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Unequal Loneliness in the Digitalized Classroom: Two Loneliness Effects of School Computers and Lessons for Sustainable Education in the E-Learning Era

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Abstract: Incorporating information and communication technology (ICT) into schooling has been one of the most conspicuous trends in education innovation for decades. Despite the education community's optimistic consensus on the digitalization of the classroom, however, evidence-based research on the educational effectiveness of ICT is an unfinished task. In this situation, this study gives renewed attention to the socioemotional effects of school computers and draws lessons for sustainable education in the e-learning era. By analyzing the Trends in International Mathematics and Science Study (TIMSS) 2015, this study identifies the causal link between school computer usage time (the independent variable) and satisfaction with peer relationships (the dependent variable) among elementary and middle school students: the loneliness deepening effect. Then, considering the issue of digital divide, it finds the positive interaction between the independent variable and academic performance (the moderating variable): the loneliness inequality effect. These two findings—summarized by the term "unequal loneliness"—call for critical reflections on the current use of school computers but do not support the Ludditish claim that wholly denies ICT's educational values and potentials. Rather, the existence of the loneliness inequality effect additionally implies an opportunity to go beyond mere technological determinism and deliberate on human users' capabilities for effective ICT usage.

Keywords: digitalization of the classroom; school computers; educational effectiveness of ICT; satisfaction with peer relationships; loneliness deepening effect; digital divide; academic performance; loneliness inequality effect; sustainable education; e-learning

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1. Introduction

This study analyzes the educational effects of school computers on elementary and middle school students and draws lessons for sustainable education in the e-learning era. Such an approach can be classified as a part of the educational effectiveness research; however, while the majority of efforts to date have focused on the academic effects of schooling, this study explores the socioemotional effects [1]. By analyzing the Trends in International Mathematics and Science Study (TIMSS) 2015, a dataset of international students' assessment in the mid-2010s, this study identifies the negative effect of school computer usage time (the independent variable) on satisfaction with peer relationships (the dependent variable) among fourth and eighth graders, naming it the loneliness deepening effect. Furthermore, this study finds the positive interaction between the independent variable and academic performance (the moderating variable), naming it the loneliness inequality effect. The term "unequal loneliness" summarizes these two findings.

As is well known, incorporating computer hardware, software, and the Internet—information and communication technology (ICT) in general—into schooling has been one of the most conspicuous trends of education innovation since the release of the first personal computers in the late 1970s. Particularly in the past quarter century, many countries have witnessed the advent of the e-learning era, with experiments such as bring-your-own-device policies, blended learning, massive open online courses, flipped learning, and digital textbooks [2–5]. Furthermore, the COVID-19 pandemic seems to provide additional momentum with a call for distance education [6].

The United States has been at the forefront of the movement, and one of the defining moments was the National Educational Technology Plan in 1996. It proclaimed the objective of equipping every classroom in the nation with computers and the Internet and led to the E-Rate program, investing US $1–2 billion per year over two decades [7]. South Korea has joined the trend since the late 1990s under the banner of "informatization of education" (*gyoyukjeongbohwa*). Thus, on-screen presentation has been substituted for blackboard writing as the universal teaching method since the 2000s, and digital textbooks began to be introduced in the 2010s [8,9].

However, despite the optimistic consensus in the education community on the digitalization of the classroom, concerns over the adverse effects have also been steadily raised. Unfortunately, the discussions have largely relied on episodic observations or anecdotal experiences, and evidence-based research is an unfinished task. Because of these limitations, the debate has even escalated into a fierce battle between optimism and skepticism [10].

Most empirical studies so far, conducted in the context of educational effectiveness research, have analyzed the effects of ICT on students' academic performance; however, such endeavors have often run into methodological limitations, settling for agnostic or eclectic conclusions. The most frequent efforts were randomized experiments, but they were not free from obstacles such as the Hawthorne effect. The next most frequent were analyses of non-experimental survey data (e.g., TIMSS); as computer use in the classroom is not randomly assigned, however, these efforts faced controversy relating to the endogeneity of the independent variable. Reverse causality was a particular problem, as schools and teachers may have strategically introduced ICT as instructional tools in consideration of students' prior academic performance. In the beginning, the randomness or selectivity of some ICT investments allowed for quasi-experimental techniques, such as the instrumental variables model or the regression discontinuity design, but this possibility quickly became smaller as ICT investment approached saturation [11,12].

Furthermore, the problem has grown more complicated with the theoretical issue of validity of the dependent variable. The key discussion point is whether it is valid to measure the academic effects of ICT using conventional subject-based test scores, disregarding new potential gains such as "digital literacy" and "21st-century skills" [13,14].

In this deadlock, this study aims to give renewed attention to the non-academic effects of school computers, which have been relatively neglected, and the findings do have critical implications. The identification of the loneliness deepening effect by itself calls for a serious, honest reflection on the current use of school computers. Furthermore, the simultaneous identification of the loneliness inequality effect intensifies the cautionary message over the digital divide. These two effects can be seen as a threat to the principle of sustainable education—enhancing excellence and equity of schooling by ensuring quality learning and support for all students—posing a fundamental question on the cause of the e-learning [15].

Nevertheless, this study does not support the Ludditish claim that wholly denies ICT's educational values and potentials. Rather, as discussed in Section 6, the existence of the loneliness inequality effect additionally implies an opportunity to go beyond mere technological determinism and deliberate on human users' capabilities for effective ICT usage.

2. Literature Review and Theoretical Background

2.1. Optimistic Consensus: Humanization, Democratization, and Cooperativization of Education

It is fair to state that an "optimistic consensus" on the digitalization of the classroom has been established across the education community [16]. Thus, a series of literature has presented a variety of educational benefits of ICT; while academic effects were the main focus, socioemotional ones also represented a significant part.

The most seminal piece was *Mindstorms* (1980) by Seymour Papert, a mathematician and computer scientist. According to him, simulation, modeling, and other hands-on activities through computers provide vivid images for abstract knowledge such as mathematics. The primary effects he cites are academic ones, where such computer-aided instructions eschew rote memorization and enhance the ability to think. However, he also remarks that these are accompanied by certain socioemotional effects: the on-screen visualization of subject knowledge turns classes into an inviting and fun process, putting an end to the anxieties of learning such as "mathophobia," liberating the suppressive climate of classrooms, and ultimately bringing the humanization and democratization of education [17].

Subsequent literature has inherited the Papertian perspective, only supplementing a few new visions such as the cooperativization of education [2–4,18]. Here lie two backgrounds: first, the technical one is the enhancement of the interactive functions of computers owing to the commercialization of the Internet, the onset of the Web 2.0 era, and the spread of smart devices; second, the pedagogical one is the constructivist movement in education since the 1980s, replacing teacher-led/knowledge-transmitting classes with student-centered/knowledge-constructing ones.

Thus, amid new experiments like project-based learning, computers and the Internet began to grow in popularity as tools to assist the creative, problem-solving activities of students. In this context, "activities" commonly refers to group works rather than individual tasks—in other words, practices of cooperative learning based on teacher-student and student-student interactions. Thus, the prospect has been developed that the unprecedented flexibility and connectivity of ICT would maximize student participation, transforming the one-to-many structure of old classes into a many-to-many one and constructing a learning community that befits the ideal of collective intelligence.

Meanwhile, Marc Prensky, a speaker and writer on education, has proposed the generational concept of "digital natives". According to him, the generations born after 1980 are digital natives; being fluent in digital language just like a mother tongue, they demonstrate entirely different thinking and behavior patterns from the older generations of "digital immigrants". Therefore, he asserts that schooling should be changed to suit these characteristics, with ICT at the center.

