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# **Heterogeneous Effects of ICT on Students Outcomes**

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# Heterogeneous Effects of ICT on Students Outcomes\*

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# Abstract

Globally, the use of information and communication technology (ICT) in schools has been growing in recent years. While much of the existing literature focuses on the overall impact of ICT on academic performance, this paper examines its heterogeneous effects on both students' cognitive and non-cognitive skills. Based on fixed effects estimations using a panel data set of students and school surveys, we find no overall effects on students' test scores in Japanese and math, as well as on grit, whereas the regular use of ICT in class likely improves self-efficacy. Further examination reveals that the effects of ICT on these cognitive and non-cognitive skills depend on students' initial learning levels and school factors, highlighting the importance of considering heterogeneous effects when integrating ICT into the classroom.

*JEL classification*: I21 *Keywords*: ICT, Cognitive skills, Self-efficacy, Grit

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### **1. Introduction**

The rapid spread of innovative technologies, such as artificial intelligence (AI), robotics, Internet of Things (IoT), and big data, has led to an increasingly digitalized society. In line with this societal change, the adoption of information and communication technology (ICT) by schools has been growing steadily in recent years. For example, the ratio of personal computers to students in public schools in Japan has increased from 0.2 in 2019 to 1.1 in 2024, driven by a government-led initiative.<sup>1</sup> Given the dramatic advancements in the provision of ICT equipment over the past several years, a key issue for policymakers and educators now is how to integrate it effectively into the classroom.

Prior studies on the impact of ICT on students are largely focused on their cognitive skills, as measured by test scores (Bulman & Fairlie, 2016; Comi et al., 2017; Hong, Liu, & Zhang, 2024). By contrast, its effect on non-cognitive skills is still less known, although non-cognitive skills are becoming increasingly important for success in this rapidly changing society (Heckman, Stixrud, & Urzua, 2006; Weinberger, 2014). While evidence in the existing literature is limited, Munakata and Utsumi (2024) find that the use of ICT potentially influences students' grit and self-efficacy, but the effects vary based on students' characteristics, such as gender and socio-economic status (SES). This finding points to the importance of understanding not only how ICT may affect students, but also under what conditions these effects may differ. Building upon the work of Munakata and Utsumi (2024), we extend our analysis to investigate the heterogeneous effects of ICT use in schools on both students' non-cognitive and cognitive skills. In particular, we explore how differences in students' initial learning levels and school environments may influence the effect of ICT on student outcomes.

The key contributions of this paper are twofold. First, we highlight the effects of ICT use not only on academic performance, but also on non-cognitive skills, an outcome that has received limited attention in the literature to date. Second, we provide a new analysis on the heterogeneous effects of ICT. There is scant research that examines heterogeneous effects, partly because much of the prior research finds negligible overall impacts of ICT (Bulman & Fairlie, 2016; Hull & Duch, 2018). While some studies analyze how the impact of ICT on student learning may vary by student

<sup>&</sup>lt;sup>1</sup> The statistics are obtained from the survey conducted in 2023 by the Ministry of Education, Culture, Sports, Science and Technology (MEXT) and available at the following website: https://www.mext.go.jp/a menu/shotou/zyouhou/detail/mext 00062.html

characteristics, such as sociodemographic background, there is limited research on the differential impacts of ICT by school characteristics, let alone its effects on non-cognitive skills. Therefore, the findings from our analysis can contribute to filling this gap in the literature.

Using a panel data set from Saitama prefecture in Japan and annual school surveys managed by the Ministry of Education, Culture, Sports, Science and Technology over the period between 2018 and 2023, we conduct fixed effects estimations and find varying effects of ICT on non-cognitive skills. No overall effect of ICT is observed for grit, but further examination reveals that the adoption of digital textbooks is associated with higher grit, especially in schools with less teacher training. In terms of self-efficacy, we find that the frequent use of ICT in class tends to enhance self-efficacy, particularly for students initially in the lower half of the Japanese score distribution and those in the non-top quartile for math. The increased use of ICT in math class also appears to augment self-efficacy, with larger effects in schools that invest more in teacher training. Furthermore, the introduction of digital textbooks likely improves self-efficacy in schools with a less cooperative atmosphere among teachers. With respect to cognitive skills, no average effect of ICT is found for Japanese and math test scores. However, additional analysis shows that the regular use of ICT in class is more likely to improve students' scores in schools with less favorable disciplinary cultures, which may help narrow the academic performance gap between schools with and without discipline problems. Some of these findings are contrary to what one might expect, yet they shed light on the potential heterogeneous effects of ICT on students, based on their learning levels and school characteristics.

The remainder of the paper is structured as follows. Section 2 provides a conceptual framework for how ICT may affect student outcomes. Section 3 presents information on the data used in this paper. Section 4 describes the estimation strategy used in our regression analysis. Sections 5 and 6 discuss the regression results for non-cognitive skills and cognitive skills, respectively. Section 7 concludes with policy implications.

### 2. Conceptual Framework

The introduction and use of ICT may affect student outcomes in various ways. Figure 1 summarizes the possible mechanisms proposed in Munakata and Utsumi (2024). ICT is likely to affect student learning, for example, by enabling individualized learning, allowing teachers to offer timely feedback, encouraging students to acquire new skills, and supporting interactive and

collaborative learning. These features of ICT may also contribute to the development of students' non-cognitive skills. In general, grit is enhanced by four key factors, including interest, practice, purpose, and hope (Duckworth et al., 2007), while self-efficacy is strengthened through accumulating successful experiences, having vicarious experiences, receiving verbal persuasion from others, and managing physiological and emotional states (Bandura, 1977). Effective use of ICT has the potential to stimulate these sources of non-cognitive skills development.<sup>2</sup>

The impact of ICT on student skills may differ by their backgrounds. In Japanese elementary and junior high schools, children from various academic backgrounds are generally placed in the same classroom and receive the same instruction. However, each student has a different learning level, which means their understanding of class content is likely to vary. Similarly, the speed and process of acquiring new knowledge and skills, including the use of ICT, can differ according to their learning abilities. As a result, the introduction of ICT may have a greater positive impact on students, particularly those with higher learning abilities, as they may be able to master the use of new learning tools more quickly. Conversely, students with lower learning levels may benefit from the individualized learning opportunities offered by ICT (de Barros & Ganimian, 2024). In either case, it is essential to take these differences in student characteristics into account when evaluating the impact of ICT.

