2018; Martínez-Abad et al., 2018).

Negative or No Relations. The literature search did not yield any studies with negative or no relations between AUTICT and science.

3.11 ICT Inclusion in Social Interaction (SOIAICT)

Mathematics

Positive Relations. Martínez-Abad et al. (2018) found a positive association between students' SOIAICT and mathematics performance in PISA 2015 for Spanish students.

Negative Relations. Student enjoyment of social interactions involving ICT was negatively connected to student mathematics scores in PISA 2015 (Hu et al., 2018). Similarly, in PISA 2015, a negative correlation was found between mathematics scores and social relatedness of using ICT for Spanish Czech and Chinese and German students, respectively (Gamazo et al., 2018; Juhaňák et al., 2018; Meng et al. 2018).

No Relations. The literature search did not yield any relations between SOIAICT and mathematics.

<u>Science</u>

Positive Relations. Martínez-Abad et al. (2018) found a positive association between SOIAICT and science performance in PISA 2015 for Spanish students.

Negative Relations. Student enjoyment of social interactions involving ICT was negatively connected to student science scores in PISA 2015 (Hu et al., 2018). Meng et al. (2018) reported a negative correlation between Chinese and German students' science scores and their social relatedness of using ICT in PISA 2015. Similarly, Juhaňák et al. (2018) and Gamazo et al. (2018) found negative relationships between science scores and SOIAICT for Czech and Spanish students, respectively.

No Relations. The literature search did not yield any relationship between SOIAICT and science.

3.12 Literature Review Discussion

This review has summarized the literature exploring the relationships among students' mathematics and science scores with the ICT variables used by PISA, yielding mixed results. This is likely due to the very particular nature of ICT influencing students' scores. There are many facets of ICT that intersect with students' daily lives and each facet can be associated with a different academic outcome. The variation in results may also be attributed to the different measures countries included and timeframes used. Even studies that use PISA data can differ due to the changes in the *ICT Familiarity Questionnaire* (OECD, 2014b) since its inception, as pointed out by Zhang and Liu (2016). This literature review reflects some of the variety in previous findings.

Researchers found positive, negative, and null relationships when looking into different aspects of ICT and their connection with academic achievement. Some researchers included several countries, while others focused on pairs or a single country, as shown in Table 2. The complexity of the types of relations between ICT and performance led researchers to use the methods shown in Table 5, such as multiple linear regression, HLM, structural equation modelling, EFA, logistic regression, propensity score matching, instrumental variables, and chi-squared automatic interaction detection. The data examined in the reviewed publications consisted of PISA iterations from 2000 to 2015. The majority of the studies (seven) used HLM for their analysis. Five studies used MLR and two studies used Structural Equation Modelling (SEM).

Given the wealth of literature on the topic of ICT and learning, this review focused on studies that used PISA ICT data from 2000 to 2015. Individually or in pairs, 11 countries were examined in 12 articles. These countries include Australia, Canada, China, the Czech Republic, Finland, Germany, Italy, Korea, Spain, Turkey, and the United States of America. Otherwise, eight studies included a large group participating countries, as seen in Table 5. One study employed data from the first version of PISA in 2000, two used PISA 2006, two use PISA 2009, six used PISA 2012, eight used PISA 2015, one study used data from PISA 2000 to PISA 2012, and one study used data from PISA 2003 to PISA 2015, as seen in Table 3. From the publications reviewed, Hu et al. (2018), Areepattamannil & Santos (2019), and Koğar (2019) used the most up-to-date version of PISA (i.e., 2015) and analyzed data from all participating countries. However, Koğar (2019) did not use the same variables in question as the other studies. This highlights the need for large-scale multiple group analysis of the current PISA data. Hu et al. (2018) used HLM, but a more robust approach such as structural equation modelling may better explain the complex relationships using latent variables and other incorporated methods, as demonstrated by Areepattamannil & Santos (2019).

Results from the studies reviewed varied but some trends were observed. First, Finland seemed to have more null results for ICT use and availability when compared to Turkey (Bulut & Cutumisu, 2017). Perhaps there is less variation in the ICT scores for Finland, or it is possible that ICT effects academic scores in fewer ways. Not many articles were found that discussed the impact of AUTICT or use of SOIAICT. However, the two that did (Hu et al., 2018; Meng et al., 2018) agreed that AUTICT use was positively associated with mathematics and science scores, while using ICT as a topic in social interactions was associated negatively with mathematics and science scores. Although Meng et al. (2018) found a negative relationship, most other studies reported a positive relationship (Koğar, 2019; Hu et al., 2018; Zhang & Liu, 2016 Luu & Freeman, 2011; Papanastasiou et al., 2003) and some reported a null relationship (Kubiatko & Vlckova, 2010; Meng et al., 2018; Papanastasiou, 2003) between COMPICT and mathematics and science dependent on country. INTICT was more frequently found to be positively associated with academic scores (Hu et al., 2018; Koğar, 2019; Meng et al., 2018) with the exception of Germany (Meng et al., 2018). No reviewed studies found null results for this relationship. ICTHOME and ICTSCH held a positive relationship for Turkey and a null relationship for Finland for both mathematics and science (Bulut & Cutumisu, 2017). Hu et al.

(2018) reported negative relationships for ICT availability at home and null relationships for availability at school. A negative relationship between USESCH and academic scores was found by Petko et al. (2017), Hu et al. (2018), Luu and Freeman (2011), Bulut and Cutumisu (2017), as well as Skryabin et al. (2015). Only Skryabin et al. (2015) found that USESCH was negatively related to mathematics. Petko et al. (2017), Hu et al. (2018), Luu and Freeman (2011), Bulut and Cutumisu (2017), and Skryabin et al. (2015) found this negative relationship with science scores as well. However, Meggiolaro (2018) and Koğar (2019) found positive relationships between USESCH and mathematics scores. Skryabin et al. (2015) was the only study to report a negative relationship between HOMESCH and mathematics scores. ENTUSE was also not associated with mathematics but it was positively associated with science (Hu et al., 2018). The Reboot Foundation (2019) report showed that mild usage of technology available to the students was the best predictor for higher mathematics and science scores even after controlling for demographic and economic data. Rather than examining science scores, Areepattamannil and Santos (2019) investigated how students' COMPICT and AUTICT related to their thoughts and feelings towards science in general, finding a positive relationship between higher COMPICT and AUTICT and positive views towards science. These included an interest in science, enjoyment of science, self-efficacy of science, and conceptions about science. Therefore, promoting ICT COMPICT and AUTICT in school can make a more receptive environment to learning science material in the classroom. Students' COMPICT was examined as a more influential factor, with results indicating that an increased USESCH, HOMESCH, and ENTUSE was related to an increase in COMPICT in Chinese and Korean students from PISA 2015 (Su, 2017). As seen in other studies (Fuentes & Gutiérrez, 2012; Hu et al., 2018; Koğar, 2019; Luu & Freeman, 2011; Martínez-Abad et al., 2018; Papanastasiou et al., 2003; Zhang & Liu, 2016), self-perceived competence was a positive predictor for higher mathematics and science scores, indicating that the relationship between ICT predictors is as complicated as the relationship with academic outcomes.

Another trend in results is the frequency of ICT use. Juhaňák et al. (2018) reported that Czech students who used the Internet between 30 minutes and six hours a day performed better academically than students who spent over six hours or under 30 minutes on the Internet. More specifically, students performed worse when they used the Internet at school more often, whereas they performed best when they used two to four hours of Internet at home. Luu and Freeman (2011) reported that moderate, very high, and very low ICT usage levels negatively affected Canadian and Australian academic scores in PISA 2006. The Reboot Foundation (2019) showed that students from PISA 2003 to 2015 performed worse if they used either no ICT or high ICT. Students with moderate ICT use performed the best on academic assessments. As seen in these studies, moderate ICT usage promotes the best academic performance when compared to little or no use, or excessive use.

Rodrigues and Biagi (2017) studied the connection between frequency of use and Socio-economic status in PISA 2015. Socioeconomic background or Economic, Social, and Cultural Status (ESCS) is a factor that can influence both academic scores and ICT in schools. ESCS is a continuous latent variable created by PISA that is comprised of wealth and social status indicators, such as number of books in the house and number of household possessions that reflect wealth (OECD, 2017a). Students with low ESCS have less opportunities to succeed than their peers. Students who use low levels of ICT from mid to low ESCS tend to benefit from an increase in use at home (Rodrigues & Biagi, 2017). Conversely, students with mid to high ESCS who are low frequency users of ICT benefit the most from an increase of ICT use at school. Type of school that the student attends is also a factor that plays a role in understanding academic achievement and ICT (Juhaňák et al., 2018). The type of school has been found to mediate this relationship. In the Czech Republic, schools known as primary schools, 6-year and 8-year gymnasiums have a stronger negative relationship for USEICT than other school types. Rodrigues and Biagi (2017) reported that the positive relationship for HOMESCH and science scores was stronger for students with low ESCS in private schools with a greater number of computers available.

3.13 Literature Review Limitations

This literature review constitutes a first step in elucidating the role of various aspects of ICT in students' mathematics and science academic achievement. Thus, it presents a number of limitations, many of which are shared by the reviewed studies. Two types of limitations are distinguished: practical and methodological.

From a practical perspective, this literature review is not as comprehensive as a systematic literature review and, therefore, it may not contain all the relevant literature at the time of this publication. Also, the present literature review was constrained by the number of published articles on this topic, especially as the PISA assessment is only administered every three years. However, the current results serve to provide examples of positive relations between the ICT variables and achievement, which can potentially be used to enhance student achievement.

From a methodological perspective, several limitations of this review were identified. All studies reviewed are correlational and cross-sectional, due to the nature of the PISA data. Therefore, limited cause-and-effect relationships can be drawn from these results. Even studies that use multiple iterations of PISA cannot be used longitudinally to find causation because the methods, measures, and sample change over the iterations. Using PISA data, the authors are unable to discern definitive causes for the differences in positive, negative, or null relationships among ICT. The details available about the context of ICT use provided by the *ICT Familiarity Questionnaire* (OECD, 2014b) are limited, as they do not indicate the quality of the devices or the meaningfulness or frequency of the use. Quality of ICT use is an important predictor for academic achievement and is needed for students to have a positive relationship between ICT and quality of learning (Lei, 2010; Lei & Zhao, 2007). The ICT measures are also limited as they do not indicate more specific contexts of ICT in school. For example, it cannot be deduced what ICT devices are used for mathematics classes or science classes. Unfortunately, the numbers of teachers or parents who are skilled in ICT are not included in the *Student Questionnaire*. This would be a valuable covariate to include in analysis (Giacquinta, Bauer, & Levin, 1993; Goldhaber & Brewer, 2000).

All of the reviewed studies are limited by the number of covariates that they can include. It would be impossible to identify, measure, and control all the possible covariates that can affect academic achievement. It is also ill advised to include any and all covariates that might be related to your outcome variable (Achen, 2005). Researchers cannot be certain whether or not ICT is the true reason for different levels in academic scores. As mentioned by Meng et al. (2018), measurement invariance that has been established in some countries cannot be easily transferred to other countries. As a result, measurement invariance would need to be established in all countries which would be a laborious task. When it comes to choosing a country, theoretical reasons must be explained for the choice. For example, economic state, ICT environment, and whether or not the country will be representative of others should be part of the decision. The *ICT Familiarity Questionnaire* in PISA consists of self-reported data, therefore the

ICT measures may not perfectly reflect true scores. Another limitation is the sample used in these studies. Specifically, several countries do not take part in the PISA surveys fewer implement the optional *ICT Familiarity Questionnaire*. Furthermore, as the participants are all 15-year-old students, the results are only generalizable to 15-year-olds who are in school.

In addition, the PISA survey is far from being a perfect measure. The data collection is not always completely representative of the country's indigenous schools or special-needs students (C. D. Howe Institute, 2018; LeRoy, Samuel, Deluca, & Evans, 2018). In addition, the results provided by PISA must be viewed with a level of uncertainty as they are only able to present ranges of results and imperfect methods of analysis (Murphy, 2010; Ercikan, Roth, & Asil 2015; OECD "FAQ," n.d.).

3.14 Literature Review Recommendations

Clearly there is a gap in the literature that needs to be addressed. There has been a large focus on ICT use measures in the majority of studies to date. As a result, variables like COMPICT, INTICT, and AUTICT are more often disregarded. Understanding the factors that would make students more comfortable with ICT and the attributes that promote meaningful ICT among students should inform decisions regarding how much countries should spend on their educational ICT budget. In this review, the most frequently studied variables were HOMESCH, USESCH, and ENTUSE. The least frequently used variables were INTICT, AUTICT, and SOIAICT. This review found positive, negative, and null results for all variables except AUTICT and SOIAICT. AUTICT did not show any negative and null relationships, while SOIAICT did not show any null relationships. This could be due to these variables being strongly associated with academic achievement. Alternatively, there has not been enough investigation to find the situations in which negative and null relationships are found. Either way, more research needs to be conducted to examine the softer measures of the *ICT Familiarity Questionnaire* (OECD, 2014b). All avenues of ICT must be understood in order to effectively promote or limit the correct types of inclusion that improve education world-wide.

The mixed results between ICT and academic performance yielded by the literature review suggests that more research needs to be done using rigorous statistical methods to examine and compare all available countries for a more in-depth comparison and understanding. In the near future, when PISA 2018 data is released, this literature review can provide a base of knowledge for researchers to guide their future research questions. In an attempt to mitigate the limitations mentioned above, research can take steps to ensure quality results. Researchers should use theoretical reasoning and other correlational research to pinpoint the ideal covariates and psychological factors available in PISA to act as control variables. This is how researchers can find more accurate results without over-controlling in their models. Similar methods as past studies can be replicated using the same countries in new iterations of PISA to see if the relationships change over time. If there are any changes, the authors can attempt to explain it by examining any shifts in the educational system. As pointed out by Tan and Hew (2018), it would be beneficial to see more use of mixed methodologies when investigating ICT to achieve a deeper understanding.