Properties of digital natives listed by Prensky are mostly individual characteristics—receiving information quickly, being good at multitasking, and so on—but also include a collective one: digital natives perform best when networked. This implies that ICT-enabled cooperative learning would provide more effective, suitable education for the new generations [19].

2.2. Techno-Skepticism: Problem of Distraction

Still, not all discussions drew rosy outlooks. A series of techno-skepticism, although small in number, was posed against the optimistic consensus and expressed concerns on the adverse effects of ICT [10].

The most pioneering piece was *Teachers and Machines* (1986) by Larry Cuban, an educational historian. He pointed to the historical precedents of how the 20th-century educational technologies like movies, radio, and television failed to innovate the classroom despite their early popularity and predicted that computers would follow the same path. At the surface, the rationale was teachers' distrust of computers; however, a more fundamental reason was lack of clear evidence for persuading them. While the biggest doubt was about its effects on students' academic abilities, Cuban also mentioned concerns over a cutting of the ties between teachers and students resulting from over-engagement with computer activities [20].

Then, criticisms with sharper tones have arisen since the 1990s [21–25]. The critics all pointed out the problem of distraction. The argument was that early and excessive exposure to the computer screen with fast-paced visual stimuli would not only lead to declines in literacy, thinking skills, and other academic abilities, but also negatively impact human relationships in the classroom.

With the analytic framework of the media effects research, the literature so far can be summarized into the three hypotheses [26]. The first is a relatively simple, physical one: the time displacement hypothesis: with more time spent in front of screens, the time for face-to-face communication in the classroom grows shorter.

However, the objection was soon made to it: it is too hasty to predicate that the total communication time has declined, as social media and other interactive tools enable extra communication outside the classroom. Another hypothesis was therefore added as a counter- counterargument: although the Internet ensures broad connectivity, the "weak ties" produced by the online communication cannot quantitatively or qualitatively replace the "strong ties" in the traditional classroom—verbal and nonverbal exchanges such as conversation, listening with attention, and empathy. This is the medium-specific hypothesis, which essentially states that computers and the Internet have a special media effect, going beyond being simple tools.

In addition, there is the content-specific hypothesis, which criticizes the quality of content delivered by computers and the Internet; for example, it was pointed out that educational software relies too much on visualization or gamification under the cloak of "edutainment." Critics argued that while bringing momentary fun, it would ultimately hurt the classroom atmosphere, negatively impacting both academic work and communication.

Problems were also raised with the concept of digital natives [24,27]. The critics insisted that while present-day children may be more familiar with digital culture than older generations, they should not be glamorized as digital natives given the underdevelopment of interpersonal skills, lack of empathy, and other side effects in socioemotional development brought on by over-immersion to digital devices. According to the critics, the digitalization of the classroom would be adding fuel to the fire, given the need for guarding against excessive influence of digital devices in the lives of young students.

2.3. Conflicting Promises within the Optimistic Consensus: Cooperativization versus Personalization of Education

The previous discussions can give the impression that they oversimplify the matter with the dichotomy of yes or no. However, aside from the aforementioned criticisms from techno-skepticism, two conflicting promises within the optimistic consensus added an issue: cooperativization versus personalization of education [28,29].

The cooperativization of education is as described in Section 2.1: computers encourage creative activities like project-based learning, the majority of which consist of cooperative learning based on teacher-student and student-student interactions. Among the technological factors that are expected to enable this are portable computer hardware (tablets, smartphones, etc.) as well as interactive Internet services (social media, video communications, etc.).

At the same time, however—and even in the same piece of literature—the personalization of education was also promised: while previous classes corresponded to a "standardized" education where teachers uniformly delivered the contents of textbooks, new classes under ICT would be a "personalized" education that respects the ability and aptitude of each student; in this way, it would overcome the limitations of one-to-many learning—also referred to as "the factory model"— and realize the long-cherished dream of one-to-one learning. Relevant technologies are adaptive learning programs applying artificial intelligence and immersive virtual and augmented realities [4].

However, as the personalization received praise, the alternative promise of cooperativization quietly faded. As explained in Section 2.1, the cooperativization of education involved utilizing the interactive nature of ICT to convert one-to-many to many-to-many learning. This naturally led to the question of how the realization of one-to-one learning, which began from the same criticism of one-to-many learning but constituted a very different—and at times contrasting—alternative, could coexist.

The dissonance was admitted in a recent piece of literature that speaks for the optimistic consensus [4]. It led to the addition of provisions such as "personalization is not to be confused with isolation" and "some of the best learning that takes place is not just personalized, but collaborative as well"; this is reminiscent of the concept of "networked individualism" in the social network theory [30]. However, it is hardly deniable that such provisions are not yet specific enough to resolve the conflict.

2.4. Digital Divide: ICT and Educational Inequality

As mentioned in Section 1, this study identifies the loneliness inequality effect together with the loneliness deepening effect. The framework reflects the problem of educational inequality, another cornerstone of the ICT discussion.

As is well known, the digital divide is a concept that symbolizes the problem. Since its first appearance in 1995, the concept has expanded to three levels of meaning. The first-level divide refers to the gap in the physical access to ICT resources across socioeconomic categories (class, race, etc.). Up to the early 2000s, the concept retained this simplest meaning. However, as the supply of ICT resources advanced to certain degrees, the first level naturally gave way to higher levels. From the mid-2000s, the gap in the usage of ICT appeared as the second-level divide. Then, the third-level divide, the gap in the outcomes from utilizing ICT, gained attention [31].

Obviously, this has been an issue that encompasses all of society; however, discussions on education have followed this path as well [11,32]. In the beginning, the first-level divide—differentiated opportunities to access ICT resources between advantaged and disadvantaged students—became a major problem. This re-highlighted the responsibility of schools for equality of opportunity under the cause of digital bridging, justifying massive investments in ICT since the 1990s. Then, as computers and the Internet gradually became ubiquitous in schools, the discussion shifted to the second- and third-level issues. Questions began to arise around how different schools or students may have different learning experiences and outcomes from computers and the Internet.

There has been some controversy over the questions, and the debate between the optimistic consensus and techno-skepticism (see Sections 2.1 and 2.2) has been reproduced [28]. Optimists expected that advantages of ICT such as the humanization, democratization, and cooperativization of education would provide extra learning opportunities to disadvantaged students who had been alienated from the traditional classroom, reducing educational inequality [33–35]. On the other hand, skeptics were concerned about the possibility of ICT failing to reduce—or worse, exacerbating—educational inequality. They have argued that side effects of ICT such as poor literacy or distraction may be even more destructive to disadvantaged children who lack the opportunity for supplemental learning outside of school [23,36].

2.5. Calling for Evidence-Based Research

Thus far, this study has outlined the discussions on the digitalization of the classroom focusing on the socioemotional effects. However, as they have largely relied on experiences and intuitions, it has been difficult to draw any definite conclusions therefrom. Evidence-based research is required, like that being attempted by this study.

As pointed out in Section 1, previous empirical studies on the educational effectiveness of ICT have mostly been based on students' academic performance as the dependent variable and have faced methodological and theoretical challenges. In this situation, this study expands the scope of investigation to the non-academic effects of ICT, hoping to resume and diversify the discussion. Few similar attempts have been made.

Slightly widening the range of the literature review, there have been intermittent attempts at empirical research in the psychological field, covering the effects of ICT on the psychological well-being of children [37]. However, as these studies have analyzed the effects of home computers, they are far removed from the interest of this study—the effects of school computers [12].

Moreover, the effects of home computers themselves remain unclear due to the endogeneity problem. Particularly at issue here is the possibility of reverse causality; usage of home computers itself is dependent on the current psychological state of each student. For example, a recent analysis showed that 15-year-olds who spend more than six hours a day on the Internet clearly feel lonelier than others; however, this fact does not shed light on whether the Internet makes them lonely or whether their loneliness takes them to the Internet [11] (pp. 43–46).

