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INTERRELATIONSHIP AMONG STUDENTS' ICT USAGE, ATTITUDE, AND ACADEMIC PERFORMANCE IN NORDIC COUNTRIES: MULTILEVEL STRUCTURAL EQUATION MODELING ON PISA 2018 AND TIMSS 2019

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A Dissertation Presented

by

DUKJAE LEE

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DEDICATION

In memory of my beloved grandparents…

보고 싶고 사랑하는 할아버지 할머니께…

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ABSTRACT

INTERRELATIONSHIP AMONG STUDENTS' ICT USAGE, ATTITUDE, AND ACADEMIC PERFORMANCE IN NORDIC COUNTRIES: MULTILEVEL STRUCTURAL EQUATION MODELING ON PISA 2018 AND TIMSS 2019

February 2024

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The usage of digital devices has been an interest in the field of education as one of the useful instructional methods for students' better learning. Although the usage seemed to be related to their academic performance (e.g., Pekto et al., 2017; Skryabin et al., 2015), it was still unclear if the usage itself directly affected better academic results. Therefore, this dissertation explored an interrelationship between students' usage of digital devices and academic performance with a mediation effect of their attitude toward using digital devices. The study analyzed the datasets of five Nordic countries collected from PISA 2018 and TIMSS 2019, where digital devices have been integrated into a part of their educational curricula (Godhe, 2019). A multilevel mediation analysis in the context of multilevel structural equation modeling with demographic control variables was applied to reflect the hierarchical structure of international assessments (i.e., students clustered into schools).

The analysis figured out several findings. First, students' frequent usage of digital devices was associated with their interest in using digital devices (i.e., ICT Interest) and willingness to use them actively to solve problems (i.e., ICT Autonomy), influencing their performances on the two international assessments. Second, there were differences among the variables of interest, depending on their demographic information. Finally, the direction of interrelationship tended to show different patterns across PISA 2018 and TIMSS 2019. Based on the findings, this dissertation expects to contribute to future educational policies regarding the integration of digital devices into education. For example, it would be necessary to find ways to improve students' interest or autonomous behaviors when they are involved in activities that accompany digital devices.

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CHAPTER 1

INTRODUCTION

1.1 International Large-Scale Assessment

As global communication of education increases, there has been a lot of interest in research studies that focus on international large-scale assessments (ILSAs) in the field of education. Usually administered by non-profit international organizations, ILSAs focus on how students in primary and/or secondary education from all over the world learn and improve their cognitive performance across various subject areas. In addition to cognitive proficiency, ILSAs also collect diverse information on potential factors that are relevant to and could affect students' academic performance such as their parental backgrounds, teachers and schools, physical and mental well-being, and even financial or global competency. Such collected large-scale datasets are usually published online for other educational researchers to conduct further analyses. Thanks to the access to collected data for the public without cost, there have been published a lot of secondary data analyses using the datasets from ILSAs in the field of educational research. The topics of analysis could cover various student aspects, either concentrating on a single country or comparing multiple countries.

1.1.1 Types of ILSAs

Among the various types of ILSAs, four assessments are frequently reflected in the field of educational research: Programme for International Student Assessment (PISA), Programme for the International Assessment of Adult Competencies (PIAAC), Trends in International Mathematics and Science Studies (TIMSS), and Progress in International Reading Literacy Study (PIRLS). PISA and PIAAC are directed by the Organisation for

Economic Cooperation and Development (OECD), while TIMSS and PIRLS are directed by the International Association for the Evaluation of Educational Assessment (IEA). These ILSAs are widely used to examine students' academic performance in various subject fields from all over the world. For example, PISA explores students' literacy in reading, mathematics, and science (OECD, 2019a), and PIAAC concentrates on their literacy and numeracy skills (OECD, 2022a). Similarly, TIMSS studies students' cognitive proficiency in mathematics and science (Martin et al., 2020), while PIRLS focuses on their reading comprehension (Mullis & Martin, 2015).

1.1.2 Practical Use of ILSAs

There has been an increasing number of participating countries in ILSAs until recently. For example, the number of participating countries in PISA increased from 42 in 2000 to 79 in 2018 (including both members and non-members of OECD), while that in TIMSS increased from 42 in 1995 to 64 in 2019 (Raudonyte, 2019). The results from ILSAs are frequently used by the government or the public departments in charge of education for setting agendas in educational policies, informing how the policies are implemented or administered, and evaluating if their current policies function well or need a change on the current system when they receive unsatisfying results (OECD, 2015; Raudonyte, 2019). For example, in the case of PISA 2000, Finland attributed its high performance to the current educational system with both high quality and equality, while Germany made a significant change to its educational system after receiving outcomes with low academic performance (20^{th} rank out of 32 countries) (Grek, 2009). Although ILSAs do not make direct decisions regarding educational policies, the results could function as a milestone for the future plan of policies.

1.2 Use of Digitalization in Education

The integration of technology using digital devices has been an interesting topic in the field of educational research. As technology develops, students have more access to digital devices or the Internet anywhere than before, which leads to more opportunities and resources to obtain knowledge through digital devices (Chen et al., 2020; Delgado et al., 2015). Not only as an instructional method, but digital technology is also developed for evaluating students as tests are being administered using computers, which are useful for including interactive question types, managing security, scoring quickly, adapting tests based on their level, and collecting additional information of students (Araneda et al., 2022; Blazer, 2010). Due to such advantages, there have been discussions about appropriate ways to include the usage of digital devices in education, which would be beneficial for improving the quality and effectiveness of learning in the digital age (Delgado et al., 2015). While many discussions regarding the integration of digital technology into education have been considered, the outbreak of Coronavirus disease 19 (i.e., SARS-CoV-2; COVID-19) in 2019 has changed and accelerated the usage of digital devices for online learning.

1.2.1 Digital Device Usage for Education After COVID-19

After the outbreak of COVID-19, the degree of students' digital device usage has increased for educational purposes. Many schools all over the world have switched their instruction method from an in-person format to an online, contactless learning format to avoid the spread-out of the virus. Students started to meet their teachers and classmates and take classes through online platforms such as Zoom or Google Classroom by turning on their computers or laptops. Exams are also administered through computer-based tests, and teachers provide scores and feedback online. To sum up, the application of digital technology has become inevitable and important in the recent field of educational research not only because digital technology helps students to explore various knowledge beyond textbooks but also because it could connect teachers and students through online learning during the pandemic, not making students left behind (OECD, 2020).

1.2.2 Digital Transformation in Education for Nordic Countries

While there is an increased interest and application of digitalization in education, it seems to receive more attention in five northern European countries (i.e., Denmark, Finland, Iceland, Norway, and Sweden), which are often referred to as the Nordic countries and currently the members of the Nordic Council of Ministers. Not only are they geographically close to each other, but these five countries also share various aspects in common such as language, social welfare, and educational policies. From the linguistic perspective, their official languages (i.e., Danish, Icelandic, Norwegian, Swedish) are classified as a member of North German languages in the Indo-European language family except for Finnish (Finno-Ugric language family); people whose first languages are in this family can understand basic phrases in other languages within the same family (Tof, 2022). Nordic countries are also well-known for their high level of welfare services and social safety. Social welfare services such as health benefits, childcare, or parental leaves are supported by the government without cost regardless of their socioeconomic status, which is also referred to as “the Nordic model” (Herning, 2022).

In terms of educational policy, there was a curricular reformation across Nordic countries with more focus on improvement in the learning environment for enhancing basic skills and digitalization of society and education (Godhe, 2019; Reimer et al., 2018). While they used different terminology, Nordic countries agreed that digital literacy or competence should be considered an important factor in education, and the usage of digital devices is becoming a part of educational curricula for some countries (Godhe, 2019). For example, using computer programs has become a part of the educational curriculum for mathematics and science in Finland, Norway, and Sweden, such as searching for knowledge, designing and conducting algorithms for simulation, or enhancing problem-solving skills in scientific experiments (Kelly et al., 2020).

1.3 Statement of Problem

Digital devices have functioned as a part of the instructional method, and their usage is becoming more important than in the past because not only the topics are being developed but also it is considered an effective method for administering remote, online education during the COVID-19 pandemic. Moreover, there is increasing usage of computerized tests because they are easy to administer and score items, allow flexible time management, and let researchers collect additional, useful information such as response behaviors, response time, or availability of test accommodations compared to traditional paper-based tests (Araneda et al., 2022). Therefore, it seems interesting to see how students' usage of digital devices is related to their academic performance from computerized exams.

Although there have been a lot of studies that explored the significant effect of students' digital device usage and academic performance (e.g., Hu et al., 2018; Juhaňák et al., 2018; Kong et al., 2022; Lim & Jung, 2019; Xiao et al., 2019), it was unclear if the usage itself directly affects their academic performance, especially in computer-based exams. Rather than the usage itself, the students' attitudes toward using digital devices may be more important although it may be that usage is related to academic performance. When students spend time using digital devices more often, they would get accustomed to using them and feel more relaxed or comfortable, especially when tests are administered using computers. As a result, this seems relevant to their results of academic performance from computer-based exams.

There have been several research studies regarding the relationships between the usage of digital devices, attitude toward digital device usage, and academic performance, but most of them focused on the dyadic relationships between each of the two variables rather than the interrelationship of all variables (e.g., Gómez-Fernández & Mediavilla, 2021; Hu et al., 2018; Juhaňák et al., 2018; Lee & Wu, 2012; Lim & Jung, 2019; Park & Weng, 2020). Therefore, this dissertation aims to explore how students' usage of digital devices would affect their academic performance on computerized tests, taking their attitude toward using digital devices and other relevant variables into consideration. Specifically, this study will explore the topics focusing on the five Nordic countries since there has been an increasing trend of digitalization of teaching and learning in these countries (Laterza et al., 2020).

1.4 Research Questions and Hypotheses

The purpose of this dissertation is to explore how students' usage of digital devices and attitudes toward using digital devices are associated with their academic performance in computer-based exams. Focusing on the mediation effect of students' attitudes toward using digital devices on the relationship between the usage of digital devices and academic performance in different ILSAs, this study will also investigate potential level-relevant demographic control variables that could influence the difference of relationship across the five Nordic countries. Three research questions are posed to explore this research, followed by relevant sub-questions for each question:

1. What is the interrelationship among students' usage of digital devices, attitude toward using digital devices, and academic performance?

    1a. What does the association between students' usage of digital devices for educational purposes and academic performance look like?

    1b. Is there an indirect association between students' usage of digital devices for educational purposes and academic performance, mediated by their attitude toward using digital devices?

2. What are the potential demographic factors that would affect differences in the variables of interest across the Nordic countries?

    2a. Do students' gender and/or parents' educational level affect differences in the variables of interest?

    2b. Do school-mean economic, social, and cultural status or school strata (e.g., location, type, etc.) affect differences in the variables of interest?

3. Does the hypothetical structural model show similar patterns across the five Nordic countries in PISA 2018 and TIMSS 2019?

1.4.1 Usage of Digital Devices and Academic Performance

The first research question is projected to study the relationship between students' usage of digital devices for educational purposes and academic performance in ILSAs (i.e., reading, mathematics, and science literacy), using the idea of mediation analysis. It will explore the total effect of students' usage of digital devices on academic performance, its direct effect after controlling for the mediation effect, and the mediation effect of students' attitude toward using digital devices in the linear association between usage and academic performance. Two relevant hypotheses will be studied throughout the research as follows:

- H1a: Students' usage of digital devices for educational purposes significantly impacts their academic performance, and its direct effect after controlling for the mediation effect of attitude toward using digital devices is also significant.
- H1b: There is an indirect association between students' usage of digital devices for educational purposes and academic performance, mediated by their attitude toward using digital devices.

Several studies showed that there is a significant relationship between students' usage of digital devices and academic performance (e.g., Hu et al., 2018; Juhaňák et al., 2018; Kong et al., 2022; Lim & Jung, 2019; Xiao et al., 2019); however, there seems to be a weak rationale for the simple association because it could have been influenced by external variables. For example, students' attitudes toward using digital devices (i.e., self-efficacy of using digital devices for solving problems) would also have influenced the relationship. When students use digital devices more frequently, they would have more positive attitudes toward using digital devices and more confidence and/or self-efficacy to solve problems, which would result in better academic performance, especially for computer-based exams. Therefore, it seems necessary to include students' attitudes toward using digital devices as an additional variable to explore how much it could explain any explanatory effect between students' usage of digital devices and academic performance. Mediation analysis will be applied to explore this relationship, which could explain how or why a relationship between two variables would exist by including an additional variable (i.e., mediator variable; Kim et al., 2001, Kline, 2015). Students' attitudes toward using digital devices will be included as an additional variable that mediates the relationship between students' usage of digital devices and their academic performance.

1.4.2 Level-Relevant Demographic Control Variables

The second research question is proposed to explore the influence of various demographic variables on the variables of interest (i.e., students' usage of digital devices, attitude toward using them, and academic performance). Nordic countries are usually economically developed with little economic inequality and share similar educational and/or social factors in common (Herning, 2022; Nordic Co-operation, 2021; Tof, 2022). However, the frequency of using digital devices or the degrees of positive attitude toward using digital devices could be different depending on various demographic factors such as students' gender, parental backgrounds, or types of schools. Here, two relevant hypotheses will be answered throughout the study as addressed below:

- H2a: Students' gender and parents' educational level are significant student-level control variables that influence the patterns of models across the five Nordic countries.
- H2b: School-mean economic, social, and cultural status and school strata are significant school-level control variables that influence the patterns of models across the five Nordic countries.

The mediation model will include multiple levels (i.e., student and school levels) because the student data are clustered within schools, and the model will be explored for each country separately. A multilevel model for exploring the interrelationship will be first determined for each country by checking model fit indices, which measure the overall model-data correspondence (Kline, 2015, p. 262). The level-relevant control variables will then be added, exploring if the control variables show differences in the variables of interest on each level. This could be a clue for studying potential cultural differences.

1.4.3 Difference in PISA 2018 and TIMSS 2019

The third question aims to see if the hypothesized structural model shows similar patterns across different ILSAs, focusing on PISA 2018 and TIMSS 2019 (Grade 8). These two ILSAs will be analyzed because they could complement each other in exploring students' academic performance. For example, PISA 2018 had a special focus on reading literacy compared to mathematical and science literacy, while TIMSS 2019 had attention only on mathematics and science literacy (Martin et al., 2020; OECD, 2019a). Moreover, PISA 2018 has more survey questions for exploring students' behaviors when using digital devices than TIMSS 2019 (IEA, 2020a; OECD, 2017b). In addition, TIMSS 2019 was not administered in Denmark and Iceland, so PISA 2018 would be useful for exploring the mathematical and science literacy of students from Denmark and Iceland. Therefore, the combination of these two ILSAs would provide a broader understanding of academic performance. There is one relevant hypothesis as follows:

- H3: The hypothesized structural model across the five Nordic countries shows different patterns for PISA 2018 and TIMSS 2019, respectively.

This research will explore how the patterns of the hypothesized structural model look across the five Nordic countries, exploring these two ILSAs. The model could be applied differently for the two ILSAs not only because they include different samples of students and schools but also because the number of included countries is different.

1.5 Significance

This dissertation plans to explore an interrelationship between students' usage of digital devices and their academic performance, including their attitude toward digital devices as a mediating variable that might have causal effects on the relationship across the five Nordic countries. As the usage of digital devices increases in students' everyday lives, and the COVID-19 pandemic has impacted a new trend of online, remote learning, the integration of digital devices into education seems to be considered more important than before to make use of remote learning. Digital devices can be effective instructional tools as students can learn content with more interest and ease by searching for information on web browsers, taking notes, and reviewing them by using various online platforms. Moreover, the frequency of students' usage of digital devices and their attitude toward using digital devices might differ by country as each country has a different level of economic status and accessibility to digital devices. From this viewpoint, this dissertation is expected to provide a significant overview of including the usage of digital devices as a major source of instructional methods in education, which could contribute to managing educational policy with digital technology in the future education not only for the Nordic countries but also for other countries as well.

CHAPTER 2

LITERATURE REVIEW

2.1 Programme for International Student Assessment

Programme for International Student Assessment (i.e., PISA) is a comprehensive international assessment administered every three years, which explores both cognitive and non-cognitive aspects of 15-year-old students globally, administered by OECD. The most recent PISA was administered in 2018, while PISA 2021 was postponed to 2022 due to the COVID-19 pandemic. PISA has chosen a computer-based format as their primary method of test administration from PISA 2015, but the test is still provided in a paper-based format as well for several countries where computers or digital devices are not easy to access (OECD, 2017a). In PISA 2018, 80 countries participated including 38 OECD countries and 42 non-OECD members.

PISA tests three aspects of students' cognitive domain: reading, mathematical, and scientific literacy. While all aspects are always examined, PISA puts special attention on one of the three domains for each administration; for example, reading literacy was the main focus in 2018, scientific literacy in 2015, and mathematical literacy in 2012. The next PISA 2022 focused on mathematical literacy. All proficiency scales of the three cognitive domains were scaled with a mean of 500 and a standard deviation (SD) of 100 (OECD, 2019a). Each of the cognitive aspects will be explained in the following sections.

2.2 Trends in Mathematics and Science Literacy

Trends in International Mathematics and Science Studies (i.e., TIMSS) is an international assessment which measures students' achievement in mathematics and science every four years administered by IEA, specifically those in their fourth (Grade 4) and eighth grades (Grade 8). Although the exact ages of students vary depending on each country's curriculum, Grade 4 is approximately equivalent to the ages of 9 to 10, while Grade 8 corresponds to the ages of 14 to 15. The most recent TIMSS was administered in 2019, and the following one is scheduled to be administered in 2023. TIMSS 2019 also made a transition to an electronic version of TIMSS like PISA with more innovative item formats and better construct representation, which is referred to as eTIMSS (Martin et al., 2020; Mullis & Martin, 2017). In TIMSS 2019, there were 58 countries that participated in Grade 4, while there were 39 participating countries for Grade 8 (Martin et al., 2020).

2.3 Cognitive Measures

When referring to academic performance in ILSAs, there are three cognitive domains that are generally measured, which are students' literacy in reading (e.g., PISA, PIAAC, PIRLS), mathematics (e.g., PISA, PIAAC, TIMSS), and science (e.g., PISA, TIMSS). The specific terms referring to each cognitive measure were different depending on the assessments. In terms of the two ILSAs in this research, both mathematics and science were measured in PISA 2018 and TIMSS 2019, while reading was only included and measured in PISA 2018.

2.3.1 Reading Literacy

In PISA 2018, reading literacy was defined as "an individual's capacity to understand, use, evaluate, reflect on and engage with texts in order to achieve one's goals, develop one's knowledge and potential, and participate in society" (OECD, 2019a, p. 14). The definition of reading literacy has been extended not only to understand traditional written texts but also to understand and critically analyze online digital texts. It has changed because of the increased amount of usage of the Internet through digital devices, and humans now collect a variety of information by reading both written texts on paper and digital texts in the digital world (OECD, 2019a). Items for measuring reading literacy in PISA intend to analyze students' cognitive approaches and/or strategies (i.e., processes) when reading multiple types of sources including related themes (i.e., text) and their competence in integrating and understanding the purpose of overall contexts (i.e., scenarios) (OECD, 2019a).

2.3.2 Mathematical Literacy

The cognitive measure related to mathematics was referred to as "mathematical literacy" in PISA 2018, while it was simply called "mathematics" in TIMSS 2019. While both assessments aim to measure students' mathematical literacy, the content and cognitive domains were represented in a slightly different way as indicated in the terms they use. The definition of students' mathematical literacy in PISA 2018 followed the one established in 2012, which is "an individual's capacity to formulate, employ and interpret mathematics in a variety of contexts" (OECD, 2019a, p. 14). This includes "reasoning mathematically and using mathematical concepts, procedures, facts and tools to describe, explain, and predict phenomena" (OECD, 2019a, p. 75). PISA 2018 uses more generalized terms to define a content domain in mathematical literacy (e.g., change and relationships, space and shape, quantity, uncertainty and data, etc.) since it focuses more on the application of existing knowledge to solve broader problems rather than memorizing mathematical concepts (OECD, 2019a). However, TIMSS 2019 tends to reflect terms in the curricula of mathematics education (e.g., number, algebra, geometry, measurement, data) to measure desired subject matters for each grade (Mullis & Martin, 2017). In terms of the cognitive domains, both ILSAs aim to measure students' proficiency in conceptualizing problems mathematically, applying knowledge in mathematics to solve problems, interpreting the results, and communicating those with others (Mullis & Martin, 2017; OECD, 2019a).

2.3.3 Scientific Literacy

The definition of scientific literacy in PISA 2018 was established in 2015 as "the ability to engage with science-related issues, and with the ideas of science, as a reflective citizen" (OECD, 2019a, p. 100). This cognitive measure was referred to as "scientific literacy" in PISA 2018, while it was simply called "science" in TIMSS 2019. These terms would imply that PISA 2018 puts more focus on the advanced application of knowledge in science in real-world situations, while TIMSS 2019 focuses on a general understanding of knowledge. While the focus was slightly different, the content and cognitive domains for scientific literacy looked similar for both assessments. The content domains cover the four broad themes in science (i.e., physics, chemistry, life sciences, earth/space systems), and the cognitive domains tend to measure whether students are competent in explaining phenomena scientifically, evaluating and designing scientific inquiry, and interpreting data and evidence scientifically in addition to basic knowledge in science (Mullis & Martin, 2017; OECD, 2019a).

2.3.4 Results of Cognitive Measures in Nordic Countries

In accordance with the topic of this study, this section explored how students from the Nordic countries performed in the two recent ILSAs, on average. Table 2.1 shows the summary of the results of the academic performance for the three cognitive domains only for the five Nordic countries (Schleicher, 2019). The average performance scores of reading literacy across OECD countries was 487 (SD = 99), that of mathematical literacy was 489 (SD = 91), and that of scientific literacy was 489 (SD = 94). Nordic countries generally showed better performance than the average of OECD countries for all cognitive domains. Finland showed the best performances across the three literacy domains, followed by Sweden, Denmark, and Norway. Iceland reported lower performances than those of the OECD average for reading and scientific literacy.

Table 2.1. PISA 2018 Results of Nordic Countries

	Reading		Mathematical		Scientific	
	Mean	SD	Mean	SD	Mean	SD
Finland	520	100	507	82	522	96
Sweden	506	108	502	91	499	98
Denmark	501	92	509	82	493	91
Norway	499	106	501	90	490	98
Iceland	474	105	495	90	475	91

Note. SD = Standard deviation (Schleicher, 2019).

Table 2.2 shows the summary of the results of the academic performance for the two cognitive domains in TIMSS 2019 across Grades 4 and 8 (Mullis et al., 2020). Not all Nordic countries participated in the assessments; Iceland did not participate in TIMSS 2019, while Denmark participated only for Grade 4. Similar to PISA 2018, the academic performance of TIMSS 2019 was scaled with a mean of 500 and a standard deviation of 100. Based on the reports, Norway tended to perform better than other Nordic countries in mathematics for Grade 4, while Finland performed the best for Grade 8. In terms of science, Finland showed better performances than other Nordic countries for both grades.

Table 2.2. TIMSS 2019 Results of Nordic Countries

	Grade 4				Grade 8			
	Mathematics		Science		Mathematics		Science	
	Mean	SD	Mean	SD	Mean	SD	Mean	SD
Norway	543	74	539	67	508	73	495	89
Finland	532	76	555	71	509	73	543	87
Denmark	525	73	522	68				
Sweden	521	73	537	74	503	77	521	95

Note. Iceland did not participate in TIMSS 2019; Denmark only participated in TIMSS 2019 Grade 4 (Mullis et al., 2020).

2.4 Information and Communication Technology

In addition to the various types of cognitive domains, both PISA 2018 and TIMSS 2019 provided additional survey questionnaires to collect supplementary information about students' non-cognitive aspects such as student's psychological well-being and social connection with their teachers at school, parental and school backgrounds, activities and enjoyment in reading, mathematics, and science at or outside of schools, familiarity in information and communication technology, financial literacy, and educational career. Not only for the students, but surveys were also provided to school principals and teachers to collect data such as school background, school climate, and teacher beliefs and attitudes. Among the various non-cognitive aspects, this study will focus on the familiarity with using ICT or digital devices in PISA 2018 (i.e., PISA 2018 ICT Familiarity Questionnaire) and TIMSS 2019 (i.e., eTIMSS Questionnaire), which will be addressed in the following sections (IEA, 2020a; OECD, 2017b).

2.4.1 Definition

Digital devices are more integrated into education than before as an effective instructional tool in the digital world, so students are expected to develop better levels of information and communication technology (ICT). Since more assessments are being developed on computer-based forms, familiarity with using ICT also becomes crucial. However, there was no single, clear definition of what ICT means in terms of education. For example, PISA defined ICT in education 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 in Odell et al., 2021). Besides, the United Nations Educational, Scientific and Cultural Organization

(UNESCO) defined ICT as "a diverse set of technological tools and resources used to transmit, store, create, share, or exchange information" (2009, p. 120). ICT can be also referred to as "all devices, networking components, applications and systems that combined allow people and organizations to interact in the digital world" (Pratt, 2019). Combining such multiple definitions, ICT could be summarized as a multidimensional concept which not only includes the activity of using digital devices but also includes technology-related activities of managing digital data and abilities to analyze and interpret data in order to communicate it with other people. Since digital information is usually processed by using digital devices, the terminology of using ICT will be referred to as the usage of digital devices interchangeably.

As students become able to use digital devices in their daily lives at school and outside of school, there has been an effort to apply ICT to education as an effective method for instruction or assessment. The integration of ICT into education could be beneficial for students to learn additional knowledge outside of textbooks by searching for online sources and studying at their own pace (Kulik et al., 1983). Teachers can also make use of ICT during instruction and evaluation by preparing class materials with diverse visual and auditory guides or providing feedback on students' performances efficiently and interactively (Kulik et al., 1983). Therefore, students' familiarity with using ICT (i.e., ICT familiarity) becomes one of the crucial aspects of making use of ICT within the educational field. While there are several ways to operationally define the abstract concept of ICT familiarity, this study focused on two ways that frequently appeared in previous studies (e.g., Gubbels, et al., 2020; Lee & Wu, 2012; Odell et al., 2020b). One way is to explore how often and frequently students use digital devices for educational purposes (i.e., ICT

Usage), and the other one is to investigate what attitudes students have when they use digital devices (i.e., ICT Attitude).

2.4.2 ICT Usage

Students' usage of digital devices, which is referred to as ICT Usage in this study, became one of the important factors in their academic performance as digital devices are used as a new method for instruction and assessment. Especially, its importance has increased during the COVID-19 pandemic as all instruction and assessments were administered through digital devices such as computers or tablets. Both PISA 2018 and TIMSS 2019 provided additional survey questions to collect information about how often students have a chance and use digital devices. Both assessments are interested in the frequency and purposes of using digital devices at school and outside of school (i.e., at home), while PISA 2018 provided more detailed questions than TIMSS 2019 (IEA, 2020a; OECD, 2017b).

2.4.2.1 Locations of ICT Usage

Generally, students' usage of digital devices (i.e., ICT Usage) can be classified into two categories based on the locations where they use them: (1) ICT Usage at home (i.e., ICT Home) and (2) ICT Usage at school (i.e., ICT School). In most cases, students would frequently use digital devices at home. According to the report of the International Computer and Information Literacy Study by IEA in 2013, about 87% of Grade 8 students who participated in the survey responded that they had access to digital devices (i.e., computers) and used them at least once a week at home for various activities such as writing and editing documents, create presentations, or use educational software for additional assistance with school studies (Fraillon et al., 2014). Students also have a chance to use digital devices at school as more than 50% of students answered that they use computers at least once a week at school for diverse activities like writing reports and/or essays, completing tests, or working with peers from their schools (Fraillon et al., 2014).

2.4.2.2 Purposes of ICT Usage

While students often use digital devices either at home or at school, there are various purposes for using digital devices. PISA 2018 ICT Questionnaire asked students about the purposes of using digital devices at home and at school (OECD, 2017b). Students tended to use digital devices for educational purposes (e.g., search for information, follow up lessons, do homework), for entertainment (e.g., play one-player or collaborative online games), or for social communication with other people such as peers, teachers, or random public (e.g., chat online, use email, participate in social networks) (OECD, 2017b). This study will focus on ICT Usage for educational purposes to explore how effectively digital devices could be used to make students learn and understand class materials, which would be related to their academic performance. The eTIMSS Questionnaire from TIMSS 2019 also asked questions regarding the availability of digital devices at home or school (e.g., "Do you have any of these things at your home?") and the educational purposes of using them (e.g., working on school assignments, schoolwork on mathematics and/or science), but the questions were less detailed than those in PISA 2018 (IEA, 2020a).

2.4.3 ICT Attitude

While the usage of digital devices is considered a crucial factor in students' academic performance, there also exist other facets that could significantly affect their performances. One of them is their attitudes toward activities using digital devices, which is referred to as ICT Attitude in this study. PISA 2018 and TIMSS 2019 not only explored students' usage of digital devices either at home or school but also asked questions regarding how they feel when using digital devices (IEA, 2020a; OECD, 2017b). Since attitude is an abstract concept which is difficult to define in a sentence, there were several ways to conceptualize students' ICT Attitude, and this research focused on three aspects that frequently appeared in relevant previous studies, which are (1) students' competence in using digital devices (i.e., ICT Competence), (2) their interests in using digital devices (i.e., ICT Interest), and (3) their autonomous behaviors when using digital devices (i.e., ICT Autonomy). The following sections will explore each aspect in detail.

2.4.3.1 Competence in Using ICT

The first aspect of ICT Attitude that commonly appears in the research is ICT Competence, which refers to "one's own beliefs about one's own competence in using digital media and digital devices" (Areepattamannil & Santos, 2019, p. 50). This facet focuses on how individuals perceive their knowledge about general digital media and digital devices and about how to use them to solve problems, which is often also referred to as ICT Self-efficacy (Chen & Hu, 2020). As the usage of digital devices is becoming more integrated into the educational field, students who have knowledge and competence in using digital devices would adapt easily to the new instructional method and show good performances in computer-based assessments.

In order to explore students' ICT Competence, both ILSAs included questions in their surveys asking how much knowledge students have about various kinds of digital devices and how much they feel comfortable and/or confident when using digital devices. For example, the PISA 2018 ICT Questionnaire used questions such as "I feel comfortable using digital devices that I am less familiar with," "I feel comfortable using my digital devices at home," or "When I come across problems with digital devices, I think I can solve them" (OECD, 2017b). The eTIMSS Questionnaire included multiple questions to explore students' ICT Competence in two sections. One section explored their knowledge of diverse terminology regarding ICT (e.g., Wi-Fi, cut and paste, icon, drag and drop, etc.), and the other one explored their confidence in using digital devices such as "I am good at using a computer," "I am good at typing," "I can use a touchscreen on a computer, tablet, or smartphone," and "It is easy for me to find information on the internet" (IEA, 2020a).

2.4.3.2 Interest in Using ICT

Another aspect of ICT Attitude is how much they are interested in using digital devices, which is called ICT Interest in this study. In relevant studies, ICT Interest refers to an individual's intrinsic motivation that represents their long-term preference and engagement in dealing with ICT-related topics, tasks, or activities (Chen & Hu, 2020; Goldhammer et al., 2016; Ma & Qin, 2021). Students' general interest in using digital devices for various activities would need to be considered as one of the significant factors that influence their academic performance in the current era of integrating digital devices into education. Students who have more interest when using digital devices would actively participate in classes using digital devices to obtain information and solve problems, leading them to have more positive attitudes toward learning integrated with digital devices. This would also affect students' performances in computer-based tests as they would be familiar with solving questions in the context of using digital devices.

Questionnaires from PISA 2018 and TIMSS 2019 collected information regarding students' ICT Interest using the following questions. For example, PISA 2018 provided survey statements such as "I forget about time when I'm using digital devices," "I am really excited discovering new digital devices or applications," or "I like using digital devices" to measure how students feel interest when engaged in activities using digital devices (OECD, 2017b). While PISA 2018 included multiple questions regarding students' ICT Interest, TIMSS 2019 only had one relevant question to ICT Interest, which was "Did you like that this test was on a computer or tablet" (IEA, 2020a).

2.4.3.3 Autonomous Behavior When Using ICT

In addition to students' competence and interest in using ICT, it is meaningful to explore how much they perceive control and/or independence while using digital devices, which is referred to as ICT Autonomy in this study (Ma & Qin, 2021). Areepattamannil and Santos (2019) defined ICT Autonomy as "one's perceptions of personal independence (i.e., lack of external constraints or controls) in competently using digital media and digital devices" (p. 50). Especially for education where the usage of digital devices is integrated as a new instructional method, students' autonomous behavior when using them would need to be considered as a significant factor that would affect academic performance in computer-based assessments. Students with greater autonomy in using digital devices are expected to achieve better academic performance as they would be adept at managing and making plans for their own learning processes with digital tools, which would lead them to feel more confident when solving problems provided in digital contexts (Ma & Qin, 2021).

