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Students' Self-Efficacy in General ICT Use as a Mediator Between Computer Experience, Learning ICT at School, ICT Use in Class, and Computer and Information Literacy

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Abstract

Self-efficacy is related to a specific domain and is a result of capabilities and beliefs of one's own performance in a specific domain given a specific task, depending on the levels of anxiety, motivation, feeling of success, and positive and negative rewards. Computer experience, the learning of information and communication technology tasks at school, and the use of general applications in class are known to be related to computer and information literacy. This study investigates the mediation effect of student computer self-efficacy in using general applications in these relationships using a structural equation model. The data used in this study stems from nine European educational systems participating in the International Computer and Information Literacy Study in 2018. The results show that in nearly all educational systems, the self-efficacy regarding the use of general applications has significant mediation effects in the relationship between computer and information literacy and each of the three information and communication technology variables in the model. The mediation effects are strongest for general applications in class and weakest for learning of information and communication technology tasks at school. The results are discussed against the educational systems' context with recommendations for improving student computer self-efficacy.

Keywords: computer and information literacy; computer self-efficacy; mediation; computer experience; ICT use at school; ICT learning at school; general use of ICT

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1. Introduction

Information and communication technology (ICT) has permeated all spheres of life, including education, where it has found its place in providing opportunities for instruction and learning, delivering content, assessment and evaluation, feedback, extending the learning environment, improving collaboration, and adjusting the pace of learning. However, the use of these technologies for learning purposes at school does not go without issues (Mirazchiyski & Černe, 2023). Usually, research focuses on the relationships between the possession/access, use of technology, and their academic and general outcomes (see Mirazchiyski & Černe, 2023 for an overview). If used at all, the psychological and emotional characteristics of students are usually added as auxiliary variables without receiving a more prominent focus. Students with high levels of computer anxiety are disadvantaged in terms of academic performance in technology-mediated education and feel threatened when it comes to adopting technology. Previous research has found that anxiety and the perceived ease of use (i.e., being free from effort) of technology are negatively correlated (Warden et al., 2022). In any activity, the perceived self-efficacy in a particular task is related to the emotional and psychological characteristics and can have an effect on the outcome. Individuals' emotional and psychological perceptions regarding their own capabilities to use computer devices are part of the so-called "computer self-efficacy"—one's own perceptions of his or her capabilities in specific computer skills and knowledge. Computer self-efficacy is seen as rooted in the general theory of self-efficacy that needs to be briefly outlined below to put computer self-efficacy into perspective.

Self-efficacy is defined as the capability to organize and execute courses of action to manage prospective situations. It is related to one's own anxiety and experience, requiring certain performance given specific competence needed (Hargittai & Shafer, 2006). Self-efficacy is related to one's behavior in specific settings and has an effect on how this behavior is exhibited (Compeau & Higgins, 1995; Nurhikman et al., 2021). Perceptions of one's own self-efficacy influence decisions about what behavior should be undertaken, how much effort to exert, persistence in attempting the behaviors, and the emotional responses (e.g., stress and anxiety) while performing the behavior, as well as affecting the perception of the actual attainment pertinent to the behavior (Compeau & Higgins, 1995). Thus, it is important to note that "skills can be easily overruled by self-doubts, so that even highly talented individuals make poor use of their capabilities under circumstances that undermine their beliefs in themselves" (Bandura, 1997, p. 37). On the other hand, if self-efficacy provides a sense of resilience, one can make individuals perform extraordinarily despite the overwhelming circumstances using their skills (Bandura, 1997).

So far, research has revealed strong relations between one's specific beliefs of one's self-efficacy and the actual performance. The self-efficacy belief systems are multidimensional, and the construct is measured in terms of particularized judgments of capability. These judgments may vary across different types of activities and depend on the demands a task poses within a domain of activity and within different situations with different circumstances. That is, self-efficacy depends on the context and is multifaceted, where self-efficacy can be high in one domain of activity but low in others (Bandura, 1997). This is why measures of self-efficacy must be tailored to specific domains of functioning, representing gradations of task demands within these same domains. Only then can the measures of self-efficacy have explanatory and predictive power. "This requires clear definition of the activity domain of interest and a good conceptual analysis of its different facets, the types of capabilities it calls upon, and the range of situations in which these capabilities might be applied" (Bandura, 1997, p. 42). These relations are stronger between the general judgments of one's own skills and achievement measures (Hatlevik et al., 2018). This is related to the general theory of self-efficacy as well, as it pertains to any other area (not just ICT). In this regard, Bandura (1997) notes that, for example, although opera stars may have general judgments about their overall performance, there is a lot of variation in these judgments across specific aspects of their own performance: vocal, emotive, and theatrical. Related to this, perceived self-efficacy in a given area is not related just to exercising control over one's own actions but is also concerned with self-regulation of thought processes, motivation, and affective and psychological states. That is, the perceived self-efficacy is not about the number of skills one possesses but about what one believes he or she can do with them under different circumstances. Thus, individuals with similar skills, or the same individual under different circumstances, may perform differently depending on the differences in their self-efficacy (Bandura, 1997).

Self-efficacy beliefs are also related to motivation and willingness to take a course of action on a specific task: "Unless people believe they can produce desired results and forestall detrimental ones by their actions, they have little incentive to act or to persevere in the face of difficulties" (Bandura, 2001, p. 10). As noted earlier, self-efficacy was found to affect thinking processes and motivation. It also affects one's feelings in a situation, which play a role in performance. Student anxiety and self-efficacy are important factors in educational settings (Nurhikman et al., 2021). Thus, often computer self-efficacy, or more precisely "computer-related self-efficacy", is viewed as related to one's anxiety towards technology (Hargittai & Shafer, 2006). Previous studies have found that higher self-efficacy learners tend to be more willing to learn, as they have more positive feelings towards the subject (Dang et al., 2016), and that self-efficacy is also related to satisfaction in computer-based activities (Carraher Wolverton et al., 2020). The consequence of possessing a certain degree of self-efficacy is that it influences the way people think—pessimistically or optimistically—about their course of action, and the approach can be self-hindering or self-enhancing (Bandura, 2001). Along these lines, mastery experience itself is a confidence gained from prior success when participating in a given activity. Those who have accomplished tasks using technology are more likely to exhibit higher self-efficacy and will further engage in e-learning activities (Mensah et al., 2024). That is, improving student ability itself can also improve student computer self-efficacy.

Probably the first strict and formal definition of computer self-efficacy is provided by Compeau and Higgins (1995), who simply see it as referring "to a judgment of one's capability to use a computer" (Compeau & Higgins, 1995, p. 192). Compeau and Higgins (1995), however, do not see it as referring to simple component sub-skills (e.g., formatting diskettes or entering formulae in spreadsheets), but as incorporating judgments on one's ability to apply these simple component sub-skills to broader tasks (e.g., in preparation of a written report or analysis of financial data) (Compeau & Higgins, 1995). Later, Moos and Azevedo (2009) define computer self-efficacy as the perception of one's own capabilities into specific computer skills and knowledge (Moos & Azevedo, 2009). More recently, Dang et al. (2016) provide a simple definition of computer self-efficacy as "one's self-efficacy specifically for computer and information technology" (Dang et al., 2016, p. 120). Lastly, Hatlevik et al. (2018) see it as a general judgment about one's computer competence compared to self-efficacy in a specific computer task. That is, "Task-specific ICT self-efficacy is defined as perceptions of one's ability to perform specific computer-related tasks, while perceptions of general computer competence are related to judgment of one's skills across multiple computer application domains" (Hatlevik et al., 2018, p. 108). Previous studies have concluded that self-efficacy with computer technologies has a significant role in learning in computer-based learning environments and that computer self-efficacy relates not only to the processes of learning but also to the outcomes (Hatlevik et al., 2018).

The research on the theoretical foundations of computer self-efficacy was very active at the end of the 20th and the beginning of the 21st century, starting with a seminal paper from Compeau and Higgins (1995). The literature on the topic was largely influenced by e.g., Bandura's (1977, 1997, 2001) general psychological theory of self-efficacy, followed by attempts to refine the self-efficacy concept (Moos & Azevedo, 2009). Some of the literature review papers at that time focused on the computer self-efficacy in specific settings or technologies (e.g., Hodges, 2008). Contemporary research on computer self-efficacy includes topics on e-learning anxiety (e.g., Azizi et al., 2022), determinants of student engagement, teaching styles, and computer self-efficacy (e.g., Alzahrani et al., 2023), intentions to use specific computer technologies depending on computer self-efficacy (e.g., Li et al., 2024), investigating the effect of demographic variables on computer or information self-efficacy (e.g., Atikuzzaman & Ahmed, 2023), and the relationship between self-efficacy and home learning environment (e.g., Bonanati & Buhl, 2022).