On the other hand, this study focuses on the non-academic byproducts of school computers, used only for the purpose of schoolwork in the highly controlled environment of the classroom. Such a research design makes it free from the reverse causality problem, one of the most problematic obstacles in the educational effectiveness research. Therefore, a more robust causal inference compared to psychological research on home computers is expected.

Furthermore, this study identifies the loneliness inequality effect caused by the interaction between school computers and student characteristics; such an approach is also rarely attempted. Revisiting the three levels of the digital divide, the vast majority of existing empirical studies on ICT and educational equality have focused on whether the opportunities for physical access are being equally guaranteed in classrooms [38], while there are only a few ones on the different usage of school computers across socioeconomic categories and even fewer on the different outcomes [32].

2.6. Peer Relationships and Loneliness: A New Frontier in the Educational Effectiveness Research

As mentioned in the beginning, this study is a part of the educational effective research: a field that derives policy implications for sustainable education by identifying school/teacher-level variables that have effects on students' learning outcomes. Naturally, the most representative outcome variable so far has been academic performance—the extent to which a student has achieved understanding and application ability in key subjects such as mathematics, science, and reading. However, over the past two decades, quite a few attempts have also been made to explore the non-academic—socioemotional or physical—outcomes (attitude, behavior, health, etc.) [1,15].

This study is a reflection of this latest trend. The point of departure is peer relationships, which form the basis of classroom life along with teacher-child relationships. It is generally agreed that positive peer relationships make critical contributions to the supportive school climate, having a profound effect on students' well-being and schools' connectedness [39,40].

However, there are two ways to approach the issue of relationships: addressing the objective experiences or the subjective feelings therefrom. This study's choice is the latter due to the data availability; thus, the dependent variable is not the state of peer relationships itself but the degree of satisfaction with it, and the negative effect of the independent variable on the very feeling is named with the concept of loneliness—rather than social isolation [41]. Such a shift of focus does not alter the implications of this study. Actually, chronic loneliness of children and adolescents is reported to be associated with weakened peer relationships, which again produces negative effects on children's socioemotional developments and experiences (e.g., less self-esteem, more social anxiety) [42].

2.7. Academic Performance as the Control/Moderating Variable

Meanwhile, academic performance is given new roles in this study. First, it functions as the control variable in the identification of the loneliness deepening effect. Although the research design prevents reverse causality, it cannot be concluded that endogeneity has been perfectly eliminated. Thus, academic performance is utilized to assess the possibility. Academic performance is the factor that teachers consider to be most important when introducing teaching tools and strategies. Furthermore, directly linked to the degree of participation in classes, it is likely to have a certain level of impact on students' psychological states. Therefore, if there are still some omitted variables that affect both the independent and dependent variables, the most likely influence would be academic performance;

and if there is no significant difference in the estimation even after inserting academic performance as the control variable, we would safely determine the causal direction.

Second, academic performance works as the moderating variable in the identification of the loneliness inequality effect, and this function is actually more pivotal. The point is to consider the variable as an indicator of students' status in the classroom; students with higher academic performance are in a relatively advantageous position in the classroom, usually playing a leading role in schoolwork. In addition, they are more likely to be better positioned in terms of family background, such as parents' socioeconomic status (SES). Thus, once the negative effect of the independent variable on the dependent variable is identified at average, the simultaneous identification of the positive interaction between the independent variable and academic performance can be interpreted as another manifestation of the digital divide in education, where students with lower academic performance experience the negative effect more strongly, and vice versa.

3. Materials and Methods

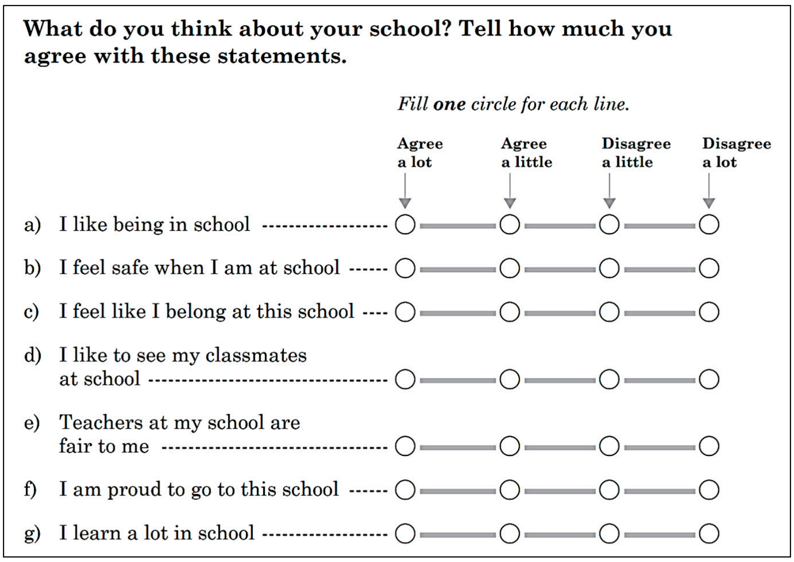
3.1. Data

This study analyzes the dataset of the year 2015 from TIMSS, which evaluates the mathematics and science performances of fourth and eighth graders worldwide and surveys their family/school lives every four years [43]. Considering the rapid changes in technology, it is regrettable that TIMSS 2019 has not yet been released; nevertheless, TIMSS 2015 also takes into account the recent trend of e-learning and retains its timeliness. The data file can be downloaded from the official website [44]. STATA 15.1 is used for all statistical work.

Of the 57 countries that participated in TIMSS 2015, 31 had both their Grade 4 and 8 populations participate. Observations with missing values are removed by listwise deletion before the analyses, so from a total of 259,095 fourth graders and 257,685 eighth graders in the original data file, 251,860 and 251,288 observations remain, respectively. The ratio of missing data does not exceed 3%.

3.2. Variables

The dependent variable is satisfaction with peer relationships of each student, sourced from four-point Likert item-responses in the TIMSS 2015 Student Questionnaire [45]. Items (a) to (g) state satisfaction with school life in various aspects, and responses (a) to (g) ask students' degree of agreement—from "Agree a lot" to "Disagree a lot"—on the respective items (see Figure 1).


What do you think about your school? Tell how much you agree with these statements.

*Fill **one** circle for each line.*

	Agree a lot	Agree a little	Disagree a little	Disagree a lot
a) I like being in school	○	○	○	○
b) I feel safe when I am at school	○	○	○	○
c) I feel like I belong at this school	○	○	○	○
d) I like to see my classmates at school	○	○	○	○
e) Teachers at my school are fair to me	○	○	○	○
f) I am proud to go to this school	○	○	○	○
g) I learn a lot in school	○	○	○	○

Figure 1. Item-responses on satisfaction with school life in the Trends in International Mathematics and Science Study (TIMSS) 2015 Student Questionnaire [45].

Of the seven item-responses, item-response (d) ("I like to see my classmates at school") is the key to this study's interest. However, using this as is leads to the issue of response bias from the subjective tendencies or attitudes of the respondents—an inherent weakness of the Likert scale [46]. Therefore, this study adopts the following scoring strategy to minimize the effects of response bias: let y_a, y_b, y_c, and y_d be four-point scores coded from responses (a), (b), (c), and (d), respectively, and let $\overline{y}$ be the average of y_a, y_b, and y_c (if there is any missing value among y_a, y_b, and y_c, $\overline{y}$ is calculated by the remaining ones); then $y = y_d - \overline{y}$ is the dependent variable defined in this study, while responses (e), (f), and (g) are not considered as they may be affected by the psychological aftereffect from response (d).