Students' autonomous behavior when using digital devices was investigated in PISA 2018 and TIMSS 2019 using diverse statements. For instance, ICT Autonomy was represented such as "If I need new software, I install it by myself," "I use digital devices as I want to use them," or "If I have a problem with digital devices, I start to solve it on my own" in PISA 2018 ICT Questionnaire (OECD, 2017b). Compared to PISA 2018, survey questions in TIMSS 2019 were less clear for exploring ICT Autonomy. A few statements in the eTIMSS Questionnaire such as "I can look up the meanings of words on the Internet," "I can write sentences and paragraphs using a computer," and "I can edit text on a computer" could be considered to represent ICT Autonomy (IEA, 2020a).

2.5 Relationship between ICT and Academic Performance

In accordance with the growing interest in using digital devices as a part of the new instructional methods, the potential influence of using digital devices on students' academic performance has been a topic of research interest. Diverse types of advanced statistical modeling methods like multiple linear regression analysis (e.g., Agasisti et al., 2020; Aypay, 2010; Srijamdee & Pholphirul, 2020; Xiao & Hu, 2019; Xiao et al., 2019), mediation and/or moderation analyses with applying structural equation modeling (e.g., Jiang et al., 2019; Kong et al., 2022; Lee & Wu, 2012; Ma & Qin, 2021; Odell et al., 2020a; Park & Weng, 2020), or multilevel modeling (e.g., Gómez-Fernández & Mediavilla, 2021; Hu et al., 2018; Juhaňák et al., 2018; Kong et al., 2022; Lim & Jung, 2019; Ma & Qin, 2021; Park & Weng, 2020; Pekto et al., 2017; Skryabin et al., 2015) were usually applied to explore the relationships between the unobservable ICT-related factors (i.e., ICT Usage and ICT Attitude) and students' academic performance.

2.5.1 ICT Usage and Academic Performance

Various previous studies explored how the students' usage of digital devices for educational purposes is related to their academic performance in reading, mathematical, and scientific literacy using the results from PISA and TIMSS. It was generally expected that students' ICT Usage for educational purposes would be positively associated with their academic achievements, especially in the context of computer-based assessments, since students would spend more time learning knowledge in a similar atmosphere. However, the results showed different patterns of associations depending on the focus of variables.

2.5.1.1 ICT Home

Interestingly, overall relevant studies showed that students' ICT Usage at home for schoolwork was negatively correlated with their academic performance (e.g., Agasisti et al., 2020; Gómez-Fernández & Mediavilla, 2021; Hu et al., 2018; Juhaňák et al., 2018; Lee & Wu, 2012; Odell et al., 2020a; Ozola & Grinfelds, 2019; Park & Weng, 2020). It was hard to find a clear reason for the result, but it seemed to be attributed to students' initial academic proficiency. The negative association could have happened since those who frequently use digital devices at home for studying purposes would rather have lower academic proficiency, so they would need time at home to do complementary studies (Gómez-Fernández & Mediavilla, 2021). Another reason was the malfunctioning quality of the survey questionnaires which asked about the usage of digital devices for academic reasons as the frequency of usage itself is insufficient to explain how deeply students learned and understood the knowledge (Park & Weng, 2020). As there could exist other variables, researchers tended to agree that the results should be interpreted with caution and that additional studies are necessary (Juhaňák et al., 2018; Park & Weng, 2020).

In contrast to these results, there were also a few studies which showed different results. For example, some studies revealed that the usage of digital devices at home for educational or school-related purposes was positively associated with their test scores on PISA 2012 (e.g., Pekto et al., 2017; Skryabin et al., 2015; Srijamdee & Pholphirul, 2020). Besides, Gubbels et al. (2020) showed a slightly different perspective that students with moderate use of ICT at home reported higher reading performances. The study of Lee and

Wu (2012) showed that the indirect effect of students' ICT Usage at home was positively associated with reading literacy when it was mediated by students' online reading activities although the direct effect was negatively correlated. Some studies showed that students' ICT Usage for educational schoolwork was not a significant factor that influenced reading proficiency (Aypay, 2010; Xiao et al., 2019). To sum up, there was no one obvious association between students' usage of digital devices at home for educational purposes and their academic performance in ILSAs.

2.5.1.2 ICT School

As general common sense, it was anticipated that students' ICT Usage at school for academic purposes is positively associated with their academic performance on the computerized tests. Interestingly, however, ICT Usage at school for educational purposes also tended to show a negative correlation with academic performance (e.g., Gómez-Fernández & Mediavilla, 2021; Hu et al., 2018; Juhaňák et al., 2018; Kong et al., 2022; Odell et al., 2020a; Ozola & Grinfelds, 2019; Park & Weng, 2020; Skryabin et al., 2015; Xiao et al., 2019) or not significantly associated (Aypay, 2010; Lee & Wu, 2012). The negative association could have been attributed to inadequate usage of digital resources or a lack of instructors who are good at using digital devices (Gómez-Fernández & Mediavilla, 2021; Xiao et al., 2019). Moreover, Juhaňák et al. (2018) pointed out that the negative relationship could have happened due to the property of the questionnaires. As the survey statements in the PISA 2018 ICT Questionnaire ask about ICT Usage at school including for education, entertainment, and social communication purposes, the usage at school would include students who do not focus on studying but rather focus on playing games or chatting with their friends through digital devices (Juhaňák et al., 2018).

Interestingly, there was another study where the association was not linear. The study by Gubbels et al. (2020) focused on the reading literacy of Dutch students and found that ICT Usage at school showed a negative quadratic effect (i.e., an inversed U-shaped curve) on students' academic performance, which indicated that students with moderate but not excessive usage of ICT at school reported higher reading performances than others. The negative association between students with excessive usage of digital devices and academic performance could be explained by the findings that those who struggle with their learning would spend more time using digital devices for additional practice.

2.5.1.3 ICT Usage as an Additional Variable

Some studies explored the influence of students' ICT Usage both at home and at school for academic and/or educational purposes as a mediator or moderator variable on their academic performance rather than a predictor variable. For example, Xiao and Hu (2019) showed that students' ICT Usage for schoolwork would significantly moderate the positive association between their socioeconomic status (SES) and performance on reading literacy tasks; for those with higher SES, the more students use ICT for schoolwork, the better reading performance they show. Moreover, the research of Chiao and Chiu (2018) discovered that students' ICT Usage for obtaining new information significantly mediates the relationship between students' SES and academic achievement, which infers that the chances to explore information with digital devices and high-quality Internet made a difference in academic performance among the students from different levels of SES.

In contrast, other studies implied that ICT Usage would not significantly mediate or moderate the associations. For instance, Jiang et al. (2019) explored the association between students' SES and their academic performance in seven East Asian countries, including ICT Usage as a mediator and moderator variable separately to explore how they have an impact. They found that various aspects of ICT Usage do not significantly affect the association between students' SES and their academic performance, questioning an alternative way to integrate ICT Usage in education for better academic performance. Also, while ICT Usage for retrieving information was significant, ICT Usage for learning or schoolwork was found not to be a significant mediator for the relationship between students' SES and academic achievement, indicating that it "could not effectively reduce the achievement gaps cause by SES" (Chiao & Chiu, 2018, p. 117). As a result, the effect of students' ICT Usage on their academic performance tended to show different results depending on the studies with different conditions such as countries, survey questions, and the patterns of relationships.

2.5.2 ICT Attitude and Academic Performance

In addition to the relationship between ICT Usage and academic performance, the next section explored the association between students' attitudes toward using digital devices and cognitive domains in the three types of literacy in ILSAs. Generally, it was expected that the relationship would show positive results as students with more positive attitudes toward using digital devices would make use of those tools better, feel more interest and engagement during the instructions, and solve problems more actively with autonomous behaviors and ease.

Overall, previous studies tend to show that ICT Attitude is positively correlated with academic achievements in various ILSAs (e.g., Kong et al., 2022; Lee & Wu, 2012; Lim & Jung, 2019; Odell et al., 2020a; Park & Weng, 2020). When having a deeper look at the relationship, there seemed to exist a gender difference regarding the relationship between ICT Attitude and academic performance, which usually favored boys over girls. For example, the relationship between ICT Attitude and reading literacy was stronger for boys than that for girls (Kong et al., 2022). In addition, after controlling for the effect of SES, boys were found to overperform girls in reading literacy of digital texts (Lim & Jung, 2019). However, when having a closer look at each study, the results were slightly different depending on the various dimensions of ICT Attitude and the sample of countries on which the research concentrated.

2.5.2.1 ICT Competence

Some studies figured out that students' perceived ICT Competence was found to be positively correlated with their academic performance (e.g., Hu et al., 2018; Lee & Wu, 2012; Lim & Jung, 2019; Odell et al., 2020a; Park & Weng, 2020). Students with stronger self-efficacy and beliefs in using digital devices tended to show better results in academic performance from computer-based tests as they would be "more likely to frequently use software or online resources for studying" (Park & Weng, 2020, p. 9). Interestingly, Lee and Wu (2012) found that students' confidence in using digital devices not only had a significant, positive direct effect on PISA reading literacy but also showed a significant, positive indirect effect mediated by online reading.

However, other studies showed different patterns of relationships. For example, Xiao et al. (2019) explored in their study that perceived ICT Competence was negatively associated with students' reading scores, while Juhaňák et al. (2018) figured out that ICT Competence itself was not significantly associated with academic performance. Ma and Qin (2021) figured out that the relationship showed different directions depending on the countries; Asian countries tended to show a negative association, while European and

American countries showed a positive correlation. Interestingly, Gubbels et al. (2020) found that the relationship showed a positive quadratic trend (i.e., a U-shaped curve). Students with a moderate level of ICT Competence showed lower reading achievement, and they thought that students need to reach a certain threshold to get benefits from increased ICT Competence (Gubbels et al., 2020).

The relationship between students' ICT Competence and academic performance also seemed to be affected by external variables. For instance, the relationship was moderated by economic inequality, where students from low-income families tended to have less confidence in using digital devices due to a lack of ICT Usage, which might have led to lower reading literacy (Park & Weng, 2020). In addition, although the direct relationship itself was not significant, Juhaňák et al. (2018) found that students' perceived ICT Competence was significantly associated with academic performance when moderated by gender; boys with more ICT Competence tended to perform better, while girls showed an opposite trend.

2.5.2.2 ICT Interest

It was generally anticipated that students who have more interest in using digital devices would perform better in computer-based tests as they could both learn and take tests in the same context. As previously expected, students' ICT Interest tended to show a positive correlation with academic performance (e.g., Gómez-Fernández & Mediavilla, 2021; Hu et al., 2018; Odell et al., 2020a; Park & Weng, 2020; Xiao et al., 2019). Students with a higher interest in using digital devices were more likely to spend more time participating in learning activities using computers or using the Internet more often, which would lead them to be motivated and have positive attitudes toward learning integrated with digital devices and show good academic performance (Park & Weng, 2020). Besides, the study of Gubbels et al. (2020) showed that students' ICT Interest showed a negative quadratic effect on academic achievements; the performances were the highest for students with moderate levels of interest in digital devices, but it decreased either for students who lack interest or have an excessive interest in using digital devices.

However, there was a different opinion in that the relationship between interest in using digital devices and academic performance could have been confounded by some external factors. Ma and Qin (2021) explored that the positive relationships between ICT Interest and academic performance in PISA usually appeared in East Asian countries, while it was either positive or negative for Western countries. They attributed it to the possibility of cultural expectations on the students. Students in East Asia (e.g., Korea, Japan, China, etc.) are usually expected to show good performances in standardized tests to get admission to top-ranked universities, which is considered a social success, so they might have put more effort into achieving the best performances (Ma & Qin, 2021).

2.5.2.3 ICT Autonomy

Unlike ICT Competence and ICT Interest, students' ICT Autonomy was found to be positively correlated with academic performance quite universally (e.g., Gubbels et al., 2020; Hu et al., 2018; Juhaňák et al., 2018; Ma & Qin, 2021; Odell et al., 2020a; Park & Weng, 2020; Xiao et al., 2019). Students with more autonomous and/or independent behaviors when using digital devices would actively make use of technology and search for the Internet to obtain knowledge and/or solve problems by taking control of their learning processes with detailed plans, which might have led them to better results (Juhaňák et al., 2018; Park & Weng, 2020). Due to this positive relationship, some researchers suggest that teachers and parents encourage students to reflect on their ICT learning process, be aware of their accomplishments, and give feedback on what they lack to enhance their autonomous behaviors in education using ICT (Ma & Qin, 2021). In addition, they were suggested to make students familiarize themselves with different types of technology to let them have more positive attitudes toward using digital devices by decreasing their degrees of technophobia, which would also lead them to improve performances in computer-based assessments (Kong et al., 2022).

2.5.3 Relationship Across Nordic Countries

In spite of various research regarding the relationship between students' usage of digital devices and academic performance, there were not many published studies that explored such relationships specifically for Nordic countries. Many previous studies either explored the overall relationship across multiple countries (e.g., Hu et al., 2018; Park & Weng, 2020) or selected single (e.g., Gómez-Fernández & Mediavilla, 2021; Juhaňák et al., 2018) or a few countries with details (e.g., Agasisti et al., 2020; Kong et al., 2022; Ma & Qin, 2021; Xiao et al., 2019). Five studies included the results of Nordic countries (Agasisti et al., 2020; Kong et al., 2022; Odell et al., 2020a; Pekto et al., 2017; Xiao et al., 2019), so this review will focus on these studies and explore how the relationship appeared for Nordic countries. Among the five Nordic countries, Finland appeared in all five studies, while Denmark, Iceland, and Sweden only appeared in one or two studies (Agasisti et al., 2020; Pekto et al., 2017). Finland tended to be often selected in the studies using data from ILSAs as the students from this country tended to show good academic performance and complete the ICT questionnaires (Kong et al., 2022; Xiao et al., 2019). One thing that should be noted is that the results of Norway did not appear in any of the five studies.

2.5.3.1 ICT Usage in Nordic Countries

In terms of ICT Usage at home, it generally showed a negative relationship with academic performance in Finland (Agasisti et al., 2020; Kong et al., 2022; Odell et al., 2020a; Pekto et al., 2017; Xiao et al., 2019). The other countries tended to show different results depending on research and cognitive domains. For example, Denmark showed positive associations overall (Agasisti et al., 2020; Pekto et al., 2017), while Iceland showed negative relationships for mathematical and scientific literacy but no significant result for reading literacy (Pekto et al., 2017). Sweden showed a positive association for reading literacy, but the relationships for mathematical and scientific literacy were not significant (Agasisti et al., 2020; Pekto et al., 2017). In terms of ICT Usage at school, its association with academic performance tended to show negative results overall, while it was not significant for Iceland (Kong et al., 2022; Pekto et al., 2017; Xiao et al., 2019). As a result, the relationship between ICT Usage and academic performance across Nordic countries is difficult to summarize with one general statement.

2.5.3.2 ICT Attitude in Nordic Countries

In terms of the relationship between ICT Attitude and academic performance, the study of Agasisti et al. (2020) was excluded because it did not include variables regarding ICT Attitude. Overall, the patterns of relationship were found to be congruent in that the associations were positive for all Nordic countries that appeared in the research (Kong et al., 2022; Odell et al., 2020a; Pekto et al., 2017; Xiao et al., 2019). Interestingly, one study showed that students' perceived ICT Competence was not significantly correlated with reading literacy (Xiao et al., 2019). While students in Nordic countries tended to show positive relationships, it is difficult to generalize as there was no result for Norway.

2.6 Multilevel Mediation Analysis

The previous section explored how students' usage of digital devices and their attitudes toward using them are associated with their academic performance. However, such variables cannot be directly observed (i.e., latent variables), so they need to be measured indirectly. In the previous studies, the first two latent variables were usually measured using the student questionnaires asking how often they use digital devices at home or school and how much they feel confident or have positive attitudes when they use them. Their academic performance (i.e., proficiency) was measured using cognitive items administered in PISA and TIMSS, where the scores are scaled on a mean of 500 and a standard deviation of 100 (Mullis & Martin, 2017; OECD, 2019a). The interrelationship among the latent variables can be explored using an advanced statistical approach called structural equation modeling (SEM).

2.6.1 Structural Equation Modeling

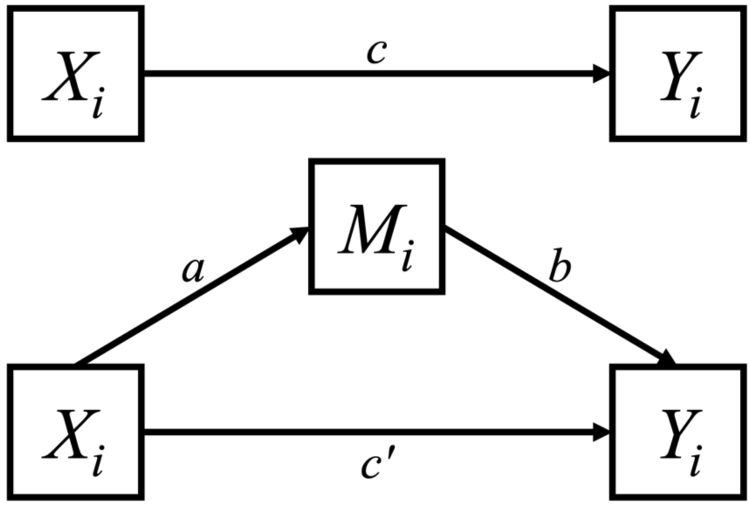
SEM is a statistical "modeling approach that combines latent variables defined through factor analysis with path models that can specify a variety of direct, mediating, and reciprocal effects" (Heck & Thomas, 2015, p. 6). Research studies in education or social science usually deal with unobservable, latent variables. Especially, one of the interesting topics in the field of educational research is the factors that could influence students' academic performance. As such factors are latent and cannot be directly observed, they are usually measured indirectly by formatting survey questionnaires to represent latent factors, and then the relationships among the measured latent variables are explored. In other words, latent variables are first conceptually operationalized using observable items, and then the strength of associations among the variables is quantified. In the process of conducting SEM (i.e., structural regression model), the former step is referred to as a measurement model and the latter as a structural model (Kline, 2015). The measurement model is usually explored by a confirmatory factor analysis (CFA), which explores how well the observed items represent the latent variables (Civelek, 2018). The structural model is then explored using a path model, which is usually represented as a series of regression equations (Civelek, 2018).

Once a hypothesized structural model is defined by researchers and applied to observed data, the degree of appropriateness of the model that fits the observed data is evaluated using various model fit indices. Model fit indices like (1) model chi-square (χ^2) statistics and its *p*-value, (2) comparative fit index (CFI) or Tucker-Lewis index (TLI), (3) root mean square error of approximation (RMSEA) and its 90% confidence interval (CI), and (4) standardized root mean-square residual (SRMR) are frequently used in the analysis using SEM (Kline, 2015). Model χ^2 statistics would show a *p*-value greater than .05 when the proposed model is likely to fit the observed data, but it is subject to various factors. Moreover, models with a good fit would show a greater value of CFI and TLI, while RMSEA and SRMR would be smaller (Hu & Bentler, 1999). Although all model fit indices may not show congruent results, researchers make decisions on the fitness of the hypothesized model by holistically reviewing the fit indices.

2.6.2 Mediation Analysis

SEM is useful not only for representing latent variables in a quantitative way but also for investigating a relationship among the latent variables using path analyses. When two variables are found to be significantly correlated, it is often misinterpreted that one variable has caused a change in the other one. However, it should be interpreted carefully because there could exist other potential factors that actually influence the relationship between the two variables. For example, there are two possible stories to explain the positive correlation between students' usage of digital devices and their reading literacy (Pekto et al., 2017). The usage itself could have directly affected their literacy, but it is also possible that the usage first affected students' attitudes toward using them, and the more positive attitudes would have influenced better results in reading literacy. In order to explore such causal relationships between the two variables including an external variable that would have a potentially significant influence on the relationship, mediation analysis can be used by applying a principle of path analysis.

The mediation effect is defined as a "causal hypothesis that one variable causes change in another variable, which in turn leads to changes in the outcome variable" (Kline, 2015, p. 134). It aims to explore how or why a relationship between the two variables, often referred to as predictor and outcome variables, exists by including a mediator variable (Kim et al., 2001). Figure 2.1 shows a basic hypothetical model for exploring the effect of the mediator (M) between an association of a predictor (X) and an outcome (Y). The total effect of Variable X on Y (i.e., c) is a combination of a direct effect of Variable X on Y after controlling for the mediator (i.e., c') and an indirect effect of Variable X on Y through the mediator (i.e., a and b) (Little et al., 2007; Livingston & Haardörfer, 2019; Tofighi & Thoemmes, 2014). The mediation effect is confirmed when the two pathways indicating the indirect effect through the mediator variable (i.e., a and b in Figure 2.1) are statistically significant (Kim et al., 2001; Little et al., 2007; Livingston & Haardörfer, 2019). The relationship between the predictor and outcome variables is assumed to be significant before analyzing the mediation effect (Kim et al., 2001).



Note. M = Mediator variable; c = Total effect; c' = Direct effect after controlling for the effect of mediator; a and b = Indirect effect through mediator

Figure 2.1. Basic Mediation Effect Model

Single-level mediation analysis in Figure 2.1 can be expressed in a set of multiple linear regression equations as in Equation 2.1, where i stands for individual data, β_0 for an intercept, and e_i for the measurement errors. The first part of Equation 2.1 represents the linear regression equation for the mediation model part, and the second one shows the one for the outcome model part. The mediator variable is regressed on the predictor variable, and the outcome variable is regressed on both the mediator and predictor variables. When combining the two models, it can be found that the indirect effect through the mediator variable is a product of the two pathways between Variables X and Y (i.e., $a \times b$). Also, the total effect of Variable X on Y (i.e., c) is an addition of the direct effect of Variable X on Y (i.e., c') after controlling for the effect of the mediator and the indirect effect, which can be represented as $c = a \times b + c'$ (Little et al., 2007; Livingston & Haardörfer, 2019).

$$\begin{aligned} &\text{Mediation:} \quad && M_i = \beta_0 + aX_i + e_i \\ &\text{Outcome:} \quad && Y_i = \beta_0 + c'X_i + bM_i + e_i \end{aligned} \tag{2.1}$$

2.6.3 Multilevel Framework in Mediation Analysis

Not only with a single level but the mediation analysis using the SEM method also can be extended by including multiple levels, which is often referred to as multilevel modeling (MLM). Basically, MLM is an extension of the ordinary least squares regression model which could investigate relationships between different levels of grouped data with a hierarchical structure of data, accounting for the variances among variables at different levels (Woltman et al., 2012). Depending on the research fields, this method could also be called in diverse terms such as hierarchical linear modeling, mixed-effects or random-effects modeling, random-coefficient regression modeling, or covariance components modeling (Raudenbush & Bryk, 2002). The concept will be referred to as MLM throughout this dissertation.

Including more than one level is especially useful when analyzing datasets from ILSAs because individual data of students are usually clustered into hierarchical grouping levels, where scores within each group or unit are not supposed to be independent (Kline, 2015). For example, students are clustered within schools, schools are clustered within regions, and regions are clustered within countries. In this context, MLM is advantageous because it could disaggregate variances of each clustering level on individual data, which enables us to explore whether the student data can be attributed to an individual solely or any higher-ordered clustering levels (e.g., schools, regions, test languages, countries). Due to this advantage, the multilevel framework has been frequently applied in previous research with ILSAs (e.g., Areepattamannil & Santos, 2019; Aru & Kale, 2019; Chen & Hu, 2020; Gubbels et al., 2020; Hatlevik et al., 2015; Hu et al., 2018; Lim & Jung, 2019; Park & Weng, 2020; Seddig & Lomazzi, 2019).

2.6.3.1 Multilevel Structural Equation Modeling

Based on the general concept of SEM and MLM, the two frameworks could be integrated to explore a structural model among latent variables not only from the student level but also from the higher-ordering levels. This new method is often referred to as multilevel structural equation modeling (MLSEM), an advanced modeling technique with multiple hierarchical levels for analyzing data with complex structures (Heck & Thomas, 2015; Kline, 2015). This review focused on MLSEM with two levels as there are fewer components to be estimated and analyzed.

One of the key characteristics of MLSEM is to decompose the individual-level (i.e., within-group) and group-level (i.e., between-group) variances (Davidov et al., 2012; Goldstein et al., 2007; Heck & Thomas, 2015; Preacher et al., 2010). Due to its property, MLSEM is widely used for analyzing data in educational research, especially for ILSAs like PISA and TIMSS, since it could analyze the relationship between latent variables at multiple levels and compare them across different countries (e.g., Akgenç & Pehlivan, 2019; Bellens et al., 2019; Goldstein et al., 2007; Pritikin et al., 2017; Yan & Cai, 2021).

The framework of MLSEM starts from the measurement model of latent variables using observable items, which is usually measured using multilevel confirmatory factor analysis (MLCFA), and then moves on to the structural model of the latent variables with path analyses (Davidov et al., 2012; Davidov et al., 2018; Seddig & Lomazzi, 2019). Equation 2.2 presents the general mathematical expressions of MLCFA with two levels with detailed explanations of each notation in Table 2.3, where the first line shows the within-group variation, and the second part shows the between-group variation (Davidov et al., 2012; Hox, 2013; Meuleman, 2019; Seddig & Lomazzi, 2019).

$$\text{Level 1 (Within):} \quad y_{ijk} = \alpha_{jk} + \lambda_{Wk}\eta_{Wij} + \varepsilon_{Wijk}$$
$$\text{Level 2 (Between):} \quad \alpha_{jk} = \upsilon_k + \lambda_{Bk}\eta_{Bj} + \varepsilon_{Bjk} \tag{2.2}$$

Table 2.3. Parameters in Equation 2.2

Parameter		Explanation
Level 1 (Within)	y_{ijk}	Observed value of individuals *i* of group *j* on indicator variable *k*
	α_{jk}	Intercept of indicator variable *k* in group *j*
	λ_{Wk}	Within-level factor loading of indicator variable *k*
	η_{Wij}	Score of individual *i* of group *j* on the within-level latent variable η_W
	ε_{Wijk}	Within-level residual for individual *i* of group *j* on indicator variable *k*
Level 2 (Between)	υ_k	Cross-group grand intercept of indicator variable *k* (i.e., grand mean when the between-level latent variable equals 0)
	λ_{Bk}	Between-level factor loading of indicator variable *k*
	η_{Bj}	Score of group *j* on the between-level latent variable η_B
	ε_{Bjk}	Between-level residual for group *j* on indicator variable *k*

Note. *i* = Individual; *j* = Group; *k* = Indicator variable; *W* = Within level (Level 1); *B* = Between level (Level 2) (Davidov et al., 2012).

When the two models in Equation 2.2 are combined as one equation, the general measurement model of MLSEM can also be summarized as Equation 2.3, where all values are now stored in vectors and matrices. Table 2.4 shows the dimensions and explanations of each vector and matrix in Equation 2.3 that includes a subscript of *j* on both variables and the parameter matrices. This indicates that several elements within these matrices could potentially vary over groups (Hox, 2013; Meuleman, 2019; Preacher et al., 2010; Preacher, 2011; Seddig & Lomazzi, 2019; Sideridis et al., 2018).

$$\begin{aligned} y_{ijk} &= (\upsilon_k + \lambda_{Bk}\eta_{Bj} + \varepsilon_{Bjk}) + \lambda_{Wk}\eta_{Wij} + \varepsilon_{Wijk} \\ &= \upsilon_k + \lambda_{Bk}\eta_{Bj} + \lambda_{Wk}\eta_{Wij} + \varepsilon_{Bjk} + \varepsilon_{Wijk} \\ Y_{ij} &= \upsilon_j + \Lambda_j\eta_{ij} + \varepsilon_{ij} \end{aligned} \tag{2.3}$$

Table 2.4. Parameters in Equation 2.3

Parameter	Dimension	Explanation
Y_{ij}	$p \times 1$	Vector of measured variables
υ_j	$p \times 1$	Vector of intercepts
Λ_j	$p \times m$	Matrix of factor loadings
η_{ij}	$m \times 1$	Vector of latent variables (random effects)
ε_{ij}	$p \times 1$	Vector of error terms

Note. i = Individual; j = Group; p = Number of measured variables; m = Number of latent variables across both within and between levels with random slopes if any are specified (Preacher et al., 2010).

The second step of MLSEM is to explore the structural model of measured latent variables by allowing some coefficient matrices to vary at the grouping level (Preacher et al., 2010; Preacher, 2011). Equation 2.4 shows the general mathematical expressions of the structural model for MLSEM, followed by the detailed explanations of each notation in Table 2.5 (Meuleman, 2019; Preacher et al., 2010; Preacher, 2011; Sideridis et al., 2018).

$$\begin{aligned} &\text{Level 1 (Within):} \quad && \eta_{ij} = \alpha_j + B_j \eta_{ij} + \zeta_{ij} \\ &\text{Level 2 (Between):} \quad && \eta_j = \mu + \beta \eta_j + \zeta_j \end{aligned} \tag{2.4}$$

Table 2.5. Parameters in Equation 2.4

	Parameter	Dimension	Explanation
Level 1 (Within)	η_{ij}	$m \times 1$	Vector of latent variables
	α_j	$m \times 1$	Vector of latent intercepts
	B_j	$m \times m$	Matrix of structural coefficients (random slopes) at Level 1
	ζ_{ij}	$m \times 1$	Residual values of latent variable and random effect regressions for Level 1
Level 2 (Between)	η_j	$r \times 1$	All random coefficients from υ_j, α_j, and B_j
	μ	$r \times 1$	Means of random coefficients of between-structural equations
	β	$r \times r$	Structural coefficients of random effects regressed on each other
	ζ_j	$r \times 1$	Residual values of latent variable and random effect regressions for Level 2

Note. i = Individual; j = Group; r = Number of random coefficients (Preacher et al., 2010; Preacher, 2011).

2.6.3.2 Multilevel Mediation Using MLSEM

Single-level mediation analysis can be combined with the principle of MLSEM by adding multiple hierarchical levels to the model, which results in multilevel mediation analysis. Literally, multilevel mediation analysis is a combination of MLM and mediation analysis, which could explore both direct and indirect effects on multiple levels together (Hu et al., 2020; Hülsheger et al., 2013; Preacher et al., 2010; Preacher, 2011; Tofighi & Thoemmes, 2014). Applying the single-level mediation model for data with hierarchical clustering variables could be inappropriate because it is likely to produce biased standard errors due to the violation of the assumption of independence of observations (Preacher et al., 2010). In this case, MLSEM would function better when exploring a mediation effect with hierarchical levels because it "does not require outcomes to be measured at Level 1, nor does it require two-stage analysis" (Preacher et al., 2010, p. 213).

The design of a multilevel mediation model can be referred to as a set of numbers depending on the levels where the variables are measured. Corresponding to the order of the predictor variable (*X*), mediator (*M*), and the outcome variable (*Y*), it is often notated as 1 if the variable is measured at Level 1 (i.e., within-level) and 2 when it is measured at Level 2 (i.e., between-level) (Preacher et al., 2010). For example, if all variables are measured at Level 1, it is called a 1-1-1 multilevel mediation model, indicating that the mediation effect would happen at both levels. If the predictor variable was measured only at Level 2 whereas the other variables were measured at Level 1, it is referred to as a 2-1-1 multilevel mediation model, where the mediation effect would happen at the between-level (Hülsheger et al., 2013; Preacher et al., 2010). Figure 2.2 visually presented the 1-1-1 multilevel mediation model, where all variables were measured at the within-level.