Given the mixed results revealed by this literature review, it is clear that student achievement is related to ICT differently depending on the country of the students and the subject that is targeted. A model needs to be constructed to attempt to explain these relationships for different countries and subjects, while also including appropriate confounding variables. In the near future, policy will need to be crafted on the basis of recent findings. Results from studies covered here can contribute to inform practice in schools involving ICT. As context is an important aspect of ICT inclusion in relation to academic achievement, and because the various contexts have different relations with mathematics and science scores, policy and practice will need to promote the positive and meaningful use, while trying to limit the less helpful aspects.

Findings of this study also recommend that curricula should not necessarily focus on increasing a country's rankings on the PISA list, given that these measures are very specific and do not provide a holistic view of a country's level of achievement (Rieckmann, 2017; Dall, 2011). Moreover, rankings are meaningless to a country's performance because the smallest shifts can cause large jumps in placing (Gorur, 2014). Furthermore, placings are often used for shaming and blaming countries who cannot top the charts (Grey & Morris, 2018). If a country does adopt curricula that match only the needs of PISA, they risk lowering their students' inquiry-based learning skills, concomitantly increasing their anxiety (Davie, 2017; Sjøberg, 2017).

3.15 Chapter Summary

This literature review has explored the relations between ICT variables and academic achievement in mathematics and science for 15-year-old students who took the *ICT Familiarity Questionnaire* administered as part of the 2015 PISA assessment. This review makes the following contributions: 1) it synthesizes the relevant literature on ICT and performance in mathematics and science in PISA, a large international assessment; 2) it highlights the gaps in the literature that explores the relation between ICT and performance in mathematics and science, including the types of statistical methods used to analyze these relations, the countries, and the variables examined; 3) it reveals the need to conduct more research, as it found mixed results for most of the variables examined; and 4) it sheds light on the importance of students' autonomy in enhancing their academic outcomes.

Overall, findings revealed mixed results of ICT with performance in mathematics and science. Of all the ICT variables, students' self-reported autonomy around the use of ICT yielded only positive performance outcomes. Other variables were a mix of negative, positive, or null results, depending on the country. Future work should explore these same relations in multiple countries by including all available countries who completed the *ICT Familiarity Questionnaire* in PISA 2015 into a multiple-group model using SEM.

Chapter 4: Methods

4.1 Data Sources

This research employs publicly available data from the 2015 PISA database that contains approximately 540,000 students from 72 countries. PISA is designed by experts in measurement, evaluation, and various content areas to test student learning and whether students are able to apply their knowledge (OECD, 2017b). Additionally, the surveys are used to measure other variables related to education such as involvement with ICT, which constitutes the focus of this research. The test items are delivered as paper or computer-based questionnaires and quizzes every three years. The data used for this research include the *ICT Familiarity Questionnaire* (OECD, 2014a) and the *Student Questionnaire* (OECD, 2014b) from 48 participating countries. These scales were all collected using computer-based questionnaires.

4.2 Sample Description

The sample for the final SEM consisted of n = 11,810 students who attended school part-time or full-time in their countries (OECD, 2016b; 2017b). Of that sample, 5,928 students were from Bulgaria and 5,882 were from Finland. The sample for the mathematics and science Alignment models were n = 369,450 and the sample for the ICT Alignment model was n = 332,522. The age of the students ranges from 15 years and 3 months to 16 years and 2 months.

Participants were randomly chosen within their cluster sample of schools. Weighting variables were used to compare students from different schools, with the aim to ensure that all countries were equally represented. Many of the countries used in this study have contrasting economies and implementation of technology, and were partly identified by consulting the *Growing United: Upgrading Europe's Convergence Machine* report by the World Bank on the European Union (Ridao-Cano & Bodewig, 2018). This report uses PISA and economic data to determine the divides that exist between European countries.

4.3 Procedures

The primary goal of PISA is to test if students can apply concepts learned in school to real-world issues. Typical subject areas in PISA include science, mathematics, reading, financial literacy, and collaborative problem solving. The results are used to understand the constructs that underlie the learning of young students and to influence education policy to promote equitable learning for all groups in each country. PISA questionnaires are administered every three years to detect changes in outcomes resulting from policy recommendations implemented from previous PISA results.

Data collection for the 2015 PISA main survey started in March 2015 and ended in December 2015 (OECD, 2017b). The surveys were split up between schools and administered to randomly-assigned students. At least 150 schools were sampled in each country. OECD ensures a high quality of standards for composing their surveys including a field trial, multiple reviews, National Centre Quality Monitor, PISA Quality Monitor, and revisions and translation analyses (OECD 2017a; 2017b). The testing procedures for PISA 2015 mathematics did not vary much from 2012, other than moving to mainly computer-based testing. In preliminary trials, the results from paper-based or computer-based testing did not differ significantly for each country.

Therefore, the results between these two methods were combined for analysis (OECD, 2016b). When comparing the final reports of 2012 and 2015, a small correlation of .18 was found between mathematics performance and the change between computer-based and paper-based testing, which may be explained by a change in a small number of the items.

4.4 Measures

All measures used in this research were obtained from the PISA 2015 database. The outcomes or dependent variables are the mathematics and science plausible values. The predictors or independent variables are the nine ICT subscales from the *ICT Familiarity Questionnaire*.

4.4.1 Outcome Variables

The observed outcome variables in this study are mathematical and scientific literacy. To measure these dependent variables, different groups of students were given similar sets of parallel, overlapping items from a total pool of 82 mathematics or science items (OECD, 2017b). PISA compared students' performance scores using Item Response Theory (IRT) to account for several challenges (Mislevy, Beaton, Kaplan, & Sheehan, 1992). Specifically, PISA uses complex sample designs (i.e., including unequal probabilities and stratifications) that must be taken into account when approximating scores. Distilling many test statistics into fewer plausible values enables researchers to add scores to their analyses rather than performing more advanced statistics to make the same comparisons. The IRT provides an improved estimation, even if the marginal analysis is not ideal. Based on this model, PISA imputed a total of ten plausible values for mathematics and science for each student "using information from the student context questionnaire in a population model" (OECD, 2017b, p. 128). Proficiency was given on a scale of 0 to 1000 with an overall mean of 500 and standard deviation of 100 across all OECD countries. The ten plausible values were drawn as indicators for the latent mathematical and scientific literacy variables. For each student, PISA computed ten plausible values for mathematics and ten for science based on students' answers to mathematics and science items. The goal is to represent their knowledge in each of the mathematics and science competencies measured. As the scale proficiency values for mathematics and science are not observed, PISA treated them as "missing" data (Rubin, 1987). Thus, PISA uses plausible values calculated by multiple imputation from questions and background information, aiming to estimate a students' academic performance from individual item scores as well as to better represent the variability in students from schools, areas, and countries. More details on the necessity and use of plausible values are included in the PISA Technical Report (OECD, 2017b). As PISA statisticians have already produced the plausible values, each ten plausible values were used as latent-variable indicators to get a more accurate estimate of the latent values for *Mathematics* and *Science*.

4.4.2 Predictor Variables

The predictor variables from the *ICT Familiarity Questionnaire* include nine self-reported Likert-subscales on a logit scale, where zero represents the OECD average (OECD, 2014a). Descriptions and examples of these nine items provided by PISA are available in Table 4. Each question measures a slightly different non-cognitive aspect of ICT use, availability, and comfort. Cronbach's alpha (α) is calculated by OECD and recorded for each subscale to compare internal consistencies between countries (OECD, 2017b). A value of 1 signifies perfect internal consistency, while a value of .7 indicates acceptable internal consistency. These variables are briefly described below and Appendix A shows examples of each subscale. A full list of scale reliabilities for all participating countries is included in Table 16.64 of the *2015 PISA Technical Report* (OECD, 2017b).

ICT use. Three subscales derived from the PISA items were employed to assess ICT use: ENTUSE for ICT use outside of school leisure; HOMESCH for ICT use outside of school for schoolwork; and USESCH for use of ICT at school in general (OECD, 2017b). In the *ICT Familiarity Questionnaire*, these are recorded as items IC008, IC010, and IC011, respectively (OECD, 2014a). For each subscale, students responded to a set of questions such as “How often do you use digital devices for the following activities at (or outside of) school.” They were then presented with a list including social media, email, video games, and more. Responses were given on a 5-point ordinal scale with options of 1 = *Never or hardly ever*, 2 = *Once or twice a month*, 3 = *Once or twice a week*, 4 = *Almost every day*, or 5 = *Every day*. These three subscales are included in Appendix A among all of the nine ICT subscales and their questions.

ICT comfort. Four subscales derived from the PISA items were used to inquire about ICT comfort and familiarity: COMPICT for students’ perceived ICT competence; AUTICT for students’ perceived autonomy related to ICT use; INTICT for students’ ICT interest; and SOIAICT for students’ inclusion of ICT as a topic in social interaction (OECD, 2017b). In the *ICT Familiarity Questionnaire*, these are recorded as items IC009, IC013, IC015, and IC016, respectively (OECD, 2014a). Each subscale was based on a set of questions such as, “Thinking about your experience with digital media and digital devices: to what extent do you disagree or agree with the following statements?” Respondents then answered the items on a 4-point scale with the options: 1 = *Strongly disagree*, 2 = *Disagree*, 3 = *Agree*, or 4 = *Strongly disagree*.

ICT availability. Finally, the two subscales that assess the ICT availability at school (ICTSCH) and at home (ICTHOME) were used in the analysis. The subscales were created based on a set of questions on the availability of ICT-related equipment. ICTHOME is the availability of ICT in the home and is calculated by the sum of available items answered in question IC001 (OECD, 2014a). ICTSCH is derived the same way from question IC014. The ICTSCH and ICTHOME subscales were treated by PISA 2015 statisticians as indices that were computed as the sum across all their comprising availability items, while the rest of seven subscales (e.g., AUTICT, USESCH, etc.) were scaled indices computed based on IRT. For a detailed description of these measures and the methods for creating them, see the PISA 2015 Technical Report (OECD, 2017b).

4.5 Analytic Plan

All the analyses conducted in this research employed *Mplus 8* (Muthén & Muthén, 1998-2017) and SPSS (IBM, 2019). To answer the first research question, the *SEM* method was used. Specifically, an EFA and Confirmatory Factor Analyses (CFAs) were conducted for Bulgaria and Finland, where mathematics and science plausible values were the outcome variable and the nine ICT subscales were the predictor variables. The purpose of an EFA is to find the ideal number and organization of predictor factors into latent variables (Overall, 1964). A CFA is then used to test those latent variables (Kline, 2015). Specifically, four separate models were used for the mathematics and science relationships for Bulgaria and Finland. To answer the second research question, the *Alignment* method was employed to build three separate models for mathematics, science, and ICT with multiple countries as one large group. Missing values in the ESCS and ICT variables were labeled as 99 or 97 in order to be identified by the software.

4.5.1 Structural Equation Model

Prior to attempting the Alignment method, SEM was used to investigate the relationship between ICT and mathematics and science, respectively, for each of the two countries with disparate ICT, Bulgaria and Finland. The research question addressed by this analysis was: *To what extent does ICT help or hinder students' mathematics and science learning in Bulgaria and Finland, respectively, two countries with different ICT profiles, when controlling for students' socio-economic status? Specifically, is more access to ICT associated with worse mathematics and science performance in each country?* The two chosen countries were Bulgaria and Finland because they represent countries with widely different ICT inclusion. As mentioned in the *Theoretical Framework* section, Finland is classified as a Digital Frontrunner, while Bulgaria is a Digital Challenger (Novak et al., 2018). On this scale, Finland is on the end of more technologically advanced and higher academic performance, whereas Bulgaria lies on the end of less technological prowess and lower academic scores on average (European Union, 2019b; 2019c; OECD, 2016b). Thus, two separate models were prepared for each country (Bulgaria and Finland, respectively): one focused on mathematics scores and the other on science scores.

Step 1: Exploratory Factor Analysis. The purpose of this first step was exploratory. Tests of association revealed that some of the predictor variables were correlated with each other, warranting a factor analysis, as shown in Table 9 and Table 10. Thus, an EFA was conducted with the nine ICT predictors to ascertain the ideal number and configuration of ICT predictors. The EFA showed that splitting into two factors resulted in eigenvalues of 1.5 and 1.6 for Finland and Bulgaria, respectively, as illustrated in Table 7. With three factors, the eigenvalues were .99 for both countries. With four factors, the eigenvalues drop to .77 and .66 for Finland and Bulgaria, respectively. Thus, the three-factor solution was chosen, as it allowed for the most logical combination of factors without dropping significantly under a threshold value of 1. Empirically, none of the cross loadings generated by the three-factor solution was alarmingly high. After applying the *geomin* oblique rotation, the nine ICT predictor variables loaded well into three factors (Muthén & Muthén, 2012). The variables with the highest significant values were grouped together to create the three latent predictor variables. The final model includes three latent predictor factors because the nine variables provided by the PISA 2015 data fit well into three factors: ICTUSE (i.e., HOMESCH, ENTUSE, and USESCH) representing students' ICT use at home for schoolwork, for entertainment, and at school; ICTAVB (i.e., ICTHOME and ICTSCH) representing students' ICT availability at home and at school; and ICTCOMF (i.e., AUTICT, COMPICT, SOIAICT, and INTICT) representing students' self-reported autonomy around the use of ICT, self-reported ICT competence, inclusion of ICT as a topic in social interactions, and interest in ICT.