This strategy is justified given the difference in contents between items (a), (b), and (c) on the one hand and item (d) on the other. The former items ask about general satisfaction associated with "school", whereas the latter asks about specific satisfaction with "classmates". In fact, Tables 1 and 2 indicate that the correlations among y_a, y_b, and y_c are more than 0.4, while the remaining correlations with y_d consistently fall below it.

Table 1. Correlations among responses (a), (b), (c), and (d) in Grade 4.

Response	(a)	(b)	(c)	(d)
(a)	1.000	0.406	0.405	0.253
(b)	0.406	1.000	0.432	0.304
(c)	0.405	0.432	1.000	0.328
(d)	0.253	0.304	0.328	1.000

All observations of fourth graders were pooled. Source: TIMSS 2015 dataset.

Table 2. Correlations among responses (a), (b), (c), and (d) in Grade 8.

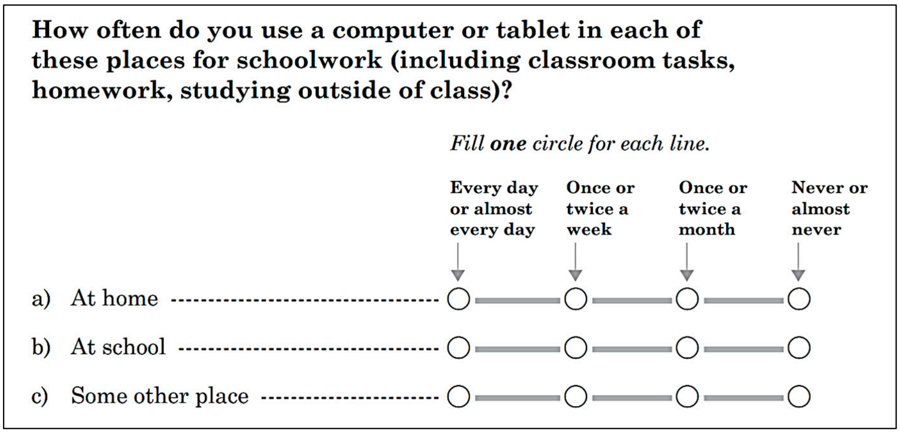
Response	(a)	(b)	(c)	(d)
(a)	1.000	0.450	0.474	0.329
(b)	0.450	1.000	0.508	0.348
(c)	0.474	0.508	1.000	0.387
(d)	0.329	0.348	0.387	1.000

All observations of eighth graders were pooled. Source: TIMSS 2015 dataset.

Constructing $y = y_d - \overline{y}$ can be seen as an effort to identify momentary fluctuations of emotions that students may experience from the following two-step question while forfeiting the measurement of an absolute level of satisfaction: "Is school going well for you? (. . .) How are your relationships with friends?" For example, a student who responds "Agree a lot" to items (a), (b), and (c) may suddenly respond "Agree a little" to item (d), which indicates $y = -1$. However, a student who responds "Disagree a lot" to items (a), (b), and (c) may suddenly respond "Disagree a little" to item (d); this would indicate $y = 1$. As an analogy, students who have earned a C in a class averaging at D would be evaluated higher than a student who earned a B in a class averaging at A.

The independent variable is school computer usage time of each school. This is again sourced from an item-response in the TIMSS 2015 Student Questionnaire [45]: the question about how often the student uses a computer or tablet for schoolwork at school (see item (b) in Figure 2). However, as digitalization is an educational policy imposed on the whole school, it is more appropriate to prepare a school-level aggregate variable for it. Thus, the four categories of response (b)—from "Every day or almost every day" to "Never or almost never"—are coded into number of days in a week, 5, 1.5, 0.375, and 0, respectively, and the school averages are calculated, weighted by the student sampling weight (TOTWGT) in the TIMSS 2015 dataset.

The control/moderating variable is academic performance of each student. A key subject's test score can be used as a proxy for it, and this study adopts the first of the five "plausible values" of mathematics performance (ASMMAT01, BSMMAT01) estimated by the multiple imputation technique in the TIMSS 2015 dataset. The score indicates how well each student understands the curriculum contents of Grade 4 (number, geometric shapes and measures, data display) and Grade 8 (number, algebra, geometry, data and chance) [43].


How often do you use a computer or tablet in each of these places for schoolwork (including classroom tasks, homework, studying outside of class)?

*Fill **one** circle for each line.*

	Every day or almost every day	Once or twice a week	Once or twice a month	Never or almost never
a) At home	○	○	○	○
b) At school	○	○	○	○
c) Some other place	○	○	○	○

Figure 2. Item-responses on using computers for schoolwork in the TIMSS 2015 Student Questionnaire [45].

Table 3 shows the descriptive statistics of the three variables, calculated by grade and country. The most notable is the dependent variable; the sample means in all countries are close to zero, with sample standard deviations between 0.6 and 0.7. As most observed values are concentrated around zero, this can be said to be a very conservative variable. This is a natural result, as responses (a), (b), and (c) would be somewhat similar to response (d) in Figure 1. It is an inevitable price of using the scoring strategy to minimize the response bias. The point is to see whether the statistically significant effects could be identified despite the conservative nature of the dependent variable.

Table 3. Descriptive statistics.

Countries	Grade 4				Grade 8			
	Dep	Indep	Con/Mod	Obs	Dep	Indep	Con/Mod	Obs
Australia	0.49 (0.67)	1.73 (1.04)	517.72 (83.10)	5951	0.48 (0.70)	2.81 (1.42)	506.00 (81.46)	9878
Bahrain	0.33 (0.75)	1.41 (0.57)	452.78 (83.35)	4031	0.60 (0.81)	0.85 (0.34)	455.36 (79.18)	4652
Armenia	0.09 (0.56)	1.19 (0.55)	487.13 (78.71)	4630	0.37 (0.63)	0.86 (0.36)	472.09 (80.52)	4776
Botswana	n/a	n/a	n/a	n/a	0.25 (0.78)	1.42 (0.50)	396.90 (79.84)	5704
Bulgaria	0.22 (0.55)	0.84 (0.53)	527.00 (81.22)	4137	n/a	n/a	n/a	n/a
Canada	0.38 (0.65)	1.20 (0.74)	511.55 (74.46)	12,059	0.34 (0.66)	2.09 (1.07)	528.18 (68.81)	8517
Chile	0.26 (0.71)	1.00 (0.47)	460.55 (72.42)	4645	0.30 (0.71)	1.01 (0.40)	428.13 (78.47)	4754
Chinese Taipei	0.35 (0.74)	0.86 (0.37)	597.14 (69.94)	4251	0.40 (0.64)	0.75 (0.34)	598.78 (96.39)	5691
Croatia	0.63 (0.64)	0.55 (.46)	502.64 (66.15)	3946	n/a	n/a	n/a	n/a
Cyprus	0.57 (0.79)	0.93 (0.97)	524.58 (79.01)	4041	n/a	n/a	n/a	n/a
Czech Republic	0.59 (0.66)	0.47 (0.52)	528.53 (70.00)	5129	n/a	n/a	n/a	n/a
Denmark	0.34 (0.55)	1.87 (1.24)	539.39 (74.69)	3590	n/a	n/a	n/a	n/a