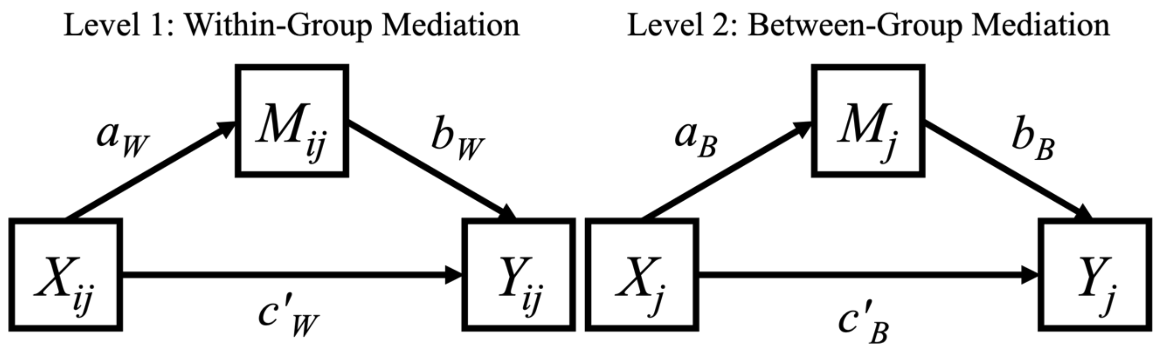


Figure 2.2. 1-1-1 Multilevel Mediation Model with Two Levels

Figure 2.2 can also be written as a set of multiple linear regression equations as in Equation 2.5 with detailed explanations of notations in Table 2.6. The upper part represents the mediation model with two levels, while the lower part shows the outcome model with two levels, and both models include random intercepts and slopes (Tofighi et al., 2013). The predictor ($X_{ij} - \overline{X}_j$) and the mediator variables ($M_{ij} - \overline{M}_j$) are group-mean centered, which is useful for partitioning out within- and between-clusters information although variables are measured on Level 1 (Asparouhov & Muthén, 2018; Tofighi et al., 2013).

$$
\begin{aligned}
&\underline{\text{Mediation}} \\
&\text{Level 1 (Within):} && M_{ij} = d_{1j} + a_j(X_{ij} - \overline{X}_j) + e_{1ij} \\
&\text{Level 2 (Between):} && d_{1j} = d_1 + a_B\overline{X}_j + u_{d_{1j}} \\
& && a_j = a_W + u_{a_j} \\
&\underline{\text{Outcome}} \\
&\text{Level 1 (Within):} && Y_{ij} = d_{2j} + c'_j(X_{ij} - \overline{X}_j) + b_j(M_{ij} - \overline{M}_j) + e_{2ij} \\
&\text{Level 2 (Between):} && d_{2j} = d_2 + c'_B\overline{X}_j + b_B\overline{M}_j + u_{d_{2j}} \\
& && c'_j = c'_W + u_{c'_j} \\
& && b_j = b_W + u_{b_j}
\end{aligned}
\tag{2.5}
$$

Table 2.6. Parameters in Equation 2.5

	Parameter	Explanation
Variable	$\overline{X}_j$	Observed mean of predictor variable for group j
	$X_{ij} - \overline{X}_j$	Group-mean centered value of predictor variables
	$\overline{M}_j$	Observed mean of mediator variable for group j
	$M_{ij} - \overline{M}_j$	Group-mean centered value of mediator variables
Mediation	a_W	Within-cluster effect of X on M
	a_B	Between-cluster effect of X on M
	d_1	Intercept of mediation model
	e_{1ij}	Level 1 residual value for mediation model
	u_{a_j}	Level 2 residual value of slopes for X on M
	$u_{d_{1j}}$	Level 2 residual value of intercepts for mediation model
Outcome	b_W	Within-cluster effect of M on Y
	b_B	Between-cluster effect of M on Y
	$c_W^{'}$	Within-cluster effect of direct effect
	$c_B^{'}$	Between-cluster effect of direct effect
	d_2	Intercept of outcome model
	e_{2ij}	Level 1 residual value for outcome model
	u_{b_j}	Level 2 residual value of slopes for M on Y
	$u_{c_j^{'}}$	Level 2 residual value of slopes for direct effect
	$u_{d_{2j}}$	Level 2 residual value of intercepts for outcome model

Note. i = Individual; j = Group; W = Within level (Level 1); B = Between level (Level 2) (Tofighi et al., 2013).

2.7 MLSEM for Cross-Cultural Comparison

Datasets from ILSAs have a specific property in that the scores of students could be clustered into schools, and the schools could be grouped into countries. This indicates that each student's performance can be attributed not only to the student-related factors but also to the school- and/or country-related variables they belong to. When it comes to the educational policies directed by schools and/or the national government, it becomes crucial to differentiate them so that they can manage school- and/or country-related factors for better improving academic atmospheres for students. Specifically, comparing results from ILSAs with the global average and/or other countries would function as a milestone for the governments to evaluate if their educational policies and/or curricula are good enough to keep or need changes. However, treating data from ILSAs as single-level data could lead to biased interpretations of the analyses as it is difficult to figure out if students' performances are affected by their innate proficiencies or their belongingness to certain countries. In this perspective, MLSEM has functioned as a useful method for analyzing data from ILSAs which include multiple levels for cross-national or cross-cultural comparison studies. MLSEM could investigate how both individual-level and country-level variables would affect scores of individual students clustered into countries (e.g., Cheung & Au, 2005; Goldstein et al., 2007; Meuleman, 2019). When designing a cross-cultural comparative study using MLSEM, several aspects would need to be considered to make research reasonable: the number of levels and countries included in the analysis.

2.7.1 Number of Levels

Students' data from ILSAs can be usually clustered into three levels: individual (student), school, and country levels. A relevant issue that arises here is the number of levels to include for multilevel analysis. Studies either included all three levels or focused on two levels. When the study focused on two levels, the analyses either (1) included the student and country levels, while excluding the school level or (2) included student and school levels, while treating the countries as separate groups.

Generally, in terms of cross-cultural comparison, multilevel analyses using ILSA data included three levels (i.e., student, school, and country levels) (e.g., Areepattamannil & Santos, 2019; Dronkers & Robert, 2008; Hu et al., 2018; List et al., 2020; Ma & Qin, 2021; Sebastian & Huang, 2016; van Langen et al., 2006). In these studies, a variety of predictors were included in MLSEM as level-related control variables to explore whether these factors make differences among students. For example, control variables such as students' gender, immigration status, and socioeconomic status were included at the student level (e.g., Areepattamannil & Santos, 2019; Hu et al., 2018; Sebastian & Huang, 2016). For school-level variables, school-mean socioeconomic status, school type (i.e., private or public), or school sizes were generally included (e.g., Areepattamannil & Santos, 2019; Dronkers & Robert, 2008; Hu et al., 2018; Ma & Qin, 2021; Sebastian & Huang, 2016; van Langen et al., 2006). In terms of country-level predictors, studies usually imported the information on economic levels of countries from external datasets such as the human development index (HDI), gross domestic product (GDP), or wealth inequality index (i.e., GINI index) (e.g., Areepattamannil & Santos, 2019; Davidov et al., 2012; List et al., 2020; Ma & Qin, 2021; van Langen et al., 2006).

However, some cross-cultural comparative studies included two levels excluding the school level (i.e., including the student and country levels only) (e.g., Park & Weng, 2020; Pekto et al., 2017). Especially, although students are clustered in schools, Pekto et al. (2017) decided not to include the school level in their analysis because it was difficult to conduct multilevel modeling with the PISA data which only have student weights but no school weights. In different ways, some studies focused on the student and school levels in the multilevel analyses and treated countries as a separate group analysis (e.g., Chen & Hu, 2020; Kong et al., 2022). Rather than including the country level in the analyses, they decided to explore the relationship of the latent factors in the hypothesized model for each country separately. This could sound reasonable as each country has different educational systems and/or policies, so the hypothetical model for the relationship between the latent factors could be difficult to be directly compared.

2.7.2 Number of Countries

The other issue to consider when conducting cross-national comparison analyses using MLSEM is the number of countries to be included. Given the country is a Level 2 unit, one of the reasons why MLSEM is applied is to explore how strongly the country-related factors affect outcomes on the individual student level. It is recommended to have as many countries as possible to explore enough significance of the country effect, but one question was posed on the minimum number of countries to be included because it is not always possible to have many different countries (groups) when collecting real data.

In order to figure out answers to this question, several researchers explored how many countries would be necessary to make the MLSEM analyses reasonable by using Monte Carlo simulation methods. For example, Meuleman and Billiet (2009) found that the minimum number of countries may depend on the purpose of MLSEM; 40 countries seem to be enough for a simple between-level model, 60 for detecting large structural effects at the between-level (greater than 0.50) model, and 100 for an acceptable probability of detecting smaller effects (Meuleman & Billiet, 2009). However, different studies showed fewer recommended number of countries for MLSEM analyses. For example, in contrast to the research of Meuleman and Billiet (2009) that 20 countries might not seem enough for estimating between-model parameters in MLSEM, Hox et al. (2012) indicated that 20 countries would be enough for estimating parameters when the Bayesian method is used. Similarly, Bryan and Jenkins (2016) figured out that linear models would require at least 25 countries, while logit models would need at least 30 countries at the Level-2 unit for reliable parameter estimates (i.e., both fixed and random) as the standard error and non-coverage rates become closer to 0.

Meanwhile, the minimum number of required countries seems to be different depending on the parameter estimation methods. The Bayesian estimation method usually requires fewer countries compared to the maximum likelihood estimation (MLE) as the Bayesian approach provides better credible interval coverages of estimated parameters and smaller biases (Hox et al., 2012; Stegmueller, 2013). In one example, when 20 countries are included in MLSEM, the Bayesian method tended to show smaller parameter bias and better coverage of between-level factor loadings and structural effects (Hox et al., 2012). However, the Bayesian method is not the perfect answer for this because it showed larger error variances than MLE (Hox et al., 2012).

When reviewing the previous cross-cultural comparison studies that applied the MLSEM method, many studies included more than 20 countries (e.g., Areepattamannil & Santos, 2019; Chen & Hu, 2020; Cheung & Au, 2005; Davidov et al., 2012; Davidov et al., 2018; He et al., 2019; Hu et al., 2018; Lee & Wu, 2012; Odell et al., 2021; Park & Weng, 2020; Yi & Kim, 2019). These studies were useful for exploring a global pattern of relationships between the latent variables and any potential effects of countries across diverse continents on such relationships. However, there were also a significant number of studies which included fewer countries than 20 (e.g., Agasisti et al., 2020; Bellens et al., 2019; Eklöf et al., 2014; Erdogdu & Erdogdu, 2015; Jiang et al., 2019; Kong et al., 2022; Lim & Jung 2019; Ma & Qin, 2021; Odell et al., 2020a). These studies were also useful in that they focused on how the patterns of such relationships differed by the selected countries, quantitatively presenting the estimated parameter values. Since each country has its own educational policies and cultures, it was better to understand how the relationship varies across different countries.

2.8 Summary of Literature

The review of previous literature provided an insight into how the relationship between students' usage of digital devices (i.e., ICT Usage), attitudes toward using digital devices (ICT Attitude), and academic performance appeared. Although the results were different depending on the conditions of analyses, students' ICT Usage generally showed a negative association with their academic performance, while ICT Attitude showed more results of positive associations. The literature review also explored the general concept of multilevel mediation analysis by applying the MLSEM method. The mediation analysis is useful for exploring the indirect effect of an external variable on a linear relationship between two variables. Moreover, MLSEM is useful for decomposing the within- and between-group variances specifically for cross-national comparison studies. While there is no limit to the number of levels included in the analysis, it seemed general to include either two or three levels. In terms of the number of countries, there was no specific rule as it could include many countries or only focus on a few of them.

Although there have been a lot of published studies regarding the relationship between ICT Usage, ICT Attitude, and academic performance, it was difficult to figure out published studies that explored such relationships for Nordic countries. Specifically, the review failed to find studies that show the results of Norwegian students. Therefore, the present research aims to see how the interrelationship among the three concepts would appear across Nordic countries by analyzing the most recently published datasets from two ILSAs (i.e., PISA 2018 and TIMSS 2019) and by applying the idea of multilevel mediation analyses. Detailed plans for data analyses will be addressed in the following chapter.

CHAPTER 3

METHOD

3.1 Data and Variable Description

The main purpose of this dissertation is to explore the interrelationship among students' usage of digital devices, attitudes toward using digital devices, and their academic performance, concentrating on the results from the five Nordic countries (i.e., Denmark, Finland, Iceland, Norway, and Sweden). This study conducted a secondary data analysis on the datasets from PISA 2018 (OECD, 2019c) and TIMSS 2019 (Fishbein et al., 2021), which were publicly released on the website of OECD PISA and IEA TIMSS & PIRLS Center. These are the two most recent ILSAs whose results were publicly released before the outbreak of the COVID-19 pandemic. It would be more reasonable to use the results from PISA 2022 and TIMSS 2023 in order to investigate how the pandemic affected students' educational activities using digital devices; however, since there have been no recent assessments, this dissertation would function as preliminary research for predicting the associations among the variables using the two ILSAs at this point.

3.1.1 Samples of Nordic Countries

Students from Nordic countries for both ILSAs were included. In terms of TIMSS 2019, this study only included students in Grade 8 as their ages closely match those of students who participated in PISA 2018, which is 15 years old on average. Table 3.1 shows the sample sizes of students, schools, and the average number of students per school from the published datasets in both ILSAs (Fishbein et al., 2021; OECD, 2019c). Denmark and Iceland did not participate in TIMSS 2019 Grade 8, and Norway was excluded from the analyses for PISA 2018 since no answers were provided to the ICT Questionnaire.

Table 3.1. Samples of Nordic Countries from PISA 2018 and TIMSS 2019

	PISA 2018			TIMSS 2019		
Country	Student	School	Average	Student	School	Average
Denmark	7,657	348	22.00			
Finland	5,649	214	26.40	5,570	154	36.17
Iceland	3,296	142	23.21			
Norway				5,215	157	33.21
Sweden	5,504	223	24.68	4,565	150	30.43

Note. Student = Number of students; School = Number of schools; Average = Average number of students per school.

3.1.2 Academic Performance

The first variable included in the analysis is students' academic performance. PISA 2018 explored students' academic proficiency in reading, mathematical, and scientific literacy, while TIMSS 2019 focused on mathematics and science. Since students do not usually take all items presented in ILSAs, it is difficult to directly compare students' individual scores to others as the scores are based on different items. In this perspective, plausible values are usually reported in ILSAs rather than a single score, which are the estimated scores of each student's performance (Aparicio et al, 2021). These values account for all possible cases with an assumption that students went through all items in ILSAs, which is usually useful for increasing the accuracy of the estimates (OECD, 2017a; Rutkowski et al., 2010). PISA 2018 reported ten plausible values, and TIMSS 2019 reported five values to show how students performed on each cognitive measure, where both are scaled with a mean of 500 and a standard deviation of 100. Therefore, plausible values were used to define students' academic performance.

When using plausible values in secondary data analyses for students' academic proficiency, there were two ways to treat them in the previous studies: (1) choosing one plausible value among multiple plausible values (e.g. Agasisti et al., 2020; Park & Weng, 2020), and (2) computing the average or the median value of the values (e.g., Hu et al., 2018; Jiang et al., 2019; Juhaňák et al., 2018; Ma & Qin, 2021). Although these strategies have an advantage in that they could make the analyses brief and easy by using a single value, they should be treated carefully as there is a possibility of underestimating standard errors (Rutkowski et al., 2010). This research took the average of multiple plausible values to measure different domains of cognitive proficiency and used these means to measure the latent construct of academic performance by applying the CFA method (e.g., Kong et al., 2022; Odell et al., 2020a; Xiao et al., 2019).

3.1.3 ICT Usage

In addition to the questions for measuring cognitive measures, PISA 2018 and TIMSS 2019 also provided other survey questionnaires to collect information related to students' academic lives. Among various aspects, students' usage of digital devices (i.e., ICT Usage) and their attitudes toward using them (i.e., ICT Attitude) are the two variables in this research. Since these variables cannot be directly measured, survey items in PISA 2018 ICT and TIMSS 2019 eTIMSS Questionnaires were utilized to measure the latent variables (IEA, 2020a; OECD, 2017b). For several items scaled on a 4- or 5-point Likert scale, there was an option indicating non-applicability such as "Never or hardly ever" or "Not at all true of me." Since the original numbers coded for these options seemed not straightforward to understand, they were recoded as 0, and the other options were also recoded based on this process (i.e., 1 to 5 into 0 to 4).

The latent variable for students' usage of digital devices (i.e., ICT Usage) was measured using the survey statements which asked about their activities and length of time using digital devices and/or the Internet, which were clustered into two sub-categories: (1)

ICT Usage at home (i.e., ICT Home) and (2) ICT Usage at school (i.e., ICT School). Although there are various purposes for using digital devices, this study focused on the statements for educational purposes. Appendix A shows the full list of selected survey statements from PISA 2018 ICT and TIMSS 2019 eTIMSS Questionnaires that were used for measuring the latent variable of students' ICT Usage.

3.1.3.1 ICT Home

Survey statements that are related to students' ICT Usage at home for educational purposes are selected to measure the "ICT Home" variable. The survey set "IC010" in the PISA 2018 ICT Questionnaire asked how often students use digital devices for certain activities outside of school (i.e., at home) (OECD, 2017b). Within this survey set, 6 out of 12 statements were chosen, which asked about their usage of digital devices for educational purposes. The full list of selected statements for ICT Home in PISA 2018 is presented in Table A.1 in Appendix A. All selected items were scaled on a 5-point Likert scale.

In terms of TIMSS 2019, the Grade 8 Student Questionnaire asked a set of questions about students' ICT Usage at home, but it simply asked if the students possess certain digital devices or Internet connections at home rather than the actual activities using digital devices (IEA, 2020b). The research eventually decided not to include ICT Home because the possession of digital devices itself would be weak to explain students' usage at home.

3.1.3.2 ICT School

Similar to ICT Home, survey statements that are related to students' ICT Usage at school for educational purposes were selected to measure the "ICT School" latent variable. The survey set "IC011" in the PISA 2018 ICT Questionnaire asked how often students use digital devices for certain activities at school (OECD, 2017b). Within this set, 5 out of 10 statements were selected, where the usage was specifically for educational purposes. The full list of selected statements for ICT School for PISA 2018 is presented in Table A.2 in Appendix A, where all items were scaled on a 5-point Likert scale.

In terms of TIMSS 2019, the Grade 8 eTIMSS Questionnaire had a set of questions for students' ICT Usage at school, asking how often students use computers or tablets at school (IEA, 2020a). All statements were selected to measure ICT School for TIMSS 2019, which were scaled on a 4-point Likert scale. As the current study decided not to put ICT Home for TIMSS 2019, this aspect was considered as ICT Usage of students. The full list of selected statements for ICT Usage in TIMSS 2019 is in Table A.3 in Appendix A.

3.1.4 ICT Attitude

Similar to ICT Usage, survey statements in the two questionnaires asking about students' overall emotions, thoughts, or behaviors when they use digital devices and/or the Internet were used to measure students' attitudes toward using digital devices (i.e., ICT Attitude). ICT Attitude was clustered into three sub-categories: (1) ICT Competence, (2) ICT Interest, and (3) ICT Autonomy. Across both ILSAs, the survey statements for ICT Attitude were coded with a 4-point Likert scale, where 1 indicates "strongly disagree" and 4 refers to "strongly agree". Appendix B presents the full list of selected survey statements from PISA 2018 ICT and TIMSS 2019 eTIMSS Questionnaires that were used to measure the latent variable of students' ICT Attitude.

3.1.4.1 ICT Competence

Students' feeling of positive perspective and comfort when using digital devices (i.e., ICT Competence) was measured using several survey questionnaires in both ILSAs. For the PISA 2018 ICT Questionnaire, the item set "IC014" included statements asking how comfortable and positive students feel when they are engaged in activities using digital devices (OECD, 2017b). All five statements were included to measure the latent variable of ICT Competence, which were scaled on a 4-point Likert scale. The full list of selected survey items for ICT Competence in PISA 2018 is presented in Table B.1 in Appendix B.

3.1.4.2 ICT Interest

The degree of students' interest when using digital devices (i.e., ICT Interest) can also be measured using the survey statements in both ILSAs. The item set "IC013" within the PISA 2018 ICT Questionnaire seemed appropriate for measuring ICT Interest, so all six items in this set were included in the analysis (OECD, 2017b). All statements were also scaled on a 4-point Likert scale. The full list of survey items for ICT Interest in PISA 2018 is presented in Table B.2 in Appendix B.

3.1.4.3 ICT Autonomy

The last aspect of ICT Attitude, which is students' autonomous behaviors when using digital devices (i.e., ICT Autonomy), was measured using the item set "IC015" in the PISA 2018 ICT Questionnaire. These questions aim to focus on how much students feel autonomy or personal independence when using digital devices to solve problems by themselves (OECD, 2017b). All five statements in the item set were included, where the responses were scaled on a 4-point Likert scale. The full list of survey items for ICT Autonomy in PISA 2018 is presented in Table B.3 in Appendix B.

3.1.4.4 ICT Attitude in TIMSS 2019

While the PISA 2018 ICT Questionnaire included diverse survey items which could measure different aspects of ICT Attitude, it seemed difficult for the TIMSS 2019 eTIMSS Questionnaire to apply the same method because the items were fewer than those in PISA

2018. For example, only one statement in the eTIMSS Questionnaire (i.e., Did you like that this test was on a computer or tablet?) seemed relevant for measuring ICT Interest (IEA, 2020a). However, at least three observed items or indicators are usually preferred to measure latent variables with good model-fit indices when conducting CFA (Kline, 2015). Because of the recommended minimum requirement, this study decided to treat the latent variable of ICT Attitude as one variable, using one questionnaire set with seven survey statements in the TIMSS 2019 eTIMSS Questionnaire, which seemed useful for measuring students' overall attitudes when using digital devices (IEA, 2020a). All survey statements in this set were included for the analysis, which are scaled on the 4-point Likert scale. The entire list of questions for ICT Attitude in TIMSS 2019 is in Table B.4 in Appendix B.

3.1.5 Demographic Control Variables

While this research aims to focus on the interrelationship among the three latent factors, there are several additional variables to be included to explore potential level-related factors that could affect the difference of the variables of interest across Nordic countries. A few control variables were included for the hypothesized model for both student (i.e., within level) and school levels (i.e., between level) while treating each country as a separate variable. Control variables have been added to each level in the previous studies using MLSEM because they could indicate whether the characteristics of students and/or schools have an impact on explaining the fit of hypothesized models by measuring the amount of unexplained variances (e.g., Areepattamannil & Santos, 2019; Gubbels et al., 2020; Hu et al., 2018; Lee & Wu, 2012; Skryabin et al., 2015; Yi & Kim, 2019). Nordic countries are geographically adjacent and usually share common thoughts, but each has a different educational policy and social background. Therefore, it would be beneficial to investigate how diverse factors could impact the relationship and explain any potential differences among the countries. Since PISA 2018 and TIMSS 2019 collected different background information about students and schools, the hypothesized structural models included different types of control variables for each ILSA separately.

3.1.5.1 Student-Level Variables

In terms of student-level control variables, students' gender and their parents' educational level were added for both ILSAs, usually found to be significant for explaining variances in digitally assessed academic performance of students (e.g., Areepattamannil & Santos, 2019; Aru & Kale, 2019; Burns et al., 2021; Hu et al., 2018). First, gender was coded dichotomously (i.e., 1 = Girls; 0 = Boys). For the parents' educational level, PISA 2018 reported it using the "PARED" variable, which is "an internationally standardized transformation of [parents' highest education level] into years of education" (OECD, 2022c, p. 11-12), which ranged from 3 to 16 years. TIMSS 2019 originally categorized parents' educational level into five groups by the highest level of education they received (Fishbein et al., 2021), but they were regrouped into two groups (e.g., higher than post-secondary vs. lower than secondary degrees) for ease of analyses in this research.

3.1.5.2 School-Level Variables

For the school-level control variables, the school average of students' economic, social, and cultural status (ESCS) and an additional school-related variable were added, which were often included in the previous studies (e.g., Areepattamannil & Santos, 2019; Hu et al., 2018; Srijamdee & Pholphirul, 2020). Schools with better social or financial status are more likely to provide activities using digital devices to students, which could affect their usage and attitude toward digital devices. For PISA 2018, school-mean ESCS took the group-mean of students' ESCS for each school, provided as a standardized, continuous variable, while TIMSS 2019 categorized the school ESCS into three ordered options (i.e., disadvantaged, moderate, and affluent).

Besides, the analysis included different additional school-relevant variables for the analyses to explore how the relationship can be affected by school characteristics. PISA 2018 selected participating schools using several strata variables by each country (e.g., school type, school location; OECD, 2022b). TIMSS 2019 classified schools into five groups based on their location (Fishbein et al., 2021), regrouping them into two categories (i.e., urban vs. rural areas) to make the analyses easier. It is thought that schools in cities would generally have easier access to digital devices than those in rural areas. Table 3.2 presents the full list of control variables and how they are coded across ILSAs. The list of school stratum variables for PISA 2018 is provided in Appendix C.

Table 3.2. Control Variables for PISA 2018 and TIMSS 2019

		PISA 2018	TIMSS 2019
Student (Within)	Gender	1 = Girls; 0 = Boys	1 = Girls; 0 = Boys
	Parents' Education Level	Internationally standardized transformation of highest-level of education into years of education (i.e., 3 to 16 years) (OECD, 2022c)	1 = University or Higher, Post-Secondary but not University 0 = Upper Secondary, Lower Secondary, Some Primary, Lower Secondary, or No School
School (Between)	School-Mean ESCS	Group-mean of student ESCS: standardized numeric values (i.e., -8.17 to 4.21) (OECD, 2022c)	3 = More Affluent 2 = Neither Affluent nor Disadvantaged 1 = More Disadvantaged
	Additional School Variable	School Stratum Vary by Countries	School Location 1 = Small Town or Village, Remote Rural 0 = Urban, Suburban, Medium Size City or Large Town

Note. Numbers indicating non-applicability (N/A) are not listed.

3.2 Analysis Approach

3.2.1 Hypothesized Model

By analyzing the ICT questionnaires from the two ILSAs, this dissertation mainly aimed to explore the association between students' ICT Usage and academic performance, including the mediation effect of students' attitudes toward ICT Usage. This association was investigated at both student (i.e., within level) and school levels (i.e., between level) to reflect the hierarchical structure of the datasets, where students are clustered into schools. The research also analyzed how the level-relevant demographic control variables affect the hypothesized models by country, which could imply potential differences across countries. The entire analyses were conducted separately for each country. Details are addressed in the following sections.

3.2.1.1 Measurement Model for Latent Variables

There are three main latent variables measured for the analyses: ICT Usage, ICT Attitude, and academic performance. MLCFA was used to measure the latent variables at the student and school levels, where the students' observed responses on the questionnaire items measured each sub-construct at both levels. While TIMSS 2019 does not have sub-constructs, PISA 2018 includes multiple sub-constructs under the main variables; ICT Usage has two sub-constructs (i.e., ICT Home and ICT School) and ICT Attitude has three (i.e., ICT Competence, ICT Interest, and ICT Autonomy). Therefore, when measuring the latent variables in PISA 2018, the MLCFA let the relevant sub-constructs under each latent variable covary with each other to explore how much they are correlated. Figure 3.1 presents an example of a diagram for measuring ICT Usage with two sub-constructs for PISA 2018 using MLCFA. This approach would allow us to estimate and compare both student- and school-level variances separately and explore different factor structures at each level as well (Geldhof et al., 2014; Wright et al., 2015). The proposed diagrams for the other measurement models are presented in Appendix D.

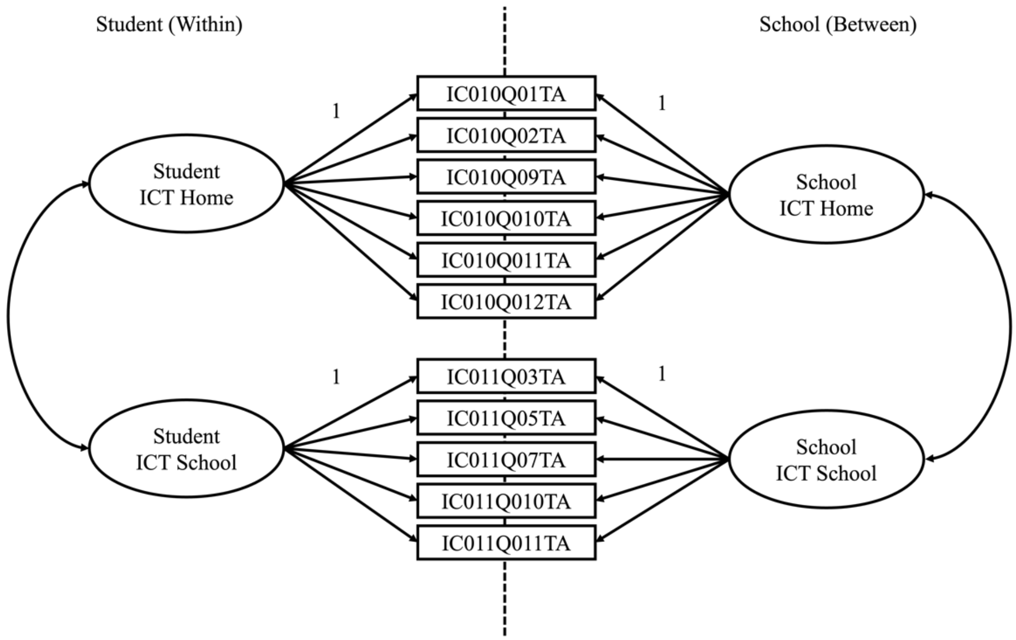


Figure 3.1. Measurement Model of ICT Usage for PISA 2018

Moreover, specifically for PISA 2018, if the sub-constructs seem to significantly covary each other, there is a possibility that they could be combined into a bigger construct both at student and school levels. In order to check whether it is preferable to collapse sub-constructs into one factor, two models (i.e., a model in which all sub-constructs are treated separately vs. a model in which the sub-constructs are combined into a single construct) were compared when the former model shows that the sub-constructs covary significantly. Model fit indices were used to decide whether it is better to treat sub-constructs separately or collapse into one single construct.

However, unlike a traditional single-level CFA, it needs caution when exploring the model fit indices in MLCFA due to the multiple levels. In the event of detecting a poor model fit index from the MLCFA model, it is difficult to recognize whether the poor fit happened at the lower level or upper level, or even both (Ryu, 2014). Therefore, a saturated model was used to compare the model fit at each level, where latent variables are measured at one level only while letting the observed variables on the other level covary without measuring the latent variables (Ryu, 2014; Sadikaj et al., 2019; Wu et al., 2017).

Figure 3.2 shows an example of two saturated models to measure ICT Usage in PISA 2018 at the student level. Model A measures the two sub-constructs of the ICT Usage variable only at the student level and treats them separately while letting the observed variables at the school level covary without measuring latent variables. Model B applies the same idea, but the ICT Usage variable is measured as a single construct. One of the two models was selected to design the student-level part by comparing their model fit indices. The same process was also applied to decide the final model for measuring the school-level part and ICT Attitude variables for each Nordic country.

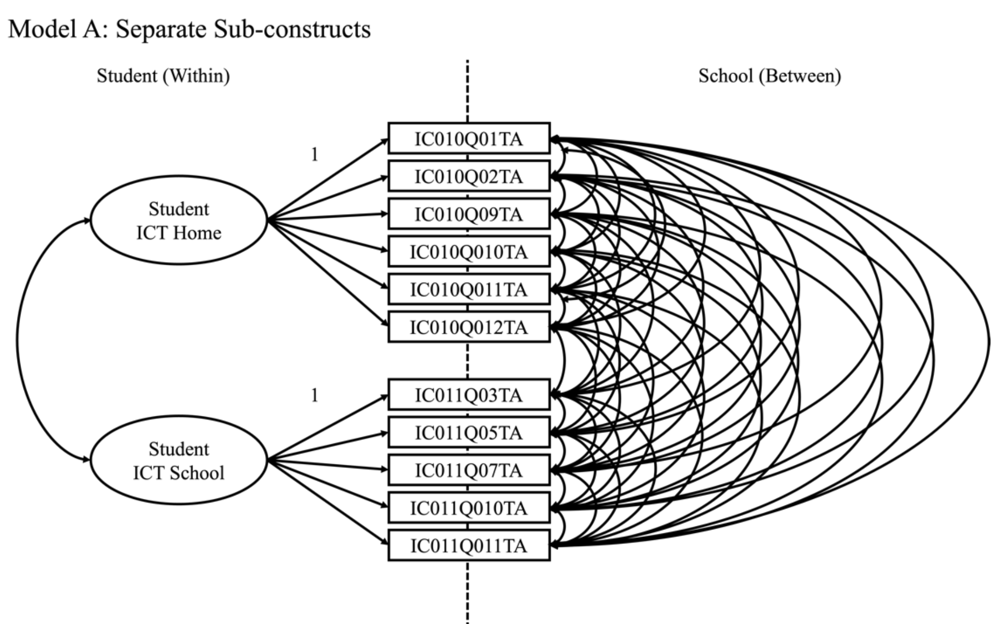


Figure 3.2. Saturated Models: PISA 2018 ICT Usage at the Student Level

Model B: One Sub-construct

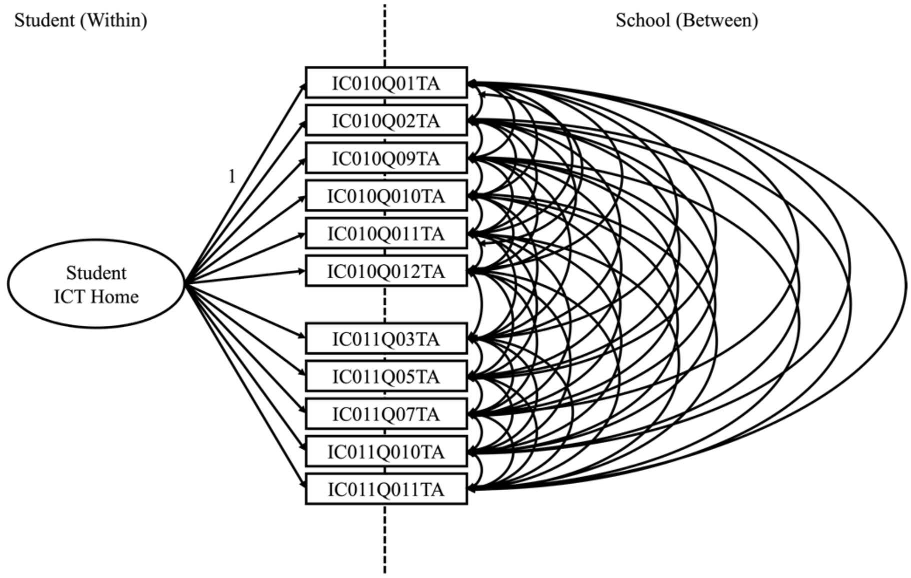


Figure 3.2. (cont.)