These modern topics have their merit in revealing important relationships that help improve student computer self-efficacy in order to maximize outcomes from computer use. Many of them use computer and information literacy (or similar) as outcome variables. These studies, however, do not take into account the role of self-efficacy in the relationship between variables related to computer use for educational purposes, on the one hand, and the outcomes in computer and information literacy, on the other. This study fills this gap by using a structural equation model (path analysis) aimed towards estimating the mediation effect of computer self-efficacy in this relationship.

The relationship between computer self-efficacy and performance (including computer-related tasks) has been outlined above. The remainder of this section provides an overview of the variables related to both computer self-efficacy and student performance in computer-related tasks, as identified in the literature. The rest of the text in this introduction is devoted to the description of the most important correlates of computer-related self-efficacy and performance, which motivate this study and serve as a base for selecting the variables from the ICILS 2018 database to construct the study's empirical model.

1.1. Self-Efficacy and Competence in Using Technology

Competence in using technology are defined in many different ways to label different abilities related to ICT with a focus on different aspects. As noted above, computer self-efficacy is not just about performing simple operations, such as formatting disks or entering formulae in spreadsheets, but also using information to complete a task and is related to both skills and knowledge (see, for example, Compeau & Higgins, 1995; Dang et al., 2016; Moos & Azevedo, 2009). Thus, this study uses the definition of computer and information literacy (CIL) from ICILS 2018: an individual's ability to use computers to investigate, create, and communicate in order to participate effectively at home, at school, in the workplace, and in the community (Fraillon et al., 2019a, p. 18). The definition is further complemented with four strands (conceptual cateagories), each consisting of different aspects (content categories) to specify precisely the content and expected behavior (for more information see Fraillon et al., 2019a). Some earlier studies have found a positive association between computer self-efficacy and the ability to complete ICT tasks. Hatlevik et al. (2018) also found that ICT self-efficacy explains the variation in CIL in all 14 educational systems in their study using data from ICILS 2013. The strength of the relationship itself, however, showed quite a large variation across all educational systems (Hatlevik et al., 2018). ICILS 2018 found a positive and strong correlation between ICT self-efficacy in using general applications and CIL in all participating educational systems (Fraillon et al., 2019b). Hatlevik et al. (2015) also found that ICT self-efficacy predicts student digital competence, but none of the predictors in their study (ICT self-efficacy, cultural capital, language integration, strategic information use, and previous academic achievements) can predict the outcome alone. That is, these predictors affect the digital competence in concert and together with other background and contextual variables, such as home environment and personal preferences. Hatlevik et al. (2015) also stress that self-efficacy is an important factor for developing digital competence and enables the use of ICT for learning. The findings from Rohatgi et al. (2016) clearly show that ICT self-efficacy and CIL are related. However, this relationship holds for the basic ICT skills (e.g., searching information on the internet or editing documents), where more confident students had a better performance on the CIL test. This finding is later explained by Fraillon et al. (2019b) who state that specialist applications self-efficacy is about advanced use (e.g., programming or database management) and not about the general use of computers for information gathering, communication, etc., which are required by the CIL test.

1.2. Self-Efficacy and Computer Experience

Experience in using computers is related to emotional responses and attitudes towards computers, but also anxiety and computer use and, ultimately, drives the computer-related behavior (Smith et al., 1999). The experience with computer technology is also related to

ICT self-efficacy (Hatlevik et al., 2018). In educational settings, the computer experience has been found to have a significant effect on the e-learning system self-efficacy (Kundu, 2020). Students with greater experience in online/remote learning also have greater self-efficacy in online education settings and more successful academic outcomes compared to those with less experience. Kundu (2020) finds that those having less experience with online learning have fewer chances of completing an online course, although some previous studies (see Jan, 2015) show no differences. This is in line with Bandura's (1977) notion of corrective experiences that reinforce the sense of efficacy, eliminating defensive behavior when one persists in subjectively threatening activities that are actually relatively safe. This can be explained by the dissatisfaction that motivates the corrective behavior as a result of the perceived negative discrepancies between one's own performance and the standards (Bandura, 1977):

> Both the anticipated satisfactions of desired accomplishments and the negative appraisals of insufficient performance thus provide incentives for action. Having accomplished a given level of performance, individuals often are no longer satisfied with it and make further self-reward contingent on higher attainments. (Bandura, 1977, p. 193)

However, the effect of the obstacles and negative experiences may not always be motivating, and low and high self-efficacy in online education may interact with environmental factors, predicting four different variables: success, depression, apathy, and maximizing efforts (Kundu, 2020). Those who consider the outcomes as personally determined and at the same time lack the necessary skills are likely to experience a low sense of efficacy and have a sense of futility about the activity (Bandura, 1977). Bandura (1977) defines a number of positive and negative patterns of outcomes depending on the interaction between efficacy beliefs and outcome expectations—from productive engagement and personal satisfaction to resignation, apathy, and self-devaluation.

Jan (2015) finds a positive and significant relationship between computer self-efficacy, on the one hand, and prior experience and satisfaction with online learning, on the other. Different studies find student computer self-efficacy to be significantly correlated with satisfaction in online learning and student learning readiness (Carraher Wolverton et al., 2020). Computer experience is also found to be significantly associated with computer self-efficacy not only for learners but also for instructors (Kundu, 2020).

However, it is not the quantity (i.e., duration) of the computer experience but its quality (i.e., presence of technical support, as well as mastery experience) that matters (Hatlevik et al., 2018). Computer experience can be objective (externally and directly observable human-technology interactions) and subjective (private psychological state, latent and not directly observable, on the events of direct or indirect engagement with computers) (Smith et al., 1999). The unidimensional quantitative measures of computer experience have been defined as the amount of computing experience in terms of time (e.g., hours or years). Multidimensional (and qualitative) measures of objective computer experience, on the other hand, are defined as the diversity of experience, sources of information, and the opportunity to use computers related to the amount of time (Smith et al., 1999). This paper uses a unidimensional and subjective measure of computer experience (i.e., the number of years students used computers), as it is the only available variable in ICILS 2018, given that the study is cross-sectional and, by design, does not have the premises to track students in order to permit collection of multidimensional and objective measures of computer experience.

1.3. Self-Efficacy and Learning ICT at School

The level of competence is related to the skills and, subsequently, outcomes. Previous studies have found that high-level computer skills and competence in ICT in secondary school are strongly related to interest and acquired computer knowledge. Interest in computer technology is, in turn, related to information literacy. There is also evidence that ICT competence is related to interest, and fostering interest in ICT is related to the development of self-efficacy with computer technologies (Aesaert & van Braak, 2014; Chen & Hu, 2020). Along these lines, mastering more simple ICT-related tasks at school improves student ICT attitudes and ICT self-efficacy, and the introduction of more complex and challenging ICT tasks shall be performed gradually through the course of schooling (Aesaert & van Braak, 2014). This is also supported in a study with college students by Karsten and Roth (1998), who found significant differences in pre- and post-course computer self-efficacy where the students took introductory training. They conclude that "perhaps introductory courses play an important, confidence-building part in confirming, as well as initially developing, the skills necessary for successful computer use in college courses" (Karsten & Roth, 1998, p. 21). Students with low competence in ICT should be given the opportunity to learn with a focus on ICT competence, but also on accurate ICT self-efficacy perceptions through easier and more appropriate tasks they can master. This way, students will perceive mastering these tasks as a successful experience and will increase their computer self-efficacy (Aesaert et al., 2017).

1.4. Self-Efficacy and General Use of Applications at School

The results from educational studies on the use of computers for learning in classrooms on various school subjects (mathematics, science, reading, and CIL) are discrepant. Earlier studies (see Hatlevik et al., 2018 for an overview) found no differences in outcomes from learning when using computers in the classrooms. Some even found a negative relationship between these two. Newer studies also found no significant association or negative association (Hatlevik et al., 2018). Although the findings on the relationship between learning outcomes in different subjects and the use of computers in classroom instruction are ambiguous, the use of computers at school is related to student computer self-efficacy. As noted in the introduction, self-efficacy is related to one's own anxiety and experience, requiring certain performance given specific competence needed (Hargittai & Shafer, 2006). Students with high computer anxiety are found to face a disadvantage when it comes to computer performance and can feel threatened by the adoption of technology. With the introduction of computer technologies in the classrooms, a concern is that anxious students will be at a disadvantage when interacting with technology on a task, and this will impair their computer self-efficacy. Also, the perceived usefulness of technology and its ease of use are predictors of both continuous use of e-learning and computer self-efficacy (Warden et al., 2022). Previous studies have found a negative association between the perception of ease of use and anxiety and that when classes are conducted online, the reactions include feelings of stress. The willingness to embrace technology, on the other hand, is related to higher computer self-efficacy levels when classes are conducted online. Being ready to embrace technology is also related to engagement in ICT tasks, as learners who have higher levels of "technology readiness" (the overall propensity for embracing and using ICT to reach goals at home, in life, and at work, characterized by higher levels of optimism and innovativeness and lower levels of discomfort and insecurity) will be more engaged in classes where technology is used (Warden et al., 2022). Similar findings on the relationship between computer self-efficacy and engagement have been made by several other studies (see Carraher Wolverton et al., 2020). Studies on computer self-efficacy in electronic learning contexts have found that ease of use of technology can be significantly influenced by self-efficacy (Dang et al., 2016). Also, student engagement in classes where ICT is used is affected by their ICT self-efficacy, as those with higher ICT self-efficacy also have more resilience and self-regulated learning (Kundu, 2020). In turn, students who are more positively engaged can complete more complex tasks and have higher achievement, while students with lower technology readiness are likely to opt out of online classes (Warden et al., 2022).