Table 3. *Cont.*

Countries	Grade 4				Grade 8			
	Dep	Indep	Con/Mod	Obs	Dep	Indep	Con/Mod	Obs
Finland	0.36 (0.53)	0.81 (0.45)	534.99 (66.94)	4979	n/a	n/a	n/a	n/a
France	0.36 (0.67)	0.65 (0.51)	489.34 (74.00)	4785	n/a	n/a	n/a	n/a
Georgia	0.17 (0.58)	1.11 (0.66)	468.27 (83.51)	3672	0.36 (0.72)	0.65 (0.37)	455.46 (89.72)	3939
Germany	0.49 (0.71)	0.50 (0.48)	526.62 (65.47)	3315	n/a	n/a	n/a	n/a
Hong Kong	0.40 (0.79)	1.08 (0.77)	613.91 (65.92)	3577	0.42 (0.73)	1.02 (0.70)	593.86 (77.11)	4128
Hungary	0.42 (0.67)	0.66 (0.56)	530.00 (87.92)	5000	0.51 (0.79)	1.06 (0.40)	514.74 (92.07)	4851
Indonesia	0.06 (0.40)	0.77 (0.76)	393.08 (88.69)	3880	n/a	n/a	n/a	n/a
Iran	0.14 (0.68)	0.75 (0.82)	425.43 (99.65)	3682	0.37 (0.77)	1.05 (0.52)	436.15 (93.27)	6054
Ireland	0.49 (0.63)	0.72 (.67)	548.26 (72.64)	4276	0.54 (0.67)	1.02 (1.11)	523.81 (72.63)	4623
Israel	n/a	n/a	n/a	n/a	0.36 (0.74)	1.03 (0.72)	511.72 (100.28)	5429
Italy	0.52 (0.69)	0.62 (0.45)	507.61 (70.81)	4302	0.71 (0.73)	0.35 (0.35)	494.56 (73.62)	4453
Japan	0.40 (0.61)	0.60 (0.36)	593.81 (68.28)	4352	0.29 (0.58)	0.36 (0.24)	586.27 (88.20)	4732
Kazakhstan	0.11 (0.56)	0.87 (0.71)	544.89 (82.37)	4640	0.26 (0.54)	1.06 (0.50)	527.83 (92.90)	4829
Jordan	n/a	n/a	n/a	n/a	0.31 (0.72)	1.03 (0.43)	389.66 (91.19)	7615
Korea	0.22 (0.56)	0.82 (0.36)	608.29 (67.57)	4643	0.22 (0.52)	0.73 (0.37)	604.88 (85.50)	5304
Kuwait	0.27 (0.77)	1.33 (0.58)	352.09 (102.07)	3251	0.59 (0.76)	0.90 (0.65)	393.94 (89.87)	4113
Lebanon	n/a	n/a	n/a	n/a	0.33 (0.86)	0.98 (0.70)	443.88 (74.51)	3662
Lithuania	0.40 (0.59)	0.40 (0.37)	535.64 (70.69)	4471	0.44 (0.67)	0.61 (0.36)	511.02 (77.02)	4305
Malaysia	n/a	n/a	n/a	n/a	0.44 (0.66)	0.68 (.039)	466.25 (85.07)	9656
Malta	n/a	n/a	n/a	n/a	0.69 (0.82)	0.75 (0.18)	495.02 (86.51)	3763
Morocco	0.03 (0.55)	0.57 (0.84)	383.54 (89.75)	4643	0.13 (0.71)	0.64 (0.41)	387.11 (78.64)	12,543
Oman	0.15 (0.66)	1.66 (0.51)	427.51 (99.72)	8764	0.34 (0.73)	1.16 (0.34)	404.70 (95.53)	8455
Netherlands	0.36 (0.64)	1.33 (0.79)	530.28 (55.91)	4358	n/a	n/a	n/a	n/a
New Zealand	0.41 (0.64)	2.14 (0.92)	492.24 (88.82)	6183	0.42 (0.66)	2.13 (1.07)	493.82 (86.72)	7902
Norway	0.34 (0.51)	1.03 (0.73)	549.60 (69.73)	4196	0.37 (0.56)	1.73 (1.00)	511.35 (69.15)	4643
Poland	0.72 (0.73)	0.52 (0.30)	535.22 (71.97)	4705	n/a	n/a	n/a	n/a
Portugal	0.19 (0.44)	0.62 (0.42)	541.59 (72.27)	4666	n/a	n/a	n/a	n/a
Qatar	0.33 (0.83)	1.48 (0.62)	441.85 (96.56)	4991	0.56 (0.83)	1.35 (0.80)	440.57 (100.25)	5270

Table 3. *Cont.*

Countries	Grade 4				Grade 8			
	Dep	Indep	Con/Mod	Obs	Dep	Indep	Con/Mod	Obs
Russia	0.44 (0.66)	0.83 (0.77)	564.19 (72.07)	4881	0.48 (0.72)	1.40 (0.56)	537.13 (79.86)	4747
Saudi Arabia	0.27 (0.75)	1.02 (0.82)	388.83 (88.68)	4014	0.62 (0.83)	1.09 (0.44)	371.74 (83.38)	3618
Serbia	0.37 (0.62)	0.59 (0.59)	520.47 (85.65)	3962	n/a	n/a	n/a	n/a
Singapore	0.33 (0.71)	0.77 (0.41)	617.89 (84.57)	6493	0.31 (0.67)	1.19 (0.82)	619.89 (82.01)	6081
Slovak Republic	0.47 (0.68)	1.02 (0.62)	499.35 (79.00)	5704	n/a	n/a	n/a	n/a
Slovenia	0.57 (0.71)	0.74 (0.45)	520.85 (68.60)	4392	0.72 (0.76)	0.67 (0.38)	516.13 (67.94)	4215
South Africa	n/a	n/a	n/a	n/a	0.13 (0.76)	0.97 (0.70)	376.57 (85.13)	12,061
Spain	0.33 (0.63)	0.96 (0.90)	505.83 (69.18)	7681	n/a	n/a	n/a	n/a
Sweden	0.41 (0.54)	1.36 (0.94)	520.22 (68.28)	4096	0.42 (0.61)	2.81 (1.59)	500.86 (70.88)	3965
Thailand	n/a	n/a	n/a	n/a	0.30 (0.64)	1.77 (0.70)	431.06 (88.21)	6437
United Arab Emirates	0.32 (0.73)	1.31 (0.67)	454.19 (103.61)	20,537	0.23 (0.80)	1.36 (0.93)	465.94 (96.98)	17,629
Turkey	0.07 (0.55)	1.60 (1.06)	485.02 (93.55)	6358	0.22 (0.75)	0.69 (0.43)	458.92 (103.21)	5999
Egypt	n/a	n/a	n/a	n/a	0.29 (0.81)	1.14 (0.46)	396.60 (96.03)	7520
United States	0.39 (0.74)	1.62 (0.86)	541.71 (79.80)	9737	0.42 (0.77)	2.06 (1.14)	518.77 (82.22)	10,061
England	0.44 (0.64)	1.33 (0.48)	546.52 (84.89)	3854	0.62 (0.68)	1.75 (0.73)	519.07 (78.36)	4714
Northern Ireland	0.48 (0.62)	1.29 (0.58)	571.75 (84.83)	3085	n/a	n/a	n/a	n/a
Belgium (Flemish)	0.38 (0.69)	0.67 (0.44)	545.98 (60.79)	5325	n/a	n/a	n/a	n/a

Dep: dependent variable; Indep: independent variable; Con/Mod: control/moderating variable; Obs: number of observations. Figures are sample means with sample standard deviations in parentheses, weighted by the student sampling weight (TOTWGT) from the data file. The control/moderating variable (academic performance) is standardized by grade and country before the analyses. Source: TIMSS 2015 dataset.

In terms of the independent variable, the impression may be that most figures are quite a bit smaller than expected, overshadowing decades of mass investment in ICT. For example, New Zealand is the only country showing two days or more per week of school computer usage time in Grade 4, although the list somewhat expands in Grade 8 (Australia, Canada, New Zealand, Sweden, and the United States). However, it may be too cursory to determine that Table 3 indicates the contradictory reality of "overinvestment" and "underuse" of ICT resources in schools [47]. It should be remembered that the independent variable is derived from the item-response asking students about their using computers for schoolwork at school (see Figure 2). Thus, there is a possibility that some teacher-led computer activities were not counted as a part of school computer usage time. Fortunately, such an underestimation does not affect the consistency of the measurement.