3.2.1.2 Multilevel Mediation Model for Interrelationship

Once the MLCFA models for the analysis were confirmed, mediation models were analyzed to explore the interrelationship among the measured variables. Besides, as the student data are clustered into schools for both ILSAs, this research included multiple levels rather than conducting a single-level analysis. Among the different strategies for choosing the number of levels (see Chapter 2.7.1), this study decided to include two levels (i.e., student and school levels) for the analysis, treating the country level as a separate group to explore how the patterns of associations differ by Nordic countries.

The analysis aims to explore the mediation effect of students' ICT Attitude on the relationship between their ICT Usage and academic performance at both student and school levels. The relevant hypothesis was that students' frequent usage of digital devices either at home or at school would have more positive attitudes when using digital devices with greater competence, interest, and/or autonomy. This would also positively impact their academic performance on computer-based tests as the students are accustomed to using computers without discomfort. Also, by including both student and school levels, the analysis could explore how the belongingness of students to schools has an impact on the associations. Figure 3.3 shows the multilevel mediation model which was applied to both ILSAs, where *i* is an indicator for a student and *j* for a school.

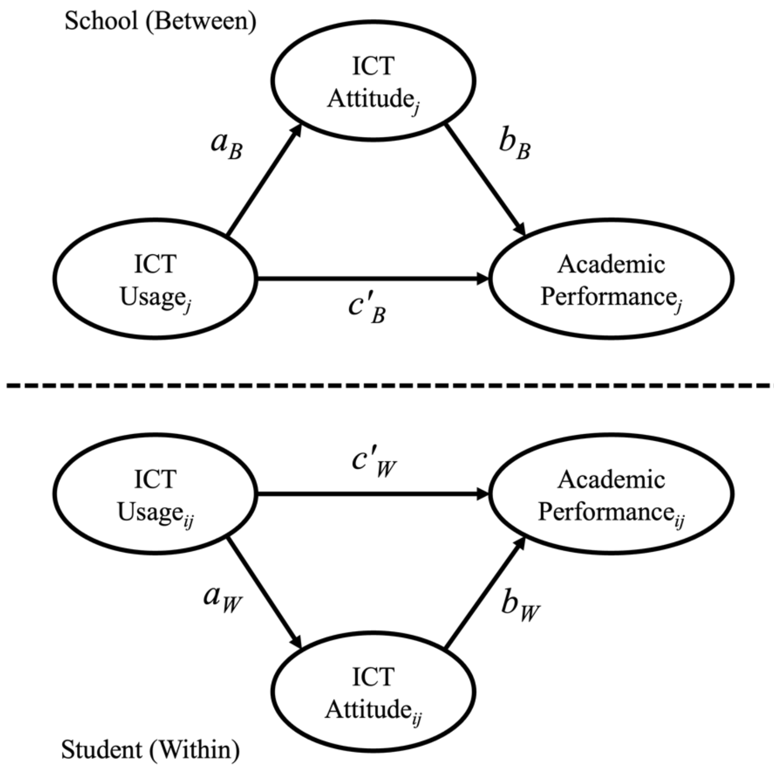


Figure 3.3. Proposed Multilevel Mediation Model

3.2.1.3 Modeling with Demographic Control Variables

MLSEM is useful for the multilevel mediation analysis because it could not only account for the variances of different levels but also explore potential variables that may affect school-level differences, which could infer the measurement non-invariance of the structural models across schools (Davidov et al., 2012; Davidov et al., 2018). As each student and school has different characteristics, control variables relevant to each level were added to the latent variables. Students' gender and their parents' educational level were added as student-level control variables. For the school-level control variables, the school-mean ESCS and an additional school-relevant variable were included: the school strata information for PISA 2018 (i.e., private or public schools, urban or rural) and the school location variable (e.g., rural, suburban, urban, etc.) for TIMSS 2019. Figure 3.4 shows the final hypothetical model that was analyzed by multilevel mediation with the level-relevant control variables.

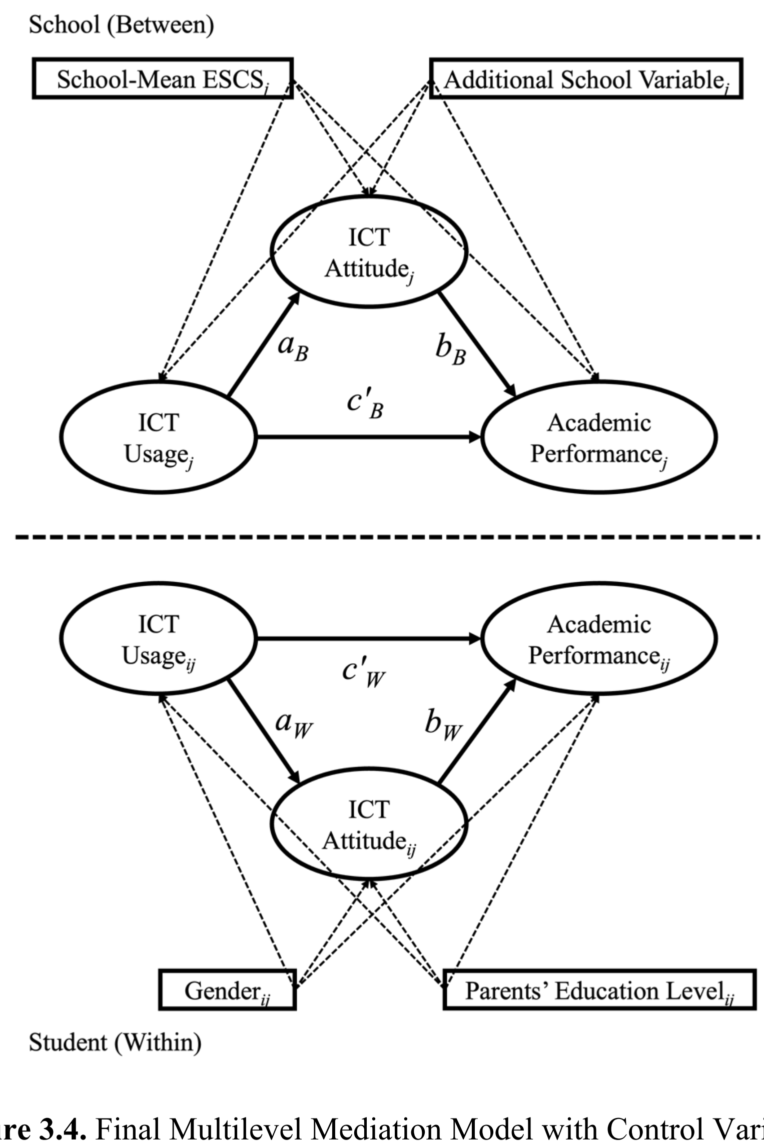


Figure 3.4. Final Multilevel Mediation Model with Control Variables

3.2.2 RStudio and Mplus Software

In order to analyze the hypothesized structural models, two methods of statistical software programming were used: RStudio (RStudio Team, 2020) and Mplus (Muthén & Muthén, 2017). Within the large-scale datasets, the research focused on several variables for Nordic countries, and RStudio was used to clean the large-scale data before the actual analysis. Once the datasets were trimmed out using RStudio, they were exported to Mplus Version 8.1. to measure the latent variables using observed survey items and conduct the multilevel mediation analysis, including the level-relevant control variables. Although RStudio has several software packages to conduct multilevel modeling analyses (e.g., *lavaan*, *semTools*, etc.), Mplus is an easier and more preferred program to handle when conducting analyses with multiple levels. It could estimate parameters using Bayesian estimation and handle missing values by applying the full information maximum likelihood method, which is expected to present more accurate results from the multilevel modeling analyses (Asparouhov & Muthén, 2020; Schminkey et al., 2016). Appendices F and G show the sample of Mplus codes used for the analyses.

3.2.3 Missing Data Management

While it is ideal to have a complete dataset, there always exist missing values in a large-scale dataset, especially for educational or social science studies. Missing data may influence the correct analysis and interpretation of results as they would leave significant information out. In terms of MLSEM studies, several methods have been studied to deal with the missingness. Previous studies handled the missing values by removing cases that include any missing values (i.e., complete-case analysis; CCA) (e.g., Agasisti et al., 2020; Al-Rahmi et al., 2020; Gubbels et al., 2020; Ma & Qin, 2021; Skryabin et al., 2015; Xiao

& Hu, 2019), estimating model parameters by incorporating all information of individual observed cases with maximizing the likelihood function (i.e., full information maximum likelihood; FIML) (e.g., Areepattamannil & Santos, 2019; Odell et al., 2020a; Schminkey et al., 2016), or simulating several sets of data which is likely to substitute the missing values and imputing the summarized values (i.e., multiple imputations; MI) (e.g., Gómez-Fernández & Mediavilla, 2021; Xiao et al., 2019).

Among the various methods for handling missing values, this research decided to apply the FIML method, which has been recommended by multiple studies when handling missing values using MLSEM (e.g., Heck & Thomas, 2015; Hox et al., 2010; Schminkey et al., 2016). FIML is one of the maximum likelihood estimation methods that estimate parameters by considering every existing point of data and treating the missing data as a distribution of possible values (Heck & Thomas, 2015; Schminkey et al., 2016). It is useful since it works well for the data missing either at random or not at random, allows flexibility in MLSEM, and does not require balanced groups for accurate estimates (Heck & Thomas, 2015; Hox et al., 2010).

It was found that some studies simply used the CCA method (e.g., Agasisti et al., 2020; Gubbels et al., 2020; Ma & Qin, 2021; Skryabin et al., 2015), but it needs caution since the trimmed data do not fully represent the population (Schafer & Graham, 2002). MI method was also frequently used as it estimates missing values by treating parameters as random and applying the Bayesian estimation method, which does not usually require big sample sizes (Schafer & Graham, 2002). Moreover, it usually functions well whether the values are missing at random or not at random. However, MI becomes less effective than FIML for estimating predictors at the upper level with increased parameter biases

(Heck & Thomas, 2015). Therefore, the FIML method was applied to deal with missing data which could manage the missingness both within and between levels together.

3.2.4 Reported Statistics

As a result of multilevel mediation analyses using MLSEM, various types of statistics were reported to explain the interrelationship between students' ICT Usage, ICT Attitude, and academic performance across the Nordic countries. All results were reported for each Nordic country separately. First, as descriptive statistics, means and standard deviations of students' responses to the selected survey questionnaires and plausible values indicating their academic performance (i.e., ten values for PISA 2018; five values for TIMSS 2019) were reported. Also, the reliability coefficient alpha (i.e., Cronbach's α) was included as a measure of the internal consistency of the selected survey questions for measuring the latent constructs (Tavakol & Dennick, 2011).

For the measurement model, the standardized estimated factor loading parameters and the model fit index were collected to test if the hypothesized model fits the data well. For the multilevel mediation analysis of the interrelationship, the standardized estimated parameters and their 95% credible intervals (95% Cr.I.) of the fixed effects for all paths (i.e., total, direct, and indirect effects) were collected. As Mplus estimates parameters by using Bayesian estimation for the multilevel mediation analysis, it is more plausible to report 95% Cr.I., which give the posterior probability of coefficients lying in the interval (Asparouhov & Muthén, 2018; Stegmueller, 2013). In addition, the proportion of the mediation effect was computed by dividing the indirect effect by the total effect to explore the practical significance of the indirect effect if appropriate (Preacher & Kelly, 2011). The full results are presented in Chapter 4.

CHAPTER 4

RESULTS

4.1 Descriptive Statistics

The first section of Chapter 4 displays the descriptive statistics (i.e., mean and standard deviation) of students' academic performance and their responses to the survey questions to the PISA 2018 ICT Questionnaire and TIMSS 2019 eTIMSS Questionnaire. In addition, reliability coefficients (i.e., Cronbach's α) for the latent constructs measured by the survey statements were computed, using the "cronbach.alpha" function included in the *ltm* R package (Rizopoulos, 2006).

4.1.1 PISA 2018

4.1.1.1 Demographic Information

Table 4.1 presents the frequency or descriptive statistics of students and schools grouped by each student-level (i.e., gender & parents' educational level) and school-level variables (i.e., school-mean ESCS and school type variables) across countries in PISA 2018. Remind that Norway was excluded since students did not respond to the ICT Questionnaire. Frequencies of students and schools were counted for the gender and school type variables (i.e., categorical), and the means and standard deviations were reported for the parents' educational level and school-mean ESCS variables (i.e., continuous).

Students from Denmark participated the most in PISA 2018, followed by Finland, Sweden, and Iceland. In terms of student-level control variables, all countries tend to have almost an equal proportion of girls and boys (i.e., 50:50). Also, the number of years to achieve the highest level of education was around 14 to 15 years on average, which means parents of students in Nordic countries tend to have a high level of education.

Table 4.1. Demographic Information of Nordic Countries: PISA 2018

		Denmark	Finland	Iceland	Sweden
Student (Within)					
Frequency		7,657	5,608	3,296	5,502
Gender	Girls	3,816 (49.8%)	2,763 (49.3%)	1,656 (50.2%)	2,763 (50.2%)
	Boys	3,841 (50.2%)	2,845 (50.7%)	1,640 (49.8%)	2,739 (49.8%)
Parent Education Level (Years)	Mean	14.97	14.84	14.75	14.40
	SD	2.09	1.91	2.14	2.44
School (Between)					
Frequency		348	206	142	222
School-Mean ESCS	Mean	0.355	0.276	0.372	0.348
	SD	0.428	0.374	0.431	0.400
School Type					
Denmark	Low Minorities	161 (46.3%)			
	High Minorities	187 (53.7%)			
Finland	Urban Area		171 (83.0%)		
	Rural Area		35 (17.0%)		
Iceland	Capital Area			55 (38.7%)	
	Non-Capital Area			87 (61.3%)	
Sweden	Private School				50 (22.5%)
	Public School				172 (77.5%)

Note. SD = Standard deviation; School-mean ESCS was standardized (i.e., mean = 0, standard deviation = 1), which ranged from -8.17 to 4.21.

The number of schools that participated in PISA 2018 was the greatest in Denmark, followed by Sweden, Finland, and Iceland. For the school-level variables, the standardized school-mean ESCS was slightly above 0 for all countries. As the ESCS was standardized with a mean of 0 and standard deviation of 1 (OECD, 2019b) using the average across OECD countries, it could be inferred that schools in Nordic countries tend to have better economic, social, and cultural status compared to other OECD countries.

The school type variable differed by country. The original dataset classified the school types with multiple categories (i.e., stratum), but they are categorized into two types for ease of this analysis. The original stratum values used for PISA 2018 are presented in Appendix C. Schools in Denmark were categorized into those with low minorities (i.e., no or low minority) and high minorities (i.e., mid to high minority). Schools with high minorities were slightly more (53.7%) than those with low minorities (46.3%). In addition, schools in Finland and Iceland were categorized by location of schools (e.g., urban/capital areas vs. rural/non-capital areas). Many schools in Finland were in urban areas (83.0%), while many schools in Iceland were located in non-capital areas (i.e., areas other than Reykjavik) (61.3%). One thing to note is that 8 schools (41 students) in Finland with special needs & inclusion were excluded since they were difficult to classify into either group. For Sweden, schools were classified into either private or public schools, where most schools were public (77.5%). Here, one school with two students was deleted since there was no data collected.

4.1.1.2 Analysis Variables

The following section shows the descriptive statistics used for the actual MLSEM analysis for exploring the interrelationship: academic performance, ICT Usage, and ICT Attitude. Table 4.2 shows the means and standard deviations of students' plausible values across countries as an indicator of their academic performance. The means were computed by taking the average of ten plausible values for each student and computing the average values across students for each cognitive domain. Finland showed the highest average academic performance across all three domains, followed by Sweden, Denmark, and Iceland. The values were slightly different from those reported by OECD in Table 2.1.

Table 4.2. Descriptive Statistics for PISA 2018 Academic Performance

	Reading		Mathematics		Science	
	Mean	SD	Mean	SD	Mean	SD
Finland	521.49	95.44	508.49	75.04	522.97	90.35
Sweden	505.59	103.66	502.43	84.35	499.38	92.24
Denmark	488.08	91.18	497.27	77.83	479.60	89.03
Iceland	473.31	101.11	494.78	82.76	474.55	85.94

Note. Norway was excluded since it did not provide answers to the ICT Questionnaire.

Table 4.3 presents the mean, standard deviation, and reliability coefficients (i.e., Cronbach's α) for all the survey statements included in the analysis. Responses were coded using a 5-point Likert scale for ICT Usage statements (i.e., ICT Home and ICT School) or a 4-point Likert scale for ICT Attitude statements (i.e., ICT Competence, ICT Interest, and ICT Autonomy). For ICT Usage, scales are recoded by subtracting 1 from each value to make sense of "Never or hardly ever" as 0. Greater numbers indicate more frequent usage of digital devices or more positive attitudes toward using digital devices.

For the two ICT Usage variables, students in Denmark, Iceland, and Sweden tended to answer around "Once or twice a month" or "Once or twice a week," which could be considered moderate to frequent usage of digital devices both at home and at school for educational purposes. Students in Finland tended to answer that they use digital devices at home and at school for such activities less frequently than the other countries, while the mean of answering the statements "Browsing the Internet for schoolwork" at home (IC010Q01TA) and at school (IC011Q03TA) showed similar levels compared to the others. In terms of the three ICT Attitude variables, all countries tended to answer around "Agree," which could imply that they tend to have moderately positive attitudes when using digital devices. When it comes to reliability, all latent constructs showed reliability coefficients greater than 0.7, which is considered acceptable or good reliability (Ursachi et al., 2015).

Table 4.3. Descriptive Statistics for PISA 2018 ICT Questionnaire

ICT		Denmark Mean	Denmark SD	Finland Mean	Finland SD	Iceland Mean	Iceland SD	Sweden Mean	Sweden SD
Home									
IC010	Q01TA	2.265	1.049	1.663	0.977	1.690	1.004	2.056	1.089
	Q02TA	1.934	1.165	1.166	1.112	1.813	1.032	2.092	1.076
	Q09TA	2.785	1.088	1.112	1.060	1.564	1.120	1.987	1.266
	Q10TA	1.256	1.297	0.921	1.081	1.567	1.153	1.377	1.277
	Q11TA	1.582	1.342	1.006	1.079	1.241	1.177	1.307	1.282
	Q12TA	1.152	1.318	0.957	1.109	1.279	1.197	1.213	1.272
	α	0.807		0.900		0.916		0.878	
School									
IC011	Q03TA	2.832	1.055	1.960	1.081	2.250	1.142	2.903	1.105
	Q05TA	1.304	1.357	0.825	1.129	0.563	1.084	1.105	1.348
	Q07TA	1.985	1.206	0.946	1.094	1.365	1.226	1.564	1.251
	Q08TA	2.501	1.337	0.712	1.096	1.238	1.197	1.341	1.384
	Q10TA	1.656	1.424	1.046	1.124	1.259	1.249	1.346	1.341
	α	0.701		0.864		0.833		0.805	
Competence									
IC014	Q03NA	2.867	0.733	2.327	0.777	2.431	0.845	2.918	0.797
	Q04NA	2.982	0.746	2.843	0.754	2.852	0.816	2.985	0.799
	Q06NA	3.340	0.627	3.161	0.669	3.042	0.723	3.395	0.674
	Q08NA	3.080	0.697	2.878	0.748	2.929	0.791	3.091	0.745
	Q09NA	3.024	0.732	2.853	0.766	2.890	0.811	2.969	0.814
	α	0.827		0.851		0.873		0.865	
Interest									
IC013	Q01NA	2.667	0.816	2.565	0.778	2.701	0.862	2.554	0.863
	Q04NA	3.317	0.671	3.100	0.676	3.146	0.735	3.161	0.737
	Q05NA	3.230	0.689	3.066	0.673	3.058	0.736	3.207	0.738
	Q11NA	2.834	0.788	2.683	0.756	2.768	0.837	2.915	0.786
	Q12NA	2.761	0.845	2.471	0.828	2.348	0.862	3.119	0.844
	Q13NA	3.330	0.652	3.136	0.662	3.115	0.722	3.294	0.724
	α	0.742		0.804		0.839		0.813	
Autonomy									
IC015	Q02NA	2.793	0.870	3.139	0.781	2.893	0.981	2.813	0.902
	Q03NA	2.620	0.852	2.514	0.824	2.911	0.876	2.808	0.839
	Q05NA	3.124	0.660	3.110	0.693	3.078	0.791	3.156	0.682
	Q07NA	2.982	0.715	2.986	0.745	2.970	0.845	3.007	0.758
	Q09NA	3.150	0.673	3.180	0.690	3.043	0.838	2.897	0.825
	α	0.845		0.835		0.920		0.901	

Note. SD = Standard deviation; α = Reliability coefficient (i.e., Cronbach's α); Detailed explanations of each survey statement and scales are listed in Appendices A and B.

4.1.2 TIMSS 2019

4.1.2.1 Demographic Information

Table 4.4 shows the frequencies of students and schools classified by each student-level (i.e., gender & parents' educational level) and school-level control variables (i.e., school-mean ESCS and school location variables) across countries in TIMSS 2019. Remind that Denmark and Iceland did not participate in TIMSS 2019 Grade 8. Students from Finland participated the most in TIMSS 2019, followed by Norway and Sweden. For the gender variable, there were slightly more boys than girls across all countries. Some students did not answer what their gender is, resulting in several missing values. In addition, the parents' educational level variable was categorized into two groups based on whether their parents were involved in post-secondary education. There were more parents who received degrees in post-secondary education than those who did not have degrees in post-secondary education. Here, about 40% of students' responses regarding their parents' education levels were missing across all three countries.

For the school-mean ESCS variable, Finland showed that the majority of participating schools had a moderate level of ESCS (55.8%), followed by more affluent schools (27.9%) and disadvantaged schools (9.7%). For Norway and Sweden, many schools were classified as more affluent schools, followed by moderate and more disadvantaged schools. In terms of the school location variable, schools were classified into two groups based on whether they were in urban or rural areas. For Finland, there were slightly more schools located in rural areas, while there were more schools located in urban areas in Norway and Sweden. Some schools did not provide responses regarding these variables, where Norway had more missing values than Finland and Sweden.

Table 4.4. Demographic Information of Nordic Countries: TIMSS 2019

		Finland	Norway	Sweden
Student (Within)				
Frequency		5,570	5,215	4,565
Gender	Girls	2,687 (48.3%)	2,447 (46.9%)	2,188 (47.9%)
	Boys	2,842 (51.0%)	2,480 (47.6%)	2,288 (50.1%)
	No Information	41 (0.7%)	288 (5.5%)	89 (2.0%)
Parent Education Level	No Post-Secondary	1,236 (22.2%)	306 (5.9%)	533 (11.7%)
	Post-Secondary or Higher	2,216 (39.8%)	2,956 (56.7%)	2,044 (44.8%)
	No Information	2,118 (38.0%)	1,953 (37.4%)	1,988 (43.5%)
School (Between)				
Frequency		154	157	150
School ESCS	More Affluent	43 (27.9%)	63 (40.1%)	89 (59.4%)
	Moderate	86 (55.8%)	40 (25.5%)	29 (19.3%)
	More Disadvantaged	15 (9.7%)	12 (7.6%)	12 (8.0%)
	No Information	10 (6.5%)	42 (26.8%)	20 (13.3%)
Location	Rural Area	77 (50.0%)	53 (33.8%)	68 (45.3%)
	Urban Area	76 (46.4%)	66 (42.0%)	79 (52.7%)
	No Information	1 (0.6%)	38 (24.2%)	3 (2.0%)

Note. Denmark and Iceland did not participate in TIMSS 2019 Grade 8.

4.1.2.2 Analysis Variables

Table 4.5 shows the descriptive statistics of academic performance in TIMSS 2019. The means were computed by taking the average of five plausible values for each student and computing the average values across students for each cognitive domain. Finland tended to score the highest for both mathematics and science, followed by Sweden and Norway. The values were slightly different from those reported by IEA in Table 2.2.

Table 4.5. Descriptive Statistics for TIMSS 2019 Academic Performance

	Mathematics		Science	
	Mean	SD	Mean	SD
Finland	509.61	70.99	543.90	82.68
Sweden	507.25	75.18	526.09	91.90
Norway	506.54	76.63	498.09	86.30

Table 4.6 presents the mean, standard deviation, and reliability coefficients for all the survey statements included in the analysis. Students' responses were coded using a 4-point Likert scale for both ICT Usage and ICT Attitude statements. The scales for ICT Usage statements were recoded by subtracting 1 from each value to make sense of "Never or almost never" as 0. Greater numbers indicate more frequent usage of digital devices or more positive attitudes toward using digital devices.

For the ICT Usage statements, students from Finland tended to answer around "Once or twice a week," which could imply that they frequently use digital devices for doing schoolwork or taking tests, followed by those from Sweden. In contrast, students from Norway tended to answer around "Once or twice a month," which could be considered that they use digital devices less frequently for doing schoolwork than the other countries. In terms of the ICT Attitude, students from all three countries tended to answer around "Disagree" to statements such as "I am good at using a computer," "It is easy for me to find information on the Internet," or "I can write sentences and paragraphs using a computer," which showed different patterns from the relevant statements in PISA 2018. When it comes to reliability, the latent construct of ICT Attitude across all countries showed good degrees of reliability coefficients, greater than 0.8 (Ursachi et al., 2015). The reliability coefficients for ICT Usage were lower than 0.8, but they could be still considered an acceptable level since they were between 0.6 and 0.7 (Ursachi et al., 2015).

Table 4.6. Descriptive Statistics for TIMSS 2019 eTIMSS Questionnaire

ICT		Finland		Norway		Sweden	
		Mean	SD	Mean	SD	Mean	SD
Usage							
2	a)	1.546	0.712	0.753	0.834	0.602	0.878
	b)	2.318	0.904	1.577	0.946	2.177	1.068
	c)	2.092	0.881	1.484	0.928	1.236	0.991
	d)	2.359	0.735	1.752	0.808	2.037	0.928
	α	0.666		0.677		0.668	
Attitude							
3	a)	1.724	0.696	1.657	0.720	1.559	0.671
	b)	1.666	0.678	1.500	0.664	1.465	0.635
	c)	1.213	0.477	1.234	0.558	1.276	0.571
	d)	1.393	0.591	1.362	0.596	1.417	0.606
	e)	1.353	0.579	1.262	0.537	1.280	0.548
	f)	1.363	0.583	1.191	0.474	1.193	0.470
	g)	1.429	0.621	1.278	0.570	1.329	0.609
	α	0.870		0.842		0.838	

Note. SD = Standard deviation; α = Reliability coefficient (i.e., Cronbach's α); Detailed explanations of each survey statement and scales are listed in Appendices A and B.

4.2 Analysis of Interrelationship

The following part of the research was to conduct a multilevel mediation analysis in the context of MLSEM to explore the interrelationship of students' ICT Usage, ICT Attitude, and academic performance. Mplus applied the Bayesian method for estimating parameters, and each model provided the posterior predictive *p*-values (PPP), which "checks the proportion of iterations for which the replicated χ^2 exceeds the observed χ^2" (Hoofs et al., 2018, p. 539), and the deviance information criteria (DIC), which is a "Bayesian generalization of the [Akaike's information criterion (AIC)] that balances model parsimony and fit" (Wang & Wang, 2020, p. 27). Both indices have been used to evaluate model fits from the Bayesian estimation. PPP values greater than 0.05 can be interpreted that the proposed model does not significantly differ from the observed data (Cain & Zhang, 2019); however, like the model χ^2 statistics in MLE estimation, this value is subject to large sample sizes and possess a possibility to reject the credible model (Hoofs et al., 2018). Instead of exploring PPP, this study compared the DIC values of the model where all sub-constructs are treated separately (i.e., Model A; see Figure 3.2) and the model where the sub-constructs are combined into a single construct (i.e., Model B; see Figure 3.2) and planned to select the one with a lower DIC value as the final model, which could indicate a relatively better fit (Goldstein et al., 2007; Wang & Wang, 2020).

As indicated in Chapter 3.2.1.1, specifically for PISA 2018, two saturated models for measuring latent variables at each level were compared to choose the final measurement model. The initial MLCFA analyses showed that the sub-constructs under the ICT Usage and ICT Attitude variables seemed to covary significantly across all countries. Therefore, additional analyses were conducted by comparing Models A and B at each level to determine whether it is meaningful for the sub-constructs to merge into one construct for the measurement model. The DIC values of each model were compared, where the one with a smaller value was considered better.

Table 4.7 shows the DIC values of the MLCFA model at each level for PISA 2018 across countries. First, in terms of the student level, Model A showed smaller DIC values across all countries, in which the sub-constructs were treated separately and covary each other. However, in terms of the school level, the two DIC values were close to each other. Interestingly, Finland showed a smaller DIC value for Model B, where the sub-constructs collapsed into one factor. Since there was no clear reason to treat them separately, this study decided to separately measure sub-constructs of the ICT Usage and ICT Attitude variables at the student level but measure one big construct at the school level (see Figure 4.1 for ICT Usage and Figure D.2 in Appendix D for ICT Attitude) (Cain & Zhang, 2019).

Table 4.7. Deviance Information Criterion (DIC): PISA 2018

Level	Model	Denmark	Finland	Iceland	Sweden
Student	A	389,720.927	284,562.348	159,341.080	290,006.687
	B	396,865.751	296,300.371	168,499.205	300,709.995
School	A	403,365.252	297,700.594	166,950.234	300,602.989
	B	403,635.002	282,667.541	166,984.675	300,832.101

Note. Model A = Separate sub-constructs for ICT Usage and ICT Attitude; Model B = One construct for ICT Usage and Attitude.

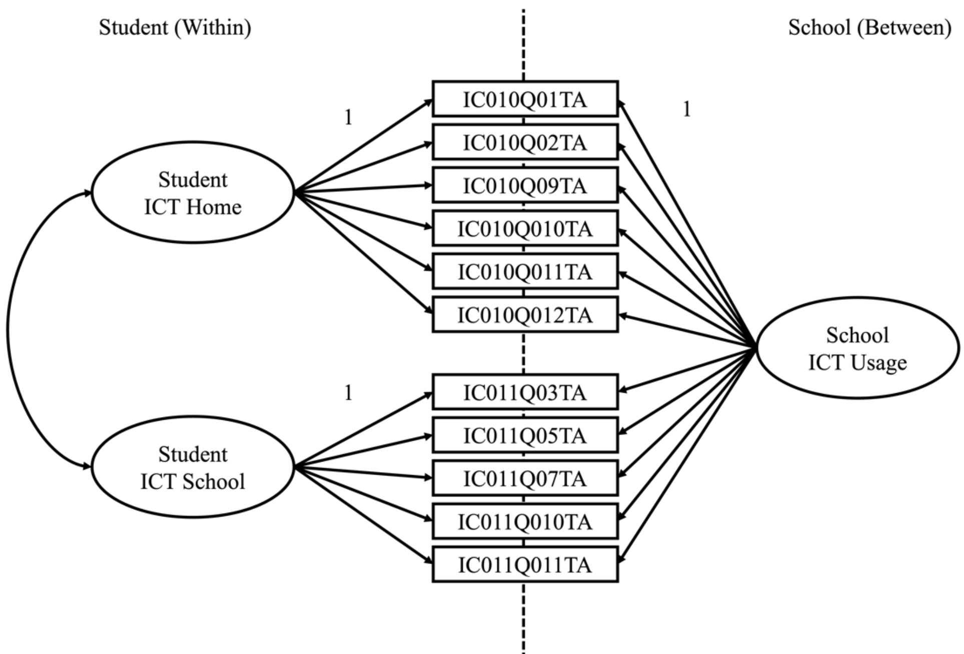


Figure 4.1. Final Measurement Model for PISA 2018 ICT Usage

4.2.1 Denmark

Denmark did not participate in TIMSS 2019 Grade 8, so the interrelationship was only explored for PISA 2018. Schools in Denmark were classified as schools with low minorities and high minorities. Table 4.8 shows the standardized estimated parameters and their 95% Cr.I. for the path analyses for the entire mediation analyses, and the covariances among the sub-constructs of the ICT Usage and ICT Attitude variables. The standardized estimated factor loadings are listed in Table E.1 in Appendix E.

First, significant total effects of the ICT Usage variables on students' academic performance were detected at both levels. At the student level, academic performance was negatively associated with ICT Home (H $\rightarrow$ AP: $c_W = -0.337$, 95% Cr.I. = [-0.390, -0.284]), while the direction of association was positive with ICT School (S $\rightarrow$ AP: $c_W = 0.172$, 95% Cr.I. = [0.117, 0.229]). Besides, at the school level, ICT Usage was positively associated with academic performance (Use $\rightarrow$ AP: $c_B = 0.227$, 95% Cr.I. = [0.138, 0.314]). When it comes to the direct effects, after controlling for all ICT Attitude variables, both ICT Home and ICT School showed the same direction of associations as the total effects do at the student level, but no significant direct effect was found at the school level.