To summarize the findings from the literature review above, student computer self-efficacy has been found related to student competence in using technology. Further, computer experience, learning ICT tasks at school, and using applications are also related to competence in ICT, CIL in particular (see Fraillon et al., 2019b), but they are also related to computer self-efficacy. On the one hand, competence is predicted by self-efficacy, computer experience, learning ICT at school, and using ICT at school. On the other hand, experience, learning ICT at school, and using general applications at school are related to self-efficacy (also see Table 2 in the Results section). All of these findings suggest that self-efficacy has a mediating role in the relationship between computer experience, learning of ICT tasks at school, and use of general applications in class on the one hand and student CIL on the other. As mentioned above, so far, the research literature on computer self-efficacy does not provide any findings on its mediating role in any such relationships. This study fills this gap in research. The hypothesis of this paper is as follows: Student ICT self-efficacy regarding the use of general applications is a mediator between computer experience, learning of ICT tasks at school, and use of general applications in class on the one hand and student CIL on the other. The study uses data from the IEA's International Computer and Information Literacy Study (ICILS) 2018 from all participating European educational systems. This study is important, as it finds the strongest mediation of computer self-efficacy between CIL and its covariates and, thus, outlines possible avenues of how to strengthen an adequate self-efficacy in students, which, in turn, can improve their CIL.

2. Materials and Methods

2.1. Data

This study uses data from the ICILS 2018 (IEA & ACER, 2019). The data from nine participating European educational entities (national educational systems and benchmarking participants) are used: Denmark, Finland, France, Germany, North Rhine-Westphalia (Germany), Italy, Luxembourg, Portugal, and Moscow (Russian Federation). The term "educational system" is preferred throughout this paper, as not all participants represent a country. Moscow and North Rhine-Westphalia (Germany) are just sub-entities of the Russian and German educational systems, respectively. The Moscow sample represents only schools in the city of Moscow and not the entirety of Russia. Similarly, the sample from North Rhine-Westphalia represents only its own provincial educational system separately from entire Germany. These two educational systems are called "benchmarking participants", as their data is included in ICILS scaling but are not considered as countries. This study focuses on the European educational systems participating in ICILS 2018, as these have similar educational contexts, cultural contexts, and paths in the development in ICT and its adoption in education, and most of them are part of the European Union (EU). ICILS is a large-scale student assessment with complex sampling and assessment design (see the next sub-sections for an overview of the statistical complexities). The student target population of ICILS is "all students enrolled in the grade that represents eight years of schooling, counting from the first year of ISCED Level 1, providing the mean age at the time of testing is at least 13.5 years" (Tieck, 2020, p. 59). Table 1 provides information on the sample sizes and the corresponding estimates for the target student population sizes. The samples in ICILS are representative of the student target population in each educational system.

Table 1. Educational systems' sample sizes and their population estimates.

Educational Systems	Sample Sizes	Population Estimates	(SE)
Denmark	2404	65,707.66	(1797.23)
Finland	2546	58,251.99	(1408.72)
France	2940	801,969.13	(12,327.38)
Germany	3655	730,824.71	(11,322.06)
Italy	2810	541,124.23	(8390.39)
Luxembourg	5401	6215.55	(5.12)
Moscow (Russian Federation)	2852	90,583.64	(2594.13)
North Rhine-Westphalia (Germany)	1991	164,197.19	(3002.30)
Portugal	3221	99,087.44	(2146.74)

()—standard errors appear in parentheses.

ICILS uses a complex sampling design where students are not selected randomly in the population, but a complex two-stage stratified random sampling with probability proportional to the size (PPS) of the primary sampling units is used. In each educational system, a sample is drawn independently from all other educational systems using its own sampling frame consisting of records of its entire target population. In the first stage, the schools (primary sampling units) from a complete sampling frame within an educational system are sorted by their size. The schools are sampled through a sampling interval. In some educational systems different (implicit and/or explicit) stratification variables were used to ensure good representation of students from different groups and improve sampling precision. A minimum of 150 schools were sampled per educational system. At the second sampling stage, 20 students in the target population were sampled at random regardless of which class in the school they belong to. Three implicit stratification variables were used for the student selection in each school to ensure good representation of the within-school samples: gender, class allocation, and birth year prior to sampling. For more details on the sampling strategy and implementation, see Tieck (2020).

2.2. Measures

ICILS 2018 collects data on two self-efficacy constructs: (1) advanced self-efficacy (i.e., self-efficacy in using specialist applications); and (2) self-efficacy in using general applications. Self-efficacy in using general applications was chosen as a mediator in this study. The reason for this is that, as noted in the background section, Fraillon et al. (2019a) stated that the specialist use of applications self-efficacy is not related to CIL, and this is expected, as it "is made up of information literacy and communication skills that are not necessarily related to advanced computer skills such as programming or database management" and "the CIL construct itself does not emphasize high-level computer-based technical skills" (Fraillon et al., 2019a, p. 9). This study uses student variables from the ICILS 2018 database on computer experience in years (S_EXCOMP), learning ICT tasks at school (S_ICTLRN), the use of general applications in class (S_GENCLASS), and ICT self-efficacy regarding the use of general applications (S_GENEFF). S_EXCOMP was created as a simple index composed of questions on how long (from never or less than a year to seven or more years) students have used desktop or laptop computers, tablet devices or e-readers, and smartphones for purposes other than calling and texting. S_ICTLRN, S_GENCLASS, and S_GENEFF are complex scales created using Item Response Theory (IRT) modeling. The model applied to questionnaire data for these scales is the partial credit model.

S_ICTLRN is created using eight questions on learning different ICT tasks (e.g., searching for information, evaluating the trustworthiness of information, using ICT to collaborate with others, etc.) where students had to evaluate to what extent they have learned these tasks at their schools. The statements had four Likert-type response options: (1) "Not at all"; (2) "To a small extent"; (3) "To a moderate extent"; and (4) "To a large extent". S_GENCLASS was created using data from three items on how often students used different tools (word-processing software, presentation software, and computer-based information resources). The response options were as follows: (1) "Never"; (2) "In some lessons"; (3) "In most lessons"; and (4) "In every or almost every lesson". The S_GENEFF scale was created using data from eight questions related to student self-evaluation on how well they are able to perform different tasks using ICT (e.g., edit digital images, create multimedia presentations, install a program, etc.). The response options were as follows: (1) "I do not think I could do this"; (2) "I have never done this but I could work out how to do this"; and (3) "I know how to do this".

As the metric for the individual student scores from the IRT scaling for S_ICTLRN, S_GENCLASS, and S_GENEFF is N(0, 1), it is not convenient to work with in an analysis; it was altered to N(50, 10) by the ICILS 2018 study center. For more information and specific details on the questionnaire scales' scaling procedures, see Schulz and Friedman (2020).

All background scales in ICILS 2018 were tested for measurement invariance at the time they were created using Confirmatory Factor Analysis (CFA). The results for the scales used in this study show a high (scalar) level of measurement invariance across the educational systems (see Schulz & Friedman, 2020).