In terms of the control/moderating variable, considerable performance gaps between countries do exist, but it is beyond the scope of this study to discuss such gaps. Further, using the values from Table 3, the variable is standardized by grade and country before the analyses. This manipulation has no statistical effects on the results in Section 4, being only for ease of interpretation, particularly in Section 4.2.

3.3. Models and Estimations

In identifying the loneliness deepening effect, this study uses the simplest form of the linear regression model (Model 1). The coefficient β_1, the influence of the independent variable X_i on the dependent variable Y_i, is estimated by grade and country.

$$Y_i = \beta_0 + \beta_1 X_i + \varepsilon_i \text{ (Model 1)} \quad (1)$$

More sophisticated identification strategies [48] are not used, because the definitions of the independent and dependent variables largely prevent the issue of endogeneity, as mentioned in Section 2.5. The independent variable is the frequency of using school computers for schoolwork under the instruction of teachers, while the dependent variable is an unintended emotional consequence that is irrelevant to schoolwork. Therefore, in principle, this study is free from reverse causality.

Further, as explained in Section 2.7, this study utilizes academic performance as the control variable to detect the residual chance of the endogeneity. Let Model 2 be an expansion of Model 1, with the control variable C_i and its squared, cubic terms added. The coefficient β_1 is then estimated by grade and country, each estimate being compared with the previous one from Model 1.

$$Y_i = \beta_0 + \beta_1 X_i + \beta_2 C_i + \beta_3 {C_i}^2 + \beta_4 {C_i}^3 + \varepsilon_i \text{ (Model 2)} \quad (2)$$

In identifying the loneliness inequality effect, academic performance now functions as the moderating variable, as explained in Section 2.7. Let Model 3 be another expansion of Model 1, with the moderating variable M_i and the interaction term X_iM_i added. The coefficients β_1 and β_3, which together form the slope of the independent variable X_i, are then estimated by grade and country.

$$Y_i = \beta_0 + \beta_1 X_i + \beta_2 M_i + \beta_3 X_i M_i + \varepsilon_i \text{ (Model 3)} \quad (3)$$

As examined in Section 4.1, there would be no significant difference in the estimation of β_1 between Models 1 and 2. This implies that X_i could be considered an exogenous variable. However, it is theoretically still possible for M_i to be an endogenous variable. Therefore, X_iM_i, the product of the two, could be an endogenous variable. Fortunately, some simulation results indicate that it is possible to estimate the coefficient of an interaction term between endogenous and exogenous variables in a fairly robust manner by simply using the linear regression model [49].

The ordinary least squares (OLS) estimator is used in the estimations. Although the weighted least squares (WLS) estimator reflects the different sampling probabilities of the observations, its actual benefit is less significant in this study, as simply confirming the statistical significance and sign of each estimate, rather than its detailed value, is sufficient. Furthermore, WLS estimates usually have larger standard errors than OLS ones, with decreased statistical powers [50,51].

Considering that the data are clustered by schools, this study calculates the cluster-robust standard errors. As the TIMSS 2015 was conducted in more than 100 schools in each country, it meets the asymptotic assumption of the cluster-robust standard errors. The vce (cluster clustvar) option in the regress command in STATA 15.1 is used for the calculations [48,52].

4. Results

4.1. Identification of the Loneliness Deepening Effect

Table 4 shows the estimation of the coefficient β_1 in Models 1 and 2 by grade and country. First, the estimates for Model 1 show statistically significant results for 14 out of 48 countries (29.2%) in Grade 4 and 13 out of 40 countries (32.5%) in Grade 8.

Table 4. Estimates of β_1 in Models 1 and 2 for identifying the loneliness deepening effect.

Country	Grade 4		Grade 8	
	Model 1	**Model 2**	**Model 1**	**Model 2**
Australia	−0.03 **	−0.03 **	−0.04 ***	−0.03 ***
Bahrain	−0.03	−0.02	−0.01	0.01
Armenia	−0.03	−0.02	0.06	0.06
Botswana	n/a	n/a	−0.13 ***	−0.09 ***
Bulgaria	−0.04	−0.03	n/a	n/a
Canada	−0.03 **	−0.04 ***	−0.01	−0.01
Chile	−0.05	−0.06	−0.03	−0.04
Chinese Taipei	0.02	0.01	−0.03	−0.04
Croatia	−0.11 **	−0.11 **	n/a	n/a
Cyprus	−0.03	−0.03	n/a	n/a
Czech Republic	−0.02	−0.02	n/a	n/a
Denmark	−0.01	−0.01	n/a	n/a
Finland	−0.08 **	−0.08 **	n/a	n/a
France	−0.05 *	−0.05 *	n/a	n/a
Georgia	−0.07 **	−0.05 *	−0.10	−0.10
Germany	−0.05	−0.06	n/a	n/a
Hong Kong	0.01	0.01	0.00	−0.01
Hungary	−0.04	−0.03	−0.13 *	−0.15 *
Indonesia	−0.03 *	−0.03 *	n/a	n/a
Iran	0.02	0.01	−0.06 *	−0.07 *
Ireland	−0.06 *	−0.07 *	0.00	0.00
Israel	n/a	n/a	−0.02	−0.02
Italy	−0.11 **	−0.11 **	−0.06	−0.07
Japan	0.04	0.02	−0.04	−0.05
Kazakhstan	−0.02	−0.02	−0.03	−0.03
Jordan	n/a	n/a	−0.04	−0.02
Korea	−0.01	−0.01	0.00	−0.01
Kuwait	0.03	0.04	−0.04	−0.03
Lebanon	n/a	n/a	−0.07	−0.04
Lithuania	−0.04	−0.02	0.10 *	0.09 *
Malaysia	n/a	n/a	−0.09 **	−0.08 **
Malta	n/a	n/a	−0.05	−0.06
Morocco	0.01	0.01	−0.06 **	−0.06 *
Oman	−0.05 *	−0.04 *	−0.01	0.00
Netherlands	−0.01	−0.01	n/a	n/a
New Zealand	−0.02	−0.02	−0.03 *	−0.03 *
Norway	−0.04 ***	−0.04 ***	0.00	0.00
Poland	−0.01	−0.01	n/a	n/a
Portugal	0.02	0.01	n/a	n/a
Qatar	−0.04	−0.02	−0.09 ***	−0.08 **
Russian Federation	−0.04 *	−0.04 *	−0.02	−0.01
Saudi Arabia	−0.04	−0.03	−0.17 ***	−0.16 ***
Serbia	−0.03	−0.02	n/a	n/a
Singapore	0.00	0.00	−0.05 ***	−0.04 ***
Slovak Republic	−0.08 **	−0.06 *	n/a	n/a
Slovenia	−0.07	−0.07	0.00	0.00
South Africa	n/a	n/a	−0.02	−0.01
Spain	−0.02	−0.02	n/a	n/a
Sweden	−0.02	−0.02	−0.01	−0.01
Thailand	n/a	n/a	0.00	0.00
United Arab Emirates	−0.01	0.00	−0.04	−0.06 *
Turkey	0.00	0.00	−0.01	0.00
Egypt	n/a	n/a	−0.13 ***	−0.08 *
United States	−0.01	−0.02	−0.03 *	−0.02 *
England	0.00	−0.02	−0.03	−0.02
Northern Ireland	−0.07 *	−0.08 **	n/a	n/a
Belgium (Flemish)	0.06	0.05	n/a	n/a

*** $p < 0.001$; ** $p < 0.01$; * $p < 0.05$. Cluster(school)-robust standard errors are calculated. Source: TIMSS 2015 dataset.