The plausible variables for mathematics were highly correlated, as they measured the mathematics knowledge of an individual student, likewise for science plausible values. Therefore, all ten variables were combined into an overall mathematics and science latent variable, named *MATH* and *SCIENCE*, respectively.

Cronbach's alpha (α) is calculated by OECD and recorded for each subscale to compare internal consistencies among countries, as shown in Table 8 (OECD, 2017b). This is useful for comparing schools and regions within a country, however more analysis is needed to measure the invariance and comparability across more than one country. A value of 1 signifies perfect internal consistency, whereas a value of .7 indicates acceptable internal consistency. The values are higher in Bulgaria than in Finland for each variable with the average of .89 in Bulgaria and .84 in Finland. The variable with the highest α for both countries is HOMESCH and the lowest is INTICT.

Step 2: SEM Confirmatory Factor Analysis. Then, Confirmatory Factor Analysis (CFA) models were run using a latent variable represented by the ten plausible values for mathematics and science predicted by all nine scales loaded onto three latent variables. Specifically, separate mathematics and science models were designed with the three latent predictor variables, ICTUSE, ICTAVB, and ICTCOMF predicting a MATH or SCIENCE latent variable, respectively. This model has good model fit, but also showed that some predictor indicators were correlated beyond the factor correlations, meaning that some of the observed variables were measuring similar constructs. The correlations of all nine observed ICT predictor variables and the latent outcome variables are shown in Table 9 and Table 10 for Bulgaria and Finland, respectively.

Step 3: Bifactor Variable Creation. Reviewing the nine subscales, it was clear that they were measured in a similar fashion and each one assessed students' general ICT experience as well as unique aspects related to use, comfort, and availability of ICT. Given this, a bifactor model was used to partial out and control for the shared variance of all the observed predictor ICT variables (Holzinger & Swineford, 1937; Kline, 2015). The bifactor latent variable ShareICT was created with the nine ICT predictor variables. The latent outcome variable was then regressed onto ShareICT the latent outcome variable was regressed onto the bifactor to treat it as a covariate. Thus, the nine ICT predictor variables simultaneously load onto both the ShareICT variable and the three specific ICT constructs. In this way, the unique effects for ICTUSE, ICTCOMF, and ICTAVB could be distinguished after accounting for general ICT experience.

Step 4: Final SEM. The final models that were designed are shown in Figure 1 and Figure 2. Two models consisted of the mathematics scores for Bulgaria and Finland, respectively, while the other two consisted of the science scores of Bulgaria and Finland, respectively. An index of economic, social, and cultural status (ECSC) provided by PISA 2015 was added as a control variable so that students' economic status would not interfere with the relationship of mathematics or science with ICT (OECD, 2017b, p. 339). Many modification indices were used to achieve model convergence and to test for invariance. Starting values were achieved from the model output of the previous step.

4.5.2 The Alignment Method

Measurement invariance is a statistical process of establishing whether or not the same construct is being measured across different groups and is necessary to establish before cross group comparisons can occur (Vandenberg & Lance, 2000). A review of measurement invariance testing by Byrne and van de Vijver (2017) found that researchers acknowledge the need for measurement invariance tests for multiple group comparisons. However, the majority of studies only used two groups for comparison. The amount of studies further drops as the number of focal groups increases. The Alignment method was proposed as a solution to estimate the means and intercepts of many groups, while allowing for some flexibility in measurement invariance. It outperforms multiple-group techniques, such as multiple-group SEM, as it facilitates invariance testing with many groups (Asparouhov & Muthén, 2014). The goal of measurement invariance is to test whether or not constructs represent the same underlying attributes and measured scores have the same meaning in different conditions or groups (Meade & Lautenschlager, 2004). Measurement invariance must be established before means from different groups can be compared or else the comparison would not be meaningful (Millsap, 2012). The Alignment option is a better choice than a CFA because a CFA may fail due to many modification indices and poor scalar model fit. Full invariance is rarely achieved in large datasets due to troublesome modification indices and complicated models from releasing constraints. The Alignment method simplifies and automates invariance testing among groups with expected non-invariance (e.g., culture in different countries; Muthén & Asparouhov, 2014; Byrne & van de Vijver, 2017). Typically, using SEM to complete a CFA for multiple groups means making many one-to-one comparisons, each requiring a baseline model, which would result in a lot of tedious work (Byrne & van de Vijver, 2017). For example, over one thousand individual comparisons would be needed for the present sample of 48 countries. When studying large groups, which are considered as a fixed mode of variation, there is a large degree of measurement non-invariance. In the current sample, this is caused by different countries with different backgrounds and cultures. This method can be based on either maximum-likelihood or Bayes estimation and can be performed with either free or fixed estimation. Free Alignment is suggested by Asparouhov and Muthén (2014) as a better option but it is possible that the model will not be identified. If that is the case, then fixed Alignment should be used. The difference between the two is that either all factor loadings and intercepts are freely estimated or one group is selected to have a factor mean set to zero and an intercept set to one. Free estimation allows more bias overall across all the parameters and works best when there is about 10% to 20% of non-invariant parameters.

Alignment minimizes the amount of measurement non-invariance by estimating the factor means and variances. This is possible despite the fact that these parameters are not identified without imposing scalar invariance because a different set of restrictions are imposed that optimizes a simplicity function (Muthén & Asparouhov, 2014). The simplicity function is optimized at a few large non-invariant parameters and many approximately invariant parameters rather than many medium sized non-invariant parameters. According to Muthén and Asparouhov (2014, p.2), "Adding a simplicity function gives the necessary restrictions to identify the model. The simplicity function minimizes with respect to [factor means] and [factor variance] the total loss/simplicity function *F* which accumulates the total measurement non-invariance over the items."

There are two steps that occur automatically during the Alignment analysis. The first is an estimation of a configural model, where loadings and intercepts are constrained across groups, factor means are fixed at zero, factor variances are fixed at one, while factor loadings and intercepts are freely estimated. In the end, the final Alignment model will have the same fit as this configured model. The second step is Alignment optimization, where factor means and variances are assigned values based on a pattern of parameter estimates using a simplicity function to minimize the total amount of non-invariance for every pair of groups and every intercept and leading using a simplicity function similar to rotations in an EFA. The estimation stops when the least amount of non-invariant parameters is achieved.

The Alignment method works well unless there are small group sizes or a high proportion of significant non-invariant parameters. The Alignment method has several disadvantages: cross loadings cannot be accommodated, models with covariates cannot be estimated, and relationships between variables cannot be estimated (Asparouhov & Muthén, 2014; Marsh et al., 2018). These limitations restrict the Alignment method to an exploratory tool. The non-invariance cutoff point is 25% and the minimum number of groups is 30 (Muthén & Asparouhov, 2014).

The Alignment output provides a table of which groups are invariant for a given parameter. The latent means for each parameter are also given for every group. This output also shows which groups have a significantly lower mean than the mean of the group being examined. The R-square value is provided for each parameter and demonstrates the variance across groups that can be explained by the variation in factor means and variances (Byrne & van de Vijver, 2017). A value of one indicates complete invariance because the variability in item parameters is completely explained by group mean differences. A value near zero indicates that the group mean differences explain none of the variability in item parameters (Asparouhov & Muthén, 2014).

4.5.2.1 ICT Alignment

Initially, three structural equation Alignment models were devised to explore whether mathematics scores, science scores, and ICT factors are measurement invariant across the 48 participating countries, and to compare means. This method was used to answer the research question: *Are the ICT, science, and mathematics variables measurement invariant across the countries participating in the PISA ICT questionnaire?* In these models, the MLR, or maximum likelihood estimation with robust standard errors, estimator was used to incorporate the weighting variable (W_FSTUWT) to allow for cross country comparisons. The country ID variable (CNTRYID) was used to define the 48 countries as latent classes. Table 11 shows all country IDs. The default number of iterations was preserved, the number of random sets of starting values was set to 60 (double the default), and convergence was restricted to .001, as suggested by the *Mplus 8* user manual (Muthén & Muthén, 1998-2017). At first, free estimation was used to find a reference group for fixed estimation because the models were not identified with free Alignment. The reference groups used were the countries with the factor means closest to zero, either positive or negative. For the ICT model, the country with the three factor means closest to zero was chosen as the reference group. The requested outputs were TECH1 and SVALUES for the starting values of the parameters, TECH8 for the optimization history, and

ALIGN for factor loadings and intercept comparisons as well as measurement invariance of each country for the factors.

Several warnings were included in the output after running the ICT model.

a) "One or more parameters were fixed to avoid singularity of the information matrix. The singularity is most likely because the model is not identified, or because of empty cells in the joint distribution of the categorical variables in the model."
b) "Warning: The sample variance of ICTHOME is 0.000."
c) "Warning: The sample variance of ICTSCH is 0.000."
d) "Data set contains cases with missing on all variables except x-variables. These cases were not included in the analysis. Number of cases with missing on all variables except x-variables: 31383"

The investigation of the source of these warnings revealed that the residual variances of ICTHOME and ICTSCH were fixed for Germany (CNTRYID 276). Indeed, Germany was missing all values for ICTHOME and ICTSCH and was subsequently removed from the ICT Alignment analysis. The new sample size without Germany was n = 362,946. With Germany removed from the dataset, a free Alignment model was conducted and The Netherlands (CNTRYID 528) was found to have the sum of the absolute values of their factor means closest to zero, at .67. Therefore, the model was reconfigured to exclude Germany from the classes, resulting in 47 classes. *Mplus* did not include 30,424 cases because they contained missing values on all variables except x variables, which are the outcome variables. This updated model only produced one warning: 30,424 cases were not included due to missing on all outcome variables. This warning is not a concern, as there are a total of 362,946 observations excluding Germany. In the end, 332,522 cases were included in the dataset of 47 countries.

4.5.2.2 Mathematics and Science Alignment

Two other similar models were created to test the measurement invariance of mathematics and science plausible values. These models are the same as the ICT model, except that the latent variables “MATH” and “SCIENCE” were created from their respective ten plausible values, the fixed country was based on each free Alignment model, and Germany was included. For the mathematics model, the fixed country was Croatia (CNTRYID 191) and for the science model, the fixed country was Ireland (CNTRYID 372). The plausible values that make up the latent variables were divided by 100 to bring them closer to the scale of the ICT items.

4.6 Other Common Methods

As explained in the literature review and illustrated in Table 5, researchers have used numerous methods to explore the relationships between ICT and academic scores. Regression is the most frequently used and discussed method. Different varieties of regression have been used, ranging from linear regression and logistic regression to hierarchical linear modelling (HLM).

HLM is a type of Multilevel Linear Modelling that takes into account the nested hierarchies within the data (Field, 2018). Thus, this type of regression seems to be the best suited form of regression to answer the research questions posed in the present research because PISA data is hierarchical (i.e., students are nested within schools, and schools are nested within countries). Assumptions of linear, normal, and homoscedastic data need to be met to use this method. However, this research has employed SEM and the Alignment method instead of HLM for several reasons. For instance, as shown in Table 6, two and four of the ICT predictors are kurtotic above the recommended cutoff of ±2 (George & Mallery, 2010; Little, 2013) for Bulgaria and Finland. This violates the normality assumption of regressions, which casts a shadow on the trustworthiness of the results. The robustness of SEM is a good reason for its use

(Kline, 2015). It is a convenient combination of CFA and path analysis with plenty of informative outputs on variance and model fit. A main drawback of HLM is the laborious nature of manually inputting the hierarchies and repeating the process for all groups. Tan and Hew (2018) used this method with full maximum likelihood estimation for seven nested models, concluding that a mixed methodology approach should be taken to better understand such relationships and that more groups should be included in the analysis.

4.7 Chapter Summary

This chapter explains the methodological steps that were taken in this research. First the data source and sample were described. Next, an EFA model was used to begin the process of designing CFA models. Then, the Structural Equation Modeling (SEM) CFA models with increasing complexity were described using Bulgaria and Finland as sample countries. Finally, the Alignment method was described as a method of establishing measurement invariance across many groups simultaneously.

Chapter 5: Results

In the PISA 2015 dataset, a country's mean mathematics achievement was compared on a standardized scale with the mean of 500 points and a standard deviation of 100 for the participating OECD countries (OECD, 2016). Bulgaria achieved a score of 441 (SD = 97), placing it under the overall OECD average, while Finland scored 511 (SD = 82), placing it above the OECD average. The OECD science performance average, like mathematics, was 500 points with a standard deviation of 100 (OECD, 2016). Bulgaria performed below the OECD average with a mean score of 446 (SD = 102), while Finland performed near the top with a mean score of 531 (SD = 96). Finland is much more digitally equipped than Bulgaria, but the two countries exhibit similar computer usage (Ridao-Cano & Bodewig, 2018; Novak et al., 2018). This suggests that the effect of ICT is deeper than its sheer usage (European Union, 2019b; 2019c).

Skewness and kurtosis are presented in Table 6, which also includes information on missing data for each variable. The dependent MATH and SCIENCE variables have no missing data because those values were all calculated by the statisticians at PISA after the data had been collected (OECD, 2016). Normality of the predictor variables as well as the missing data was confirmed by examining the skewness and kurtosis of histograms as well as the descriptive statistics in SPSS. In Table 6, the bolded values show which variables have significant kurtosis beyond the acceptable range of -2 to +2 (George & Mallery, 2010), indicating that there were no variables with enough skewness to cause concern. From a PLOT TYPE 3 in *Mplus 8*, the MATH, SCIENCE, and ICTCOMF latent variables were distributed normally for both Bulgaria and Finland. The ShareICT latent variable displayed some positive kurtosis. ICTUSE was distributed normally for Bulgaria but was positively kurtotic for Finland. ICTCOMF showed positive kurtosis in both countries. Even though some of the indicator and latent variables were not distributed normally, the results can still be trusted. SEM is a fairly robust method which can include components like weighting variables and maximum likelihood estimation with robust standard errors. The weighting variable and maximum likelihood estimation with robust standard errors can account for skewness and kurtosis and helps achieve more precise standard errors, especially for large datasets like PISA (Kline, 2015). The implications of analyzing variables with high skewness and kurtosis will be discussed in the limitations section.