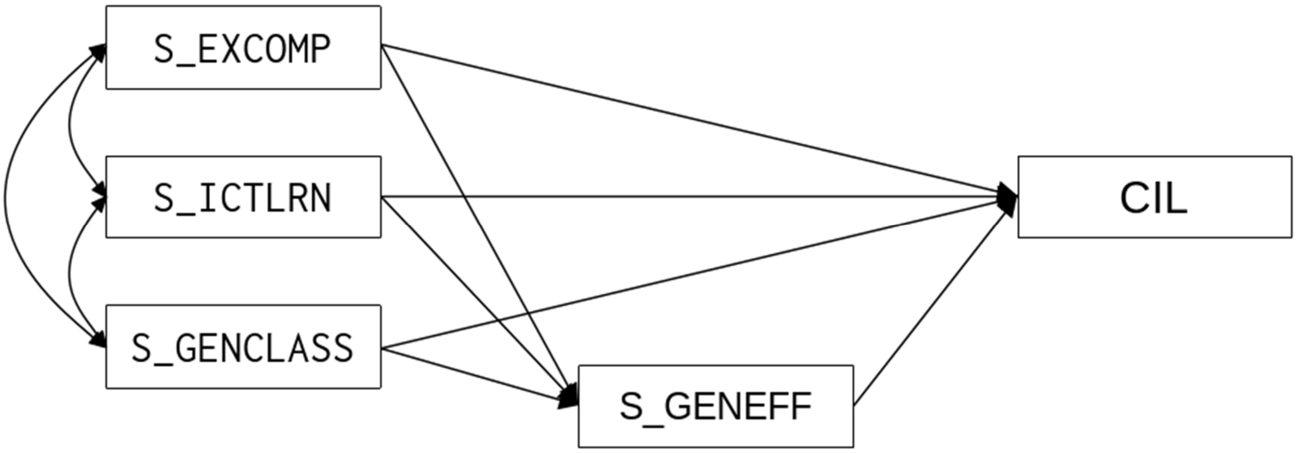
Besides the background scales used in this study, student scores on CIL were used as well. The student test consisted of five modules, each one being a set of ICT-related tasks. The total number of tasks across the five modules was 46. Each module has common tasks with other modules, ensuring a link between them. Due to the large number of tasks, each student received two of the five modules at random. As no student took all items and no item was taken by all students, but there was a link between the modules, the scaling approach was to use the so-called "plausible values" (PVs) methodology, which is suitable for such testing situations. The PV methodology uses information from the test items to estimate their item parameters (item calibration) through IRT and the information from the background questionnaires to impute the missing item responses and, together with the item parameters, to generate the student test scores. As a result of this imputation process, five final test score values (PVs) were generated for every student. For more details on the achievement test scaling methodology and the generation of the PV scores, see Ockwell et al. (2020). This has consequences, as the computations for any analysis need to consider that the PVs are imputed scores and apply the pertinent analytical methods (see the next section).

Given the theoretical background and the variables in the ICILS 2018 database, this study uses S_EXCOMP as a measure of student computer experience in years, S_ICTLRN as a measure of student learning of ICT at school, S_GENCLASS as a measure of student general use of applications in class, and S_GENEFF as a measure of student ICT self-efficacy. The five PVs of computer and information literacy (PV1CIL-PV5CIL) are used as an outcome measure.

2.3. Analysis

Given the review of literature and the working hypothesis (see the Introduction section), the analysis uses a path model where CIL (endogenous variable) is the outcome variable, "caused"[1] by the other endogenous and exogenous variables in the model. S_EXCOMP, S_ICTLRN, and S_GENCLASS are the exogenous variables in the model, the ones that presumably, or at least in theory, "cause" the outcome endogenous variable (CIL). Before the path model was constructed, the correlations between all exogenous variables and the endogenous ones (CIL and S_GENEFF) and the correlations between all exogenous variables themselves had been tested to ascertain that the assumptions of the model hold. The results were satisfying and encouraging. These are presented at the beginning of the Results section.

The path model is presented in Figure 1. The exogenous variables (S_EXCOMP, S_ICTLRN, and S_GENCLASS) are correlated with each other. All of them have assumed a "causal" relationship with CIL. S_GENEFF is an endogenous variable with a mediating role in this relationship between S_EXCOMP, S_ICTLRN, and S_GENCLASS on the one hand and CIL on the other: for each of the exogenous variables, the direct relationship with the endogenous (CIL) variable is estimated, and the indirect relationship through S_GENEF is estimated as well.



where
CIL—Computer and information literacy test scores
S_EXCOMP—Computer experience in years
S_ICTLRN—Learning of ICT tasks at school
S_GENCLASS—Use of general applications in class
S_GENEFF—ICT self-efficacy regarding the use of general applications

Figure 1. Path model diagram.

The complex sampling design of ICILS has consequences for the analysis, as the selection probability is not equal across all sampling units, as simple random or systematic random sampling would assume; the sample is stratified, so the sampling variance is estimated differently. In analyzing ICILS data, jackknife repeated replication (JRR) for estimating the sampling variance needs to be applied. In JRR the data is divided into sampling (i.e., jackknifing) zones where schools are paired in each sampling zone according to their size (number of students). In an analysis, one of the schools in the first zone receives a double of its weight, and the weight for the other will be set to zero. After computing the estimate, the weights in the first zone will be recovered, and the same procedure will be repeated with the schools in the second zone. The procedure is repeated as many times as the number of zones, and the estimates from all computations are aggregated. When PVs are involved, this procedure is repeated as many times as the number of PVs, then the results are aggregated. For more information on the sampling and imputation variance and the computation of the final standard errors in ICILS, please refer to Schulz (2020).

The path analysis of the data is performed in Mplus 8.10 (Muthén & Muthén, 2017). In line with the ICILS analysis complexities (see above) stemming from the complex sampling process (see sub-section Data), the data was analyzed accounting for the sampling variance estimation—full weighting and use of replicated weights (as per the JRR procedure) were used. As for the imputation variance from the PVs, five datasets were created with one PV in each one of them, and all of them were used to compute the estimates separately, then aggregating the individual estimates and computing their imputation variance. Mplus automatically estimates the sampling and imputation variance and produces the final standard error estimates, as described above. The total student weights were used as a weighting variable. All data preparation was performed using the RALSA (Mirazchiyski & INERI, 2025) R package version 1.5.5 (Mirazchiyski, 2021).

3. Results

As described in the background section above, previous studies found that computer experience, learning ICT at school, and the general use of ICT at school and for school purposes are related to computer self-efficacy. On the other hand, computer self-efficacy is related to skills and competencies in using ICT, as evident from the introduction and background sections. Before proceeding with the path analysis, it is necessary to test these theoretical assumptions and findings from previous studies empirically for the purpose of this paper. Thus, correlations between all of these variables and CIL were computed using data from all European educational systems participating in ICILS 2018 (IEA & ACER, 2019). Table 2 provides the correlation coefficients for the association between CIL and four scales from the ICILS 2018 international database: S_EXCOMP, S_ICTLRN, S_GENCLASS, and S_GENEFF (for the description of the CIL scores and the four scales, please refer to the Method section). As Table 2 shows, all variables are significantly related to CIL in almost all educational systems. The only exceptions are Germany, Luxembourg, North Rhine-Westphalia (Germany), and Portugal for S_ICTLRN, and Portugal for S_GENCLASS. The strongest association of CIL is with the S_GENEFF scale, where all coefficients are significant, ranging from 0.24 (Portugal) to 0.38 (Italy).

Table 2. Correlations between CIL and student computer experience, learning ICT tasks at school, use of general applications in class, and ICT general self-efficacy.

Educational Systems	S_EXCOMP and CIL	(SE)	*p*	S_ICTLRN and CIL	(SE)	*p*	S_GENCLASS and CIL	(SE)	*p*	S_GENEFF and CIL	(SE)	*p*
Denmark	0.19	(0.02)	<0.001	0.19	(0.03)	<0.001	0.18	(0.03)	<0.001	0.33	(0.03)	<0.001
Finland	0.22	(0.02)	<0.001	0.20	(0.02)	<0.001	0.26	(0.02)	<0.001	0.33	(0.02)	<0.001
France	0.11	(0.02)	<0.001	0.10	(0.03)	<0.001	0.12	(0.03)	<0.001	0.25	(0.02)	<0.001
Germany	0.12	(0.03)	<0.001	0.03	(0.04)	0.457	0.18	(0.03)	<0.001	0.26	(0.03)	<0.001
Italy	0.21	(0.02)	<0.001	0.15	(0.02)	<0.001	0.12	(0.03)	<0.001	0.38	(0.02)	<0.001
Luxembourg	0.10	(0.01)	<0.001	0.05	(0.02)	0.002	0.10	(0.02)	<0.001	0.28	(0.01)	<0.001
Moscow (Russian Federation)	0.14	(0.02)	<0.001	0.10	(0.02)	<0.001	0.09	(0.02)	<0.001	0.26	(0.03)	<0.001
North Rhine-Westphalia (Germany)	0.12	(0.03)	<0.001	0.03	(0.03)	0.282	0.22	(0.03)	<0.001	0.26	(0.03)	<0.001
Portugal	0.16	(0.02)	<0.001	−0.02	(0.02)	0.536	0.05	(0.03)	0.054	0.24	(0.03)	<0.001

()—standard errors appear in parentheses.