As discussed in Section 3.2, the statistical insignificance for about 70% of the countries can be interpreted as a result of the conservative nature of the dependent variable. However, the signs of the estimates are consistently negative for the remaining 30% with statistical significance. In Grade 4, all 14 countries show negative effects, and in Grade 8, 12 of the 13 countries do (Lithuania being the exception).

The situation is invariant even after the control variable is added. Apart from minor changes in estimates or *p*-Values, the estimation results for Models 1 and 2 remain almost the same, only the United Arab Emirates in Grade 8 shifting from a statistically insignificant effect to a statistically significant negative one. As explained in Section 2.7, this implies that the causal direction from school computer usage time to satisfaction with peer relationships can be determined quite safely.

The results are also similar between Grades 4 and 8. If the comparison is narrowed down to the 31 countries that have data for both grades, the estimates for Model 1 show statistically significant negative effects for eight countries (25.80%) in Grade 4 and nine countries (29.03%) in Grade 8. The two counts are almost the same, considering the offsetting existence of one positive effect in Grade 8 (Lithuania). In terms of countries, only one (Australia) shows negative effects in both grades; seven countries show negative effects only in Grade 4 and eight countries only in Grade 8. In short, no trend is found between the two grades.

Thus, Table 4 indicates that the digitalization of the classroom is likely to have a loneliness deepening effect on elementary and middle school students: when school computer usage time rises, there is a strong possibility that satisfaction with peer relationships goes down.

Nevertheless, it is inconceivable that school computers' effects work exactly to the same degree and in the same direction for every student. Thus, in Section 4.2, it is additionally examined how each student's academic performance moderates the loneliness deepening effect.

4.2. Identification of the Loneliness Inequality Effect

Table 5 shows the estimation of the coefficients β1 and β3 in Model 3 by grade and country. In particular, the estimates of β3, the coefficient of the interaction term, show statistically significant results for only 5 out of 48 countries (10.42%) in Grade 4 and 6 out of 40 countries (15.00%) in Grade 8.

Actually, it is a natural consequence that fewer than half the countries are statistically significant compared with the previous identification of the loneliness deepening effect. It is well known that when an interaction term is added and tested, a sample size that is at least several times bigger than the original is required to maintain the statistical power [53]. Indeed, interactions are much harder to identify than main effects.

However, it must be noted that the signs of the estimates are consistently positive for the small number of countries with statistical significance. In Grade 4, all five countries show positive interactions, and in Grade 8, five of the six countries do (Thailand being the exception). In other words, students with higher academic performance experience gentler negative slopes—or even positive ones—of the independent variable.

To take Australia in Grade 4 as an example, as the standardized score of academic performance (M_i) increases along the five points of −2, −1, 0, 1, and 2, the slope ($\beta_1 + \beta_3 M_i$) also increases along the five corresponding points of −0.082, −0.058, −0.034, −0.010, and 0.014, respectively. The value for which the sign of the slope switches ($-\beta_1/\beta_3$) is 1.42. Assuming that academic performance is normally distributed in each country, 92.22% of the students continue to experience the negative socioemotional effects of ICT, while only 7.78% enjoy the positive ones.

The sign-switching values vary across countries. Excepting Thailand in Grade 8, which shows a negative interaction, and regarding statistically insignificant estimates of β_1 as simply zero, the value goes from 0 (Lithuania, Spain, the United States) via 1.14 (Slovakia) to 1.42 (Australia) in Grade 4 and from 0 (Japan, Korea) via 1.42 (the United Arab Emirates) and 1.80 (Hungary) to 2.19 (Malaysia) in Grade 8.

Table 5. Estimates of β_1 and β_3 in Model 3 for identifying the loneliness inequality effect.

Country	Grade 4		Grade 8	
	β_1	β_3	β_1	β_3
Australia	−0.034 **	0.024 *	−0.029 ***	−0.002
Bahrain	−0.027	−0.006	−0.013	0.016
Armenia	−0.015	0.029	0.063	0.019
Botswana	n/a	n/a	−0.088 ***	0.010
Bulgaria	−0.032	0.004	n/a	n/a
Canada	−0.036 ***	0.008	−0.012	−0.011
Chile	−0.058	0.047	−0.041	0.017
Chinese Taipei	0.017	−0.045	−0.038	0.005
Croatia	−0.113 **	−0.015	n/a	n/a
Cyprus	−0.026	−0.004	n/a	n/a
Czech Republic	−0.019	−0.017	n/a	n/a
Denmark	−0.013	−0.009	n/a	n/a
Finland	−0.082 **	0.026	n/a	n/a
France	−0.050 *	0.019	n/a	n/a
Georgia	−0.048 *	0.020	−0.101	−0.001
Germany	−0.058	0.021	n/a	n/a
Hong Kong	0.004	0.010	0.007	−0.054
Hungary	−0.031	0.025	−0.164 **	0.091 *
Indonesia	−0.027 *	−0.006	n/a	n/a
Iran	0.016	−0.015	−0.064 *	−0.034
Ireland	−0.069 *	0.021	−0.003	−0.007
Israel	n/a	n/a	−0.022	−0.007
Italy	−0.109 **	−0.015	−0.065	−0.011
Japan	0.025	0.009	−0.057	0.095 **
Kazakhstan	−0.019	−0.001	−0.033	−0.012
Jordan	n/a	n/a	−0.026	0.006
Korea	−0.014	−0.001	−0.005	0.043 *
Kuwait	0.045	0.012	−0.028	−0.023
Lebanon	n/a	n/a	−0.043	−0.017
Lithuania	0.009	0.099 ***	0.102 **	0.049
Malaysia	n/a	n/a	−0.125 ***	0.057 *
Malta	n/a	n/a	−0.047	−0.118
Morocco	0.013	0.013	−0.058 *	−0.017
Oman	−0.043 *	0.013	0.002	0.047
Netherlands	−0.014	0.004	n/a	n/a
New Zealand	−0.018	−0.011	−0.028 *	0.000
Norway	−0.041 **	−0.006	−0.002	0.006
Poland	−0.004	0.034	n/a	n/a
Portugal	0.016	0.013	n/a	n/a
Qatar	−0.029	0.006	−0.094 **	0.020
Russian Federation	−0.043 *	−0.006	−0.010	−0.028
Saudi Arabia	−0.033	0.035	−0.154 **	0.051
Serbia	−0.028	−0.010	n/a	n/a
Singapore	−0.004	0.040	−0.061 ***	0.020
Slovak Republic	−0.064 *	0.056 *	n/a	n/a
Slovenia	−0.069	0.020	−0.006	0.039
South Africa	n/a	n/a	−0.025	0.014
Spain	−0.025	0.029 **	n/a	n/a
Sweden	−0.023	0.001	−0.013	0.006
Thailand	n/a	n/a	0.008	−0.022 *
United Arab Emirates	−0.007	0.001	−0.071 **	0.050 ***
Turkey	−0.001	−0.005	−0.002	−0.008
Egypt	n/a	n/a	−0.086 *	0.019
United States	−0.016	0.021 *	−0.022 *	0.004
England	−0.017	0.026	−0.029	0.019
Northern Ireland	−0.086 **	−0.022	n/a	n/a
Belgium (Flemish)	0.050	0.000	n/a	n/a

*** $p < 0.001$; ** $p < 0.01$; * $p < 0.05$. Cluster(school)-robust standard errors are calculated. Source: TIMSS 2015 dataset.