5.1 Structural Equation Models

The SEM methods were used to answer the first research question: *To what extent does ICT help or hinder students' mathematics and science learning in Bulgaria and Finland,* *respectively, two countries with different ICT profiles, when controlling for students' socio-economic status? Specifically, is more access to ICT associated with worse mathematics and science performance in each country?* Correlations of the nine predictor variables were examined for both Finland and Bulgaria. All correlations were below the Kline's (2015) collinearity cutoff of .85, therefore collinearity was not a concern. Four ICT measures in Finland were beyond the recommended ±2 standard deviations cutoff for normality, with only two in Bulgaria (George & Mallery, 2010; Little, 2013). The unevenly high ICT values in Finland may reflect the higher ICT due to their status as a Digital Frontrunner.

The main model fit statistics used in this study are the Comparative Fit Index (CFI) and the Root Mean Square Error of Approximation (RMSEA). The Chi-square test was not used for model fit because it is a very sensitive test and provides meaningless results when used with very large samples (Hayduk, 2014; Little, 2013). CFI compares the hypothesized model with an independent model with no specifications. For CFI, a value of 1 is a perfect fit, while values equal to or greater than .9 are a close fit. RMSEA estimates the overall lack of fit, with .06 or below being considered as good fit. Some of the predictor variables yielded correlations upwards of .63, which enabled the combination of variables into fewer factors.

Step 1: Exploratory Factor Analysis. The results for the EFA were used to guide the methods for the second, third, and fourth steps. These EFA results are discussed in the *Analytic Plan* section.

Step 2: Confirmatory Factor Analysis. The initial CFA of the second step had the three latent predictor ICT variables predicting the MATH or SCIENCE latent dependent variables, respectively. This model had an RMSEA of .04 and a CFI of .98 for mathematics, whereas science had an RMSEA of .04 and a CFI of .98. See Table 12 for the global model fit of all steps.

This model explained 12.6% and 3.8% of the variation in mathematics scores for Bulgaria and Finland, respectively. The science model explains 15.4% and 4.8% variation in scores for Bulgaria and Finland, respectively. The standardized results of the Bulgaria model show us that mathematics scores are negatively associated with ICTUSE and ICTAVB with respective coefficients of -.23 and -.17. ICTCOMF, however, was positively associated with mathematics scores, with a coefficient of .33. All three of these relationships were significant with a *p* value of .00. The Finland model is slightly different with ICTUSE, ICTCOMF, and ICTAVB coefficients of -.20, .36, and .06 respectively. For Finland, ICTAVB is not significant, with a *p* value above .05. These same results are mimicked in the science model with significant coefficients for ICTUSE, ICTCOMF, and ICTAVB in Bulgaria as -.25, .36, -.19, respectively. In Finland these coefficients are -.23, .22, and .03 respectively, where ICTAVB is not significant with a *p* value over .05. Table 13 shows the standardized regression coefficients for the three latent variables for Finland and Bulgaria in the CFA models.

Step 3: Bifactor Variable Creation. In this third step, the ShareICT latent variable was created to control for the shared variance of the ICT predictors. This step also showed good model fit for both countries and subjects. In the mathematics model, the RMSEA was .03 and the CFI was .99. In the science model, the RMSEA was .03 and the CFI was .99. This model explained 19.2% and 5.3% of the variation in mathematics scores for Bulgaria and Finland, respectively. The science model explained 22.2% and 5.3% of the variation in science scores for Bulgaria and Finland, respectively. The only change in relationships was that the relationship of ICTAVB became non-significant in both countries and both subjects.

Step 4: Final SEM. The final bifactor SEM models of the fourth step included ESCS and as a control on the latent dependent variable. This model continued to show good model fit with a RMSEA and CFA of .036 and .98, respectively, for math. The science model also showed good model fit with a CFI and RMSEA of .99 and .04, respectively. This model controlling for ESCS explains the mathematics and science scores better. The percentages of variation in mathematics scores explained by this model for Bulgaria and Finland are 34.3% and 19.4%, respectively. The percentages of variation in science scores by this model are 36.9% and 17.1% for Bulgaria and Finland, respectively. All path estimates are shown in Figure 1 and Figure 2. For mathematics, the ICTUSE, ICTCOMF, and ICTAVB coefficients for Bulgaria were -.27, .10, and -.17, respectively. The Finnish coefficients were -.08, .18, and -.07, respectively. For science, Bulgaria had coefficients of -.25, .36, and -.19, respectively and Finland had -.11, .18, and -.08, respectively. Interestingly, the ICTAVB relationships with mathematics and science scores became significant where they were not significant in *Step 3*. When the latent science variable was regressed onto the ESCS control variable, Bulgaria and Finland had coefficients of .41 and .34, respectively. The mathematics ESCS and ShareICT results were similar to those for science. For ESCS, Bulgaria had a coefficient of .41 and Finland had a coefficient of .38.

The major difference in the results in the CFA steps is that the relationship between ICTAVB became fully non-significant in *Step 3* then became significant in *Step 4* for mathematics and science in both countries. In the end, the relationships between ICTAVB and mathematics and science scores were negative for both countries (see Table 6). The relationships between ICTUSE and mathematics and science scores were also negative for both countries. Unlike the other associations, the relationships between ICTCOMF and mathematics and science scores were positive. For the multiple CFAs, there were issues preventing the model to converge. To combat this, starting values were taken from the no-convergence model and added to the updated CFA model. Some constraints on intercepts were also necessary to achieve model convergence and to obtain estimated latent means.

5.2 ICT Alignment

The Alignment methods were used to answer the second research question: *Are the ICT, science, and mathematics variables measurement invariant across the countries participating in the PISA ICT questionnaire?* The Alignment model shows which item intercepts and factor loadings are invariant in all of the groups. Table 14 presents the non-invariance percentages of the factor loadings and intercepts of the nine ICT items. If Muthen and Asparouhov's (2014) cutoff of 25% as the maximum amount of non-invariance is surpassed, then the latent mean estimation may be untrustworthy. All of the 9 ICT items have high amounts of non-invariance, with an average of 68.60% for intercepts and 34.8% for factor loadings. The finding of fewer non-invariant factor loadings than intercepts follows the trend of previous researchers (Crane, Belle &Larson, 2004; Meiring, van de Vijver, Rothmann & Barrick, 2005; Byrne & van de Vijver, 2017). The factor intercepts of all 9 ICT items were above the 25% cutoff. The least non-invariant intercept parameters were ICTHOME and ICTSCH with 42.60% non-invariance and the highest parameter was SOCIAICT with 87.20% non-invariance. The factor loadings were more mixed for non-invariant parameters, with five of nine being over the cutoff. The invariant factors were the loadings of ICTHOME (6.40%), HOMESCH (12.80%), ICTSCH (14.90%), and COMPICT (23.4%). The factors with the lowest amount of non-invariance would be the most useful when comparing countries. All of the factors have significant non-invariance in all 47 countries. Table 14 shows the R-square values for each of the nine ICT scales. The R-square value of ICTHOME was congruous with the non-invariance output as it was the highest at .94, which means that it is the most invariant parameter. According to the R-square, COMPICT was the next-most invariant, which is similar to the non-invariance output. With this high amount of non-invariance, the latent mean estimates or their comparisons in other models cannot be trusted using this data.

5.3 Mathematics and Science Alignment

The invariance output of the mathematics and science model had extremely low non-invariance in both factor loadings and intercepts. All plausible values included in the separate mathematics and science Alignment models were invariant. Mathematics intercepts and factor loadings had an average of 9.40% and 6.0%, respectively. Science was even lower with intercepts and factor loading percentages of .83% and 1.0%, respectively. These levels of non-invariance are well below the 25% cutoff, which suggests that the plausible values provided by PISA are invariant and can be used when comparing mathematics and science knowledge across countries. Consequently, the factor means are comparable across the 48 countries included in this study. According to both the present results and those from PISA 2015 results (OECD, 2016b), Singapore is by far the leading country in mathematics and science proficiency. The comparisons of the country means for mathematics and science scores match those from PISA identically. Table 15 and Table 16 show the ranked order of countries by factor means.

5.4 Chapter Summary

This chapter outlines the findings of the present research. For the first research question, proper CFA model estimates were established using a bifactor SEM. With ESCS and shared ICT experience as covariates, ICTUSE and ICTAVB were negatively associated with mathematics and science scores in both of the example countries. Unlike the other two latent predictor variables, ICTCOMF was positively associated with mathematics and science scores in both countries. For the second research question, using the Alignment method revealed that, for the 47 participating countries, ICT was not measurement invariant. However, the mathematics and science plausible values were measurement invariant.

Chapter 6: Discussion

6.1 Structural Equation Models

Research Question 1: To what extent does ICT help or hinder students' mathematics and science learning in Bulgaria and Finland, respectively, two countries with different ICT profiles, when controlling for students' socio-economic status? Specifically, is more access to ICT associated with worse mathematics and science performance in each country?

The purpose of the SEM CFAs were to assess the impact of various aspects of ICT on mathematics and science achievement for 15-year-old students in Bulgaria and Finland. It is important to understand how the ICT, mathematics, and science relationships vary within the context of the cultural technological landscape of that country, especially as results suggest that the models account for different amounts of variation according to country. For instance, the SEM CFA models created here can explain more of the variation in mathematics and science scores for Bulgaria than Finland . The present findings suggest that there are both helpful and harmful possibilities for ICT in relation to education. In both countries, a student's perceived competence and autonomy, use in conversation, and ICT interest were positively associated with higher mathematics and science scores, while the use and availability of ICT at home and at school for schoolwork or entertainment were found to negatively associated with mathematics and science scores. The current study adds to the existing literature by providing supporting evidence that increasing a student's exposure and use of ICT at home and at school may have a negative impact on their academic achievement. Also, the present study found that students from both countries who are more autonomous, independent, competent, and use ICT more in their social interactions were associated with higher mathematics and science scores. Cultural constructivism might explain some of these results because of the disparity of the findings between the two countries. Specifically, it is likely that cultural differences led to unequal amounts of variation accounted for in the Bulgarian models. Furthermore, the ICTCOMF findings are supported by both social-cognitive theory (Bandura, 1986) and self-determination theory (Ryan & Deci, 2000) that emphasize the relationships of performance with individuals' sense of autonomy, relatedness, competence, and confidence in their own abilities to successfully perform a behaviour. Indeed, researchers have associated a range of affordances for ICT use in mathematics and science education, with ICT promoting innovations in four major ways: cognitive acceleration, range of experience, self-management, and data collection and presentation (Webb, 2005). Moreover, the physical attributes of the learning environment could alter students' sense of autonomy in relation to ICT (Zandvliet, 2012). In essence, both teachers and parents need to gain a deeper understanding of the learning environments as well as students' self-regulated learning processes when using ICT to support student learning.

The current research shows both positive and negative associations between ICT and academic scores, which is consistent with the trend of mixed results previously discussed in *Chapter 3*. Findings indicated ICTCOMF (i.e., greater comfort and familiarity with ICT) was associated with increased mathematics and science scores across both Finland and Bulgaria. This partly aligns with the results from Hu et al. (2018) where higher interest, perceived autonomy, and perceived competence around ICT were associated with higher mathematics and science scores. Zhang and Liu (2016) also reported a positive relationship between mathematics and science scores with ICT competence throughout several iterations of PISA. Similar to the findings of Bulut and Cutumisu (2018), the current study revealed that ICTAVB and ICTUSE were not beneficial to mathematics and science scores. Petko et al. (2017) studied the impact of ICT use on mathematics and science scores. Their results are generally in concordance with the current findings. In contrast, they found that top-performing countries with students who use more ICT at home also achieved higher scores. A positive relationship between ICT use at home and scores was expected in Finland but not in Bulgaria. Instead, the present results showed a negative relationship in both countries. There were no large-scale differences between the two target countries in the current study other than varying strengths of the predicting variables or the percentages of science score variance accounted for by each model.

In contrast to Bulut and Cutumisu's (2018) findings, results from the current research yielded significant relationships between ICT availability and academic achievement. Similarities with Meng et al. (2018) began and ended with AUTICT results. The current research found a positive relationship for the ICTCOMF latent variable, contrasting the SOIAICT negative relationship findings from Hu et al. (2018) or Meng et al. (2018). Contrary to the current findings, Meggiolaro (2018) reported a positive association between ICT use and mathematics.

Similarities between Bulgaria and Finland included the increase in ICTUSE and ICTAVB associated with lower mathematics and science scores. This aligned with Hu et al. (2018) for USESCH and ICTHOME, but not for HOMESCH, ENTUSE or ICTSCH, which revealed no relationship to mathematics scores. Petko et al. (2017) found similar negative associations for ICT use at school and ICT use for entertainment, while they also found ICT use for homework was positively associated with higher mathematics achievement. Bulut and Cutumisu (2017) found that ICT availability was not associated with mathematics scores in Finland, but was positively associated in Turkey, suggesting that the availability of ICT devices to students has different effects depending on the cultural context of technology in their country. In other studies, researchers have found positive, negative, and null associations with many of the ICT subscales and academic scores.