When exploring the indirect effects of ICT Attitude variables, it first showed that for the relationship between ICT School and academic performance, ICT Interest (S $\rightarrow$ I $\rightarrow$ AP: $a_W \times b_W = 0.046$, 95% Cr.I. = [0.027, 0.069]) and ICT Autonomy (S $\rightarrow$ A $\rightarrow$ AP: $a_W \times b_W = 0.030$, 95% Cr.I. = [0.012, 0.054]) could function as significant mediators at the student level. When computing the mediation ratio for exploring the practical significance (Preacher & Kelly, 2011), ICT Interest showed a ratio of 0.267 (0.046/0.172 = 0.267), while that of ICT Autonomy was 0.174 (0.030/0.172 = 0.174). These infer that ICT Interest could explain about 26.7% of the total effect of ICT School on academic performance at the student level, and ICT Autonomy could explain approximately 17.4% of the total effect of the same association. Besides, at the school level, ICT Attitude could function as a significant mediator in the association between ICT Usage and academic performance (Use $\rightarrow$ Att $\rightarrow$ AP: $a_B \times b_B = 0.269$, 95% Cr.I. = [0.110, 0.484]). Since the direct effect was found not to be significant, it could be inferred that the total effect of ICT Usage on academic performance was affected by the mediation effect of ICT Attitude.

Table 4.8. Estimated Path Coefficients and Covariances: Denmark PISA 2018

	Student Level (Within; *W*)			School Level (Between; *B*)		
		95% Cr.I.			95% Cr.I.	
	Estimate	Lower	Upper	Estimate	Lower	Upper
<u>Total</u> (*c*)						
H → AP	-0.337	-0.390	-0.284			
S → AP	0.172	0.117	0.229			
Use → AP				0.227	0.138	0.314
<u>Direct</u> (*c*′)						
H → AP	-0.333	-0.384	-0.281			
S → AP	0.101	0.043	0.158			
Use → AP				-0.013	-0.213	0.154
<u>Use to Att</u> (*a*)						
H → C	0.060	0.007	0.112			
H → I	0.024	-0.035	0.081			
H → A	0.049	-0.003	0.101			
S → C	0.282	0.228	0.336			
S → I	0.300	0.242	0.359			
S → A	0.271	0.217	0.324			
Use → Att				0.720	0.605	0.814
<u>Att to AP</u> (*b*)						
C → AP	-0.009	-0.068	0.047			
I → AP	0.153	0.113	0.193			
A → AP	0.112	0.057	0.167			
Att → AP				0.374	0.182	0.594
<u>Indirect</u> ($a \times b$)						
H → C → AP	-0.001	-0.008	0.005			
H → I → AP	0.004	-0.007	0.016			
H → A → AP	0.005	-0.001	0.017			
S → C → AP	-0.003	-0.023	0.016			
S → I → AP	0.046	0.027	0.069			
S → A → AP	0.030	0.012	0.054			
Use → Att → AP				0.269	0.110	0.484
<u>Covariance</u>						
H ↔ S	0.707	0.684	0.729			
C ↔ I	0.522	0.495	0.548			
C ↔ A	0.718	0.700	0.736			
I ↔ A	0.428	0.398	0.457			

Note. 95% Cr.I. = 95% Credible interval; Use = ICT Usage; H = ICT Home; S = ICT School; C = ICT Competence; I = ICT Interest; A = ICT Autonomy; Att = ICT Attitude; AP = Academic performance; *a* = Effect of ICT Usage on ICT Attitude; *b* = Effect of ICT Attitude on AP; *c* = Total effect of ICT Usage on AP; *c*′ = Direct effect of ICT Usage on AP, after accounting for the indirect effect of ICT Attitude.

Table 4.9 shows the effect of control variables at each level. When first looking at the student level, no significant gender difference was found in ICT Interest. In contrast, boys showed greater degrees across the other ICT variables, while girls showed better academic performance than boys. In addition, parents' educational level was positively associated only with students' academic performance, implying that students whose parents have more years of education tended to show better performances.

At the school level, school-mean ESCS was positively related to ICT Usage and academic performance but not to ICT Attitude. Schools with higher ESCS tend to use digital devices more often and perform better in exams. Also, schools with high minorities showed lower ICT Attitude and academic performance than those with low minorities, while the degree of ICT Usage was not significantly different. Figure 4.2 visualizes all these results, with bold lines indicating significance and maroon highlighting mediation.

Table 4.9. Control Variables on Latent Variables: Denmark PISA 2018

	Student Level (Within; *W*)				School Level (Between; *B*)		
		95% Cr.I.				95% Cr.I.	
	Estimate	Lower	Upper		Estimate	Lower	Upper
Gender				Mean ESCS			
→ H	-0.051	-0.080	-0.022	→ Use	0.283	0.144	0.412
→ S	-0.078	-0.109	-0.047				
→ C	-0.208	-0.234	-0.181	→ Att	0.117	-0.015	0.248
→ I	-0.016	-0.045	0.012				
→ A	-0.279	-0.304	-0.254				
→ AP	0.038	0.014	0.063	→ AP	0.637	0.549	0.716
Parent Ed				Minority			
→ H	0.006	-0.023	0.036	→ Use	-0.043	-0.174	0.092
→ S	0.016	-0.015	0.048				
→ C	-0.018	-0.045	0.010	→ Att	-0.154	-0.270	-0.039
→ I	0.012	-0.018	0.040				
→ A	-0.011	-0.039	0.016				
→ AP	0.147	0.124	0.169	→ AP	-0.120	-0.204	-0.034

Note. Gender = 1 (Girls) or 0 (Boys); Parent Ed = Parents' educational level; Mean ESCS = School-mean ESCS; Minority = 1 (High minorities) or 0 (Low minorities).

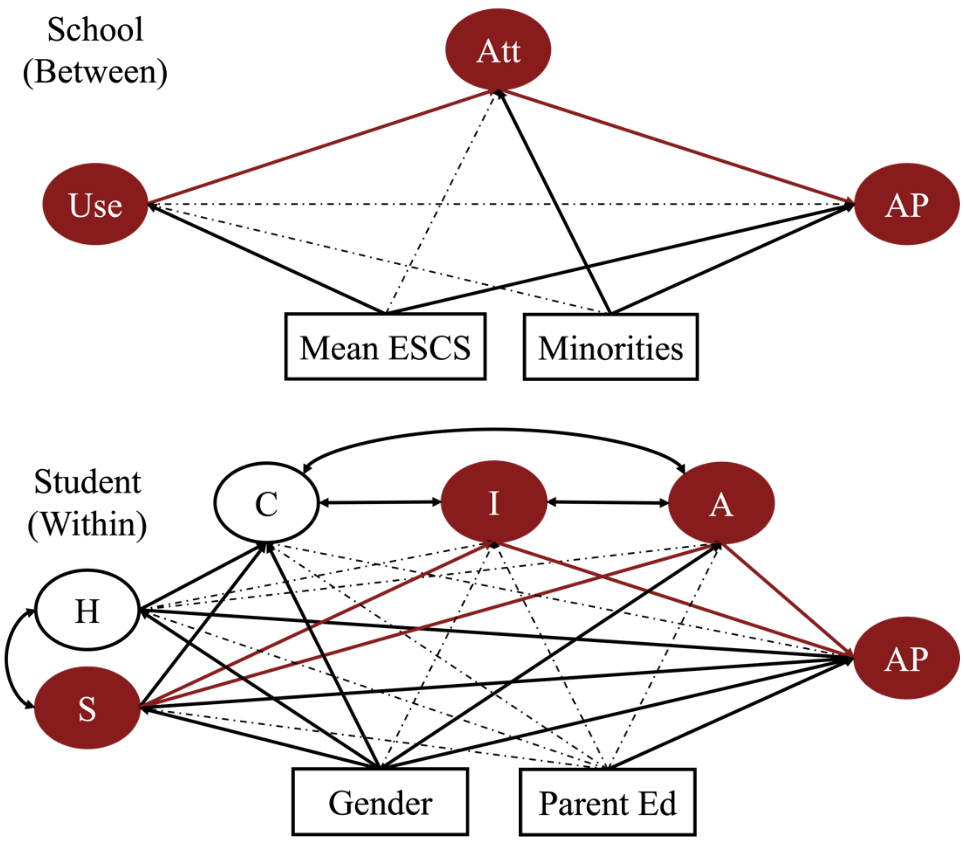


Figure 4.2. Path Diagram of Multilevel Mediation: Denmark PISA 2018

4.2.2 Finland

Finland was one of the two Nordic countries that participated in both PISA 2018 and TIMSS 2019, so the interrelationship was explored for both datasets. In terms of the school type control variable at the school level for both ILSAs, schools in Finland were categorized into two groups: schools located in urban areas and rural areas.

4.2.2.1 PISA 2018

Table 4.10 presents the standardized estimated parameters and their 95% Cr.I. for the path analyses for the entire mediation analyses, and the covariances among the sub-constructs of the ICT Usage and ICT Attitude variables. The standardized estimated factor loadings are listed in Table E.2 in Appendix E.

First, a significant total effect of ICT School on academic performance was detected at the student level. ICT School was negatively associated with students' academic performance (S $\rightarrow$ AP: c_W = -0.269, 95% Cr.I. = [-0.321, -0.217]), which corresponded to the previous studies (e.g., Hu et al., 2018; Juhaňák et al., 2018; Kong et al., 2022). On the other hand, no significant total effects were found for ICT Home on academic performance at the student level, as well as the total effect of ICT Usage on academic performance at the school level. The direct effect of ICT School, after controlling for all ICT Attitude variables, also showed the same direction of associations as the total effect did at the student level, but no other significant direct effects were found.

However, when exploring the mediation effects, the results showed that ICT Interest (H $\rightarrow$ I $\rightarrow$ AP: $a_W \times b_W$ = 0.014, 95% Cr.I. = [0.004, 0.028]) could function as a significant mediator for the association between ICT Home and academic performance at the student level. It could be interpreted that students who use digital devices more often tend to show more interest when using them (H $\rightarrow$ I: a_W = 0.096, 95% Cr.I. = [0.039, 0.152]), and those who feel more interest tend to show better performances (I $\rightarrow$ AP: b_W = 0.141, 95% Cr.I. = [0.101, 0.182]). When computing the mediation proportion, ICT Interest showed a ratio of 0.389 (0.014/0.036 = 0.389). This may infer that ICT Interest could explain about 38.9% of the total effect of ICT Home on academic performance at the student level. ICT Interest seems to play an important role in explaining the relationships, but it needs to be interpreted with caution since the total effect was not significant. In addition to this, the other ICT Attitude variables did not show significant mediation effects at the student level. Moreover, no significant mediation effect was detected at the school level as none of the path analyses were not significant.

Table 4.10. Estimated Path Coefficients and Covariances: Finland PISA 2018

	Student Level (Within; *W*)			School Level (Between; *B*)		
		95% Cr.I.			95% Cr.I.	
	Estimate	Lower	Upper	Estimate	Lower	Upper
Total (c)						
H → AP	0.036	-0.016	0.087			
S → AP	-0.269	-0.321	-0.217			
Use → AP				-0.007	-0.195	0.183
Direct (c')						
H → AP	0.019	-0.031	0.068			
S → AP	-0.276	-0.326	-0.227			
Use → AP				-0.017	-0.212	0.191
Use to Att (a)						
H → C	0.132	0.077	0.186			
H → I	0.096	0.039	0.152			
H → A	0.032	-0.025	0.087			
S → C	0.028	-0.027	0.083			
S → I	0.020	-0.037	0.078			
S → A	0.026	-0.030	0.083			
Use → Att				0.235	-0.067	0.532
Att to AP (b)						
C → AP	-0.003	-0.049	0.043			
I → AP	0.141	0.101	0.182			
A → AP	0.164	0.121	0.208			
Att → AP				0.147	-0.135	0.398
Indirect ($a \times b$)						
H → C → AP	0.000	-0.009	0.008			
H → I → AP	0.014	0.004	0.028			
H → A → AP	0.005	-0.005	0.018			
S → C → AP	0.000	-0.004	0.004			
S → I → AP	0.003	-0.007	0.014			
S → A → AP	0.004	-0.006	0.017			
Use → Att → AP				0.035	-0.072	0.212
Covariance						
H ↔ S	0.749	0.733	0.765			
C ↔ I	0.558	0.532	0.582			
C ↔ A	0.634	0.611	0.655			
I ↔ A	0.531	0.505	0.557			

Note. 95% Cr.I. = 95% Credible interval; Use = ICT Usage; H = ICT Home; S = ICT School; C = ICT Competence; I = ICT Interest; A = ICT Autonomy; Att = ICT Attitude; AP = Academic performance; a = Effect of ICT Usage on ICT Attitude; b = Effect of ICT Attitude on AP; c = Total effect of ICT Usage on AP; c' = Direct effect of ICT Usage on AP, after accounting for the indirect effect of ICT Attitude.

Table 4.11 presents the effect of demographic control variables on each level. At the student level, there were significant differences between boys and girls for all variables; girls showed greater degrees of ICT Interest and academic performance, while boys showed greater degrees for the other variables. Moreover, parents' educational level was positively associated with students' ICT Home, ICT Interest, ICT Autonomy, and academic performance but not significantly with ICT School and ICT Competence.

At the school level, it showed that school-mean ESCS was significantly associated with all variables; schools with higher ESCS showed more frequent ICT Usage, more positive ICT Attitude, and better performances. In terms of the school location variable, schools that are located in urban areas and rural areas did not show significant differences. Figure 4.3 visualizes the interrelationship, where significant paths are plotted with bold lines, and mediation effects are highlighted with maroon.

Table 4.11. Control Variables on Latent Variables: Finland PISA 2018

	Student Level (Within; *W*)				School Level (Between; *B*)		
		95% Cr.I.				95% Cr.I.	
	Estimate	Lower	Upper		Estimate	Lower	Upper
Gender				Mean ESCS			
→ H	-0.110	-0.138	-0.081	→ Use	0.561	0.427	0.670
→ S	-0.152	-0.181	-0.122				
→ C	-0.168	-0.197	-0.139	→ Att	0.298	0.020	0.560
→ I	0.049	0.019	0.081				
→ A	-0.131	-0.161	-0.100				
→ AP	0.111	0.084	0.137	→ AP	0.796	0.623	0.946
Parent Ed				Location			
→ H	0.032	0.002	0.061	→ Use	-0.074	-0.217	0.070
→ S	0.028	-0.002	0.059				
→ C	0.028	-0.003	0.058	→ Att	-0.203	-0.406	0.007
→ I	0.061	0.030	0.092				
→ A	0.043	0.012	0.074				
→ AP	0.175	0.151	0.199	→ AP	-0.087	-0.196	0.021

Note. Gender = 1 (Girls) or 0 (Boys); Parent Ed = Parents' educational level; Mean ESCS = School-mean ESCS; Location = 1 (Rural areas) or 0 (Urban areas).

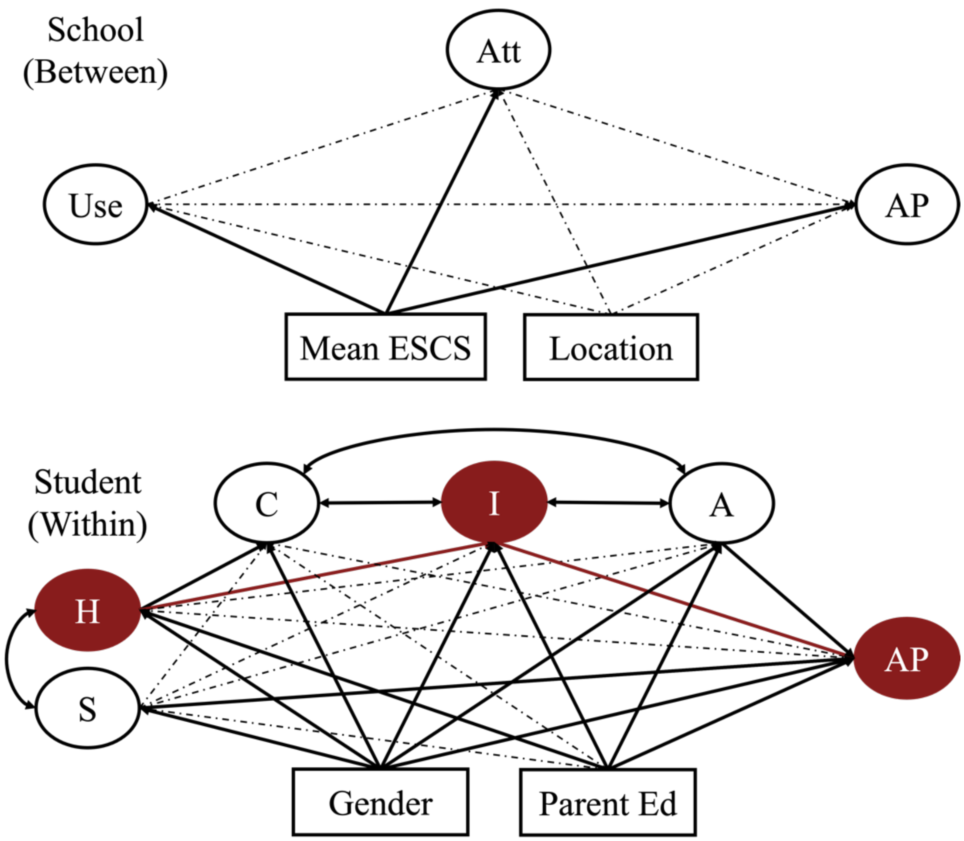


Figure 4.3. Path Diagram of Multilevel Mediation: Finland PISA 2018

4.2.2.2 TIMSS 2019

Table 4.12 shows the standardized estimated parameters and their 95% Cr.I. for the path analyses for the entire mediation analyses, and the covariance between mathematics and science. The standardized estimated factor loadings from the MLCFA analysis are presented in Table E.5 in Appendix E.

First, in terms of total effects, ICT Usage showed positive total effects on both mathematics (Use → Math: $c_W = 0.329$, 95% Cr.I. = [0.287, 0.371]; $c_B = 0.230$, 95% Cr.I. = [0.056, 0.391]) and science (Use → Scie: $c_W = 0.334$, 95% Cr.I. = [0.292, 0.375]; $c_B = 0.265$, 95% Cr.I. = [0.091, 0.422]) at both levels. The direct effects also showed the same directions of associations, after accounting for the mediation effect of ICT Attitude.

In terms of mediation, ICT Attitude did not function as a significant mediator at the student level, while a significant, negative mediation effect was detected at the school level on both performances (Use → Att → Math: $a_B \times b_B$ = -0.202, 95% Cr.I. = [-0.560, -0.020]; Use → Att → Scie: $a_B \times b_B$ = -0.196, 95% Cr.I. = [-0.556, -0.019]). More frequent ICT Usage was positively related with more positive ICT Attitude (Use → Att: a_B = 0.316, 95% Cr.I. = [0.057, 0.550]), while the ICT Attitude was negatively related with both mathematics (Att → Math: b_B = -0.639, 95% Cr.I. = [-1.019, -0.357]) and science (Att → Scie: b_B = -0.620, 95% Cr.I. = [-1.010, -0.336]) at the school level. As a note, the magnitudes of the total effects have been decreased, affected by the mediation effects.

Table 4.12. Estimated Path Coefficients and Covariances: Finland TIMSS 2019

	Student Level (Within; *W*)			School Level (Between; *B*)		
		95% Cr.I.			95% Cr.I.	
	Estimate	Lower	Upper	Estimate	Lower	Upper
Total (c)						
Use → Math	0.329	0.287	0.371	0.230	0.056	0.391
Use → Scie	0.334	0.292	0.375	0.265	0.091	0.422
Direct (c')						
Use → Math	0.334	0.291	0.376	0.437	0.231	0.730
Use → Scie	0.340	0.298	0.382	0.465	0.262	0.756
Use to Att (a)						
Use → Att	0.042	-0.008	0.092	0.316	0.057	0.550
Att to AP (b)						
Att → Math	-0.148	-0.183	-0.111	-0.639	-1.019	-0.357
Att → Scie	-0.185	-0.220	-0.149	-0.620	-1.010	-0.336
Indirect ($a \times b$)						
Use→Att→Math	-0.006	-0.017	0.001	-0.202	-0.560	-0.020
Use→Att→Scie	-0.008	-0.021	0.002	-0.196	-0.556	-0.019
Covariance						
Math ↔ Scie	0.856	0.846	0.865	0.933	0.859	0.958

Note. 95% Cr.I. = 95% Credible interval; Use = ICT Usage; Att = ICT Attitude; Math = Mathematics; Scie = Science; a = Effect of ICT Usage on ICT Attitude; b = Effect of ICT Attitude on mathematics or science; c = Total effect of ICT Usage on mathematics or science; c' = Direct effect of ICT Usage on mathematics or science, after accounting for the indirect effect of ICT Attitude.

Table 4.13 presents the effect of demographic control variables on each level. At the student level, girls showed greater degrees of ICT Usage, ICT Attitude, and science than boys, while no significant gender difference was found for mathematics. Parents' educational level affected significant differences in ICT Attitude, mathematics, and science. While students whose parents finished higher education performed better in both math and science, they showed lower degrees of ICT Attitude than those whose parents have secondary or lower degrees. At the school level, schools' ESCS status did not show significant differences for any of the variables, while school location did in that schools in rural areas tend to have greater degrees of ICT Attitude. Figure 4.4 visualizes the multilevel mediation model of Finland in TIMSS 2019, where bold lines represent significant paths, and marron indicates significant mediation effects.

Table 4.13. Control Variables on Latent Variables: Finland TIMSS 2019

	Student Level (Within; *W*)				School Level (Between; *B*)		
		95% Cr.I.				95% Cr.I.	
	Estimate	Lower	Upper		Estimate	Lower	Upper
Gender				Affluent			
→ Use	0.179	0.135	0.223	→ Use	0.035	-0.144	0.210
→ Att	0.052	0.013	0.089	→ Att	0.042	-0.198	0.281
→ Math	-0.022	-0.056	0.012	→ Math	0.080	-0.096	0.271
→ Scie	0.066	0.032	0.100	→ Scie	0.022	-0.154	0.214
Parent Ed				Disadvantage			
→ Use	0.018	-0.029	0.064	→ Use	-0.092	-0.265	0.087
→ Att	-0.091	-0.129	-0.054	→ Att	0.026	-0.222	0.263
→ Math	0.200	0.167	0.231	→ Math	-0.152	-0.335	0.039
→ Scie	0.190	0.157	0.221	→ S	-0.151	-0.331	0.039
				Location			
				→ Use	0.086	-0.091	0.255
				→ Att	0.323	0.081	0.540
				→ Math	0.102	-0.093	0.367
				→ Scie	0.150	-0.043	0.414

Note. Gender = 1 (Girls) or 0 (Boys); Parent Ed = 1 (Post-secondary or higher degrees) or 0 (Upper-secondary or lower); Affluent = 1 (More affluent schools) or 0 (Else); Disadvantage = 1 (More disadvantaged) or 0 (Else); Location = 1 (Rural) or 0 (Urban).

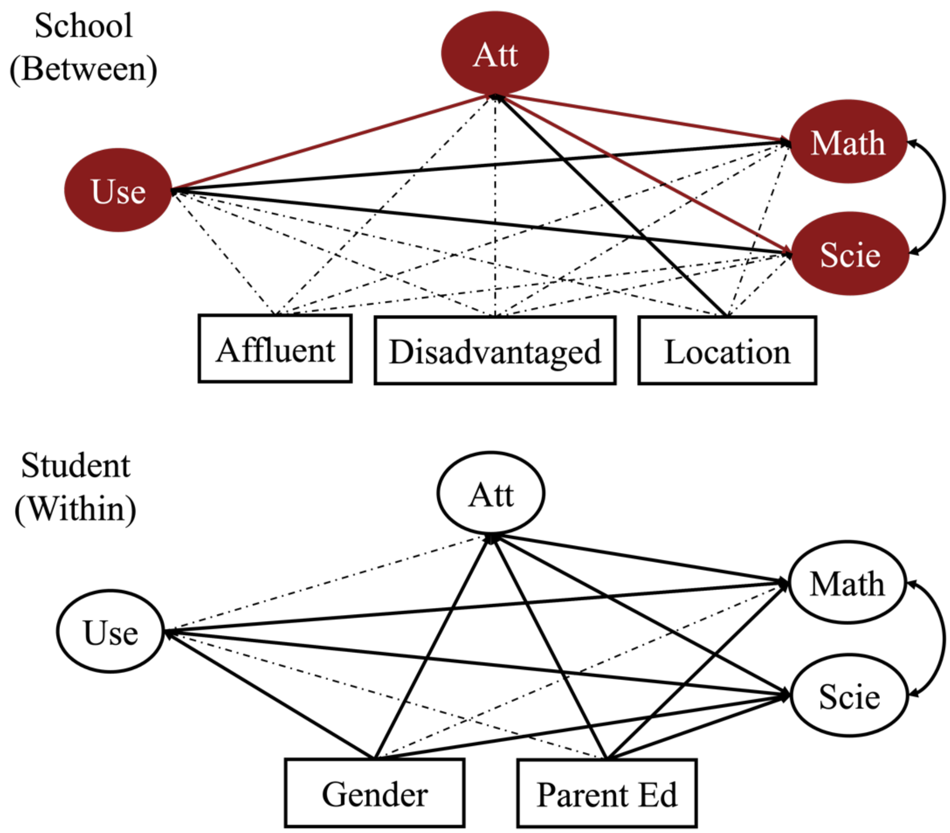


Figure 4.4. Path Diagram of Multilevel Mediation: Finland TIMSS 2019

4.2.3 Iceland

Iceland did not participate in TIMSS 2019, so the analysis of interrelationship was only conducted using the results from PISA 2018. For the school-level demographic control variables, schools in Iceland were categorized based on their regions of location, grouping by those located in Reykjavik (i.e., the capital city of Iceland), and all the other regions (Reimer et al., 2018, p. 191).

Table 4.14 presents the standardized estimated parameters and their 95% Cr.I. for the path analyses for the entire mediation analyses, and the covariances among the sub-constructs of the ICT Usage and ICT Attitude variables. The standardized estimated factor loadings are presented in Table E.3 in Appendix E.

First, significant total effects of the ICT Usage variables on academic performance were found at the student level. Academic performance showed a significant, negative association with both ICT Home (H $\rightarrow$ AP: c_W = -0.076, 95% Cr.I. = [-0.138, -0.015]) and ICT School (S $\rightarrow$ AP: c_W = -0.163, 95% Cr.I. = [-0.226, -0.098]), which corresponded to the results from the previous studies (e.g., Hu et al., 2018; Juhaňák et al., 2018; Kong et al., 2022). The direct effects of ICT Usage variables were also significant, after controlling for all ICT Attitude variables. At the school level, a significant total effect was also found for ICT Usage on academic performance (Use $\rightarrow$ AP: c_B = 0.233, 95% Cr.I. = [0.037, 0.417]), but no significant direct effect was detected after controlling for ICT Attitude.

When exploring the mediation effects, ICT Interest (H $\rightarrow$ I $\rightarrow$ AP: $a_W \times b_W$ = 0.021, 95% Cr.I. = [0.002, 0.046]) and ICT Autonomy (H $\rightarrow$ A $\rightarrow$ AP: $a_W \times b_W$ = 0.013, 95% Cr.I. = [0.003, 0.031]) seemed to function as significant mediators for the association between ICT Home and academic performance at the student level. Students who use digital devices more often tend to show more interest during the usage (H $\rightarrow$ I: a_W = 0.080, 95% Cr.I. = [0.012, 0.147]) and are more willing to actively solve problems using them (H $\rightarrow$ A: a_W = 0.095, 95% Cr.I. = [0.029, 0.162]), which leads to better academic performance (I $\rightarrow$ AP: b_W = 0.257, 95% Cr.I. = [0.202, 0.311]; A $\rightarrow$ AP: b_W = 0.140, 95% Cr.I. = [0.087, 0.192]). The total and mediation effects showed the opposite directions of association, and this could imply a suppression effect of ICT Attitude on the relationship which will be discussed later (MacKinnon et al., 2000). In contrast, ICT Attitude variables did not function as significant mediators for the association between ICT School and academic performance. Moreover, no significant mediation effect was detected at the school level as ICT Attitude was not significantly related to school-mean academic performance.

Table 4.14. Estimated Path Coefficients and Covariances: Iceland PISA 2018

	Student Level (Within; *W*)			School Level (Between; *B*)		
		95% Cr.I.			95% Cr.I.	
	Estimate	Lower	Upper	Estimate	Lower	Upper
Total (c)						
H → AP	-0.076	-0.138	-0.015			
S → AP	-0.163	-0.226	-0.098			
Use → AP				0.233	0.037	0.417
Direct (c')						
H → AP	-0.104	-0.163	-0.045			
S → AP	-0.171	-0.231	-0.110			
Use → AP				-0.080	-1.438	0.755
Use to Att (a)						
H → C	0.114	0.048	0.180			
H → I	0.080	0.012	0.147			
H → A	0.095	0.029	0.162			
S → C	0.048	-0.021	0.116			
S → I	0.049	-0.020	0.119			
S → A	-0.008	-0.076	0.060			
Use → Att				0.748	0.444	0.965
Att to AP (b)						
C → AP	-0.058	-0.016	0.002			
I → AP	0.257	0.202	0.311			
A → AP	0.140	0.087	0.192			
Att → AP				0.454	-0.617	1.922
Indirect ($a \times b$)						
H → C → AP	-0.007	-0.003	0.000			
H → I → AP	0.021	0.002	0.046			
H → A → AP	0.013	0.003	0.031			
S → C → AP	-0.003	-0.002	0.000			
S → I → AP	0.013	-0.006	0.037			
S → A → AP	-0.001	-0.015	0.012			
Use → Att → AP				0.340	-0.595	1.855
Covariance						
H ↔ S	0.693	0.666	0.718			
C ↔ I	0.616	0.585	0.644			
C ↔ A	0.605	0.575	0.633			
I ↔ A	0.522	0.488	0.554			

Note. 95% Cr.I. = 95% Credible interval; Use = ICT Usage; H = ICT Home; S = ICT School; C = ICT Competence; I = ICT Interest; A = ICT Autonomy; Att = ICT Attitude; AP = Academic performance; a = Effect of ICT Usage on ICT Attitude; b = Effect of ICT Attitude on AP; c = Total effect of ICT Usage on AP; c' = Direct effect of ICT Usage on AP, after accounting for the indirect effect of ICT Attitude.

Table 4.15 presents the effect of demographic control variables on each level. At the student level, significant gender differences were found in ICT Competence, ICT Autonomy, and academic performance. Girls showed better academic performance than boys, while boys showed greater degrees of ICT Competence and ICT Autonomy. Besides, parents' educational level was positively associated with ICT Attitude variables and academic performance but not significantly associated with ICT Usage variables. For the school-level variables, schools in higher ESCS status showed greater degrees of ICT Usage and better academic performance, while no significant associations were found between ICT Attitude. Regarding the school location, schools located either in Reykjavik or the other regions did not show significant differences across all variables. Figure 4.5 visualizes the overall multilevel mediation model of Iceland in PISA 2018, where significant paths are plotted with bold lines and significant mediation effects are colored maroon.

Table 4.15. Control Variables on Latent Variables: Iceland PISA 2018

	Student Level (Within; *W*)				School Level (Between; *B*)		
		95% Cr.I.				95% Cr.I.	
	Estimate	Lower	Upper		Estimate	Lower	Upper
Gender				Mean ESCS			
→ H	-0.008	-0.049	0.033	→ Use	0.336	0.099	0.535
→ S	-0.029	-0.068	0.011				
→ C	-0.098	-0.139	-0.059	→ Att	0.100	-0.359	0.521
→ I	0.006	-0.036	0.047				
→ A	-0.067	-0.109	-0.027				
→ AP	0.042	0.009	0.075	→ AP	0.603	0.098	0.920
Parent Ed				Capital			
→ H	0.020	-0.020	0.060	→ Use	-0.033	-0.236	0.173
→ S	0.006	-0.037	0.048				
→ C	0.043	0.002	0.085	→ Att	-0.045	-0.393	0.300
→ I	0.066	0.024	0.107				
→ A	0.051	0.009	0.092				
→ AP	0.170	0.137	0.202	→ AP	-0.088	-0.380	0.221

Note. Gender = 1 (Girls) or 0 (Boys); Parent Ed = Parents' educational level; Mean ESCS = School-mean ESCS; Capital = 1 (Non-Reykjavik areas) or 0 (Reykjavik).