As this study explores the mediating role of the student's S_GENEFF in the association between S_EXCOMP, S_ICTLRN, and S_GENCLASS on the one hand and the student CIL on the other, it is necessary to test the correlations between S_GENEFF and the variables it moderates in their relationship with CIL. These correlations are presented in Table 3, showing that the S_GENEFF is significantly correlated with S_EXCOMP, S_ICTLRN, and S_GENCLASS. All of the correlation coefficients in all educational systems are positive and statistically significant. On average, the strongest correlations of S_GENEFF are with student computer experience in years.

Given the results from these initial tests in the tables above, this study aims to test the hypothesis that the S_GENEFF is a mediator between S_EXCOMP, S_ICTLRN, and S_GENCLASS on the one hand and student CIL on the other, using data from European educational systems participating in ICILS 2018.

Table 3. Correlations of student ICT self-efficacy with computer experience, learning of ICT tasks at school, and use of general applications in class.

Educational Systems	S_EXCOMP and S_GENEFF	(SE)	p	S_ICTLRN and S_GENEFF	(SE)	p	S_GENCLASS and S_GENEFF	(SE)	p
Denmark	0.16	(0.02)	<0.001	0.34	(0.02)	<0.001	0.18	(0.03)	<0.001
Finland	0.22	(0.03)	<0.001	0.17	(0.02)	<0.001	0.21	(0.02)	<0.001
France	0.13	(0.02)	<0.001	0.18	(0.03)	<0.001	0.11	(0.02)	<0.001
Germany	0.12	(0.02)	<0.001	0.14	(0.03)	<0.001	0.14	(0.03)	<0.001
Italy	0.22	(0.02)	<0.001	0.27	(0.02)	<0.001	0.13	(0.02)	<0.001
Luxembourg	0.13	(0.02)	<0.001	0.11	(0.02)	<0.001	0.08	(0.01)	<0.001
Moscow (Russian Federation)	0.13	(0.02)	<0.001	0.13	(0.03)	<0.001	0.09	(0.02)	<0.001
North Rhine-Westphalia (Germany)	0.16	(0.03)	<0.001	0.07	(0.03)	0.026	0.11	(0.02)	<0.001
Portugal	0.12	(0.03)	<0.001	0.14	(0.02)	<0.001	0.07	(0.03)	0.004

()—standard errors appear in parentheses.

The results from the path analyses in each educational system are presented as fully standardized (i.e., standardized on all x and y variables) in the model (STDYX in the Mplus OUTPUT command). Table A1 in Appendix A presents the path model statistics in all educational systems. When predicting CIL, the regression slopes from the exogenous variables (S_EXCOMP, S_ICTLRN, and S_GENCLASS) are statistically significant in nearly all educational systems in this study, as are the coefficients for S_GENEFF. The only exception is the S_ICTLRN, where the coefficient is insignificant in France, Germany, Italy, Luxembourg, and North Rhine-Westphalia (Germany) (i.e., no significant relationship). Further, the slope coefficients for CIL on S_GENCLASS are insignificant in Moscow (Russian Federation) and Portugal (i.e., CIL achievement and S_GENCLASS are unrelated in these entities). Where the regression coefficients are significant, they are all positive, i.e., the higher the values of the exogenous variables are, the higher the CIL achievement tends to be. The only exception is the S_ICTLRN scale in Portugal, where the coefficient is negative (the more students learn of ICT tasks at school, the lower they tend to perform) and significant, but very weak ($\beta = -0.054$, $p = 0.021$). The positive significant coefficients in the rest of the cases range from less than half a standard deviation ($\beta = 0.054$ for S_GENEFF on S_GENCLASS in Luxembourg) to more than three standard deviations ($\beta = 0.344$ for CIL on S_GENEFF in Italy).

On average, the strongest relationships between the outcome variable (CIL) and the exogenous variable were found in Denmark, and the weakest in Luxembourg. The second endogenous variable in this model (S_GENEFF) is significantly related to all three exogenous variables in the model (S_EXCOMP, S_ICTLRN, and S_GENCLASS). The only exceptions are S_ICTLRN in North Rhine-Westphalia (Germany) ($\beta = 0.050$, $p = 0.112$) and S_GENCLASS in Portugal ($\beta = 0.036$, $p = 0.175$). All coefficients in this relationship (S_GENEFF regressed on S_EXCOMP, S_ICTLRN, and S_GENCLASS) are positive (i.e., the higher the values of the exogenous variables, the higher the value of the endogenous variable, S_GENEFF, tends to be) in all educational systems. The correlations between all of the exogenous variables in the model (S_EXCOMP, S_ICTLRN, and S_GENCLASS) are statistically significant in almost all educational systems. The only exceptions are the correlation between S_EXCOMP and S_ICTLRN in Luxembourg ($\beta = 0.015$, $p = 0.391$), Moscow (Russian Federation) ($\beta = 0.002$, $p = 0.925$), North Rhine-Westphalia (Germany) ($\beta = 0.002$, $p = 0.947$), and Portugal ($\beta = -0.007$, $p = 0.749$), i.e., these variables are unrelated. The explained variances for the dependent variables (CIL and S_GENEFF) in the path model are presented in Table A2 in Appendix A. The amount of explained variance for CIL ranges from 8% (Portugal) to 19% (Finland). For the S_GENEFF, it ranges from as low as 3.5% (Luxembourg) to 14.5% (Denmark).

The results related to the hypothesis of this paper (S_GENEFF is a mediator between S_EXCOMP, S_ICTLRN, and use of S_GENCLASS, on the one hand and student CIL on the other) are presented in Table A3 in Appendix A. The table presents the total, direct, and specific indirect effects (e.g., S_GENCLASS to CIL via S_GENEFF).

The S_GENEFF has a mediating effect in the relationship between S_EXCOMP and CIL in all educational systems, as all indirect coefficients are statistically significant. The indirect effect of S_GENEFF in the relationship between the S_GENCLASS and CIL is statistically significant in all educational systems, except for Portugal ($\beta = 0.008$, $p = 0.167$). The indirect effect of S_GENEFF in the relationship between S_ICTLRN and CIL is statistically significant in all educational systems, except for North Rhine-Westphalia (Germany) ($\beta = 0.012$, $p = 0.124$). In general, the coefficients for indirect effects of S_GENEFF are strongest in the relationship between S_GENCLASS and CIL compared to the relationship between CIL and the other two exogenous variables—S_EXCOMP and S_ICTLRN.

As the results for all educational systems fit the proposed model, it was not necessary to remodel the path analysis depending on the relationships. The standardized root mean squared residual (SRMR) is equal to zero in all educational systems, which is in the acceptable range (see Asparouhov & Muthén, 2018).

4. Discussion

The results from this study provide support for the hypothesis—student ICT self-efficacy regarding the use of general applications (S_GENEFF) is a mediator between computer experience in years (S_EXCOMP), learning of ICT tasks at school (S_ICTLRN), and use of general applications in class on the one hand and student CIL on the other. The main findings from the path models across the educational systems in this study are as follows:

- In general, the mediation effects of S_GENEFF are stronger for the S_GENCLASS compared to the other two exogenous variables;
- The second strongest mediation effect of S_GENEFF is in the relationship between S_EXCOMP and CIL;
- The mediation effect of S_GENEFF is weakest for the relationship between S_ICTLRN and CIL.

In most of the nine educational systems in this study, the coefficients for these indirect effects are strong and significant. The mediation effects are weak and insignificant for two of the indirect effects in just three isolated educational systems. This is the case in Italy and Portugal for the relationship between CIL and the S_GENCLASS andin North Rhine-Westphalia (Germany) for the relationship between S_ICTLRN and CIL.

For the case in Portugal, the reason is the weak association between the S_GENCLASS and CIL. For Italy, there is the generally low spread of CIL achievement across the proficiency levels in the population. In fact, in Italy 63% of the students perform at or below the lowest proficiency level (492 or less score points) (see Fraillon et al., 2019b). That is, the spread of achievement is rather low, and most of the students are at the lower end of the distribution with low variation. For North Rhine-Westphalia (Germany), it is the low association between S_ICTLRN and CIL (see Table 2 for the correlation coefficients and the total and direct effects in Table A3 in Appendix A). That is, these two variables (respectively) are unrelated to CIL in these educational systems, and, thus, there are no mediation effects.