Interestingly, PISA reports a small correlation between increased ICT use and better mathematics performance from 2012 to 2015 for 38 countries and economies (OECD, 2016). However, this did not account for differences in demographics or other possible confounds, including general levels of mathematics achievement in each country.

As ICT has become ubiquitous in the classrooms and in students' homes, the present study contributes to clarifying the role of several ICT variables to uncover their effects on students' academic achievement learning. This endeavor is important, as findings signal that ICT is currently not used to its full potential for learning and innovation, despite becoming essential in every sector of the economy of the 21st century.

An explanation for the association of ICT use and ICT availability with lower academic scores is that, perhaps, ICT use is a distraction for students who may also spend a lot of time engaging in activities at the expense of classroom learning. It could also be that students may be using technology for its own sake, rather than to support and uplift their learning (Martin-Perpiñá, Viñas i Poch, & Malo Cerrato, 2019; Naumann, 2015). Previous research has found that ICT can be misused by students and can result in deleterious effects for learning. Students who text and use social media take 62% fewer notes than other students and perform worse on a memory recall test (Kuznekoff & Titsworth, 2013). Moreover, students who take notes using ICT often fail to condense and catalogue new information (Mueller & Oppenheimer, 2014). In addition, laptop note takers perform worse on assessments and do not achieve a deeper understanding when compared to students who take notes by hand (Mueller & Oppenheimer, 2014). Another explanation could be that these students are unfamiliar with ICT and, thus, they spend more time learning how to use it rather than actually using it to advance their learning.

Turning to the current results regarding ICT comfort, it is possible that comfort with technology leads to better academic achievement, as students who enjoy using ICT and are comfortable with it are more likely to seek opportunities to use ICT as a tool to learn mathematics and science in class and to advance their education. This echoes Lee and Wu's (2012) positive correlation findings among ICT enjoyment, reading literacy, and engagement from the 2009 PISA data. Similarly, Singer (2015) found that teachers reported improved students' attitudes and productivity following an implementation of an iPad program in elementary mathematics classes. As students become more comfortable with ICT, it is possible that they become better prepared to use the ICT that is available to them to effectively learn the class material. These results make sense in light of SDT because students who are more comfortable and capable performing ICT tasks can better fill their three basic psychological needs of competence, autonomy, and relatedness. Students who scored highly on these aspects, measured by the PISA *ICT Familiarity Questionnaire* (OECD, 2014) and represented as *ICT comfort* in this study, are better able to use ICT to construct the necessary content knowledge to increase their achievement. Vygotsky's theory of social development (1978) is also reinforced here, as the communication and sharing aspect around ICT comfort, including ICT as a topic in social conversation, predicts higher mathematics scores. The inclusion of ICT as a topic in social interactions may solidify the learning process. Moreover, without the skills to use ICT effectively, more availability and use become detrimental to academic achievement. In part, this could be due to spending more time trying to learn these skills instead of class content or being distracted by ICT. However, the inverse is also a possibility: students who are proficient in mathematics or science may be drawn to using more ICT, for general use or classroom problem solving, and are thus more comfortable with it. Based on these results, it seems that if students are more comfortable with ICT, they are able to use it better and improve their mathematics and science achievement as a result.

Teaching for innovation is an intentional process and teacher preparation cannot be compensated by a technologically-rich learning environment. Teachers who embed technology in their instruction reinforce their pre-existing practices (Cuban, 2001). Finally, it could be that the pervasiveness of ICT precludes students from engaging in deeper problem-solving activities, as they can find most answers readily available online through web searches or by posting questions on social media. These results are in concordance with findings showing that ICT in a middle-school classroom restricted rather than promoted inquiry, as the mere presence of computers detracted from meaning-making activities, focusing students on individual accountability (Waight & Abd-El-Khalick, 2007).

Taken together, these results suggest the possibility that ICT that is not meaningfully integrated into students' learning, either at school or at home, is in fact hindering their mathematics and science learning. Information about teachers' lesson plans and pedagogy was not available in the PISA data but it could shed more light onto these findings. Specifically, more information on students' and teachers' views on technology within their particular learning environments may shed more light onto their perceived effectiveness for learning. It is vital to understand that teachers are unable to teach what they do not know, this is coined as the Peter Effect (Applegate & Applegate, 2004). This was first explained as teachers being unable to convey the importance of reading to their students if they did not appreciate reading. This was then extrapolated to teachers in the subject of the english language (Binks-Cantrell, Washburn, Joshi, and Hougen, 2012) and phonological awareness (Hayward, Phillips, & Sych, 2014). This theory could further extend to ICT. Where, if teachers are not competent and autonomous in their ICT use, they would be unable to effectively pass ICT comfort to their students.

Interestingly, the relationship between academic scores and available ICT for Finnish students was not significant before controlling for ESCS. However, this relationship became negatively significant after controlling for ESCS. One possible reason is that ESCS and technology may have a strong theoretical connection which would result in ESCS influencing the analysis if not controlled. Therefore, similarly to previous work (Hu et al., 2018; Meggiolaro, 2018; Petko, Cantieni, & Prasse, 2017; Luu & Freeman, 2011), ESCS was included as a control variable in the present research. The same pattern of results emerged after controlling for ESCS between Finland, a Digital Frontrunner, where the majority of students have wide access to a variety of technologies, and Bulgaria, a Digital Challenger, where most students do not have as many devices at their fingertips. This suggests that the "digital divide" encompassing the *global* (i.e., the Internet access gap between industrialized and developing societies), *social* (i.e., the information gap between a nation's rich and poor), and *democratic* (i.e., the digital resource use gap in civic engagement) divide may not be a factor when it comes to students' mathematics and science performance (Norris, 2001). Although they are different in terms of ICT, Bulgaria and Finland are two countries that belong to the European Union, where a lot of programs support teaching and learning in the digital era. Also, young people are now well anchored in social media around the world, actively participating in society as well as producing and consuming information. Perhaps changing the way available technology is used to teach mathematics and science may yield different results in future PISA administrations. Targeted pedagogy with technology programs offered by the European Union could contribute to diminishing the deleterious effects of ICT use and availability on students' academic performance. It is also possible that these results could change when controlling for some of the demographic variables collected via the PISA assessment and that factors such as ICT autonomy and interest could be culturally mediated (Zandvliet, 2012).

6.2 Alignment

Research Question 2: Are the ICT, science, and mathematics variables measurement invariant across the countries participating in the PISA ICT questionnaire? As outlined in the *Results* chapter, the ICT predictor variables displayed a large amount of non-invariance according to the Alignment output. The factor loadings of ICTHOME, HOMESCH, ICTSCH, and COMPICT were the only predictors that fell below the acceptable cutoff, which means that they would be the most trustworthy and useful in comparing means across all the participating countries. However, only the factor loadings of these four items are measurement invariant, meaning strong invariance cannot be established and factor means can not be compared (Millsap, 2012). The other five indicators are not invariant across the participating countries, which means that they cannot be compared as well. It is possible that these ICT predictors do not measure the same constructs in these vastly different countries. However, this does not mean that these countries cannot be compared by their ICT predictors. As a group, the ICT profiles of these 47 countries are not similar enough to be compared or to trust that their scales are measuring the same constructs. Alternatively, if the countries were organized into subgroups based on their similar cultural involvement with technology, then the PISA representation of ICT may be measurement invariant. This could result in organizing countries based on their place on the Frontrunner-Challenger scale. If more similar countries are compared, then measurement invariance could be established.

Conversely, the mathematics and science plausible values had very low levels of non-invariance across 48 countries. As a result, both mathematics plausible values and science plausible values can be reliably compared across countries. Therefore, when comparing the countries on a scale, based on the means of their plausible values, these results can provide the confidence that they represent the same knowledge constructs despite being measured in culturally different countries. It is important to note the contrast in measurement invariance between the mathematics and science outcome variables and the ICT scales. The mathematics and science questions and scales have received more attention since the inception of PISA as compared to the *ICT Familiarity Questionnaire* that was added in 2003 (OECD 2003, 2005, 2014a, 2017). The main difference, however, is that the ICT scale tests a construct that is more directly linked to culture than the more homogenous mathematics and science knowledge.

6.3 Limitations

Several limitations of the CFA and the Alignment methods, as well as the research design and source of data of the current research are discussed. Given that the PISA data are self-reported for the ICT indicator variables, they are subjective and may not accurately represent the true scores of the students. Aboriginal and special needs students are frequently under-sampled in the PISA assessments which may lead to an inaccurate representation of a country's population (Richard, 2018; LeRoy, Samuel, Deluca, & Evans, 2019).

The CFAs only considers two of the 72 countries that participated in PISA 2015. As a result, limited generalizations can be made until more populations are assessed and more in-depth analyses are conducted. Of the participating countries, only 47 completed the *ICT questionnaires*. Further analysis of the ICT data for all 72 countries could add to the collective understanding of the relationship between ICT and academic achievement.

As with any correlational research in social sciences, other variables may have had an effect on the outcome of the current results but causality could not be determined using the PISA data. For example, it is possible that particular ICT habits cause a change in students' scores, but it is also possible that having a certain score drives ICT involvement.

As the ICT scales are capped, some very highly-rated responses may be restricted to the limit of the scale, thereby causing a ceiling effect. The ICT scales could benefit by extending to higher levels of use and exposure for technologically-advanced countries.

The purpose of the Alignment method (Asparouhov & Muthén, 2014; Marsh et al., 2018) as an exploratory tool constitutes one of the limitations of this work. Specifically, covariates and cross loadings cannot be included and path estimates cannot be calculated, restricting the Alignment method to an exploratory method.

6.4 Implications

The practical and theoretical implications of this research are described in detail in the next subsections. These implications have direct bearing in educational situations and future cross-cultural research on ICT.

The current research draws on cognitive theories of learning, aiming to understand how a broader set of factors beyond country and ICT can affect learning. The current findings shed some light onto the mixed findings of prior research, providing a better understanding of the complex relationship between ICT and students' mathematics and science proficiency. These results can be paired with Piaget's constructivist theory (1952), which posits that children are active rather than passive learners because they are able to guide their own learning processes. Similarly, students take ownership of their learning processes, especially in environments that foster their comfort and enjoyment of ICT, to create new knowledge in the subjects of mathematics and science. If students are comfortable with ICT, then it is likely that they are able to use their prior knowledge to build upon their knowledge in class. Because the majority of ICT predictors were non-invariant, it appears that technology is treated differently depending on the country. These could be due to different cultural relationships with technology or nuanced differences in measuring these interactions with technology. Either way, ICT interactions cannot be broadly compared across large groups of countries. Conversely, mathematics and science scores are measurement invariant and can be compared across countries when measured by PISA. This implies that mathematics and science learning is either more universal than ICT or more effort was put into the design of those measures.

The findings offer ways to improve the instructional effectiveness of technology for mathematics. For instance, mathematical computer-based games and simulations have been found to enhance mathematics ability in a meta-analytic study compared to conventional media (Mayer, 2018). These technology-infused interventions can improve relevant cognitive skills and student learning. Thus, more effort could be invested in training educators on the most effective forms of ICT as well as on integrating technology into their pedagogy. Mathematics and science models were mirrored throughout the current analysis, which indicates that these results can be more broadly generalized to STEM education. According to these results, mathematics and science proficiency are affected similarly by interactions with ICT and are comparable across large groups of culturally different countries.

Chapter 7: Conclusions

The goal of this research was to elucidate the relation between ICT and academic achievement in mathematics and science in two countries with opposite ICT profiles, as well as the level of measurement invariance of ICT, mathematics, and science from PISA for the selected countries. To explain the relation between Finnish and Bulgarian students' ICT and their scores in mathematics and science, an EFA was used to inform the design of a CFA. The nine ICT subscales were organized into ICT use, ICT availability, and ICT comfort as the latent predictor variables that explained the latent dependent variable made up of either mathematics or science plausible values. When ESCS was added as a covariate, mathematics and science scores showed the same relationship with ICT for both countries. ICT use and availability were negatively associated with mathematics and science scores, whereas ICT comfort was positively associated with students' academic scores. To ascertain whether these relationships could be tested in larger groups of countries, the measurement invariance of mathematics, science, and ICT were examined using the Alignment method. Mathematics and science values are measurement invariant and can be compared across all participating countries. However, ICT was not measurement invariant and should be compared in smaller groups.

The findings show that ICT comfort predicts higher mathematics and science achievement in 15-year-old students in two countries with contrasting ICT levels. Thus, it seems that if 15-year-old students in these countries are more comfortable with ICT, they can use it better and improve their academic achievement as a result. The current study also confirmed that an increase in ICT use and availability is negatively associated with mathematics and science scores when ESCS and general ICT are controlled for. Thus, adding more technology into the school system may not necessarily increase students' performance in the classroom, as the present results showed for the 15-year-old students in Bulgaria or Finland. These findings provide an emphasis on the discrepant factors amenable to interventions that may equalize mathematics and science performance across the two countries. In the past, very few studies have connected all nine ICT variables that were included in this study to science performance. So far, only Hu et al. (2018) and Juhaňák et al. (2018) compared scores based on all nine forms of ICT. However, neither study employed structural equation modelling, which makes the contributions of the current research unique and valuable. More steps must be taken so that investments in new technology spaces can benefit areas beyond ICT literacy. Given that the present results also showed a discrepancy in the percentage of explained variance of Bulgarian and Finnish mathematics and science scores, with more variance being accounted for in Bulgarian scores, it is possible that the role of ICT in explaining students' academic performance will diminish as it has in Finland, as Bulgaria transitions to becoming a Digital Frontrunner. Taken together, the results suggest that more in-depth research needs to be conducted into factors that influence students' science performance. Also, there is potential for improving student outcomes under the right ICT conditions. Once the intricate relationship of students' ICT and their academic achievement is understood, tailored changes to how technology is used in schools can be implemented, aiming to minimize the undesirable effects and to maximize the helpful effects of ICT use in education.