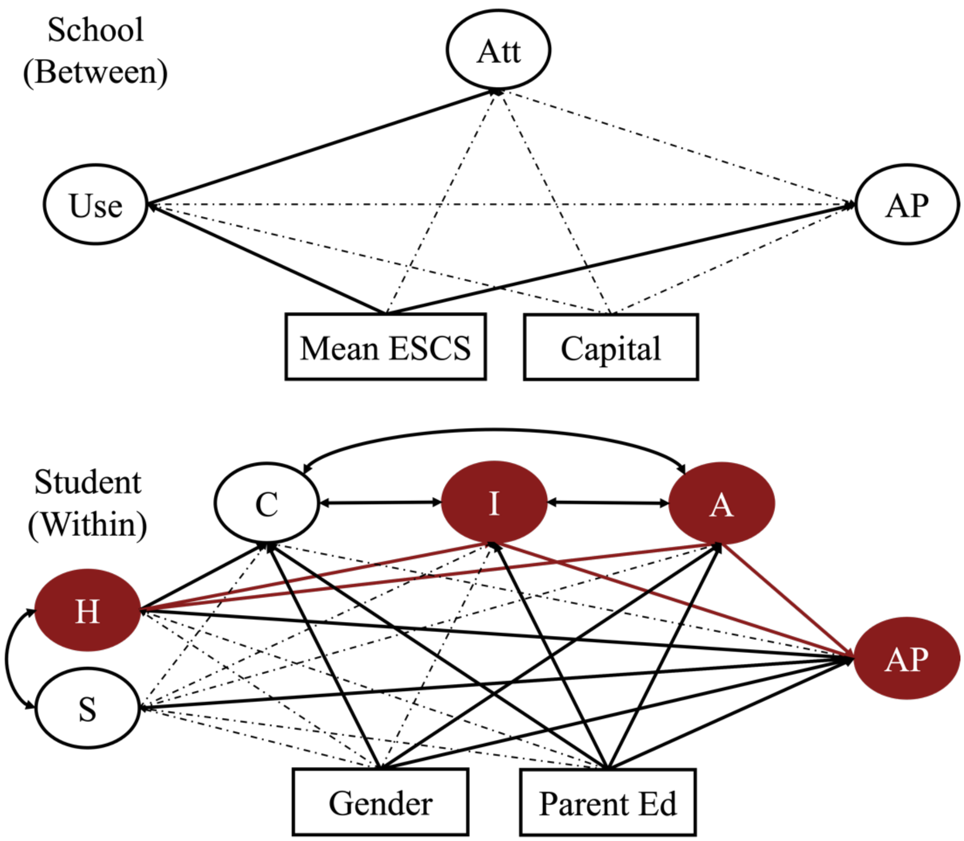


Figure 4.5. Path Diagram of Multilevel Mediation: Iceland PISA 2018

4.2.4 Norway

Norway only provided answers to the eTIMSS Questionnaire. Table 4.16 presents the standardized estimated parameters with their 95% Cr.I. for the path analyses from the mediation analyses and the covariance between mathematics and science. The standardized estimated factor loadings are presented in Table E.6 in Appendix E.

First, the results showed that ICT Usage has positive total effects on both mathematics (Use → Math: c_W = 0.053, 95% Cr.I. = [0.009, 0.098]) and science (Use → Scie: c_W = 0.068, 95% Cr.I. = [0.024, 0.113]) at the student level. The direct effects also showed the same directions of associations, after accounting for the mediation effect of ICT Attitude. However, no significant total or direct effects are detected at the school level.

In addition, a significant negative mediation effect of ICT Attitude appeared at the student level for the associations between ICT Usage and mathematics (Use → Att → Math: $a_W \times b_W$ = -0.012, 95% Cr.I. = [-0.027, -0.003]) and science (Use → Att → Scie: $a_W \times b_W$ = -0.014, 95% Cr.I. = [-0.029, -0.003]). More frequent ICT Usage was positively related with more positive ICT Attitude (Use → Att: a_W = 0.073, 95% Cr.I. = [0.021, 0.126]), while the ICT Attitude was negatively associated with both subjects (Att → Math: b_W = -0.171, 95% Cr.I. = [-0.213, -0.129]; Att → Scie: b_W = -0.189, 95% Cr.I. = [-0.230, -0.147]). However, no significant effects were found at the school level. Besides, similar to Finland, the magnitudes of the total effects have been decreased by the mediation effects.

Table 4.16. Estimated Path Coefficients and Covariances: Norway TIMSS 2019

	Student Level (Within; *W*)			School Level (Between; *B*)		
		95% Cr.I.			95% Cr.I.	
	Estimate	Lower	Upper	Estimate	Lower	Upper
Total (c)						
Use → Math	0.053	0.009	0.098	-0.171	-0.376	0.043
Use → Scie	0.068	0.024	0.113	-0.156	-0.376	0.043
Direct (c')						
Use → Math	0.065	0.021	0.109	0.074	-0.202	0.471
Use → Scie	0.082	0.037	0.126	0.083	-0.196	0.469
Use to Att (a)						
Use → Att	0.073	0.021	0.126	0.310	-0.037	0.611
Att to AP (b)						
Att → Math	-0.171	-0.213	-0.129	-0.811	-1.226	-0.480
Att → Scie	-0.189	-0.230	-0.147	-0.788	-1.190	-0.446
Indirect ($a \times b$)						
Use→Att→Math	-0.012	-0.027	-0.003	-0.251	-0.749	0.045
Use→Att→Scie	-0.014	-0.029	-0.003	-0.244	-0.727	0.044
Covariance						
Math ↔ Scie	0.857	0.847	0.868	0.892	0.553	0.946

Note. 95% Cr.I. = 95% Credible interval; Use = ICT Usage; Att = ICT Attitude; Math = Mathematics; Scie = Science; a = Effect of ICT Usage on ICT Attitude; b = Effect of ICT Attitude on mathematics or science; c = Total effect of ICT Usage on mathematics or science; c' = Direct effect of ICT Usage on mathematics or science, after accounting for the indirect effect of ICT Attitude.

Table 4.17 presents the effect of demographic control variables on each level. First, at the student level, there were no significant differences between girls and boys for any of the variables. Moreover, parents' educational level affected significant differences in ICT Attitude, mathematics, and science. While students whose parents completed higher education performed better in both subjects, they showed more negative degrees of ICT Attitude than those whose parents have secondary or lower degrees. When it comes to the school-level variables, neither affluent nor disadvantaged schools showed significant differences in any variables. Similarly, the analysis failed to detect any significant differences between the schools in rural and urban areas. Figure 4.6 visualizes the multilevel mediation model of Norway in TIMSS 2019, where significant paths are plotted with bold lines and significant mediation effect with maroon.

Table 4.17. Control Variables on Latent Variables: Norway TIMSS 2019

	Student Level (Within; *W*)				School Level (Between; *B*)		
		95% Cr.I.				95% Cr.I.	
	Estimate	Lower	Upper		Estimate	Lower	Upper
Gender				Affluent			
→ Use	0.042	-0.003	0.089	→ Use	-0.086	-0.300	0.137
→ Att	0.025	-0.019	0.068	→ Att	-0.238	-0.538	0.079
→ Math	-0.008	-0.046	0.031	→ Math	-0.005	-0.360	0.241
→ Scie	-0.023	-0.061	0.015	→ Scie	-0.022	-0.367	0.225
Parent Ed				Disadvantage			
→ Use	-0.011	-0.059	0.036	→ Use	0.049	-0.168	0.266
→ Att	-0.075	-0.121	-0.030	→ Att	0.100	-0.200	0.404
→ Math	0.183	0.146	0.221	→ Math	-0.031	-0.270	0.267
→ Scie	0.185	0.147	0.221	→ Scie	-0.070	-0.305	0.218
				Location			
				→ Use	0.115	-0.094	0.316
				→ Att	-0.238	-0.538	0.079
				→ Math	0.015	-0.230	0.302
				→ Scie	0.096	-0.145	0.375

Note. Gender = 1 (Girls) or 0 (Boys); Parent Ed = 1 (Post-secondary or higher degrees) or 0 (Upper-secondary or lower); Affluent = 1 (More affluent schools) or 0 (Else); Disadvantage = 1 (More disadvantaged) or 0 (Else); Location = 1 (Rural) or 0 (Urban).

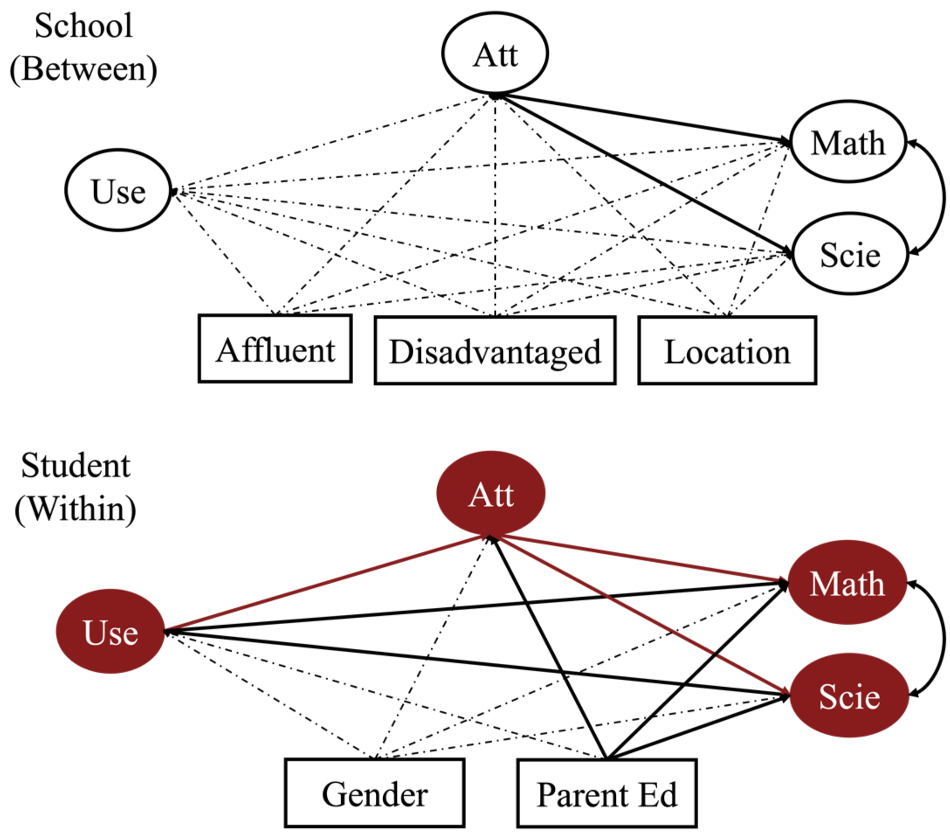


Figure 4.6. Path Diagram of Multilevel Mediation: Norway TIMSS 2019

4.2.5 Sweden

Sweden participated in both PISA 2018 and TIMSS 2019 like Finland, so the interrelationship was explored for both datasets. For PISA 2018, schools in Sweden were categorized by school type (i.e., private or public schools), while they were grouped by the school location for TIMSS 2019 (i.e., urban or rural areas).

4.2.5.1 PISA 2018

Table 4.18 presents the standardized estimated parameters and their 95% Cr.I. for the path analyses for the entire mediation analyses, and the covariances among the sub-constructs of the ICT Usage and ICT Attitude variables. The standardized estimated factor loadings are listed in Table E.4 in Appendix E.

First, significant total effects of ICT Usage on academic performance were detected at the student level. Students' academic performance was negatively associated with both ICT Home (H → AP: c_W = -0.066, 95% Cr.I. = [-0.121, -0.012]) and ICT School (S → AP: c_W = -0.195, 95% Cr.I. = [-0.251, -0.138]), which corresponded to the previous studies (e.g., Hu et al., 2018; Juhaňák et al., 2018; Kong et al., 2022). In contrast, no significant total effect of ICT Usage was detected at the school level. The direct effects of ICT Usage, after controlling for all ICT Attitude variables, also showed the same direction of associations as the total effects did at the student level but not at the school level.

In terms of the mediation effects, ICT Interest seemed to function as a significant mediator for the association between ICT Usage variables and academic performance at the student level (H → I → AP: $a_W \times b_W$ = 0.021, 95% Cr.I. = [0.005, 0.041]); S → I → AP: $a_W \times b_W$ = 0.022, 95% Cr.I. = [0.005, 0.043]). Students who use digital devices more often at home (H → I: a_W = 0.087, 95% Cr.I. = [0.026, 0.147]) and at school (S → I: a_W = 0.089, 95% Cr.I. = [0.027, 0.151]) tend to show more interest when using them, and those who feel more interest tend to show better performances (I → AP: b_W = 0.243, 95% Cr.I. = [0.203, 0.282]). The total and mediation effects showed the opposite directions, which implies a suppression effect of ICT Interest on the relationship (MacKinnon et al., 2000).

ICT Attitude also seemed to function as a significant mediator at the school level as well (Use → Att → AP: $a_B \times b_B$ = 0.192, 95% Cr.I. = [0.080, 0.339]). More frequent ICT Usage was positively associated with more positive ICT Attitude (Use → Att: a_B = 0.409, 95% Cr.I. = [0.247, 0.559]), which positively affected the school-mean academic performance (Att → AP: b_W = 0.470, 95% Cr.I. = [0.325, 0.606]). As the total and direct effects were not significant, the mediation accounts for the school-level interrelationship.

Table 4.18. Estimated Path Coefficients and Covariances: Sweden PISA 2018

	Student Level (Within; *W*)			School Level (Between; *B*)		
		95% Cr.I.			95% Cr.I.	
	Estimate	Lower	Upper	Estimate	Lower	Upper
Total (c)						
H → AP	-0.066	-0.121	-0.012			
S → AP	-0.195	-0.251	-0.138			
Use → AP				0.067	-0.054	0.187
Direct (c')						
H → AP	-0.083	-0.135	-0.029			
S → AP	-0.219	-0.274	-0.165			
Use → AP				-0.108	-0.233	0.016
Use to Att (a)						
H → C	0.145	0.087	0.202			
H → I	0.087	0.026	0.147			
H → A	0.111	0.056	0.167			
S → C	0.094	0.035	0.152			
S → I	0.089	0.027	0.151			
S → A	0.123	0.067	0.181			
Use → Att				0.409	0.247	0.559
Att to AP (b)						
C → AP	-0.004	-0.057	0.049			
I → AP	0.243	0.203	0.282			
A → AP	0.026	-0.026	0.077			
Att → AP				0.470	0.325	0.606
Indirect ($a \times b$)						
H → C → AP	-0.001	-0.012	0.010			
H → I → AP	0.021	0.005	0.041			
H → A → AP	0.003	-0.004	0.013			
S → C → AP	0.000	-0.009	0.007			
S → I → AP	0.022	0.005	0.043			
S → A → AP	0.003	-0.005	0.014			
Use → Att → AP				0.192	0.080	0.339
Covariance						
H ↔ S	0.729	0.710	0.749			
C ↔ I	0.520	0.492	0.548			
C ↔ A	0.691	0.670	0.710			
I ↔ A	0.464	0.435	0.493			

Note. 95% Cr.I. = 95% Credible interval; Use = ICT Usage; H = ICT Home; S = ICT School; C = ICT Competence; I = ICT Interest; A = ICT Autonomy; Att = ICT Attitude; AP = Academic performance; a = Effect of ICT Usage on ICT Attitude; b = Effect of ICT Attitude on AP; c = Total effect of ICT Usage on AP; c' = Direct effect of ICT Usage on AP, after accounting for the indirect effect of ICT Attitude.

Table 4.19 presents the effect of demographic control variables on each level. At the student level, no significant gender difference was found in ICT Interest and academic performance, while boys showed greater degrees than girls for the others. Moreover, the parents' educational level was not significantly related to students' ICT Autonomy, but the other variables did show significant positive associations. In terms of the school level, school-mean ESCS showed significant positive relationships with ICT Usage, ICT Attitude, and students' academic performance as well. When focusing on the school type variable, private schools showed greater ICT Usage than public schools. However, there were no significant differences between public and private schools for ICT Attitude and academic performance. Figure 4.7 visualizes the multilevel mediation model of Sweden in PISA 2018, where significant paths are plotted with bold lines, and significant mediation effects are colored maroon.

Table 4.19. Control Variables on Latent Variables: Sweden PISA 2018

	Student Level (Within; *W*)				School Level (Between; *B*)		
		95% Cr.I.				95% Cr.I.	
	Estimate	Lower	Upper		Estimate	Lower	Upper
Gender				Mean ESCS			
→ H	-0.053	-0.083	-0.022	→ Use	0.355	0.223	0.471
→ S	-0.105	-0.135	-0.073				
→ C	-0.145	-0.175	-0.115	→ Att	0.336	0.184	0.476
→ I	0.025	-0.006	0.058				
→ A	-0.277	-0.305	-0.248				
→ AP	0.004	-0.025	0.032	→ AP	0.636	0.525	0.734
Parent Ed				Type			
→ H	0.034	0.002	0.066	→ Use	-0.227	-0.354	-0.090
→ S	0.071	0.037	0.103				
→ C	0.045	0.013	0.078	→ Att	-0.016	-0.165	0.134
→ I	0.086	0.052	0.119				
→ A	0.016	-0.015	0.047				
→ AP	0.201	0.176	0.227	→ AP	0.050	-0.047	0.147

Note. Gender = 1 (Girls) or 0 (Boys); Parent Ed = Parents' educational level; Mean ESCS = School-mean ESCS; Type = 1 (Public schools) or 0 (Private schools).

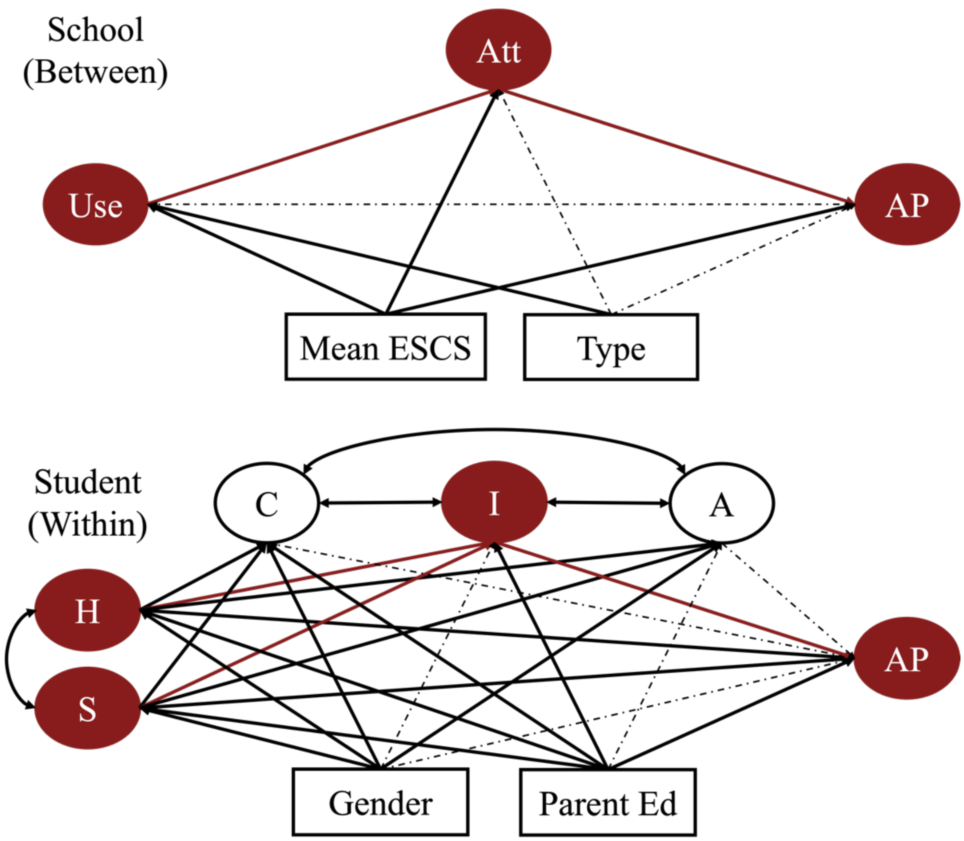


Figure 4.7. Path Diagram of Multilevel Mediation: Sweden PISA 2018

4.2.5.2 TIMSS 2019

Table 4.20 shows the standardized estimated parameters and their 95% Cr.I. for the path analyses for the entire mediation analyses and the covariance between mathematics and science performances. The standardized estimated factor loadings are presented in Table E.7 in Appendix E.

First, at the student level, ICT Usage did not show positive total effects on both mathematics and science, while it was positively significant at the school level for both subjects (Use → Math: c_B = 0.296, 95% Cr.I. = [0.129, 0.444]; Use → Scie: c_B = 0.283, 95% Cr.I. = [0.115, 0.433]). The direct effects showed the same directions, after accounting for the mediation effect of ICT Attitude, but not significant at the student level.

In terms of mediation, no significant mediation effect of ICT Attitude was detected at the school level, while it functioned as a significant, negative mediator at the student level for both subjects (Use → Att → Math: $a_W \times b_W$ = -0.036, 95% Cr.I. = [-0.050, -0.023]; Use → Att → Scie: $a_W \times b_W$ = -0.045, 95% Cr.I. = [-0.062, -0.030]). More frequent ICT Usage was positively related with more positive ICT Attitude (Use → Att: a_W = 0.153, 95% Cr.I. = [0.115, 0.191]), while the ICT Attitude negatively impacted both mathematics (Att → Math: b_W = -0.233, 95% Cr.I. = [-0.264, -0.203]) and science (Att → Scie: b_W = -0.295, 95% Cr.I. = [-0.325, -0.265]) at the student level. As the total and direct effects were not significant, the mediation effect seems to account for the student-level interrelationship.

Table 4.20. Estimated Path Coefficients and Covariances: Sweden TIMSS 2019

	Student Level (Within; *W*)			School Level (Between; *B*)		
		95% Cr.I.			95% Cr.I.	
	Estimate	Lower	Upper	Estimate	Lower	Upper
Total (c)						
Use → Math	-0.012	-0.042	0.019	0.296	0.129	0.444
Use → Scie	-0.018	-0.049	0.012	0.283	0.115	0.433
Direct (c')						
Use → Math	0.022	-0.009	0.053	0.317	0.157	0.466
Use → Scie	0.024	-0.007	0.056	0.304	0.145	0.454
Use to Att (a)						
Use → Att	0.153	0.115	0.191	0.041	-0.176	0.250
Att to AP (b)						
Att → Math	-0.233	-0.264	-0.203	-0.441	-0.609	-0.244
Att → Scie	-0.295	-0.325	-0.265	-0.453	-0.618	-0.259
Indirect ($a \times b$)						
Use→Att→Math	-0.036	-0.050	-0.023	-0.018	-0.152	0.107
Use→Att→Scie	-0.045	-0.062	-0.030	-0.019	-0.155	0.109
Covariance						
Math ↔ Scie	0.863	0.855	0.870	0.956	0.937	0.969

Note. 95% Cr.I. = 95% Credible interval; Use = ICT Usage; Att = ICT Attitude; Math = Mathematics; Scie = Science; a = Effect of ICT Usage on ICT Attitude; b = Effect of ICT Attitude on mathematics or science; c = Total effect of ICT Usage on mathematics or science; c' = Direct effect of ICT Usage on mathematics or science, after accounting for the indirect effect of ICT Attitude.

Table 4.21 shows the effect of demographic control variables. One thing to note is that the control variables at the school level were excluded for Sweden TIMSS 2019 since few of them showed significance. The original MLSEM model including the school-level control variables resulted in odd parameter estimates. At the student level, no significant gender difference was found for any variables. Regarding parents' educational levels, students whose parents finished higher education performed better in both mathematics and science but showed lower degrees of ICT Usage and ICT Attitude than those whose parents have secondary or lower degrees. Figure 4.8 visualizes the multilevel mediation model of Sweden in TIMSS 2019, where significant paths are plotted in bold lines, and significant mediation effects are colored maroon.

Table 4.21. Control Variables on Latent Variables: Sweden TIMSS 2019

	Student Level (Within; *W*)				*School Level (Between; B)*		
		95% Cr.I.				*95% Cr.I.*	
	Estimate	Lower	Upper		Estimate	Lower	Upper
Gender				Affluent			
→ Use	0.042	-0.002	0.084	→ Use	*-0.084*	*-0.278*	*0.117*
→ Att	0.028	-0.014	0.071	→ Att	*-0.281*	*-0.494*	*-0.040*
→ Math	-0.024	-0.062	0.013	→ Math	*0.142*	*-0.035*	*0.309*
→ Scie	0.030	-0.007	0.067	→ Scie	*0.191*	*0.016*	*0.353*
Parent Ed				Disadvantage			
→ Use	-0.084	-0.130	-0.041	→ Use	*-0.057*	*-0.250*	*0.143*
→ Att	-0.135	-0.178	-0.091	→ Att	*-0.024*	*-0.254*	*0.212*
→ Math	0.159	0.121	0.196	→ Math	*-0.139*	*-0.295*	*0.025*
→ Scie	0.178	0.141	0.214	→ Scie	*-0.155*	*-0.311*	*0.007*
				Location			
				→ Use	*-0.131*	*-0.297*	*0.048*
				→ Att	*0.169*	*-0.039*	*0.363*
				→ Math	*-0.202*	*-0.344*	*-0.053*
				→ Scie	*-0.146*	*-0.289*	*0.004*

Note. Gender = 1 (Girls) or 0 (Boys); Parent Ed = 1 (Post-secondary or higher degrees) or 0 (Upper-secondary or lower); Affluent = 1 (More affluent schools) or 0 (Else); Disadvantage = 1 (More disadvantaged) or 0 (Else); Location = 1 (Rural) or 0 (Urban); School-level demographic control variables are excluded from the final model estimation, but the estimates from the original model are presented just as a reference only.

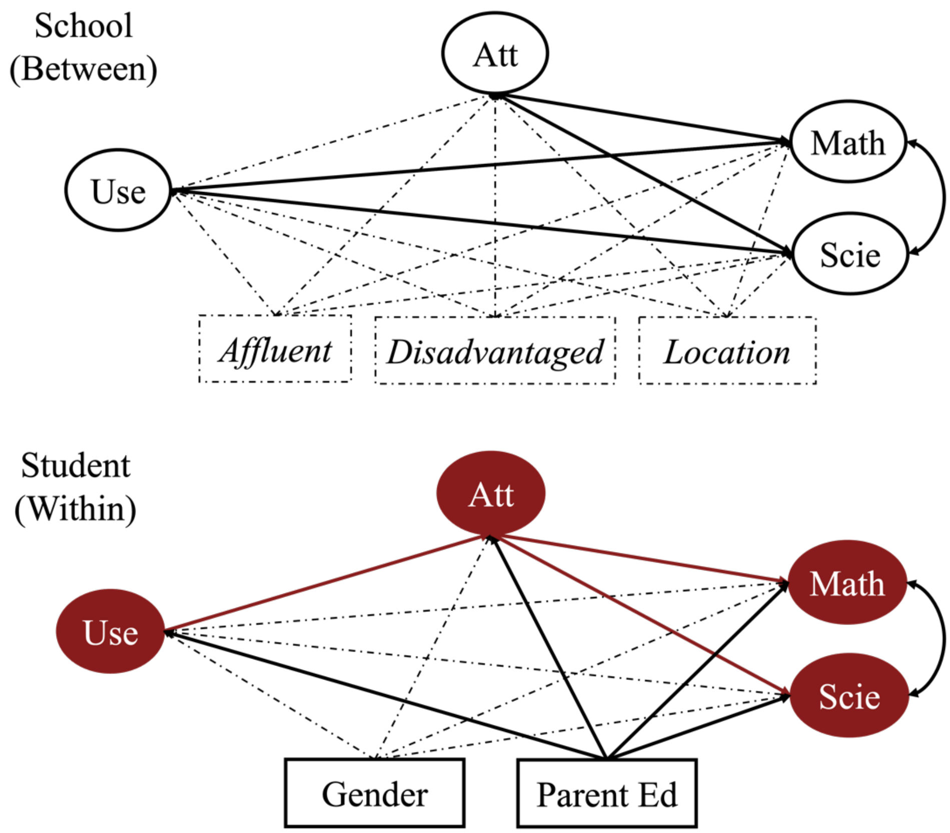


Figure 4.8. Path Diagram of Multilevel Mediation: Sweden TIMSS 2019

4.3 Summary of Results

The multilevel mediation analyses found several common results in terms of the interrelationship among students' ICT Usage, ICT Attitude, and academic performance across Nordic countries. First, ICT Attitude seemed to function as a significant mediator in the association between ICT Usage and academic performance. More frequent usage of digital devices in students' daily lives was related to more positive attitudes when they use the devices, which affected their academic performance in exams in a computer-based setting. Second, it generally turned out that girls and boys usually have different degrees of ICT Usage and ICT Attitude. Third, however, the actual patterns of the findings showed opposite directions across the two ILSAs, which will be addressed in Chapter 5.

CHAPTER 5

DISCUSSION

5.1 General Overview

The purpose of this dissertation was to explore the interrelationship among students' usage of digital devices (i.e., ICT Usage), attitudes toward using digital devices (i.e., ICT Attitude), and academic performance on computer-based examinations across five Nordic countries. To explore this, the mediation effect of ICT Attitude on the relationship between ICT Usage and academic performance was first analyzed, and then level-specific demographic control variables were added to explore if different patterns exist across the five countries when the control variables are included. Published datasets from PISA 2018 and TIMSS 2019 Grade 8 were used as they were provided to students in a computer-based format to measure their cognitive literacy and collect diverse information relevant to ICT Usage and ICT Attitude. The general discussion of results found in the previous chapter will be addressed in the following sections.

5.1.1 Interrelationship of ICT and Academic Performance

The first research question explored the interrelationship among students' ICT Usage, ICT Attitude, and academic performance by focusing on (1) the total effect of ICT Usage on academic performance and (2) the indirect effect of ICT Attitude between the association of ICT Usage and academic performance. A multilevel CFA measured the three latent variables using students' responses to survey statements regarding digital devices and their scores of cognitive literacy. Then, a 1-1-1 multilevel mediation in the context of the MLSEM method was used to explore the mediation effect of the ICT Attitude variable at both student and school levels. All analyses were conducted separately for each country.

5.1.1.1 Total and Direct Effects of ICT Usage

For PISA 2018 first, the analyses generally showed that there is a significant, negative total effect of ICT Usage on students' academic performance at the student level. Students who use digital devices more often either at home or at school were associated with poorer academic performance in computer-based exams. Such findings corresponded with the previous studies (e.g., Gómez-Fernández & Mediavilla, 2021; Juhaňák et al., 2018; Ozola & Grinfelds, 2019; Park & Weng, 2020), which could be attributed that students with lower academic performance would spend more time using digital devices for their complementary studies after school. Besides, the direct effect of ICT Usage on academic performance after controlling for the effect of ICT Attitude showed significant, negative associations at the student level. However, some analyses showed different patterns. For example, students who used digital devices more often at school performed better on academic performance in Denmark (see Table 4.8). Moreover, no significant direct effect between ICT Home and academic performance was detected in Finland (see Table 4.10). In terms of the school level, ICT Usage showed significant total effects on academic performance in Denmark and Iceland, but no significant direct effects were detected.

In contrast, when exploring the results using TIMSS 2019 (i.e., Finland, Norway, and Sweden), the patterns were different in that ICT Usage showed significant, positive total effects on students' performances in mathematics and science at both student and school levels. Students who answered that they used computers or tablets more frequently to finish schoolwork or take quizzes tended to show better performances. These findings look similar to the results that more frequent ICT Usage was positively associated with test scores in PISA 2012, where mathematics was the main focus (e.g., Pekto et al., 2017;

Skryabin et al., 2015; Srijamdee & Pholphirul, 2020). The direct effects of ICT Usage on academic performance after controlling for the effect of ICT Attitude were significantly positive as well. However, this pattern was not applicable to Norway (at the school level) and Sweden (at the student level) in that there was neither significant total nor direct effect of ICT Usage on academic performance. Tables 5.1 and 5.2 summarize the results of the total effects and direct effects of ICT Usage variables on academic performance in computer-based tests from both PISA 2018 and TIMSS 2019.

Table 5.1. Summary: Total Effect of ICT Usage on Academic Performance

	PISA 2018			TIMSS 2019			
	Student		School	Student		School	
	H → AP	S → AP	Use → AP	Use → Math	Use → Scie	Use → Math	Use → Scie
Denmark	–	+	+				
Finland	×	–	×	+	+	+	+
Iceland	–	–	+				
Norway				+	+	×	×
Sweden	–	–	×	×	×	+	+

Note. H = ICT Home; S = ICT School; Use = ICT Usage; AP = Academic performance; Math = Mathematics; Scie = Science; Student = Student (within) level; School = School (between) level; + = Positive association; – = Negative association; × = No significant association; TIMSS 2019 measured ICT Usage as one factor.

Table 5.2. Summary: Direct Effect of ICT Usage on Academic Performance

	PISA 2018			TIMSS 2019			
	Student		School	Student		School	
	H → AP	S → AP	Use → AP	Use → Math	Use → Scie	Use → Math	Use → Scie
Denmark	–	+	×				
Finland	×	–	×	+	+	+	+
Iceland	–	–	×				
Norway				+	+	×	×
Sweden	–	–	×	×	×	+	+

Note. H = ICT Home; S = ICT School; Use = ICT Usage; AP = Academic performance; Math = Mathematics; Scie = Science; Student = Student (within) level; School = School (between) level; + = Positive association; – = Negative association; × = No significant association; Direct effect controlled for the effect of ICT Attitude variables; TIMSS 2019 measured ICT Usage as one factor.