The reason for the lack of association between CIL and the S_GENCLASS in Portugal could be the implemented policies. Portugal has an explicit ICT curriculum that includes digital literacy, organizing competence in four domains, and the subject is mandatory in grades 5 to 9. This curriculum, as part of the general plan for “Student profile at the end of compulsory education" came into power in 2017, a year before ICILS 2018 took place (Fraillon et al., 2019b). Additional details are provided by the National Context Questionnaire (NCQ) from the ICILS 2018 international database (IEA & ACER, 2019): CIL is taught as a compulsory subject in grades 7 and 8 by teachers specialized in CIL education. The curricular goals became mandatory in the school year 2014/2015, with Security, Information, and Production content domains taught in both grades 7 and 8, and Communication and Collaboration in grade 8 only. Most of the CIL aspects were marked as explicitly stated in the national curriculum by the Portuguese national research coordinator (Fraillon et al., 2019b; IEA & ACER, 2019). That is, the weak and insignificant association between CIL and S_GENCLASS could likely be attributed to the low variation in the latter variable, as the subject is mandatory, taught to all students, and its curriculum explicitly covers most of the CIL domains. This could also explain why (as an unpublished analysis found) the variation in CIL is found to be the lowest in Portugal of all educational systems in this study.

Similarly to Portugal, Italy also implemented national policies concerning ICT in education through their National Plan of Digital School (NPDS) introduced in 2015, although the policies differ from the ones in Portugal. Digital competencies are considered transversal skills and accompaniments to different disciplines and subjects. Digital competencies are viewed not just as technical skills, but also as decision-making and problem-solving skills (IEA & ACER, 2019). The plans and policies explicitly state the development of ICT competence in students, the development and provision of digital learning materials, and the reduction of the digital divide among students. Concerning the target population of ICILS, CIL education is integrated into science and technology studies and other subjects as a non-compulsory subject. Searching for information using ICT, evaluating the reliability of information sources, presenting information for a given audience or purpose using ICT, organizing information obtained from Internet sources, and using productivity tools are explicitly stated in the curriculum (IEA & ACER, 2019). However, these aspects are emphasized just for some pathways of upper-secondary schools (e.g., some technical vocational schools or schools with a focus on applied sciences), and it is unclear if they had any influence on the outcomes from education in ICT and ICT use. Also, while the guidelines for ICT curricula implementation issued by the ministry of education are universal, each school can interpret them to create their own curricula (IEA & ACER, 2019). That is, there are quite a lot of ways these policies are implemented. Lastly, the policies were quite new when the ICILS 2018 testing took place, and their effect on the tested students may not yet have been so visible.

As for the low correlation between S_ICTLRN and CIL in North Rhine-Westphalia (Germany), no relevant contextual information could be found to provide a possible explanation for this finding. This benchmarking participant developed the "Media Competence Framework NRW" in 2017 but implemented it in June of 2018 (i.e., after the ICILS 2018 data collection and has been reworked since then); ICT does not stand as a separate subject but just an elective subject in some school tracks, and the curriculum does not place any emphasis on any of the CIL domains (Fraillon et al., 2019b; IEA & ACER, 2019). The above are just possible explanations for these diverging findings based on the data in the international database and the NCQ. As this information cannot provide definitive answers, more comprehensive and in-depth analyses on educational systems' level need to be conducted by experts in these educational systems to understand these findings and identify the additional context factors that explain these differences.

Despite these three deviations from the general pattern across the European educational systems participating in ICILS 2018, the results from this study show support for the hypothesis that student self-efficacy regarding the use of general applications is a mediating factor between computer experience in years, the learning of ICT tasks at school, and the use of general applications in class on the one hand and CIL on the other hand.

5. Conclusions

Based on the results from this study, the conclusions and policy recommendations regarding the ICT self-efficacy are as follows:

1. The strongest mediation effect of S_GENEFF is in the relationship between S_GENCLASS and CIL. Thus, the emphasis of future policies in ICT in education could be more on the use of general applications in class for educational purposes, as this would likely improve student computer self-efficacy. One avenue for achieving this is outlined by Aesaert and van Braak (2014). Teachers could assist students in understanding their negative feelings towards ICT activities and that their own negative feelings may not reflect the actual performance. In addition, mastering simple ICT tasks can lead to more positive feelings; students would receive increasingly more challenging tasks to improve their motivation and attitudes, hence, their self-efficacy. This has to be a gradual process where, with an increase in student confidence, the complexity of the tasks shall be increased as well (Aesaert & van Braak, 2014). This is in line with Bandura's (1977) notion of corrective experiences (see sub-section Self-efficacy and computer experience in the Introduction section). The final objective of this process, however, shall be matching of their own competence and their self-efficacy, which can be accurate or inaccurate (Aesaert et al., 2017; Aesaert & van Braak, 2014).
2. The second strongest mediation effect of S_GENEFF is in the relationship between S_EXCOMP and CIL. As noted earlier, it may not be so much the duration of the experience but its quality (Hatlevik et al., 2018). The ICILS 2018 measure used in this study is the computer experience in years of using desktop or laptop computers (Schulz & Friedman, 2020). The time of exposure to and engagement with computer devices out of school is important for gaining experience as a computer user, both for CIL and computational thinking (Fraillon et al., 2019b). Computer experience and frequency of use at home are positively associated with CIL in about half of the ICILS 2013 participating educational systems (Fraillon et al., 2019a). The pressing question is how systematic and focused these out-of-school experiences are to be deemed as providing a quality experience to promote the development of CIL, compared to the experience in school settings.
   Quality of computer use may be related to technical support and mastery experiences with ICT. Social persuasion (e.g., verbal persuasion or encouragement from teachers, parents, or peers) has also proved an effective means to boost self-efficacy. However, it is important to ensure that the envisioned success expressed through positive feedback or verbal encouragement is attainable. (Hatlevik et al., 2018).
3. The mediation effect of self-efficacy regarding the use of general applications is weakest for the relationship between S_ICTLRN and CIL. This does not necessarily mean that self-efficacy is an unimportant factor in this relationship. It is likely to be part of the relationship where S_GENEFF has the strongest mediation effect—CIL and S_ICTLRN. As noted previously, mastering more simple ICT tasks (such as general use of applications in ICILS 2018) improves self-efficacy, which allows for introducing more complex and challenging ICT tasks (Aesaert & van Braak, 2014). Such are the tasks included in the S_ICTLRN scale in ICILS 2018—reference internet sources, present information for a given audience, etc. That is, although the mediation effect of S_GENEFF tends to be weaker for S_ICTLRN compared to S_GENEFF, the latter two may be related. This can be a question for future research.

6. Limitations

This study does not come without limitations. First, as ICILS is a cross-sectional study, any statistical analyses do not allow for making causal inferences. Although path analysis (like any other structural equation modeling technique) makes only theoretical assumptions on "causal" chains (i.e., directions of the relationships), the method does not establish causality. Thus, the findings in this paper can be interpreted only as relationships in terms of associations, but not as one variable causing a change in another. That is, all analysis findings and their interpretations are presented and discussed only in terms of correlation and not in terms of causation, as per Kline (2016). It is, however, important that all samples are representative of the populations in the educational systems.

The second limitation comes from the subjectivity of some of the measures. CIL is measured by a large number of achievement items that measure student knowledge and ability. However, the S_EXCOMP, S_ICTLRN, and S_GENCLASS are self-reported measures of behaviors that cannot be measured directly due to practical limitations of ICILS. The variables behind these measures reflect student perceptions of the extent or frequency, rather than actual observed frequencies.

The third limitation comes from the unidimensional, subjective measure of student computer experience in years, rather than the objective, actual, and qualitative measure of computer experience (i.e., externally and directly observable human-technology interactions, diversity of experience, sources of information and opportunity to use computers, etc.). Being a cross-sectional study, and not a longitudinal one, ICILS does not have the premises to collect such information about the students.

Lastly, the model in this paper does not include all possible outcome variables and covariates. The model includes only ICT-related educational variables and student experience with computers to test very specific relationships. Other variables could also exert multifactorial influences on these results.

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Institutional Review Board Statement: This study did not need a review board statement, as it was part of publicly available international large-scale student assessment data.

Informed Consent Statement: Informed consent was obtained from the subjects involved in the study based on national regulations for this kind of research.

Data Availability Statement: The international database from ICILS 2018 is available from the IEA's Data Repository (https://www.iea.nl/data-tools/repository/icils, accessed on 1 May 2025).

Conflicts of Interest: The author declares no conflicts of interest.

Abbreviations

The following abbreviations are used in this manuscript:

CFA	Confirmatory Factor Analysis
CIL	Computer and Information Literacy
ICILS	International Computer and Information Literacy Study
ICT	Information and Communication Technology
IRT	Item Response Theory
ISCED	International Standard Classification of Education
NCQ	National Research Questionnaire
NPDS	National Plan of Digital School
PPS	Probability Proportional to the Size

PVs	Plausible Values
S_EXCOMP	Student computer experience in years scale
S_GENCLASS	Student use of general applications in class
S_GENEFF	Student ICT self-efficacy regarding the use of general applications
S_ICTLRN	Student learning ICT tasks at school
STDYX	Standardization on x and y variables in the model

Appendix A

Table A1. Standardized path model statistics.