The means of all the countries that participated in the PISA *ICT Familiarity questionnaire* cannot be reliably compared because it is possible that the ICT measure is not homogeneous for all countries. Given that measurement invariance of ICT was not established for the group of 47 countries, it may be possible to compare smaller, more similar groups with acceptable measurement invariance. On the other hand, the mathematics and science plausible values that were used as dependent variables were confirmed as measurement invariant across all countries. For instance, the quizzes used to collect the mathematics and science knowledge as well as the IRT methods to determine the plausible values were successful in creating the same scales across differing cultures. Therefore, mathematics and science means can be confidently compared across the countries used in this research.

7.1 Future Directions

The next step in this research is to organize groups of countries with similar ICT profiles that will display measurement invariance for the PISA ICT subscales. Once this is achieved, the AwC method can be used to obtain estimated means and model estimates because comparing multiple countries simultaneously to assess the relation between ICT and academic achievement may present a methodological challenge. To address this challenge, more complex methods such as AwC are required to optimally perform this complex analysis (Marsh et al., 2018). In the future, the Alignment within CFA (AwC) method will be used instead of the Alignment methods to address this limitation, as it offers a confirmatory aspect to measurement invariance testing. The AwC approach can be used to extend the Alignment method used in SEM analyses into a confirmatory tool to address a multitude of issues such as covariates and latent variable relationship estimates, as it is a combination between the Alignment and CFA methods (Marsh et al., 2018). As the Alignment method only deals with variance and means of factors, the AwC method allows for regression estimation of multiple groups. This method can test for measurement invariance across populations using the relaxed-fit style of the Alignment method and it can also provide model estimations. The AwC model has the same degrees of freedom, goodness of fit, and parameter estimates as the Alignment model, but it acts as a CFA method. Furthermore, once the PISA 2018 data is made public, this analysis can be replicated to monitor any change in ICT variables, academic scores, and their associations. Future studies will focus on research involving adolescents, exploring the relationship between ICT and academic achievement in more ecologically-valid settings. With the results of ICT comfort positively associated with mathematics and science scores, an ensuing research question could be whether or not ICT comfort acts as a moderator between academic achievement and ICT use or availability. These effects seem to be more prominent in low technology countries compared to high technology countries.

7.2 Chapter Summary

The present research found that comfort in ICT use is the most important positive ICT predictor for higher mathematics and science scores. Concomitantly, mathematics and science were measurement invariant across 48 PISA 2015 countries, whereas ICT was not across the subset of countries that participated in the ICT Familiarity Questionnaire. The current results, limitations, and suggestions will inform future researchers and will serve as a starting point into ascertaining whether ICT holds similar relationships with academic achievement in other countries.

Figures

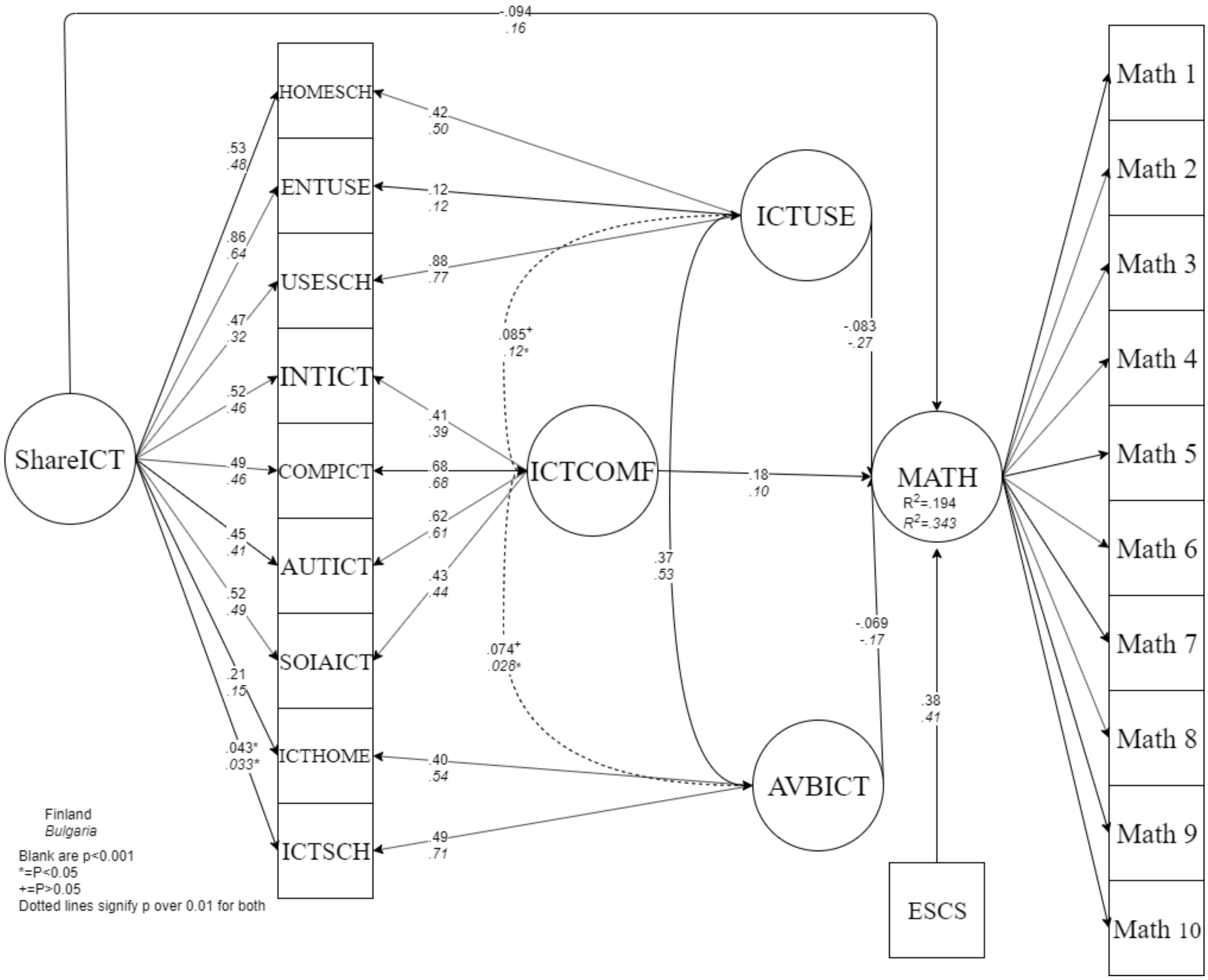

Figure 1. Bifactorial Structural Equation Model of ICT and Mathematics for Both Finland and Bulgaria with ESCS as a Covariate.

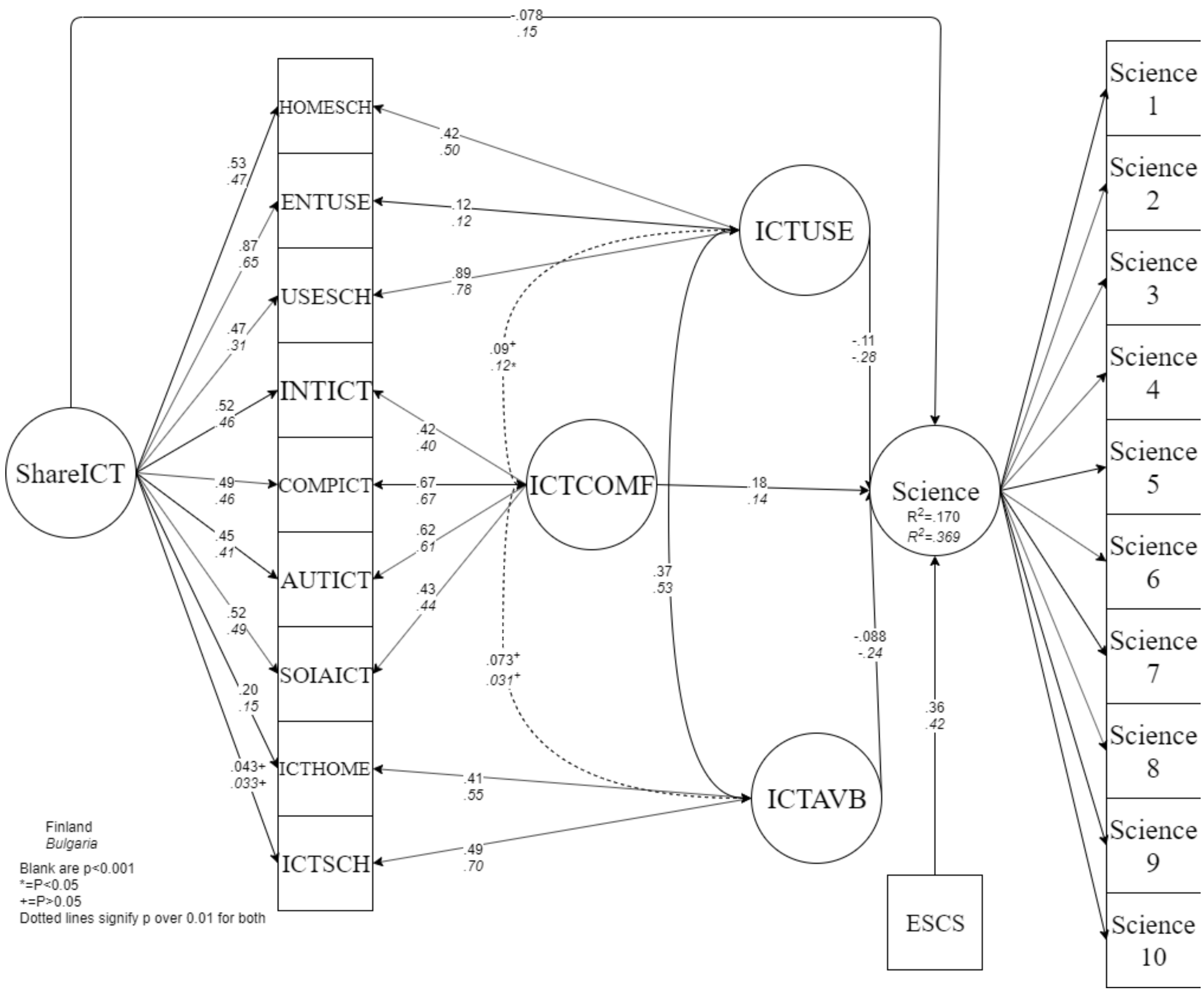

Figure 2. Bifactorial Structural Equation Model of ICT and Science for Both Finland and Bulgaria with ESCS as a Covariate.

Tables

Table 1

Articles Included in the Literature Review.

Reference	APA Reference of Reviewed Articles
[1]	Petko, D., Cantieni, A., & Prasse, D. (2017). Perceived quality of educational technology matters: A secondary analysis of students' ICT use, ICT-related attitudes, and PISA 2012 test scores. *Journal of Educational Computing Research, 54*(8), 1070-1091.
[2]	Hu, X., Gong, Y., Lai, C., & Leung, F. K. (2018). The relationship between ICT and student literacy in mathematics, reading, and science across 44 countries: A multilevel analysis. *Computers & Education, 125*, 1-13.
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Table 2

Relationships Between ICT and Scores in Mathematics and Science for the Articles Included in the Literature Review.

ICT	Math			Science		
	Positive	**Negative**	**Null**	**Positive**	**Negative**	**Null**
HOMSCH	[1] ([4] ITA) ([10] CHC) ([17] EUR-low use)	[9] ([16] QCN) ([17] EUR-mid,high use) ([18] ESP) ([19 EUR)	[2] ([6] FIN, TUR) ([14] CZE) ([16] KOR)	([1] high score countries) ([7] Czech mid use)([17] EUR-low use)	[2][1] ([5] AUS)[9] ([14] CZE) ([17] EUR-mid,high use) ([18] ESP) ([19] EUR)	([5] CAN) ([6] FIN, TUR)
USESCH	([4]ITA) [12] ([17] EUR-low use)	[1] [2] ([6] FIN, TUR) [9] ([15] ESP) ([16] QCN, KOR) ([17] EUR-mid, high use) ([18] ESP) ([22] ESP)	([10] CHC) ([14] CZE)	([5] CAN, browse Internet) ([17] EUR-low use)	[2][1] ([5] CAN, frequent use, AUS) ([6] FIN, TUR) [9] ([15] ESP) ([17] EUR-mid, high use) ([18] ESP) ([22] ESP)	([5] CAN) ([14] CZE)
ENTUSE	([4] ITA) ([1] low score countries) ([6] TUR)([17] EUR-low use) ([20] TUR)	([1] high score countries) ([6] FIN) [9] ([16] QCN, KOR) ([17] EUR-high use) ([18] ESP) ([22] ESP)	[2] ([14] CZE) ([17] EUR-mid use)	[2] ([5] CAN, AUS, browse Internet) ([6] TUR) ([17] EUR-low use)	[1] ([5] CAN, frequent use, AUS most use) ([6] FIN) ([17] EUR-high use) ([18] ESP) ([22] ESP)	[9] ([14] CZE) ([17] EUR-mid use)
ICTHOME	([6] TUR) ([21] Tur) ([22] ESP)	[2] ([10] CHC) ([18] ESP)	([6] FIN) ([14] CZE)	([6] TUR) ([11] USA) ([21] Tur)([22] ESP)	[2] ([14] CZE) ([18] ESP)	([6] FIN)
ICTSCH	([6] TUR)([22] ESP)	([12] eBook readers) [13] ([18] ESP)	[2] ([6] FIN) ([10] CHC) ([14] CZE)	([6] TUR)([22] ESP)	([12] eBook readers) [13] ([18] ESP)	[2] ([6] FIN) [11] USA) ([14] CZE)
INTICT	[2] ([3] QNC) ([12] Internet) ([18] ESP)	([3] DEU) ([14] CZE mod by gender)	([14] CZE)	[2] ([3] QNC) ([18] ESP)	([3] DEU)	([14] CZE)
COMPICT	[2] [8] ([12] unfamiliar device) ([18] ESP) ([22] ESP, attitudes and skill)	([3] QNC)	([3] DEU) ([14] CZE)	[2] ([5] CAN, AUS, basic skills, presentation software) ([8] 2009) [11] USA, writing papers) ([18] ESP) ([22] ESP, attitudes and skill)	([3] QNC)	([3] DEU) [7] ([11] USA, general use, test taking) ([14] CZE)
AUTICT	[2] ([3] QNC, DEU) ([15] ESP) ([14] CZE) ([18] ESP)	-	-	[2] ([3] QNC, DEU) ([15] ESP) ([14] CZE) ([18] ESP)	-	-

SOIAICT	([18] ESP)	[2] ([3] QNC, DEU) ([14] CZE) ([15] ESP)	-	([18] ESP)	[2] ([3] QNC, DEU) ([14] CZE) ([15] ESP)	-

Note: AUS - Australia; CAN - Canada; QCN - China; CZE - Czech Republic; EUR - European; FIN - Finland; DEU - Germany; ITA - Italy; KOR - Korea; ESP - Spain; TUR - Turkey; CHC - Confucian Heritage Culture (Hong Kong, Japan, Korea, Macau, Shanghai, Singapore, and Taipei).