5.1.1.2 Indirect Effect of ICT Attitude as a Mediator

An indirect effect of ICT Attitude as a mediating variable was also explored on both student and school levels. Overall, multilevel mediation analysis in terms of MLSEM showed that ICT Attitude could function as a significant mediating variable between the association of ICT Usage and academic performance. More frequent usage of digital devices seemed to be significantly related to a more positive attitude toward using digital devices, which would have influenced better academic performance when the students took tests in a computer-based format.

First, for PISA 2018, ICT Interest was found to function as a significant mediator between the association at the student level for all countries. Students who use digital devices more often tend to have more interest in activities using digital devices, which might affect better performances in computer-based exams with less anxiety or discomfort. Such finding seems relevant to previous studies that found a positive association between students' interest in using digital devices and academic performance (e.g., Hu et al., 2018; Odell et al., 2020a; Park & Weng, 2020). In addition, ICT Autonomy was found to function as a significant mediator between the association in Denmark and Iceland (see Tables 4.8 and 4.14). Students who use digital devices more frequently tend to be more willing to actively solve problems using digital devices, which would have influenced their better performances in computer-based exams. This finding was also relevant to the previous research that found a positive correlation between students' ICT Autonomy and academic performance (e.g., Gubbels et al., 2020; Hu et al., 2018; Juhaňák et al., 2018; Ma & Qin, 2021; Odell et al., 2020a; Park & Weng, 2020; Xiao et al., 2019). However, the mediation effect of ICT Autonomy was not found in Finland and Sweden (see Tables 4.10 and 4.18).

While ICT Interest and ICT Autonomy seemed to function as significant mediator variables, the analyses commonly showed that ICT Competence did not function as a significant mediating variable across all four countries. With a detailed look, students' ICT Competence was not significantly related to their academic performance, resulting in a non-significant mediation effect, while ICT Home and ICT School were usually associated with it. This was different from previous research that students' level of self-efficacy or competence when using digital devices was positively associated with their academic performance (e.g., Hu et al., 2018; Lee & Wu, 2012; Lim & Jung, 2019; Odell et al., 2020a; Park & Weng, 2020). Besides, the mediation effect of ICT Attitude was found to be significantly positive at the school level in Denmark and Sweden (see Tables 4.8 and 4.18).

When focusing on TIMSS 2019, ICT Attitude was also found to function as a significant mediator variable; however, the mediation effect showed a different pattern. First, ICT Usage was positively associated with ICT Attitude, which was similar to the findings in PISA 2018. On the other hand, ICT Attitude was significantly associated in a negative way with academic performance, resulting in a negative mediation effect of ICT Attitude between the association (i.e., Finland at the school level; Norway and Sweden at the student level). Such results were different from those in the previous studies in that ICT Attitude usually showed a positive association with academic performance (e.g., Kong et al., 2022; Lee & Wu, 2012; Lim & Jung, 2019; Odell et al., 2020a; Park & Weng, 2020). The difference will be addressed in more details in Chapter 5.1.3. Table 5.3 summarizes the indirect effect of ICT Attitude variables as a mediator between the association of ICT Usage and academic performance for both ILSAs. Please note that ICT Attitude in TIMSS 2019 was measured as a single factor, different from PISA 2018.

Table 5.3. Summary: Indirect Effect of ICT Attitude as a Mediator

		PISA 2018			TIMSS 2019			
		Student		School	Student		School	
	Att	H → AP	S → AP	Use → AP	Use → Math	Use → Scie	Use → Math	Use → Scie
Denmark	C	×	×					
	I	×	+					
	A	×	+					
	Att			+				
Finland	C	×	×					
	I	+	×					
	A	×	×					
	Att			×	×	×	–	–
Iceland	C	×	×					
	I	+	×					
	A	+	×					
	Att			×				
Norway	C							
	I							
	A							
	Att				–	–	×	×
Sweden	C	×	×					
	I	+	+					
	A	×	×					
	Att			+	–	–	×	×

Note. C = ICT Competence; I = ICT Interest; A = ICT Autonomy; Att = ICT Attitude; + = Positive association; – = Negative association; × = No significant association; TIMSS 2019 measured ICT Attitude as one factor.

5.1.1.3 Suppression Effect of ICT Attitude

Except for the direct effect of ICT School in Denmark, there was an unexpected, interesting finding in this study. In a mediation analysis, the direct effect after controlling for the mediation effect usually shows a weaker association than the total effect (i.e., partial mediation) or even no significant association (i.e., complete mediation) (Preacher & Kelly, 2011). However, most results showed that the direct effects of ICT Usage after controlling for the mediation effect of ICT Attitude became stronger than the total effects, which can be explained by the concept of suppression effect.

Suppression effects take place when the strength of direct effects becomes stronger than that of the total effects after including an additional variable (i.e., mediator variable; Cheung & Lau, 2008; MacKinnon et al., 2000; Peng et al., 2021). Due to such property, it is expected to increase the predictive validity when regressing a predictor variable (i.e., X in Figure 2.1) to a criterion variable (i.e., Y in Figure 2.1) as the additional variable (i.e., M in Figure 2.1) could take out the criterion-irrelevant variances (Cheung & Lau, 2008; MacKinnon et al., 2000). When the suppression effect turns out to be significant, it is preferable to interpret the direct effects along with the indirect effects rather than the total effects solely (Cheung & Lau, 2008; Gutierrez & Cribbie, 2021). When applying it to this study, although it is a bit difficult to generalize, it could be inferred that the impact of students' usage of digital devices on their academic performance would need to be studied by taking their interest and autonomy when using digital devices into account.

5.1.2 Impact of Demographic Differences

The second research question asked how the hypothesized model in the previous section looks like (1) when including student-level control variables (e.g., gender and parents' educational level) and (2) when including school-level control variables (e.g., school-mean ESCS and additional school variables). The control variables were either categorical (e.g., gender or school types) or continuous (e.g., parents' years of education or standardized school-mean ESCS) based on how they were collected. However, including school-level variables sometimes made a problem when identifying the model in Sweden for TIMSS 2019, so the school-level variables were excluded from this case. The control variables were regressed on all variables of interest (i.e., ICT Usage, ICT Attitude, and academic performance) to explore the differences among them.

5.1.2.1 Student-Level Variables

One of the two student-level control variables, gender, was categorical, setting the boys as a reference group in both ILSAs (i.e., 1 = girls, 0 = boys). Estimated coefficients greater than 0 indicate that girls have greater degrees for certain variables than boys do. When focusing on PISA 2018 first, interestingly, it showed that there is a significant gender difference in ICT Competence and ICT Autonomy across all Nordic countries. Boys tend to respond to higher scales, implying that they feel confident when using digital devices and are willing to solve problems using digital devices compared to girls. ICT Interest showed different results in that boys in Finland showed greater degrees of ICT Interest than girls, while no significant gender difference was detected for the other countries. In terms of the ICT Usage variable, it generally showed that boys tend to use digital devices more frequently at and outside of school, while no significant gender difference was found for students in Iceland. Regarding academic performance, girls tended to show better performance results compared to boys, while Swedish students did not show a significant gender difference in academic performance.

When moving on to TIMSS 2019, gender only influenced the variables of interest in Finland. Girls generally responded to greater scales on ICT Usage and ICT Attitude questionnaires as well as showing better science performances than boys. However, no gender difference was detected in mathematics. Besides, gender did not influence any significant differences in the variables of interest for Norway and Sweden.

The other student-level control variable, parents' educational level, was continuous in PISA 2018 (i.e., years of education; 3 to 16 years) and categorical in TIMSS 2019 (i.e., the final educational degree that parents earned). Originally, the education level was categorized into five groups from “Some Primary, Lower Secondary, or No School” to “University or Higher,” but they were regrouped into two groups for ease of analysis (i.e., 1 = post-secondary or higher, 0 = secondary or lower). For this case, positive coefficients indicate more frequent ICT Usage or more positive ICT Attitude for students whose parents with higher educational degrees.

When analyzing PISA 2018 first, it usually showed that parents’ educational level was positively associated with students’ academic performance, which could imply that students whose parents have longer years of education tend to show better performances in the computer-based exams across all countries. This result makes sense in that parents who with longer years of education would be more interested in their children’s education as well, supporting and investing more time or effort in better education. In addition, students would have been affected by their parents’ educational backgrounds or everyday habits. However, the ICT Usage and ICT Attitude variables were affected by parents’ educational level in different ways for each country. For Finland and Sweden, students whose parents have more years of education used digital devices at home more often than others (see Table 4.11 and 4.19), while no significant associations were found in Denmark and Iceland (see Tables 4.9 and 4.15). Also, Swedish students whose parents have longer educational years tend to use digital devices more frequently at school (see Table 4.19), but this was not true for other countries. In terms of ICT Attitude, students whose parents finished longer educational years generally showed more positive attitudes when using digital devices, while non-significant results were found in several cases (e.g., Denmark – none of ICT Attitude variables, Finland – non-significant ICT Competence, Sweden – non-significant ICT Attitude).

The results from TIMSS 2019 showed similar patterns across three countries. For instance, students' performances in mathematics and science were greater for those whose parents with higher educational levels, which was comparable to the similar results from PISA 2018. Moreover, for ICT Attitude, students whose parents have higher levels of education showed lower degrees of positive attitudes when using digital devices. ICT Usage showed a similar result as ICT Attitude in Sweden (see Table 4.21), but it did not show significant differences in Finland and Norway (see Tables 4.13 and 4.17). Table 5.4 summarizes the overall effects of student-level variables on the variables of interest. The different patterns between PISA 2018 and TIMSS 2019 will be addressed with details in Chapter 5.1.3.

Table 5.4. Effect of Student-Level Control Variables

		PISA 2018						TIMSS 2019			
		H	S	C	I	A	AP	Use	Att	Math	Scie
Gender	DNK	–	–	–	×	–	+				
	FIN	–	–	–	+	–	+	+	+	×	+
	ISL	×	×	–	×	–	+				
	NOR							×	×	×	×
	SWE	–	–	–	×	–	×	×	×	×	×
Parent Ed Level	DNK	×	×	×	×	×	+				
	FIN	+	×	×	+	+	+	×	–	+	+
	ISL	×	×	+	+	+	+				
	NOR							×	–	+	+
	SWE	+	+	+	+	×	+	–	–	+	+

Note. Parent Ed Level = Parents' educational level; DNK = Denmark; FIN = Finland; ISL = Iceland; NOR = Norway; SWE = Sweden; + = Positive coefficients (Girls > Boys or Higher educational levels); – = Negative coefficients; × = Not significant.

5.1.2.2 School-Level Variables

One of the two school-level control variables, school-mean ESCS, was continuous in PISA 2018 and categorical in TIMSS 2019. In terms of PISA 2018, each student has their standardized numeric values of ESCS with a mean of 0 and standard deviation of 1, which approximately ranged from -8.17 to 4.21. The school-mean ESCS was computed by taking the group mean of each student's ESCS from each school. For TIMSS 2019, school-mean ESCS was categorized into three groups (i.e., affluent, moderate, and disadvantaged schools), where the group of moderate schools was set as a reference group.

When first focusing on the results from PISA 2018, the degree of ESCS showed a significant, positive association with ICT Usage variables across all countries at the school level, which could imply that students at higher ESCS schools tended to use digital devices more frequently. This result seems to make sense in that students at greater ESCS schools would have more opportunities to use digital devices as schools could prepare many resources for students more comfortably and afford the costs as well. Regarding its effect on ICT Attitude, at the schools with higher mean ESCS, students tend to report more competence, interest, and autonomous behaviors to use digital devices for various activities and purposes, but no significant effect was found in Finland. Moreover, the analysis found significant, positive associations between school-mean ESCS and academic performance across all countries. When looking at the results from TIMSS 2019, the analyses detected significant effects of school-mean ESCS on the variables of interest for a few cases in Sweden (see Table 4.21). ICT Attitude was significantly greater for the schools with moderate levels of affluence, and science performance was greater for affluent schools.

In addition, one more additional school-level variable was included to explore the potential differences among schools. The additional variables differed by countries in PISA 2018 (e.g., Denmark – schools with high vs. low minorities, Finland – urban vs. rural areas, Iceland – capital vs. non-capital areas, Sweden – private vs. public schools), and it only showed significant results for a few cases. In Denmark, it showed that schools with low minorities tend to show greater degrees of attitude toward using digital devices compared to those with high minorities (see Table 4.9). In Sweden, private schools tend to use digital devices more often than public schools (see Table 4.19). Such findings could infer that schools that are not economically or geographically disadvantaged could prepare more resources for their students, which could have impacted their usage and attitudes.

For TIMSS 2019, schools were categorized into two groups: schools located in rural and urban areas. Schools located in urban areas tend to show greater ICT Attitude than those in rural areas in Finland (see Table 4.13) and show greater math performances than those in rural areas in Sweden (see Table 4.21). Other than these, no significant differences in the variables of interest were found between the schools in urban and rural areas across all countries. The overall results tend to show different patterns between PISA 2018 and TIMSS 2019, which will be addressed in Chapter 5.1.3. Table 5.5 shows the summary of the overall effects of school-level variables on the variables of interest.

Table 5.5. Effect of School-Level Control Variables

		PISA 2018			TIMSS 2019			
		Use	Att	AP	Use	Att	Math	Scie
School Mean ESCS	DNK	+	×	+				
	FIN	+	+	+	×	×	×	×
	ISL	+	+	+				
	NOR				×	×	×	×
	SWE	+	+	+	×	Mod	×	Affl
School Add Vars	DNK	×	L Min	L Min				
	FIN	×	×	×	×	Urban	×	×
	ISL	×	×	×				
	NOR				×	×	×	×
	SWE	Private	×	×	×	×	Urban	×

Note. School Add Vars = Additional school-level variables; + = Positive coefficients (Higher ESCS); × = Not significant; L Min = Favored schools with low minorities; Private = Favored private schools; Mod = Favored schools with a moderate level of affluence; Affl = Favored affluent schools; Urban = Favored schools located in urban areas; School-level variables were excluded for the actual multilevel mediation analysis for TIMSS 2019 in Sweden.

5.1.3 Comparison of PISA 2018 and TIMSS 2019

The third research question explored whether PISA 2018 and TIMSS 2019 showed similar patterns of interrelationship among students' usage of digital devices, attitude toward using digital devices, and academic performance. Among the five Nordic countries, only Finland and Sweden provided the entire responses to the ICT-related questionnaires on both ILSAs. Hence, the review of comparing analyses focused on these two countries. Overall, three interesting findings were found, which are (1) the directions of total or direct effects between ICT Usage and academic performance, (2) the directions of mediation effects because of the associations between ICT Attitude and academic performance, and (3) the difference in the variables of interest by the student-level variables.

5.1.3.1 Directions of Total and Direct Effects

Reflecting Chapter 5.1.1.1, the first difference derived from the directions of total effects between ICT Usage and academic performance (see Table 5.1). For PISA 2018, the total effects of ICT Usage generally showed negative associations with students' academic performance, which implies that students' more frequent usage of digital devices either at home or at school showed lower academic performance. This finding could be attributed that students with low proficiency spent more time using digital devices for complementary studies, which was found in the previous study by Gómez-Fernández and Mediavilla (2021). In contrast, the analyses conducted on TIMSS 2019 showed that the total effects of ICT Usage generally showed positive associations with academic performance. Students who use digital devices more frequently showed better academic results. The direct effects also showed similar directions of the associations between ICT Usage and academic performance after controlling for the mediation effect of ICT Attitude (see Table 5.2).

Such differences could have been derived from how the survey questionnaires were addressed (see Appendix A). PISA 2018 collected information on ICT Usage by asking questions like "How often do you use digital devices for the following activities at home/school?" (OECD, 2017b). The question used the term "digital devices," which could include all general types of digital devices such as tablets, smartphones, or smartwatches. In contrast, TIMSS 2019 asked questions like "At school this year, how often did you use a computer or tablet to do each of the following?" (IEA, 2020a). They specified digital devices as "computers or tablets," which are actively used for education in class. Also, the activities in TIMSS 2019 were more specifically relevant to mathematics and science (e.g., school assignments, math/science schoolwork, quizzes, etc.), which would have affected positive associations between ICT Usage and academic performance.

5.1.3.2 Direction of Mediation Effects Due to ICT Attitude

Second, when reviewing Chapter 5.1.1.2, the mediation effect of ICT Attitude showed different patterns across two ILSAs (see Table 5.3). ICT Attitude variables, except ICT Competence, tend to significantly mediate the association between the usage of digital devices and academic performance for students in Nordic countries. However, when taking a closer look, the directions of the association between ICT Attitude and academic performance were opposite in the two ILSAs. Its relationship was positive in PISA 2018, while it was negative in TIMSS 2019. While the results from PISA 2018 were congruent with the previous studies (e.g., Gómez-Fernández & Mediavilla, 2021; Hu et al., 2018; Odell et al., 2020a; Park & Weng, 2020; Xiao et al., 2019), it was interesting to figure out the negative relationship in TIMSS 2019, which was different from the expected results in advance. There could be two potential reasons for such results.

The first reason is that the ICT Attitude questions in TIMSS 2019 seemed to reflect the aspect of ICT Competence in PISA 2018 (see Appendix B; IEA, 2020a). For example, questions such as "I am good at typing," "I can use a touchscreen on a computer, tablet, or smartphone," or "I can edit text on a computer" seem to represent how confident students are in using digital devices for certain activities (i.e., ICT Competence), which turned out to be negatively or not significantly associated with academic performance.

The second reason could be attributed to how the survey statements to measure ICT Attitude were addressed as in the previous section. It could be inferred that the survey statements in TIMSS 2019 would have made students disagree with the provided statements (IEA, 2020a). For example, one of the survey questions was "I can write sentences and paragraphs using a computer". Students had a possibility of interpreting this question differently in that they disagreed with this statement not because they were not familiar with "using a computer" but, instead because they were less confident in "writing sentences and paragraphs." Such aspects could have been confounded with the statement, which might have led students to disagree with such questions, eventually resulting in the negative association between ICT Attitude and academic performance. When exploring several examples from PISA 2018 such as "I like using digital devices" or "I use digital devices as I want to use them," they tend to reflect the single aspect of attitudes when using digital devices. This seemed to reflect students' ICT Attitude without confusion, leading to its positive association with academic performance. If the statements in TIMSS 2019 are modified to solely reflect the aspect of ICT Attitude such as "I feel confident in using a computer when writing sentences or paragraphs," the direction of the relationship could be different from those in this research.

5.1.3.3 Difference Impacted by Student-Level Variables

The third point pertains to the effect of student-level variables on the differences in the variables of interest. Although each country showed different patterns, the results generally found that there were significant differences in the variables of interest depending on gender and parents' educational level. For example, while both assessments showed that girls performed better than boys in Finland, the results of gender difference in ICT Usage and ICT Attitude variables were opposite; for PISA 2018, boys usually reported more frequent usage and more positive attitudes when using digital devices than girls (except ICT Interest), while the results were opposite for TIMSS 2019 (see Table 5.4). One of the potential reasons could be that girls who often use digital devices and have positive attitudes when using them participated more in TIMSS 2019 than PISA 2018 by accident. However, it is not possible to know whether the student samples who participated in both assessments are identical due to the confidentiality issue.

In regard to the effect of parents' educational level, the results showed that students whose parents have higher educational degrees tend to perform better than those whose parents with lower educational levels in both assessments. However, when focusing on ICT Attitude, the former students tended to report more positive attitudes when using digital devices than the latter in PISA 2018, whereas they tended to report lower positive attitudes in TIMSS 2019. There could exist various reasons, but one possibility is that students with low-educated parents might feel relatively higher degrees of interest or satisfaction when engaged in activities using digital devices as they might not have many opportunities to use them at ordinary times. It was still difficult to explore more potential reasons for such findings, so further research would be necessary for clearer answers.

5.2 Limitations

Although this research is expected to function as a starting point for exploring the influence of integrating digital devices into education for students' better academic learning and proficiencies, there still exist several limitations to consider for conducting better future research. The major issues can be summarized as (1) the limited meaning of ICT Usage for educational purposes, (2) the discordance of participating Nordic countries between the two international assessments, and (3) the issue of considerable numbers of missing data across the assessments.

5.2.1 Limited Meaning of ICT Usage

The first drawback is the limited meaning of ICT Usage, especially for PISA 2018. In this research, ICT Usage was defined in terms of educational purposes (e.g., using digital devices to do homework, using learning mobile applications, searching information online to prepare for presentations, etc.) to explore the educational effect of using digital devices. However, students would also use digital devices in their daily lives not only for educational purposes but also for other purposes such as entertainment (e.g., watching YouTube videos, playing online games, etc.) or social communication (e.g., chatting or texting with their friends, post photos or videos on Instagram, etc.). It was reported that students (both teenagers and children) tended to spend on average six to seven hours per day using digital devices for entertainment or social media (e.g., American Academy of Pediatrics, 2020; Rogers, 2019), and the usage increased a lot to keep themselves socially and emotionally connected and interact with others after the outbreak of COVID-19 pandemic (Pandya & Lohda, 2021). In light of such findings, such purposes of usage also need to be taken into account when referring to the usage of digital devices.

5.2.2 Discordance between PISA 2018 and TIMSS 2019

In addition, this research showed that not all Nordic countries participated in both assessments. PISA 2018 lacked the data for Norway since it did not provide answers to the ICT Questionnaire, while TIMSS 2019 Grade 8 lacked the data for Denmark and Iceland since neither did they participate in this assessment nor provided answers. Therefore, it was not possible to compare the estimated interrelationship patterns across all Nordic countries within PISA 2018 or TIMSS 2019. Similarly, the comparisons between PISA 2018 and TIMSS 2019 were only possible for two countries (i.e., Finland and Sweden) out of five; however, due to the confidentiality issue, it is unknown whether the samples of students and/or schools that participated in both assessments are identical. The discordance of interrelationship patterns could have been affected by the difference between samples.

There is also a difference in survey statements for defining students' various aspects regarding digital devices. Both assessments provided multiple sets of questions to explore how students use digital devices in their daily lives and what kinds of attitudes they have when using digital devices. However, the statements in TIMSS 2019 were fewer than those in PISA 2018. For example, TIMSS 2019 investigated students' usage of digital devices by asking how often they used computers or tablets only at school for doing homework or schoolwork activities, while PISA 2018 explored their usage both at school and at home for self-studying to follow up lessons and for using learning applications in addition to schoolwork and homework (IEA, 2020a; OECD, 2017b). Similarly, TIMSS 2019 explored students' attitudes toward using digital devices by focusing on students' self-efficacy when using digital devices, whereas the PISA 2018 explored this aspect with more details in terms of competence, interest, and autonomous behaviors. As a result, PISA 2018 allowed the study to explore ICT Usage and ICT Attitude variables with multiple sub-constructs (i.e., ICT Home and ICT School for ICT Usage; ICT Competency, ICT Interest, and ICT Autonomy for ICT Attitude), but the meaning of these latent variables was simple for exploring the interrelationship using TIMSS 2019.

5.2.3 Missing Data Issue

The third limitation is the missing data issue, which often happens when collecting data from human beings in educational or social science studies. When exploring PISA 2018, a considerable number of students' responses were missing. For example, about 25% of responses to survey questions were missing for Denmark, about 15% for Finland, about 23% for Iceland, and about 19% for Sweden. When exploring results in TIMSS 2019, the percentages of students' missing responses were smaller than those in PISA 2018 (e.g., 2% for Finland, 5% for Norway, and 4% for Sweden). However, a considerable number of demographic variables were missing in TIMSS 2019, especially for the parents' educational levels (see Table 4.4). Missingness also happened for school-level variables, where about 25% of school-mean ESCS and school location data were missing for Norway. This could have affected several non-significant results reported in Table 5.5.

5.3 Future Research

In light of such drawbacks, this study is expected to be ameliorated with different approaches to better explore how integrating digital devices into education could affect or improve students' academic performance. Directions for future research may include (1) exploring datasets collected after the COVID-19 pandemic, (2) using different approaches of analyses such as changing the direction of mediation or adding a moderation, and (3) including other variables relevant to students' daily lives at home and at school.

5.3.1 Datasets After COVID-19 Pandemic

First of all, it is important to keep in mind that both datasets used for this research (i.e., PISA 2018 and TIMSS 2019) were administered before the outbreak of the COVID-19 pandemic. The original idea that motivated this study was to explore whether students' usage of digital devices has affected their academic performance during online, remote class activities during the pandemic through using digital devices. Although the research idea would have been better implemented when analyzing the datasets collected after the pandemic, it was impossible to use them at the current point since most assessments were postponed than the original plan. For example, PISA 2021 was administered in 2022, and the results of PISA 2022 are going to be published in 2023 (OECD, 2023). Also, the next phase of TIMSS is scheduled to be conducted in 2023 (i.e., TIMSS 2023), where results are planned to be released in 2024 (IEA, 2023). The analyses of these two ILSAs would provide better insight for projecting policies regarding the integration of digital devices into education to assist students' better academic progress by exploring if using digital devices actually affected their academic performance.

5.3.2 Analysis with Different Approaches

This study included the ICT Attitude as a mediating variable in the relationship between ICT Usage and academic performance. The results tended to show that, generally, ICT Attitude (i.e., ICT Interest and ICT Autonomy for PISA 2018, ICT Attitude for TIMSS 2019) could function as a significant mediator between students' ICT Usage and their academic performance at the student level. However, the research can also be conducted with a different idea in that ICT Usage could function as a mediator between students' ICT Attitude and academic performance. Students who have more positive attitudes toward activities using digital devices (e.g., high interest when using digital devices, strong competency and/or willingness to solve problems with using digital devices, etc.) would use digital devices more often than those who do not, which may affect their performances administered under the computer-based tests. Such exploration is expected to contribute to managing the educational curricula including digital devices into the instructions during classes to improve their attitudes toward using such innovative tools.

Another possible way to extend this study is to apply a moderation analysis to the hypothesized relationship model based on various demographic variables. A moderation analysis, which is also called an interaction analysis, explores whether the direction or size of an association between two variables is affected by an additional variable called a moderator (Hayes, 2022). It would be interesting to see how the magnitude of associations would be different depending on different groups. For instance, in this study, gender and school-mean ESCS in PISA 2018 tended to show significant differences in the variables of interest, but the size or strength of the associations was not explored based on these variables. By adding such demographic variables as a moderating variable, future research could elaborate on whether the size of associations among the ICT variables and academic performance changes depending on different demographic groups.

5.3.3 Inclusion of Other Variables

This research could also be extended by including different variables relevant to students' daily academic lives to explore other factors that could influence their academic performance. For example, the definition of ICT Usage could be expanded not only for educational purposes but also for entertainment and social communication purposes since such statements were not included in this analysis. Besides, in addition to the ICT-related variables, PISA 2018 also included survey statements to explore how much well-being students feel during their daily lives both at home and at school. PISA 2018 defined student or adolescent well-being as “the quality of students’ lives and their standard of living” (OECD, 2019a, p. 262). Students’ well-being should also be considered as it also affects their academic achievements in terms of various dimensions. The study by Govorova et al. (2020) showed that students with stronger cognitive self-efficacy (i.e., cognitive well-being), less test anxiety (i.e., psychological well-being), more resources at home (i.e., material well-being), and more enjoyment of cooperation (i.e., social well-being) tended to show greater academic achievements. Especially, material well-being could be a source for exploring the relationship between students’ academic performance in that students who have more economic resources would have more chances of access to digital devices.

5.4 Conclusion

This dissertation aimed to explore the interrelationship among students’ digital device usage, attitude toward using digital devices, and academic performance by focusing on the mediation effect of ICT Attitude between ICT Usage and academic performance across the five Nordic countries, where digital devices were integrated into an educational curriculum as a part of the instructional method in class (Godhe, 2019; Kelly et al., 2020). The multilevel mediation analyses with demographic control variables in the context of MLSEM were used to reflect the hierarchical structure of international assessments, where students are clustered into schools, and any potential differences in the variables of interest that derive from demographic aspects. Moreover, the analyses of interrelationship were conducted on the two most recent international assessments administered right before the outbreak of COVID-19 as one single assessment did not cover all five countries.

While the actual patterns of interrelationship differed by each country with different demographic variables, the overall results showed that ICT Attitude could function as a significant mediator between students' ICT Usage and academic performance, mostly at the student level. In other words, students who use digital devices more frequently either at home or school tend to have more positive attitudes such as more interest or willingness to actively solve problems using digital devices, which could affect their academic performance from computer-based tests. In addition, students' responses to the questions regarding ICT Usage and ICT Attitude showed differences depending on their gender and parents' educational level. Also, the directions of associations between the ICT variables and academic performance were opposite in the two assessments, but it could be attributed to the discordance of survey statements between the two assessments.

Reflecting such findings, this dissertation could have educational significance for developing educational curricula or instruction plans for integrating digital devices into education. First, as the school-level effects were not that obvious, the new educational policy would need to focus more on the student level. Besides, when it comes to designing instruction plans using digital devices, it would be more important not to just simply offer more time and chances to use digital devices but to figure out how to improve students' intrinsic motivation and interest when they are engaged in activities using digital devices. By reinforcing their interest and autonomous behaviors with such activities, it could have a positive influence on their academic performance (Ayub, 2010; Khoshnam et al., 2013). Although additional studies regarding this topic are still necessary, the findings from this dissertation are expected to function as a starting source to manage and plan policies about students' usage of digital devices for better education in the digital era.

APPENDIX A

ITEMS SELECETD FOR STUDENTS' ICT USAGE

Table A.1. PISA 2018 Items for ICT Usage at Home

Item		Statements	Scales
IC010		How often do you use digital devices for the following activities <u>outside of school</u>?	
IC010Q01TA	HOME1	Browsing the Internet for schoolwork (e.g., for preparing an essay or presentation).	1 – 5
IC010Q02TA	HOME2	Browsing the Internet to follow up lessons, e.g., for finding explanations.	1 – 5
IC010Q09TA	HOME3	Doing homework on a computer.	1 – 5
IC010Q10TA	HOME4	Doing homework on a mobile device.	1 – 5
IC010Q11TA	HOME5	Using learning apps or learning websites on a computer.	1 – 5
IC010Q12TA	HOME6	Using learning apps or learning websites on a mobile device.	1 – 5

Note. Items scaled on a 5-point Likert-scale; 1 = Never or hardly ever; 2 = Once or twice a month; 3 = Once or twice a week; 4 = Almost every day; 5 = Every day; Scales are recoded for the analyses by subtracting 1 from each value to make sense of "Never or hardly ever" as 0 (OECD, 2017b).

Table A.2. PISA 2018 Items for ICT Usage at School

Item		Statements	Scales
IC011		How often do you use digital devices for the following activities at school?	
IC011Q03TA	SCHL1	Browsing the Internet for schoolwork.	1 – 5
IC011Q05TA	SCHL2	Posting my work on the school's website (e.g., <intranet>)	1 – 5
IC011Q07TA	SCHL3	Practicing and drilling, such as foreign language learning or mathematics.	1 – 5
IC011Q08TA	SCHL4	Doing homework on a school computer.	1 – 5
IC011Q10TA	SCHL5	Using learning apps or learning websites.	1 – 5

Note. Items scaled on a 5-point Likert-scale; 1 = Never or hardly ever; 2 = Once or twice a month; 3 = Once or twice a week; 4 = Almost every day; 5 = Every day; Scales are recoded for the analyses by subtracting 1 from each value to make sense of "Never or hardly ever" as 0 (OECD, 2017b).

Table A.3. TIMSS 2019 Items for ICT Usage

Item		Statements	Scales
2		At school this year, how often did you use a computer or tablet to do each of the following?	
2 – a)	USE1	Work on a school assignment such as a paper, report, or presentation.	1 – 4
2 – b)	USE2	Mathematics schoolwork.	1 – 4
2 – c)	USE3	Science schoolwork.	1 – 4
2 – d)	USE4	Take a test or quiz.	1 – 4

Note. Items scaled on a 4-point Likert-scale; 1 = Never or almost never; 2 = Once or twice a month; 3 = Once or twice a week; 4 = Every day or almost every day; Scales are recoded for the analyses by subtracting 1 from each value to make sense of "Never or almost never" as 0 (IEA, 2020a).

APPENDIX B

ITEMS SELECTED FOR STUDENTS' ICT ATTITUDE

Table B.1. PISA 2018 Items for ICT Competence

Item		Statements	Scales
IC014		Thinking about your experience with digital media and digital devices: to what extent do you disagree or agree with the following statements?	
IC014Q03NA	COMP1	I feel comfortable using digital devices that I am less familiar with.	1 – 4
IC014Q04NA	COMP2	If my friends and relatives want to buy new digital devices or applications, I can give them advice.	1 – 4
IC014Q06NA	COMP3	I feel comfortable using digital devices at home.	1 – 4
IC014Q08NA	COMP4	When I come across problems with digital devices, I think I can solve them.	1 – 4
IC014Q09NA	COMP5	If my friends and relatives have a problem with digital devices, I can help them.	1 – 4

Note. Items scaled on a 4-point Likert-scale; 1 = Strongly disagree; 2 = Disagree; 3 = Agree; 4 = Strongly agree (OECD, 2017b).