Educational Systems	Endogenous Variables	Exogenous Variables	Estimate	(SE)	*p*
Denmark	S_GENEFF | ON	S_EXCOMP	0.119	(0.021)	<0.001
		S_ICTLRN	0.310	(0.026)	<0.001
		S_GENCLASS	0.096	(0.027)	<0.001
	CIL | ON	S_GENEFF	0.281	(0.033)	<0.001
		S_EXCOMP	0.123	(0.021)	<0.001
		S_ICTLRN	0.063	(0.027)	0.019
		S_GENCLASS	0.103	(0.025)	<0.001
	S_EXCOMP | WITH	S_ICTLRN	0.106	(0.021)	<0.001
		S_GENCLASS	0.127	(0.025)	<0.001
	S_ICTLRN | WITH	S_GENCLASS	0.250	(0.024)	<0.001
Finland	S_GENEFF | ON	S_EXCOMP	0.194	(0.024)	<0.001
		S_ICTLRN	0.132	(0.022)	<0.001
		S_GENCLASS	0.167	(0.026)	<0.001
	CIL | ON	S_GENEFF	0.251	(0.027)	<0.001
		S_EXCOMP	0.143	(0.020)	<0.001
		S_ICTLRN	0.108	(0.023)	<0.001
		S_GENCLASS	0.176	(0.025)	<0.001
	S_EXCOMP | WITH	S_ICTLRN	0.060	(0.024)	0.013
		S_GENCLASS	0.124	(0.020)	<0.001
	S_ICTLRN | WITH	S_GENCLASS	0.245	(0.029)	<0.001
France	S_GENEFF | ON	S_EXCOMP	0.120	(0.022)	<0.001
		S_ICTLRN	0.169	(0.028)	<0.001
		S_GENCLASS	0.069	(0.023)	0.002
	CIL | ON	S_GENEFF	0.235	(0.027)	<0.001
		S_EXCOMP	0.074	(0.019)	<0.001
		S_ICTLRN	0.036	(0.025)	0.159
		S_GENCLASS	0.080	(0.027)	0.003
	S_EXCOMP | WITH	S_ICTLRN	0.058	(0.020)	0.004
		S_GENCLASS	0.078	(0.020)	<0.001
	S_ICTLRN | WITH	S_GENCLASS	0.236	(0.024)	<0.001

Table A1. *Cont.*

Educational Systems	Endogenous Variables	Exogenous Variables	Estimate	(SE)	*p*
Germany	S_GENEFF∣ON	S_EXCOMP	0.106	(0.021)	<0.001
		S_ICTLRN	0.104	(0.034)	0.002
		S_GENCLASS	0.099	(0.026)	<0.001
	CIL∣ON	S_GENEFF	0.246	(0.033)	<0.001
		S_EXCOMP	0.081	(0.029)	0.005
		S_ICTLRN	−0.050	(0.033)	0.136
		S_GENCLASS	0.152	(0.028)	<0.001
	S_EXCOMP∣WITH	S_ICTLRN	0.049	(0.024)	0.037
		S_GENCLASS	0.105	(0.026)	<0.001
	S_ICTLRN∣WITH	S_GENCLASS	0.276	(0.020)	<0.001
Italy	S_GENEFF∣ON	S_EXCOMP	0.203	(0.019)	<0.001
		S_ICTLRN	0.245	(0.019)	<0.001
		S_GENCLASS	0.045	(0.024)	0.054
	CIL∣ON	S_GENEFF	0.344	(0.019)	<0.001
		S_EXCOMP	0.124	(0.017)	<0.001
		S_ICTLRN	0.042	(0.023)	0.064
		S_GENCLASS	0.051	(0.023)	0.029
	S_EXCOMP∣WITH	S_ICTLRN	0.065	(0.019)	0.001
		S_GENCLASS	0.103	(0.020)	<0.001
	S_ICTLRN∣WITH	S_GENCLASS	0.265	(0.023)	<0.001
Luxembourg	S_GENEFF∣ON	S_EXCOMP	0.127	(0.016)	<0.001
		S_ICTLRN	0.107	(0.018)	<0.001
		S_GENCLASS	0.054	(0.013)	<0.001
	CIL∣ON	S_GENEFF	0.271	(0.013)	<0.001
		S_EXCOMP	0.061	(0.015)	<0.001
		S_ICTLRN	−0.002	(0.015)	0.889
		S_GENCLASS	0.074	(0.016)	<0.001
	S_EXCOMP∣WITH	S_ICTLRN	0.015	(0.017)	0.391
		S_GENCLASS	0.078	(0.012)	<0.001
	S_ICTLRN∣WITH	S_GENCLASS	0.223	(0.017)	<0.001
Moscow (Russian Federation)	S_GENEFF∣ON	S_EXCOMP	0.136	(0.022)	<0.001
		S_ICTLRN	0.123	(0.030)	<0.001
		S_GENCLASS	0.063	(0.024)	0.008
	CIL∣ON	S_GENEFF	0.236	(0.026)	<0.001
		S_EXCOMP	0.110	(0.025)	<0.001
		S_ICTLRN	0.059	(0.025)	0.016
		S_GENCLASS	0.044	(0.024)	0.071
	S_EXCOMP∣WITH	S_ICTLRN	0.002	(0.025)	0.925
		S_GENCLASS	0.077	(0.016)	<0.001
	S_ICTLRN∣WITH	S_GENCLASS	0.192	(0.025)	<0.001

Table A1. *Cont.*

Educational Systems	Endogenous Variables	Exogenous Variables	Estimate	(SE)	*p*
North Rhine-Westphalia (Germany)	S_GENEFF | ON	S_EXCOMP	0.158	(0.036)	<0.001
		S_ICTLRN	0.050	(0.031)	0.112
		S_GENCLASS	0.085	(0.024)	<0.001
	CIL | ON	S_GENEFF	0.235	(0.029)	<0.001
		S_EXCOMP	0.067	(0.031)	0.029
		S_ICTLRN	−0.035	(0.032)	0.281
		S_GENCLASS	0.201	(0.028)	<0.001
	S_EXCOMP | WITH	S_ICTLRN	0.002	(0.025)	0.947
		S_GENCLASS	0.076	(0.024)	0.001
	S_ICTLRN | WITH	S_GENCLASS	0.244	(0.028)	<0.001
Portugal	S_GENEFF | ON	S_EXCOMP	0.122	(0.025)	<0.001
		S_ICTLRN	0.135	(0.024)	<0.001
		S_GENCLASS	0.036	(0.026)	0.175
	CIL | ON	S_GENEFF	0.229	(0.030)	<0.001
		S_EXCOMP	0.133	(0.020)	<0.001
		S_ICTLRN	−0.054	(0.024)	0.021
		S_GENCLASS	0.037	(0.027)	0.172
	S_EXCOMP | WITH	S_ICTLRN	−0.007	(0.020)	0.749
		S_GENCLASS	0.081	(0.021)	<0.001
	S_ICTLRN | WITH	S_GENCLASS	0.200	(0.022)	<0.001

()—standard errors appear in parentheses.

Table A2. Explained variances dependent on variables in the path model.

Educational Systems	Variables	Estimate	(SE)	*p*
Denmark	CIL	0.152	(0.020)	<0.001
	S_GENEFF	0.145	(0.014)	<0.001
Finland	CIL	0.189	(0.020)	<0.001
	S_GENEFF	0.105	(0.016)	<0.001
France	CIL	0.083	(0.015)	<0.001
	S_GENEFF	0.057	(0.012)	<0.001
Germany	CIL	0.102	(0.018)	<0.001
	S_GENEFF	0.041	(0.012)	0.001
Italy	CIL	0.173	(0.015)	<0.001
	S_GENEFF	0.118	(0.014)	<0.001
Luxembourg	CIL	0.091	(0.007)	<0.001
	S_GENEFF	0.035	(0.006)	<0.001
Moscow (Russian Federation)	CIL	0.088	(0.016)	<0.001
	S_GENEFF	0.042	(0.009)	<0.001

Table A2. *Cont.*

Educational Systems	Variables	Estimate	(SE)	*p*
North Rhine-Westphalia (Germany)	CIL	0.115	(0.015)	<0.001
	S_GENEFF	0.039	(0.013)	0.003
Portugal	CIL	0.080	(0.014)	<0.001
	S_GENEFF	0.037	(0.009)	<0.001

()—standard errors appear in parentheses.