Table 3

PISA Iterations Used by the Studies in the Literature Review.

PISA Year/ Iteration	**2000**	**2003**	**2006**	**2009**	**2012**	**2015**
Single iteration used	[11]		[5] [7]	[21] [22]	[1] [4] [6] [9] [19] [20]	[2] [3] [12] [14] [15] [16] [17] [18]
Multiple iterations used	[8]	[8] [13]	[8] [13]	[8] [13]	[8] [13]	[13]

Table 4

Observed Predictor Variables from the PISA 2015 ICT Familiarity Questionnaire (OECD, 2017b).

Measure	Description	Example
HOMESCH	ICT use outside of school for school work	"Browsing the Internet for schoolwork" and "Doing homework on a computer"
ENTUSE	ICT use outside of school for leisure	"Playing collaborative online games" and "Downloading music, films, games or software from the Internet"
USESCH	General ICT use at school	"Playing simulations at school" and "Using school computers for group work and communication with other students"
INTICT	The student's personal interest and enjoyment of ICT	"I am really excited discovering new digital devices or applications" and "I really feel bad if no Internet connection is possible"
COMPICT	The student's perceived competence with ICT	"When I come across problems with digital devices, I think I can solve them" and "If my friends and relatives want to buy new digital devices or applications, I can give them advice"
AUTICT	The student's perceived Autonomy related to ICT use	"I use digital devices as I want to use them" and "If I need a new application, I choose it by myself"
SOIAICT	Use of ICT as a topic in the student's social interaction	"I like to meet friends and play computer and video games with them" and "I learn a lot about digital media by discussing with my friends and relatives"
ICTHOME	Availability of ICT at home	"Desktop computer" and "Internet connection"
ICTSCH	Availability of ICT at school	"Data projector, e.g. for slide presentations" and "Interactive whiteboard"

Table 5

Analysis Methods Used by the Studies in the Literature Review.

Statistical Method/ Country	HLM	SEM	MLR	Logistic regression	EFA	Linear regression	CHAID	Path analysis	IEA international database analyzer	Data Mining	Propensity score matching	Instrumental variable analysis	ANOVA
Australia	[5]				[5]								
Canada	[5]				[5]								
China		[3]						[16]	[16]				
CHC*	[10]												
Czech Republic	[14]												[7]
Finland		[6]											
Germany		[3]											
Italy			[4]										
Korea								[16]	[16]				
Spain			[15]	[15]		[22]				[18]			
Turkey	[21]	[6]	[20]										
United States of America						[11]							
Europe			([17] 25)								([19] 12)	([19] 12)	
PISA 2000 all	[8]												
PISA 2003 all	[8]												
PISA 2006 all	[8]												
PISA 2009 all	[8]												
PISA 2012 all	[8] ([9] 39)		([1] 39)										
PISA 2015 all	([2] 44)					([13] 30)	([12] 35)						

Note: For multi-country studies, the number of countries sampled by each reference is included in parentheses following the reference.

Table 6

Skewness, Kurtosis, Valid, and Missing values for Finland and Bulgaria.

		HOMESCH	ENTUSE	USESCH	INTICT	COMPICT	AUTICT	SOIAICT	ICTHOME	ICTSCH
BGR	Skew.	.44	.69	.65	.40	.01	.40	.09	-.54	-.13
	Kurt.	**2.10**	**4.14**	1.17	1.19	0.40	0.39	0.68	0.12	-0.82
	Valid	4831	4986	4841	4766	4690	4705	4584	4719	4551
	Mis.	1097	942	1087	1162	1238	1223	1344	1209	1377
FIN	Skew.	.30	1.53	1.15	.56	.17	.23	.23	-.68	-.87
	Kurt.	**2.99**	**10.50**	**5.88**	**2.30**	0.56	0.50	0.81	0.84	0.87
	Valid	5464	5547	5480	5441	5407	5398	5374	5281	5254
	Mis.	418	335	402	441	475	484	508	601	628

Note: **Bolded** values indicate kurtosis above the acceptable range of [-2, 2].

Table 7

Geomin Rotated Loadings.

	Bulgaria				Finland			
Number of Factors	1	2	3	4	1	2	3	4
HOMESCH	**.82***	-.01	.16*		**.68***	-.04*	.18*	
ENTUSE	**.54***	.27*	-.011*		**.48***	.34*	-.01	
USESCH	**.54***	.02	.32*		**.67***	.04*	.18*	
INTICT	.16*	**.60***	-.046*		.19*	**.55***	-.13*	
COMPICT	-.009	**.84***	.007		-.02	**.82***	.05	
AUTICT	-.01	**.74***	.13*		-.02	**.77***	-.01	
SOIAICT	.17*	**.54***	.15*		.16*	**.60***	.066*	
ICTHOME	.08*	.006	**.51***		.007	.12*	**.40***	
ICTSCH	-.003*	-.15*	**.76***		.01	-.004	**.48***	
EIEGENVALUES	3.50	1.58	**.99**	.66	3.29	1.50	**.99**	.77

Note: Eigenvalues are included to show that a three-factor model is the strongest solution.
*p<0.05, bolded is final factor grouping.

Table 8

Cronbach's Alpha (α) Values for Bulgaria and Finland Calculated by PISA (OECD, 2017b).

	Bulgaria	Finland
HOMESCH	.95	.92
ENTUSE	.87	.80
USESCH	.93	.85
AUTICT	.88	.84
COMPICT	.87	.85
SOIAICT	.87	.85
INTICT	.85	.79

Note: A value of 1 signifies perfect internal consistency, while a value of .7 indicates acceptable internal consistency. For the α of other countries, see the PISA 2015 Theoretical Report (OECD, 2017b)

Table 9

Correlation Matrix of Bulgaria with Means and Standard Deviations of All Observed Predictor Variables and the Latent Dependent Variables.

Bulgaria	1	2	3	4	5	6	7	8	9	10
1.HOMESCH										
2.ENTUSE	.54***									
3.USESCH	.57***	.39***								
4.INTICT	.30***	.41***	.26***							
5.COMPICT	.28***	.38***	.23***	.58***						
6.AUTICT	.27***	.37***	.23***	.43***	.63***					
7.SOIAICT	.37***	.37***	.32***	.44***	.50***	.53***				
8.ICTHOME	.24***	.15***	.26***	.06**	.09***	.18***	.14***			
9.ICTSCH	.19***	.03	.30***	3.24	-.03	.04**	.1***	.39***		
10.MATH	-.1***	.07***	-.20***	.15***	.18***	.17***	.003	-.07***	-.20***	
11.SCIENCE	-.10***	.07***	-.24***	.16***	.19***	.18***	.01	-.08***	-.22***	
Unstandardized Mean	.41	.33	.41	-.14	-.042	-.14	.22	8.15	6.03	0
SD	1.22	1.39	1.20	1.16	1.02	1.04	1.00	2.20	2.76	89.92

**p*<.05, ***p*<.01, ****p*<.001

Table 10

Correlation Matrix of Finland with Means and Standard Deviations of All the Observed Predictor Variables and the Latent Dependent Variables.

Finland	1	2	3	4	5	6	7	8	9	10
1.HOMESCH										
2.ENTUSE	.40***									
3.USESCH	.57***	.44***								
4.INTICT	.17***	.39***	.24***							
5.COMPICT	.17***	.38***	.22***	.49***						
6.AUTICT	.12***	.36***	.20***	.43***	.63***					
7.SOIAICT	.28***	.40***	.22***	.39***	.54***	.50***				
8.ICTHOME	.18***	.17***	.19***	.06**	.14***	.10***	.16***			
9.ICTSCH	.20***	.09***	.21***	.02	.06**	.02	.07***	.21***		
10.MATH	-.02	-.04*	-.076***	.08***	.11***	.13***	.006	-.17	.01	
11. SCIENCE	-.05**	-.06***	-.11***	.08***	.08***	.13***	.00	-.06***	.01	
Unstandardized Mean	-.52	.04	.11	-.12	-.09	.14	.12	8.67	6.92	70.26
SD	0.95	0.86	0.74	0.91	0.91	0.91	0.93	1.57	2.14	75.97

*$p<.05$, **$p<.01$, ***$p<.001$

Table 11

List of the 48 Countries Included in the Analysis, with Latent Class Label, Country ID, and Three-Letter Code.

Latent Class	CNTRID	Country
1	36	AUS
2	40	AUT
3	56	BEL
4	76	BRA
5	100	BGR
6	152	CHL
7	158	TAP
8	170	COL
9	188	CRI
10	191	HRV
11	203	CZE
12	208	DNK
13	214	DOM
14	233	EST
15	246	FIN
16	250	FRA
17	276	DEU
18	300	GRC
19	344	HKG
20	348	HUN
21	352	ISL
22	372	IRL
23	376	ISR
24	380	ITA

Latent Class	CNTRID	Country
25	392	JPN
26	410	KOR
27	428	LVA
28	440	LTU
29	442	LUX
30	446	MAC
31	484	MEX
32	528	NLD
33	554	NZL
34	604	PER
35	616	POL
36	620	PRT
37	643	RUS
38	702	SGP
39	703	SVK
40	705	SVN
41	724	ESP
42	752	SWE
43	756	CHE
44	764	THA
45	826	GBR
46	858	URY
47	970	QCH
48	971	QES

Table 12

Global Model Fit for the Three Steps in the SEM Analysis.

Step	Model Subject	SRMR	RMSEA	CFI	TLI
2	Mathematics	.05	.04	.98	.98
	Science	.06	.04	.98	.98
3	Mathematics	.05	.03	.99	.99
	Science	.04	.03	.99	.99
4	Mathematics	.05	.04	.98	.98
	Science	.05	.04	.99	.99

Note: All cases display good model fit.

Table 13

Standardized Regression Model Results for the Second, Third, and Fourth Step of the SEM.

Subject	Country	Step	ICTUSE	ICTCOMF	ICTAVB	Rsquare
Mathematics	Bulgaria	2	-.23***	.33***	-.17***	.126
		3	-.36***	.16***	-.005	.192
		4	-.27***	.10***	-.17***	.343
	Finland	2	-.20***	.21***	.06	.04
		3	-.07***	.20***	.002	.05
		4	-.083***	.18***	-.069***	.194
Science	Bulgaria	2	-.25***	.36***	-.19***	.154
		3	-.34***	.18***	-.079	.222
		4	-.26***	.14***	-.24***	.369
	Finland	2	-.23***	.22***	.03	.05
		3	-.1***	.20***	-.009	.05
		4	-.11***	.18***	-.088***	.17

Note: Mathematics and Science latent dependent variables are regressed onto the latent ICT predictor variables.
*p < .05, **p < .01, ***p < .001

Table 14

R-square and Non-Invariance Percentage Values for the 9 ICT Scales from the Alignment Method.

	R-Square	% non-invariant factor loadings	% non-invariant intercept
ENTUSE	.10	25.5	66.0
SOIAICT	.16	51.1	87.2
AUTICT	.25	46.8	70.2
ICTSCH	.30	14.9	42.6
USESCH	.67	87.2	85.1
INTICT	.76	44.7	66.0
HOMESCH	.78	12.8	72.3
COMPICT	.83	23.4	85.1
ICTHOME	.94	6.4	42.6

Note: *R-Square* values closer to 1 indicate more invariance, while a value close to 0 indicates less invariance for that parameter. A higher percentage indicates more non-invariance for that parameter. The ICT items are arranged from smallest to largest *R-Square* value.

Table 15

Mean Comparison of the MATH Latent Variable for 48 Included Countries from the Alignment Model.