Table B.2. PISA 2018 Items for ICT Interest

Item		Statements	Scales
IC013		Thinking about your experience with digital media and digital devices: to what extent do you disagree or agree with the following statements?	
IC013Q01NA	INTE1	I forget about time when I'm using digital devices.	1 – 4
IC013Q04NA	INTE2	The Internet is a great source for obtaining information I am interested in (e.g., news, sports, dictionary)	1 – 4
IC013Q05NA	INTE3	It is very useful to have social networks on the Internet.	1 – 4
IC013Q11NA	INTE4	I am really excited discovering new digital devices or applications.	1 – 4
IC013Q12NA	INTE5	I really feel bad if no Internet connection is possible.	1 – 4
IC013Q13NA	INTE6	I like using digital devices.	

Note. Items scaled on a 4-point Likert-scale; 1 = Strongly disagree; 2 = Disagree; 3 = Agree; 4 = Strongly agree (OECD, 2017b).

Table B.3. PISA 2018 Items for ICT Autonomy

Item		Statements	Scales
IC015		Thinking about your experience with digital media and digital devices: to what extent do you disagree or agree with the following statements?	
IC015Q02NA	AUTO1	If I need new software, I install it by myself.	1 – 4
IC015Q03NA	AUTO2	I read information about digital devices to be independent.	1 – 4
IC015Q05NA	AUTO3	I use digital devices as I want to use them.	1 – 4
IC015Q07NA	AUTO4	If I have a problem with digital devices, I start to solve it on my own.	1 – 4
IC015Q09NA	AUTO5	If I need a new application, I choose it by myself.	1 – 4

Note. Items scaled on a 4-point Likert-scale; 1 = Strongly disagree; 2 = Disagree; 3 = Agree; 4 = Strongly agree (OECD, 2017b).

Table B.4. TIMSS 2019 Items for ICT Attitude

Item		Statements	Scales
3		How much do you agree with these statements?	
3 – a)	ATT1	I am good at using a computer.	1 – 4
3 – b)	ATT2	I am good at typing.	1 – 4
3 – c)	ATT3	I can use a touchscreen on a computer, tablet, or smartphone.	1 – 4
3 – d)	ATT4	It is easy for me to find information on the Internet.	1 – 4
3 – e)	ATT5	I can look up the meanings of words on the Internet.	1 – 4
3 – f)	ATT6	I can write sentences and paragraphs using a computer.	1 – 4
3 – g)	ATT7	I can edit text on a computer.	1 – 4

Note. Items scaled on a 4-point Likert-scale; 1 = Disagree a lot; 2 = Disagree a little; 3 = Agree a little; 4 = Agree a lot (IEA, 2020a).

APPENDIX C

PISA 2018 SCHOOL STRATUM VARIABLE BY COUNTRIES

Country	Variable	Code	Stratum	N
Denmark	1 = High	DNK0101	High Minority	103
	Minorities	DNK0202	Mid Minority	84
	0 = Low	DNK0303	Low Minority	113
	Minorities	DNK0404	No Minority	48
Finland	1 = Rural	FIN0002	Helsinki/Uusimaa	2
		FIN0004	Southern Finland	6
		FIN0006	Western Finland	8
		FIN0008	Northern & Eastern Finland	15
		FIN0010	Swedish Speaking Area	4
	0 = Urban	FIN0001	Helsinki/Uusimaa	51
		FIN0003	Southern Finland	34
		FIN0005	Western Finland	39
		FIN0007	Northern & Eastern Finland	36
		FIN0009	Swedish Speaking Area	11
Iceland	1 = Non-Capital	ISL0009-12	Suurnes	10
		ISL0013-16	Vesturland	11
		ISL0017-20	Vestfirir	10
		ISL0021-24	Norurland Vestra	8
		ISL0025-28	Norurland Eystra	18
		ISL0029-31	Austurland	14
		ISL0033-36	Suurland	16
	0 = Capital	ISL0001-4	Reykjavik	32
		ISL0005-8	Ngrenni Reykjavkur	23
Sweden	1 = Public	SWE0101	Lower Secondary/Metro	54
		SWE0103	Lower Secondary/Other	47
		SWE0104	Upper Secondary	9
		SWE0202	Lower Secondary/Large Cities	62
	0 = Private	SWE0205	Lower Secondary/Metro	22
		SWE0206	Lower Secondary/Large Cities	16
		SWE0207	Lower Secondary/Other	5
		SWE0208	Upper Secondary	7

Note. N = Frequency of schools (OECD, 2019c).

APPENDIX D

DIAGRAMS FOR MEASURING LATENT VARIABLES

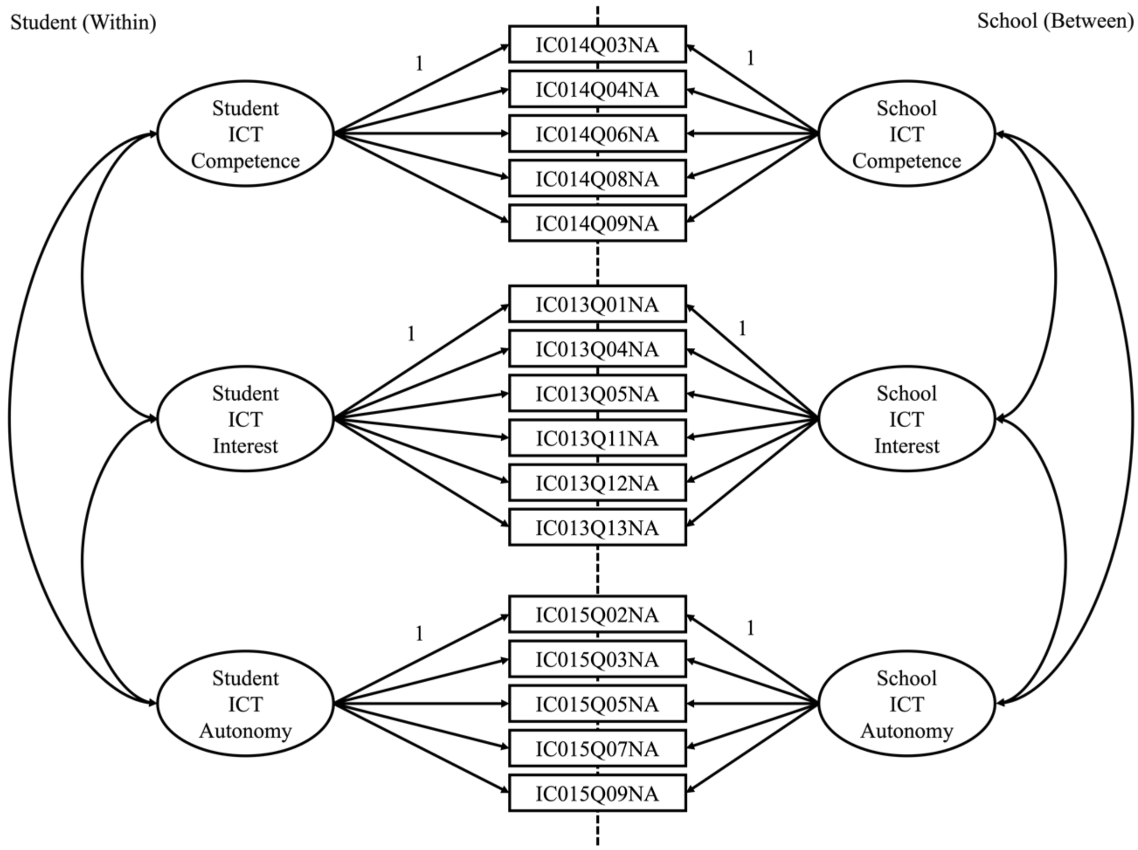


Figure D.1. Initial Measurement Model for ICT Attitude for PISA 2018

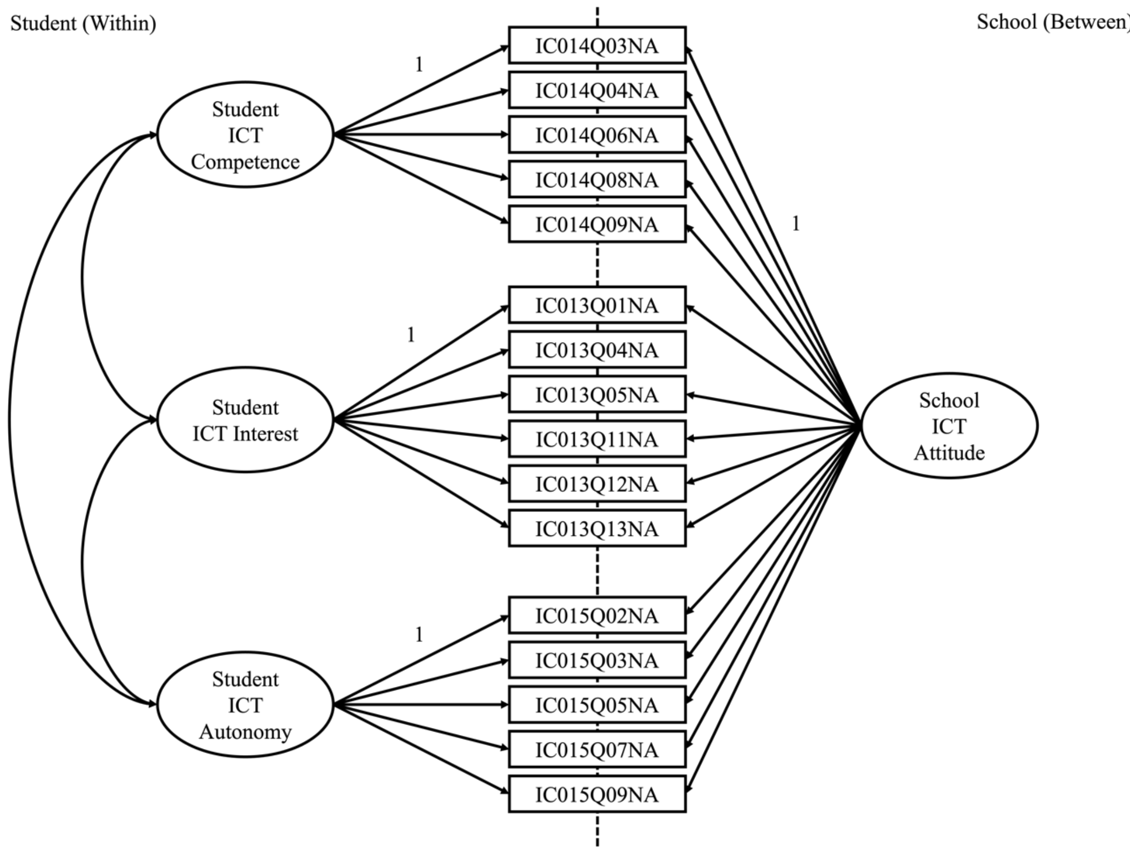


Figure D.2. Final Measurement Model for ICT Attitude for PISA 2018

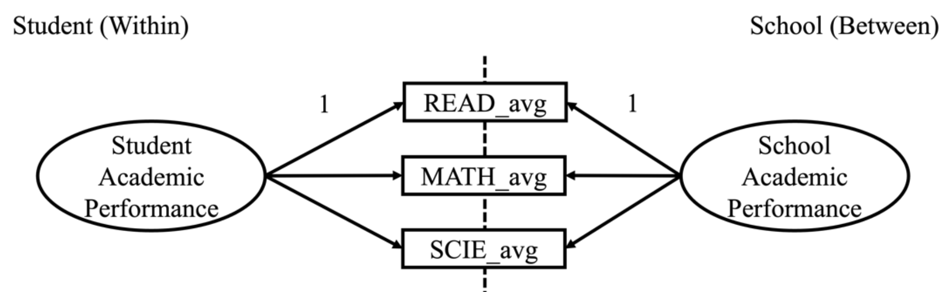


Figure D.3. Measurement Model for Academic Performance for PISA 2018

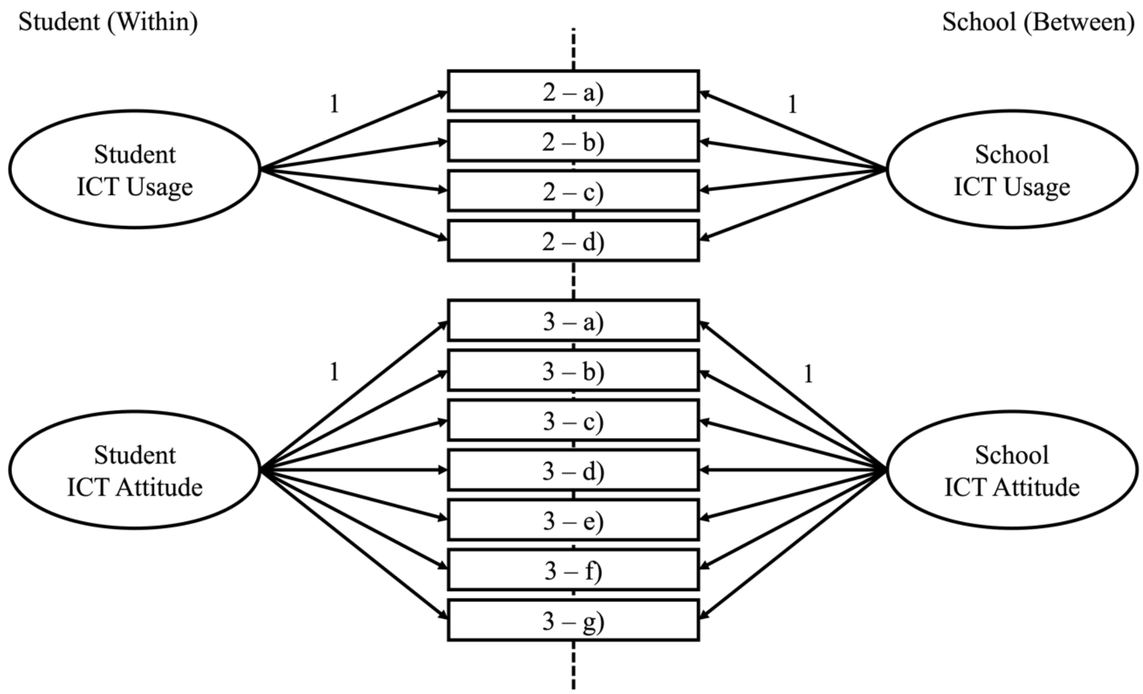


Figure D.4. Measurement Model for ICT Usage and ICT Attitude for TIMSS 2019

APPENDIX E

ESTIMATED FACTOR LOADINGS OF LATENT VARIABLES

Table E.1. Standardized Estimated Factor Loading Parameters: Denmark PISA 2018

		Student Level (Within; *W*)			School Level (Between; *B*)		
			95% Cr.I.			95% Cr.I.	
		Estimate	Lower	Upper	Estimate	Lower	Upper
HOME	1	0.652	0.627	0.677	0.993	0.992	0.994
	2	0.722	0.700	0.743	0.991	0.989	0.992
	3	0.492	0.465	0.517	0.995	0.994	0.996
	4	0.641	0.620	0.663	0.979	0.974	0.983
	5	0.699	0.679	0.717	0.987	0.984	0.989
	6	0.708	0.684	0.730	0.975	0.969	0.980
SCHL	1	0.521	0.497	0.545	0.996	0.995	0.996
	2	0.543	0.520	0.566	0.980	0.976	0.984
	3	0.676	0.655	0.695	0.991	0.989	0.993
	4	0.514	0.490	0.538	0.994	0.993	0.995
	5	0.628	0.606	0.648	0.988	0.985	0.990
COMP	1	0.548	0.526	0.568	0.966	0.957	0.973
	2	0.746	0.732	0.760	0.969	0.961	0.976
	3	0.608	0.589	0.627	0.975	0.967	0.980
	4	0.815	0.803	0.826	0.971	0.963	0.977
	5	0.809	0.797	0.821	0.970	0.962	0.977
INTE	1	0.369	0.343	0.394	0.959	0.948	0.968
	2	0.697	0.679	0.715	0.973	0.966	0.979
	3	0.735	0.718	0.751	0.972	0.964	0.978
	4	0.584	0.563	0.605	0.964	0.954	0.971
	5	0.405	0.380	0.430	0.962	0.951	0.970
	6	0.710	0.692	0.726	0.973	0.966	0.979
AUTO	1	0.756	0.742	0.769	0.967	0.958	0.974
	2	0.673	0.656	0.690	0.962	0.952	0.970
	3	0.719	0.703	0.734	0.972	0.964	0.978
	4	0.822	0.811	0.833	0.970	0.962	0.977
	5	0.684	0.668	0.701	0.973	0.965	0.978
AP	Reading	0.929	0.925	0.933	0.996	0.996	0.997
	Mathematics	0.921	0.917	0.925	0.996	0.995	0.996
	Science	0.968	0.965	0.971	0.996	0.996	0.997

Note. 95% Cr.I. = 95% Credible interval; HOME = ICT Home; SCHL = ICT School; COMP = ICT Competence; INTE = ICT Interest; AUTO = ICT Autonomy; AP = Academic performance.

Table E.2. Standardized Estimated Factor Loading Parameters: Finland PISA 2018

		Student Level (Within; *W*)			School Level (Between; *B*)		
			95% Cr.I.			95% Cr.I.	
		Estimate	Lower	Upper	Estimate	Lower	Upper
HOME	1	0.591	0.569	0.613	0.992	0.990	0.994
	2	0.661	0.643	0.678	0.986	0.982	0.989
	3	0.814	0.802	0.825	0.985	0.981	0.988
	4	0.826	0.815	0.836	0.979	0.973	0.984
	5	0.868	0.859	0.877	0.982	0.977	0.986
	6	0.854	0.844	0.863	0.981	0.975	0.985
SCHL	1	0.540	0.517	0.562	0.994	0.993	0.996
	2	0.753	0.738	0.767	0.976	0.969	0.981
	3	0.819	0.807	0.830	0.981	0.975	0.985
	4	0.816	0.804	0.828	0.971	0.962	0.977
	5	0.827	0.816	0.838	0.984	0.980	0.988
COMP	1	0.552	0.528	0.573	0.895	0.837	0.927
	2	0.778	0.764	0.791	0.926	0.883	0.950
	3	0.643	0.624	0.662	0.938	0.900	0.958
	4	0.848	0.837	0.859	0.928	0.886	0.951
	5	0.856	0.846	0.866	0.927	0.884	0.950
INTE	1	0.451	0,.426	0.476	0.905	0.851	0.934
	2	0.742	0.725	0.758	0.932	0.891	0.954
	3	0.791	0.776	0.805	0.930	0.889	0.952
	4	0.648	0.628	0.667	0.912	0.861	0.939
	5	0.450	0.423	0.475	0.899	0.842	0.930
	6	0.775	0.760	0.790	0.933	0.893	0.954
AUTO	1	0.756	0.741	0.770	0.937	0.899	0.957
	2	0.472	0.447	0.497	0.906	0.853	0.935
	3	0.762	0.747	0.776	0.936	0.897	0.956
	4	0.796	0.782	0.809	0.931	0.890	0.953
	5	0.839	0.827	0.850	0.938	0.900	0.958
AP	Reading	0.940	0.936	0.944	0.991	0.987	0.993
	Mathematics	0.913	0.908	0.918	0.988	0.984	0.991
	Science	0.981	0.979	0.984	0.991	0.987	0.993

Note. 95% Cr.I. = 95% Credible interval; HOME = ICT Home; SCHL = ICT School; COMP = ICT Competence; INTE = ICT Interest; AUTO = ICT Autonomy; AP = Academic performance.

Table E.3. Standardized Estimated Factor Loading Parameters: Iceland PISA 2018

		Student Level (Within; *W*)			School Level (Between; *B*)		
			95% Cr.I.			95% Cr.I.	
		Estimate	Lower	Upper	Estimate	Lower	Upper
HOME	1	0.700	0.676	0.722	0.997	0.995	0.998
	2	0.685	0.661	0.708	0.997	0.996	0.998
	3	0.734	0.713	0.754	0.996	0.995	0.997
	4	0.815	0.799	0.829	0.996	0.995	0.997
	5	0.880	0.868	0.891	0.994	0.992	0.996
	6	0.880	0.867	0.891	0.994	0.992	0.996
SCHL	1	0.528	0.496	0.559	0.998	0.997	0.999
	2	0.657	0.631	0.682	0.972	0.960	0.980
	3	0.705	0.681	0.728	0.995	0.993	0.997
	4	0.776	0.755	0.795	0.994	0.992	0.996
	5	0.824	0.806	0.841	0.994	0.992	0.996
COMP	1	0.510	0.479	0.540	0.922	0.842	0.960
	2	0.825	0.809	0.840	0.942	0.877	0.970
	3	0.760	0.739	0.778	0.948	0.889	0.974
	4	0.869	0.856	0.881	0.944	0.883	0.972
	5	0.879	0.867	0.891	0.943	0.881	0.971
INTE	1	0.512	0.481	0.543	0.932	0.861	0.965
	2	0.837	0.822	0.851	0.949	0.892	0.974
	3	0.855	0.840	0.868	0.946	0.886	0.973
	4	0.707	0.684	0.729	0.935	0.866	0.967
	5	0.422	0.386	0.456	0.913	0.827	0.955
	6	0.823	0.807	0.838	0.948	0.890	0.974
AUTO	1	0.778	0.760	0.795	0.942	0.879	0.971
	2	0.810	0.794	0.825	0.943	0.880	0.971
	3	0.877	0.866	0.888	0.948	0.890	0.974
	4	0.863	0.851	0.875	0.945	0.883	0.972
	5	0.894	0.884	0.904	0.947	0.888	0.973
AP	Reading	0.911	0.904	0.918	0.994	0.992	0.996
	Mathematics	0.919	0.913	0.925	0.994	0.991	0.995
	Science	0.993	0.990	0.996	0.994	0.991	0.995

Note. 95% Cr.I. = 95% Credible interval; HOME = ICT Home; SCHL = ICT School; COMP = ICT Competence; INTE = ICT Interest; AUTO = ICT Autonomy; AP = Academic performance.

Table E.4. Standardized Estimated Factor Loading Parameters: Sweden PISA 2018

		Student Level (Within; *W*)			School Level (Between; *B*)		
			95% Cr.I.			95% Cr.I.	
		Estimate	Lower	Upper	Estimate	Lower	Upper
HOME	1	0.677	0.656	0.698	0.996	0.996	0.997
	2	0.696	0.676	0.716	0.996	0.996	0.997
	3	0.669	0.649	0.688	0.996	0.995	0.997
	4	0.725	0.708	0.741	0.992	0.990	0.994
	5	0.838	0.825	0.850	0.992	0.990	0.993
	6	0.824	0.810	0.837	0.990	0.988	0.992
SCHL	1	0.337	0.307	0.366	0.998	0.998	0.999
	2	0.676	0.656	0.695	0.989	0.987	0.991
	3	0.745	0.727	0.761	0.994	0.993	0.996
	4	0.697	0.678	0.716	0.993	0.991	0.994
	5	0.798	0.783	0.813	0.993	0.991	0.994
COMP	1	0.665	0.646	0.684	0.980	0.973	0.984
	2	0.785	0.770	0.798	0.981	0.975	0.985
	3	0.615	0.593	0.636	0.985	0.980	0.988
	4	0.852	0.841	0.863	0.982	0.976	0.986
	5	0.844	0.832	0.855	0.981	0.975	0.985
INTE	1	0.391	0.364	0.418	0.972	0.963	0.978
	2	0.684	0.664	0.703	0.981	0.976	0.986
	3	0.772	0.756	0.788	0.982	0.976	0.986
	4	0.703	0.683	0.721	0.978	0.971	0.983
	5	0.585	0.562	0.608	0.981	0.975	0.985
	6	0.787	0.771	0.802	0.983	0.977	0.987
AUTO	1	0.841	0.830	0.851	0.980	0.974	0.985
	2	0.808	0.796	0.820	0.980	0.973	0.984
	3	0.722	0.706	0.738	0.983	0.978	0.987
	4	0.825	0.813	0.837	0.982	0.976	0.986
	5	0.848	0.837	0.858	0.981	0.975	0.985
AP	Reading	0.906	0.900	0.911	0.997	0.996	0.998
	Mathematics	0.939	0.934	0.943	0.996	0.996	0.997
	Science	0.979	0.976	0.981	0.997	0.996	0.997

Note. 95% Cr.I. = 95% Credible interval; HOME = ICT Home; SCHL = ICT School; COMP = ICT Competence; INTE = ICT Interest; AUTO = ICT Autonomy; AP = Academic performance.

Table E.5. Standardized Estimated Factor Loading Parameters: Finland TIMSS 2019

		Student Level (Within; *W*)			School Level (Between; *B*)		
			95% Cr.I.			95% Cr.I.	
		Estimate	Lower	Upper	Estimate	Lower	Upper
USE	1	0.210	0.159	0.255	0.991	0.989	0.993
	2	0.596	0.556	0.636	0.995	0.993	0.996
	3	0.498	0.455	0.539	0.994	0.992	0.995
	4	0.626	0.585	0.665	0.995	0.993	0.996
ATT	1	0.581	0.554	0.607	0.953	0.915	0.970
	2	0.574	0.547	0.600	0.950	0.910	0.968
	3	0.683	0.661	0.704	0.911	0.847	0.943
	4	0.771	0.752	0.788	0.929	0.875	0.955
	5	0.809	0.793	0.825	0.926	0.870	0.953
	6	0.731	0.711	0.750	0.926	0.872	0.953
	7	0.736	0.716	0.755	0.933	0.882	0.957

Note. 95% Cr.I. = 95% Credible interval; USE = ICT Usage; ATT = ICT Attitude.

Table E.6. Standardized Estimated Factor Loading Parameters: Norway TIMSS 2019

		Student Level (Within; *W*)			School Level (Between; *B*)		
			95% Cr.I.			95% Cr.I.	
		Estimate	Lower	Upper	Estimate	Lower	Upper
USE	1	0.331	0.287	0.374	0.986	0.981	0.990
	2	0.527	0.479	0.572	0.994	0.991	0.996
	3	0.863	0.806	0.933	0.993	0.990	0.995
	4	0.363	0.315	0.411	0.995	0.992	0.996
ATT	1	0.524	0.489	0.558	0.938	0.875	0.966
	2	0.548	0.515	0.581	0.926	0.852	0.958
	3	0.564	0.532	0.595	0.896	0.801	0.940
	4	0.724	0.699	0.747	0.911	0.828	0.949
	5	0.765	0.743	0.786	0.901	0.811	0.943
	6	0.728	0.704	0.751	0.889	0.791	0.936
	7	0.726	0.701	0.749	0.903	0.814	0.944

Note. 95% Cr.I. = 95% Credible interval; USE = ICT Usage; ATT = ICT Attitude.

Table E.7. Standardized Estimated Factor Loading Parameters: Sweden TIMSS 2019

		Student Level (Within; *W*)			School Level (Between; *B*)		
			95% Cr.I.			95% Cr.I.	
		Estimate	Lower	Upper	Estimate	Lower	Upper
USE	1	0.455	0.423	0.491	0.992	0.989	0.994
	2	0.234	0.203	0.266	0.998	0.997	0.998
	3	0.954	0.900	0.990	0.996	0.995	0.997
	4	0.264	0.229	0.298	0.998	0.997	0.998
ATT	1	0.578	0.554	0.601	0.963	0.946	0.974
	2	0.616	0.593	0.637	0.958	0.939	0.971
	3	0.577	0.554	0.600	0.946	0.922	0.962
	4	0.670	0.650	0.689	0.955	0.936	0.969
	5	0.734	0.716	0.751	0.946	0.923	0.962
	6	0.753	0.736	0.770	0.939	0.913	0.957
	7	0.710	0.691	0.728	0.950	0.928	0.965

Note. 95% Cr.I. = 95% Credible interval; USE = ICT Usage; ATT = ICT Attitude.

APPENDIX F

SAMPLE MPLUS CODE FOR MLSEM ANALYSIS: PISA 2018

```
TITLE: PISA 2018 MLSEM Finland;


DATA: FILE IS "pisa-2018-finland-final.csv";


VARIABLE: NAMES ARE

school
student
studSES
meanSES
stratum
gender
parentEd

home1-home6
schl1-schl5
inte1-inte6
comp1-comp5
auto1-auto5

math
read
scie;

USEVARIABLES ARE

school
meanSES
stratum
gender
parentEd

math
read
scie

home1-home6
schl1-schl5
inte1-inte6
```

```
comp1-comp5
auto1-auto5;

CLUSTER IS school;
MISSING ARE ALL (-999);

WITHIN ARE gender parentEd;
BETWEEN ARE meanSES stratum;


DEFINE:

math = math/100;
read = read/100;
scie = scie/100;

CENTER math read scie (GRANDMEAN);
CENTER parentEd (GROUPMEAN);


ANALYSIS:

TYPE IS TWOLEVEL;
ESTIMATOR = BAYES;
FBITERATION = 30000;
PROCESSOR = 2;
POINT = MEDIAN;


MODEL:

%WITHIN%

! CFA Part

homew BY home1-home6;
schlw BY schl1-schl5;
homew schlw;
homew WITH schlw;

compw BY comp1-comp5;
intew BY inte1-inte6;
autow BY auto1-auto5;
compw intew autow;
compw intew autow WITH compw intew autow;
```

```
apw BY read math scie;
apw;
read math scie;

! Control Variables

homew schlw compw intew autow apw ON gender parentEd;

! SEM Part

apw ON homew (hcw);
apw ON schlw (scw);

compw ON homew (ahcw);
compw ON schlw (ascw);
apw ON compw (bcaw);

intew ON homew (ahiw);
intew ON schlw (asiw);
apw ON intew (biaw);

autow ON homew (ahaw);
autow ON schlw (asaw);
apw ON autow (baaw);

%BETWEEN%

! CFA Part

useb BY home1-home6 schl1-schl5; [useb];
home1-home6@0; [home1-home6@0];
schl1-schl5@0; [schl1-schl5@0];

attb BY comp1-comp5 inte1-inte6 auto1-auto5; [attb];
inte1-inte6@0; [inte1-inte6@0];
comp1-comp5@0; [comp1-comp5@0];
auto1-auto5@0; [auto1-auto5@0];

apb BY read math scie; [apb];
read@0; [read@0];
math@0; [math@0];
scie@0; [scie@0];

! Control Variables

useb attb apb ON meanSES stratum;
```

```
! SEM Part

apb ON useb (ucb);
attb ON useb (aub);
apb ON attb (apab);

! Mediation

MODEL CONSTRAINT: new(

ind_hc_w ind_hi_w ind_ha_w
ind_sc_w ind_si_w ind_sa_w

ind_ac_b

);

ind_hc_w = ahcw*bcaw;
ind_hi_w = ahiw*biaw;
ind_ha_w = ahaw*baaw;

ind_sc_w = ascw*bcaw;
ind_si_w = asiw*biaw;
ind_sa_w = asaw*baaw;

ind_ac_b = aub*apab;


OUTPUT: STDYX;
```

APPENDIX G

SAMPLE MPLUS CODE FOR MLSEM ANALYSIS: TIMSS 2019

```
TITLE: TIMSS 2019 MLSEM Finland;


DATA: FILE IS "timss-2019-fin.csv";


VARIABLE: NAMES ARE

school
student
gender
parentEd

use1-use4
att1-att7

location
schSES
math
scie

schAff
schUna
schMod

mathb
scieb;

USEVARIABLES ARE

school
gender
parentEd

use1-use4
att1-att7

location
math
scie

schAff
```

```
schUna
mathb
scieb;

CLUSTER IS school;
MISSING ARE ALL (-999);

WITHIN ARE gender parentEd math scie;
BETWEEN ARE location schAff schUna mathb scieb;


DEFINE:

math = math/100;
scie = scie/100;
mathb = mathb/100;
scieb = scieb/100;

CENTER math scie (GROUPMEAN);


ANALYSIS:

TYPE IS TWOLEVEL;
ESTIMATOR = BAYES;
FBITERATION = 30000;
PROCESSOR = 2;
POINT = MEDIAN;


MODEL:

%WITHIN%

! CFA Part

usew BY use1-use4;
attw BY att1-att7;
usew attw;
use1-use4 att1-att7;

math WITH scie;

! SEM Part

attw ON usew (aw);
math ON attw (bmw);
```

```
math ON usew (cmw);
scie ON attw (bsw);
scie ON usew (csw);

! Control Variables

usew attw math scie ON gender parentEd;

%BETWEEN%

! CFA Part

useb BY use1-use4; [useb];
attb BY att1-att7; [attb];
use1-use4@0; [use1-use4@0];
att1-att7@0; [att1-att7@0];
mathb; [mathb];
scieb; [scieb];

! SEM Part

attb ON useb (ab);
mathb ON attb (bmb);
mathb ON useb (cmb);
scieb ON attb (bsb);
scieb ON useb (csb);

! Control Variables

useb attb mathb scieb ON location schAff schUna;

! Mediation

MODEL CONSTRAINT: new(

ind_m_w ind_m_b ind_s_w ind_s_b

);

ind_m_w = aw*bmw;
ind_s_w = aw*bsw;
ind_m_b = ab*bmb;
ind_s_b = ab*bsb;


OUTPUT: STDYX;
```

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