As explained in Section 3.3, these figures were calculated from the unweighted estimates and thus lack absolute accuracy. Nevertheless, once these figures are taken as given, and the normal distribution of academic performance is assumed again, at most 50% or at least 1.43% of the students are high performers in each country who experience the loneliness deepening effect's reversal—to the loneliness alleviating effect.

In this sense, despite the greater difficulty in identifying statistically significant results, Table 5 does indicate the loneliness inequality effect of the digitalization of the classroom: for elementary and middle school students with lower academic performance, school computer usage time is likely to have a stronger negative effect on satisfaction with peer relationships, and vice versa.

5. Discussion

5.1. Implications of the Loneliness Deepening Effect

The identification of the loneliness deepening effect in Section 4.1 does provide an inescapable, critical message for the education community. It confirms—in the relatively invisible socioemotional sphere—that school computers currently produce a certain degree of negative educational outcomes in the global dimension, beyond national contexts.

In the debate between the optimistic consensus and techno-skepticism, it can be regarded as a factor that raises the latter's score (see Sections 2.1 and 2.2). Or, it can be understood to demonstrate that the conflict between the two promises within the optimistic consensus will not be resolved, with the negative superiority of the personalization over the cooperativization being dominant in the end (see Section 2.3). By either explanation, it becomes clear that the present-day use of ICT in the classroom falls short of the optimistic consensus.

Some debaters, in an attempt to present a third option between the two poles of optimistic consensus and techno-skepticism, have hypothesized that there may be a threshold grade or age where computers' negative effects reverse to positive [22] (pp. 205–206). However, as examined in Section 4.1, the estimation results are similar between Grades 4 and 8, with negative effects being universal in both. In other words, insofar as the TIMSS 2015 is concerned, the hypothesis cannot be confirmed; such a threshold either does not exist or does at some point after Grade 8.

5.2. Implications of the Loneliness Inequality Effect

The identification of the loneliness inequality effect in Section 4.2 can be regarded as more evidence for critical opinions of ICT's educational effectiveness. It shows that the current usage of school computers has the additional risk of expanding the scope of educational inequality to the socioemotional dimension.

In particular, it is highly plausible that the conflict between the two promises of cooperativization and personalization is playing a decisive role (see Section 2.3). Actually, one of the few prior empirical studies addressing the second-level digital divide in education—the problem of differential usage—provides a link to support this interpretation (see Sections 2.4 and 2.5).

According to Warschauer and Matuchniak (2010), it is frequently observed that students use school computers in quite different patterns depending on their family background (SES, race, etc.) and academic performance. Disadvantaged students often seem to use computers for the purpose of "remedial drills and practices," whereas advantaged ones utilize them for "higher-order skills" like modeling, presentation, and other applications. The former is usually done within the scope of preplanned learning courses, allowing only limited variations through adaptive one-to-one feedback between the individual student and computer software or website. In that sense, it corresponds well to the personalization of education. On the contrary, the latter often encourages constructivist activities, open-ended discussions, and other collective works among teachers and students, which can be appropriately described as the cooperativization of education [32].

Thus, a mechanism can be conceived that differential school computer usage because of students' background or academic performance—high-SES/high-performing students' cooperativized use versus low-SES/low-performing ones' personalized use—leads to different socioemotional outcomes. This mechanism may not be the only cause of the loneliness inequality effect, but it seems to be the most reasonable explanation for now.

It is regrettable that this partly hypothetical explanation cannot be tested further, for the independent variable is measured solely on a quantitative dimension, without any information about differential usage. It is the limitation of this study, which has been already shared by many prior empirical studies on the educational effectiveness of ICT [54]. It will be a major challenge for follow-up studies.

Actually, the issue of cooperativization versus personalization is not that new in the field of sociology of education. As a prime example, the classical proposition of James Coleman, a sociologist and pioneer in the educational effectiveness research, assumes the irreconcilability of the two [55,56]. Regarding schools as a social organization, he demonstrated that the effectiveness of a learning process—even with identical content and quality—can differ depending on whether it is based on individuals' isolated activities or the whole classroom community's collective ones. His conclusion was that the latter is more effective than the former, and this study's finding reaffirms this. Unfortunately, the ideal of networked individualism is not yet realized, at least in the digitalized classroom [30].

6. Conclusions

6.1. Lessons for Sustainable Education in the E-Learning Era

The findings of this study suggest that the overall stance of the education community on ICT needs to be more cautious than now. In other words, a more rigorous—and sometimes even self-censoring—approach is required before bringing computers and the Internet into the classroom. Similarly, candid questions about the current logic dominating the digitalization of the classroom are called for. Has the introduction of ICT so far been done with a purely educational focus? Has the commercialism of ICT companies not been involved? Or has ICT not been misunderstood as an expedient tool to replace teachers' teaching efforts rather than promote them [10,47]?

To be sure, the findings cannot be linked to the Ludditish claim that ICT should be eliminated from the classroom, nor the technological determinism that ICT's negative effects are beyond our control. Clearly, ICT still has the potential to be a truly beneficial tool for young students. The very existence of the loneliness inequality effect confirms this. While the effect does indicate another aspect of the digital divide in education, it also shows the possibility that the ultimate effects of ICT can be moderated by human users' own capabilities. According to the explanation in Section 5.2, high-performing students seem to possess the ability to utilize computers in fairly autonomous ways, mobilizing them in their own constructive, creative, and collective works, while low-performing ones do not.

Then, the problem is not technology itself, but the subjective conditions of users that determine its effectiveness and sustainability in the last instance. For example, Jane Healy, a child psychologist who can be grouped as a techno-skeptic but who also strongly rejects any Ludditish temptations, has presented a list of prerequisites for using ICT in educational purposes in genuinely wise and effective manners. Although the list was made more than two decades ago, it still contains considerable validity and timeliness at this point, characterized by the near-universalization of ICT resources and e-learning practices [22] (pp. 245–246).

According to Healy, technology can contribute to learning:

- *if* a child has sufficient cognitive skills and social development;
- *if* it is not substituting for important developmental experience;
- *if* we are not expecting it to do what it cannot do;
- *if* parenting and teaching retain priority;
- *if* it complements a well-planned curriculum;

- *if* it does not steal funds from more important needs (e.g., early childhood education, arts programs);
- *if* we are judicious in planning and selection of computer software and activities;
- *if* we do not become seduced by flashy graphics and digital legerdemain;
- *if* parents and teachers are willing to provide a human scaffold for technology-assisted learning.

Only if such preconditions are met may young students then profit from wise choices in this emerging field of e-learning, and ICT can finally be an integral part of sustainable education—maximizing the opportunity to learn and offering adequate support for all students—both in terms of academic performance and socioemotional development [15].

6.2. Lessons for the Whole Society

The primary focus of this study has been educational. Nevertheless, some lessons can also be discussed on the broader dimension of whole society, especially from the angle of digital sociology. While convenience is certainly enhanced as digital technology's mediating role in our public and daily lives is becoming more profound, its adverse effects are the other side of the coin. Accordingly, the critical reflection that the "digital society" is also the "digital risk society" is increasingly salient, and issues such as Internet addiction disorder, privacy infringement, cyberbullying, and other forms of digital violence are cited as the "wicked problems" of the digital risk society [57,58].

The findings of this study, as an example of the weakened socioemotional ties caused by digitalization, can be understood as another manifestation of those potential risks. Furthermore, the identification of the loneliness inequality effect leads us to the issue of digital divide, another wicked problem of the digital risk society.

For sustainable use of digital technology, a balanced and realistic consideration of its opportunities and risks is essential. Such an effort can be a cornerstone of effective policy interventions and wise social practices to maximize technology's advantages and minimize its adverse effects. This study is also expected to stimulate meaningful discussions on this broader dimension, beyond the narrow, technical field of elementary and secondary education.

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