Rank	Country	Factor Means	Rank	Country	Factor Means	Rank	Country	Factor Means
1	SGP	1.23	17	IRL	0.49	33	LTU	0.18
2	HKG	1.03	18	AUT	0.40	34	HUN	0.16
3	MAC	0.98	19	NZL	0.38	35	SVK	0.14
4	TAP	0.96	20	RUS	0.37	36	ISR	0.07
5	JPN	0.84	21	SWE	0.37	37	HRV	0.00
6	QCH	0.82	22	AUS	0.37	38	GRC	-0.13
7	KOR	0.74	23	FRA	0.35	39	BGR	-0.28
8	CHE	0.70	24	GBR	0.35	40	CHL	-0.51
9	EST	0.68	25	CZE	0.35	41	URY	-0.56
10	NLD	0.59	26	PRT	0.34	42	THA	-0.60
11	DNK	0.58	27	ITA	0.31	43	MEX	-0.69
12	FIN	0.58	28	ISL	0.29	44	CRI	-0.78
13	SVN	0.56	29	QES	0.27	45	COL	-0.91
14	BEL	0.53	30	ESP	0.27	46	PER	-0.95
15	DEU	0.51	31	LUX	0.27	47	BRA	-1.07
16	POL	0.50	32	LVA	0.22	48	DOM	-1.67

Table 16

Mean Comparison of the SCIENCE Latent Variable for 48 Included Countries from the Alignment Model.

Rank	Country	Factor Means	Rank	Country	Factor Means	Rank	Country	Factor Means
1	SGP	0.63	17	IRL	0.00	33	HRV	-0.32
2	JPN	0.42	18	BEL	-0.01	34	LTU	-0.32
3	EST	0.37	19	DNK	-0.01	35	ISL	-0.35
4	TAP	0.35	20	POL	-0.01	36	ISR	-0.42
5	FIN	0.33	21	PRT	-0.02	37	SVK	-0.49
6	MAC	0.31	22	AUT	-0.09	38	GRC	-0.56
7	HKG	0.25	23	FRA	-0.09	39	CHL	-0.65
8	QCH	0.18	24	QES	-0.09	40	BGR	-0.67
9	KOR	0.16	25	SWE	-0.11	41	URY	-0.79
10	NZL	0.13	26	CZE	-0.11	42	THA	-0.96
11	SVN	0.12	27	ESP	-0.11	43	CRI	-0.98
12	AUS	0.09	28	LVA	-0.15	44	COL	-1.02
13	GBR	0.08	29	RUS	-0.19	45	MEX	-1.02
14	DEU	0.08	30	LUX	-0.23	46	BRA	-1.20
15	NLD	0.07	31	ITA	-0.26	47	PER	-1.25
16	CHE	0.04	32	HUN	-0.30	48	DOM	-2.01

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Appendices

Appendix A

ICT questions taken from 2015 PISA *ICT Familiarity Questionnaire* which are used to determine the predictor variables (OECD, 2017b).

ICTHOME: ICT available at home

IC001 Are any of these devices available for you to use at home?

(Please select one response in each row.)

		Yes, and I use it	*Yes, but I don't use it*	*No*
IC001Q01TA	Desktop computer	☐1	☐2	☐3
IC001Q02TA	Portable laptop, or notebook	☐1	☐2	☐3
IC001Q03TA	<Tablet computer> (e.g. <iPad®>, <BlackBerry® PlayBook™>)	☐1	☐2	☐3
IC001Q04TA	Internet connection	☐1	☐2	☐3
IC001Q05TA	<Video games console>, e.g. <Sony® PlayStation®>	☐1	☐2	☐3
IC001Q06TA	<Cell phone> (without Internet access)	☐1	☐2	☐3
IC001Q07TA	<Cell phone> (with Internet access)	☐1	☐2	☐3
IC001Q08TA	Portable music player (Mp3/Mp4 player, iPod® or similar)	☐1	☐2	☐3
IC001Q09TA	Printer	☐1	☐2	☐3
IC001Q10TA	USB (memory) stick	☐1	☐2	☐3
IC001Q11TA	<ebook reader>, e.g. <Amazon® Kindle™>	☐1	☐2	☐3

ICTSCH: ICT available at school

IC014 **Thinking about your experience with digital media and digital devices: To what extent do you disagree or agree with the following statements?**

(Please think of different kinds of digital devices such as for example desktop computers, portable laptops, notebooks, smartphones, tablet computers, cell phones without internet access, game consoles, or internet-connected television)

(Please select one response in each row.)

		Strongly disagree	*Disagree*	*Agree*	*Strongly agree*
IC014Q03NA	I feel comfortable using digital devices that I am less familiar with.	☐1	☐2	☐3	☐4
IC014Q04NA	If my friends and relatives want to buy new digital devices or applications, I can give them advice.	☐1	☐2	☐3	☐4
IC014Q06NA	I feel comfortable using my digital devices at home.	☐1	☐2	☐3	☐4
IC014Q08NA	When I come across problems with digital devices, I think I can solve them.	☐1	☐2	☐3	☐4
IC014Q09NA	If my friends and relatives have a problem with digital devices, I can help them.	☐1	☐2	☐3	☐4

ENTUSE: ICT use outside of school for leisure

IC008 **How often do you use digital devices for the following activities outside of school?**

(Please select one response in each row.)

		Never or hardly ever	*Once or twice a month*	*Once or twice a week*	*Almost every day*	*Every day*
IC008Q01TA	Playing one-player games.	☐1	☐2	☐3	☐4	☐5
IC008Q02TA	Playing collaborative online games.	☐1	☐2	☐3	☐4	☐5
IC008Q03TA	Using email.	☐1	☐2	☐3	☐4	☐5
IC008Q04TA	<Chatting online> (e.g. <MSN®>).	☐1	☐2	☐3	☐4	☐5
IC008Q05TA	Participating in social networks (e.g. <Facebook>, <MySpace>).	☐1	☐2	☐3	☐4	☐5
IC008Q07NA	Playing online games via social networks (e.g. <Farmville®>, <The Sims Social>).	☐1	☐2	☐3	☐4	☐5
IC008Q08TA	Browsing the Internet for fun (such as watching videos, e.g. <YouTube™>).	☐1	☐2	☐3	☐4	☐5
IC008Q09TA	Reading news on the Internet (e.g. current affairs).	☐1	☐2	☐3	☐4	☐5
IC008Q10TA	Obtaining practical information from the Internet (e.g. locations, dates of events).	☐1	☐2	☐3	☐4	☐5
IC008Q11TA	Downloading music, films, games or software from the internet.	☐1	☐2	☐3	☐4	☐5
IC008Q12TA	Uploading your own created contents for sharing (e.g. music, poetry, videos, computer programs).	☐1	☐2	☐3	☐4	☐5
IC008Q13NA	Downloading new apps on a mobile device.	☐1	☐2	☐3	☐4	☐5

IC009 Are any of these devices available for you to use <u>at school</u>?

(Please select one response in each row.)

		Yes, and I use it	*Yes, but I don't use it*	*No*
IC009Q01TA	Desktop computer	☐1	☐2	☐3
IC009Q02TA	Portable laptop or notebook	☐1	☐2	☐3
IC009Q03TA	<Tablet computer> (e.g. <iPad®>, <BlackBerry® PlayBook™>)	☐1	☐2	☐3
IC009Q05NA	Internet-connected school computers	☐1	☐2	☐3
IC009Q06NA	Internet connection via wireless network	☐1	☐2	☐3
IC009Q07NA	Storage space for school-related data, e.g. a folder for own documents	☐1	☐2	☐3
IC009Q08TA	USB (memory) stick	☐1	☐2	☐3
IC009Q09TA	<ebook reader>, e.g. <Amazon® Kindle™>	☐1	☐2	☐3
IC009Q10NA	Data projector, e.g. for slide presentations	☐1	☐2	☐3
IC009Q11NA	Interactive whiteboard, e.g. <SmartBoard®>	☐1	☐2	☐3

USESCH: Use of ICT at school in general

IC011 How often do you use digital devices for the following activities <u>at school</u>?

(Please select one response in each row.)

		Never or hardly ever	*Once or twice a month*	*Once or twice a week*	*Almost every day*	*Every day*
IC011Q01TA	<Chatting online> at school.	☐1	☐2	☐3	☐4	☐5
IC011Q02TA	Using email at school.	☐1	☐2	☐3	☐4	☐5
IC011Q03TA	Browsing the Internet for schoolwork.	☐1	☐2	☐3	☐4	☐5
IC011Q04TA	Downloading, uploading or browsing material from the school's website (e.g. <intranet>).	☐1	☐2	☐3	☐4	☐5
IC011Q05TA	Posting my work on the school's website.	☐1	☐2	☐3	☐4	☐5
IC011Q06TA	Playing simulations at school.	☐1	☐2	☐3	☐4	☐5
IC011Q07TA	Practicing and drilling, such as for foreign language learning or mathematics.	☐1	☐2	☐3	☐4	☐5
IC011Q08TA	Doing homework on a school computer.	☐1	☐2	☐3	☐4	☐5
IC011Q09TA	Using school computers for group work and communication with other	☐1	☐2	☐3	☐4	☐5

INTICT: Students' ICT interest

IC013 **Thinking about your experience with digital media and digital devices: to what extent do you disagree or agree with the following statements?**

(Please think of different kinds of digital devices such as for example desktop computers, portable laptops, notebooks, smartphones, tablet computers, cell phones without internet access, game consoles, or internet-connected television)

(Please select one response in each row.)

		Strongly disagree	*Disagree*	*Agree*	*Strongly agree*
IC013Q01NA	I forget about time when I'm using digital devices.	☐1	☐2	☐3	☐4
IC013Q04NA	The Internet is a great resource for obtaining information I am interested in (e.g. news, sports, dictionary).	☐1	☐2	☐3	☐4
IC013Q05NA	It is very useful to have social networks on the Internet.	☐1	☐2	☐3	☐4
IC013Q11NA	I am really excited discovering new digital devices or applications.	☐1	☐2	☐3	☐4
IC013Q12NA	I really feel bad if no internet connection is possible.	☐1	☐2	☐3	☐4
IC013Q13NA	I like using digital devices.	☐1	☐2	☐3	☐4

SOIAICT: Students' ICT as a topic in conversations

IC016 Thinking about your experience with digital media and digital devices: to what extent do you disagree or agree with the following statements?

(Please select one response in each row.)

		Strongly disagree	*Disagree*	*Agree*	*Strongly agree*
IC016Q01NA	To learn something new about digital devices, I like to talk about them with my friends.	☐1	☐2	☐3	☐4
IC016Q02NA	I like to exchange solutions to problems with digital devices with others on the internet.	☐1	☐2	☐3	☐4
IC016Q04NA	I like to meet friends and play computer and video games with them.	☐1	☐2	☐3	☐4
IC016Q05NA	I like to share information about digital devices with my friends.	☐1	☐2	☐3	☐4
IC016Q07NA	I learn a lot about digital media by discussing with my friends and relatives.	☐1	☐2	☐3	☐4

AUTICT: Students' perceived social interaction and autonomy related to ICT use

IC015 Thinking about your experience with digital media and digital devices: to what extent do you disagree or agree with the following statements?

(Please select one response in each row.)

		Strongly disagree	*Disagree*	*Agree*	*Strongly agree*
IC015Q02NA	If I need new software, I install it by myself.	☐1	☐2	☐3	☐4
IC015Q03NA	I read information about digital devices to be independent.	☐1	☐2	☐3	☐4
IC015Q05NA	I use digital devices as I want to use them.	☐1	☐2	☐3	☐4
IC015Q07NA	If I have a problem with digital devices I start to solve it on my own.	☐1	☐2	☐3	☐4
IC015Q09NA	If I need a new application, I choose it by myself.	☐1	☐2	☐3	☐4

HOMESCH: ICT use outside of school for schoolwork

IC010 **How often do you use digital devices for the following activities <u>outside of school</u>?**

(Please select one response in each row.)

		Never or hardly ever	*Once or twice a month*	*Once or twice a week*	*Almost every day*	*Every day*
IC010Q01TA	Browsing the Internet for schoolwork (e.g. for preparing an essay or presentation).	☐1	☐2	☐3	☐4	☐5
IC010Q02NA	Browsing the Internet to follow up lessons, e.g. for finding explanations.	☐1	☐2	☐3	☐4	☐5
IC010Q03TA	Using email for communication with other students about schoolwork.	☐1	☐2	☐3	☐4	☐5
IC010Q04TA	Using email for communication with teachers and submission of homework or other schoolwork.	☐1	☐2	☐3	☐4	☐5
IC010Q05NA	Using social networks for communication with other students about schoolwork (e.g. <Facebook>, <MySpace>).	☐1	☐2	☐3	☐4	☐5
IC010Q06NA	Using social networks for Communication with teachers (e.g. <Facebook>, <MySpace>).	☐1	☐2	☐3	☐4	☐5
IC010Q07TA	Downloading, uploading or browsing material from my school's website (e.g. timetable or course materials).	☐1	☐2	☐3	☐4	☐5
IC010Q08TA	Checking the school's website for announcements, e.g. absence of teachers.	☐1	☐2	☐3	☐4	☐5
IC010Q09NA	Doing homework on a computer.	☐1	☐2	☐3	☐4	☐5
IC010Q10NA	Doing homework on a mobile device.	☐1	☐2	☐3	☐4	☐5
IC010Q11NA	Downloading learning apps on a mobile device.	☐1	☐2	☐3	☐4	☐5
IC010Q12NA	Downloading science learning apps on a mobile device.	☐1	☐2	☐3	☐4	☐5

Appendix B

Search terms used for literature review. The asterisk in "*Technolog**" allows for the search engine to auto complete the word with any possible endings. This enables us to shorten the syntax of the search while matching technology, technologies, technological, and more.

> (*ICT OR "information and communication technolog**"), AND (mathematics achievement OR science achievement), AND (PISA OR "program for international student assessment"), AND (ICT use OR ICT availability OR ICT interest OR ICT competence OR ICT autonomy OR ICT social interactions OR ICT social relatedness OR ICT attitudes)*