Table A3. Total and specific indirect effects in the path model.

Educational Systems	Effects	Direct and Indirect Effects	Estimate	(SE)	*p*
Denmark	Effects from S_EXCOMP to CIL	Total	0.157	(0.021)	<0.001
		Specific indirect 1 | S_EXCOMP > S_GENEFF > CIL	0.034	(0.007)	<0.001
		Direct | S_EXCOMP > CIL	0.123	(0.021)	<0.001
	Effects from S_ICTLRN to CIL	Total	0.150	(0.032)	<0.001
		Specific indirect 1 | S_ICTLRN > S_GENEFF > CIL	0.087	(0.013)	<0.001
		Direct | S_ICTLRN > CIL	0.063	(0.027)	0.019
	Effects from S_GENCLASS to CIL	Total	0.130	(0.028)	<0.001
		Specific indirect 1 | S_GENCLASS > S_GENEFF > CIL	0.027	(0.008)	0.001
		Direct | S_GENCLASS > CIL	0.103	(0.025)	<0.001
Finland	Effects from S_EXCOMP to CIL	Total	0.191	(0.020)	<0.001
		Specific indirect 1 | S_EXCOMP > S_GENEFF > CIL	0.049	(0.008)	<0.001
		Direct | S_EXCOMP > CIL	0.143	(0.020)	<0.001
	Effects from S_ICTLRN to CIL	Total	0.141	(0.024)	<0.001
		Specific indirect 1 | S_ICTLRN > S_GENEFF > CIL	0.033	(0.007)	<0.001
		Direct | S_ICTLRN > CIL	0.108	(0.023)	<0.001
	Effects from S_GENCLASS to CIL	Total	0.218	(0.026)	<0.001
		Specific indirect 1 | S_GENCLASS > S_GENEFF > CIL	0.042	(0.007)	<0.001
		Direct | S_GENCLASS > CIL	0.176	(0.025)	<0.001
France	Effects from S_EXCOMP to CIL	Total	0.102	(0.020)	<0.001
		Specific indirect 1 | S_EXCOMP > S_GENEFF > CIL	0.028	(0.006)	<0.001
		Direct | S_EXCOMP > CIL	0.074	(0.019)	<0.001
	Effects from S_ICTLRN to CIL	Total	0.075	(0.027)	0.005
		Specific indirect 1 | S_ICTLRN > S_GENEFF > CIL	0.040	(0.009)	<0.001
		Direct | S_ICTLRN > CIL	0.036	(0.025)	0.159
	Effects from S_GENCLASS to CIL	Total	0.096	(0.027)	<0.001
		Specific indirect 1 | S_GENCLASS > S_GENEFF > CIL	0.016	(0.005)	0.003
		Direct | S_GENCLASS > CIL	0.080	(0.027)	0.003

Table A3. *Cont.*

Educational Systems	Effects	Direct and Indirect Effects	Estimate	(SE)	*p*
Germany	Effects from S_EXCOMP to CIL	Total	0.107	(0.031)	0.001
		Specific indirect 1 | S_EXCOMP > S_GENEFF > CIL	0.026	(0.006)	<0.001
		Direct | S_EXCOMP > CIL	0.081	(0.029)	0.005
	Effects from S_ICTLRN to CIL	Total	−0.024	(0.040)	0.550
		Specific indirect 1 | S_ICTLRN > S_GENEFF > CIL	0.026	(0.010)	0.012
		Direct | S_ICTLRN > CIL	−0.050	(0.033)	0.136
	Effects from S_GENCLASS to CIL	Total	0.176	(0.028)	<0.001
		Specific indirect 1 | S_GENCLASS > S_GENEFF > CIL	0.024	(0.006)	<0.001
		Direct | S_GENCLASS > CIL	0.152	(0.028)	<0.001
Italy	Effects from S_EXCOMP to CIL	Total	0.194	(0.020)	<0.001
		Specific indirect 1 | S_EXCOMP > S_GENEFF > CIL	0.070	(0.008)	<0.001
		Direct | S_EXCOMP > CIL	0.124	(0.017)	<0.001
	Effects from S_ICTLRN to CIL	Total	0.127	(0.023)	<0.001
		Specific indirect 1 | S_ICTLRN > S_GENEFF > CIL	0.084	(0.009)	<0.001
		Direct | S_ICTLRN > CIL	0.042	(0.023)	0.064
	Effects from S_GENCLASS to CIL	Total	0.067	(0.026)	0.011
		Specific indirect 1 | S_GENCLASS > S_GENEFF > CIL	0.016	(0.008)	0.050
		Direct | S_GENCLASS > CIL	0.051	(0.023)	0.029
Luxembourg	Effects from S_EXCOMP to CIL	Total	0.096	(0.015)	<0.001
		Specific indirect 1 | S_EXCOMP > S_GENEFF > CIL	0.034	(0.005)	<0.001
		Direct | S_EXCOMP > CIL	0.061	(0.015)	<0.001
	Effects from S_ICTLRN to CIL	Total	0.027	(0.016)	0.098
		Specific indirect 1 | S_ICTLRN > S_GENEFF > CIL	0.029	(0.006)	<0.001
		Direct | S_ICTLRN > CIL	−0.002	(0.015)	0.889
	Effects from S_GENCLASS to CIL	Total	0.089	(0.016)	<0.001
		Specific indirect 1 | S_GENCLASS > S_GENEFF > CIL	0.015	(0.003)	<0.001
		Direct | S_GENCLASS > CIL	0.074	(0.016)	<0.001
Moscow (Russian Federation)	Effects from S_EXCOMP to CIL	Total	0.142	(0.025)	<0.001
		Specific indirect 1 | S_EXCOMP > S_GENEFF > CIL	0.032	(0.005)	<0.001
		Direct | S_EXCOMP > CIL	0.110	(0.025)	<0.001
	Effects from S_ICTLRN to CIL	Total	0.088	(0.024)	<0.001
		Specific indirect 1 | S_ICTLRN > S_GENEFF > CIL	0.029	(0.009)	0.001
		Direct | S_ICTLRN > CIL	0.059	(0.025)	0.016
	Effects from S_GENCLASS to CIL	Total	0.059	(0.024)	0.015
		Specific indirect 1 | S_GENCLASS > S_GENEFF > CIL	0.015	(0.006)	0.009
		Direct | S_GENCLASS > CIL	0.044	(0.024)	0.071

Table A3. *Cont.*

Educational Systems	Effects	Direct and Indirect Effects	Estimate	(SE)	*p*
North Rhine-Westphalia (Germany)	Effects from S_EXCOMP to CIL	Total	0.104	(0.034)	0.002
		Specific indirect 1 ǀ S_EXCOMP > S_GENEFF > CIL	0.037	(0.009)	<0.001
		Direct ǀ S_EXCOMP > CIL	0.067	(0.031)	0.029
	Effects from S_ICTLRN to CIL	Total	−0.023	(0.032)	0.466
		Specific indirect 1 ǀ S_ICTLRN > S_GENEFF > CIL	0.012	(0.008)	0.124
		Direct ǀ S_ICTLRN > CIL	−0.035	(0.032)	0.281
	Effects from S_GENCLASS to CIL	Total	0.221	(0.029)	<0.001
		Specific indirect 1 ǀ S_GENCLASS > S_GENEFF > CIL	0.020	(0.006)	0.001
		Direct ǀ S_GENCLASS > CIL	0.201	(0.028)	<0.001
Portugal	Effects from S_EXCOMP to CIL	Total	0.161	(0.021)	<0.001
		Specific indirect 1 ǀ S_EXCOMP > S_GENEFF > CIL	0.028	(0.007)	<0.001
		Direct ǀ S_EXCOMP > CIL	0.133	(0.020)	<0.001
	Effects from S_ICTLRN to CIL	Total	−0.023	(0.025)	0.348
		Specific indirect 1 ǀ S_ICTLRN > S_GENEFF > CIL	0.031	(0.007)	<0.001
		Direct ǀ S_ICTLRN > CIL	−0.054	(0.024)	0.021
	Effects from S_GENCLASS to CIL	Total	0.045	(0.029)	0.123
		Specific indirect 1 ǀ S_GENCLASS > S_GENEFF > CIL	0.008	(0.006)	0.167
		Direct ǀ S_GENCLASS > CIL	0.037	(0.027)	0.172

()—standard errors appear in parentheses.

Note

1 The causal relationship is just a theoretical assumption as per the terminology used in structural equation modeling. No causal relationships are sought or established in this study. All findings and interpretations in this study are only in terms of correlation, and not in terms of causation. For more details see Kline (2016).

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