Moreover, the effectiveness of ICT may vary depending on the school environment. In this paper, we particularly focus on three school factors that may be relevant to the effective use of ICT. The first one is schools' investment in teacher training. A number of studies show that teacher quality is an important factor that influences their teaching practices and thus student learning (Rockoff, 2004; Rivkin, Hanushek, & Kain, 2005). The degree to which a school is committed to improving their teacher quality can potentially influence how effectively ICT is integrated into the classroom. Schools with higher investment in teacher training may experience a larger positive impact of ICT on student outcomes, particularly if ICT is used in ways that complement the work of trained teachers. However, there is also the potential risk that these schools could diminish the benefits of ICT if it is used in ways that substitute high-quality teaching.

The second school factor to consider is a cooperative culture among teachers. Goddard, Goddard, and Tschannen-Moran (2007) demonstrate that a supportive and collaborative

 $<sup>^2</sup>$  For more details on the potential mechanisms through which ICT can affect non-cognitive skills, see Munakata and Utsumi (2024).

environment among teachers is crucial for school effectiveness and student performance. It is, therefore, plausible that the positive effect of ICT on student outcomes will be greater for students in schools with a more collaborative atmosphere among teachers. However, it is also possible that the personalized, interactive, and collaborative learning promoted by ICT may support the efforts of teachers in less cooperative schools and, in turn, enhance student skills.

The third dimension to consider is school disciplinary culture. On the one hand, students are likely to perform better in a more favorable disciplinary climate (OECD, 2019). Students' negative behavior and an unfavorable disciplinary climate may undermine the effectiveness of new tools introduced in class. Thus, the introduction of ICT in class may be more effectively carried out in schools with stronger discipline. On the other hand, schools with a poor disciplinary climate may benefit from the use of ICT if it complements teachers by enabling personalized learning and facilitating collaboration among students. Arguably, the effects of ICT on students ultimately depend on whether it is used as a complement or a substitute, and under what conditions it is applied. In light of these possibilities, this paper examines how the effects of ICT on student outcomes may vary according to student and school characteristics discussed in this section.

### 3. Data

Two data sets from the Japanese government are employed in our analysis. First, we use a panel data set that is collected annually by the Department of Education in Saitama prefecture in Japan. The prefecture surveys all public schools residing in 62 participating municipalities and their students from grades four through nine at the beginning of a school year (in April to May).<sup>3</sup> Student characteristics and outcome measures for non-cognitive and cognitive skills are drawn from student surveys. We also use information on school characteristics, including the extent of ICT use in class and general school environment, from school questionnaires in this data set.

Second, we complement our data on the measurements of ICT by an administrative data set collected annually by the Ministry of Education, Culture, Sports, Science and Technology (MEXT) at the end of a school year (in March). MEXT surveys all public schools in Japan regarding the use of ICT in schools. Combining these two sources, we create four different measurements of ICT: i) the ratio of computers to students; ii) the use of digital textbooks; iii) the

<sup>&</sup>lt;sup>3</sup> An academic calendar starts in April in Japan. In 2020, the survey was delayed due to the pandemic and conducted in June and July.

frequency of ICT use in Japanese classes; and iv) the frequency of ICT use in math classes. The measurement (ii) is a dummy variable that takes the value of one if schools have adopted digital textbooks, and zero otherwise. The measurements (iii) and (iv) are binary variables that equal one if ICT tools are used by students in every class or almost all classes, and zero otherwise.

Our sample covers the period between 2018 and 2023. Based on the data availability, analysis on cognitive skills is based on all students, whereas analysis on non-cognitive skills is conducted by cohort. Different types of non-cognitive skills are measured across different cohorts to reduce the number of questions asked to students. Table 1 provides information on the types of non-cognitive skills measured for each cohort and the periods covered for each measurement. The first cohort, Cohort A, is assessed for grit based on questions in Duckworth et al. (2007), and the second cohort, Cohort B, is assessed for self-efficacy on a basis of questions in Pintrich et al. (1991). A five-point Likert scale is used for these questions. After summing all the values, we standardize them by year to compose each index of non-cognitive skills. Both cohorts consist of students in grades six through nine. In contrast to these non-cognitive skills, cognitive skills, measured by Japanese and math exam scores, are available for all students. The standardized values of these scores are used as an outcome variable. A unique aspect of this data set is that the Japanese and math exams conducted as part of their survey are designed using item response theory.<sup>4</sup> This design makes it possible to compare student performance across different cohorts and periods.

Considering potential differential effects of ICT use on student outcomes by school characteristics, three measurements of school environment, which may influence the effectiveness of ICT integration into the classroom, are taken into account in our analysis. The first measurement is the degree of school efforts in investing in human capital development of teachers. To measure this, we use the number of teacher training sessions held in a year. For this question, schools are asked to choose from five-scale answers, with the highest scale indicating 15 times or more of training sessions held in the previous year. The second measurement considers school culture related to teachers, in particular, cooperative atmosphere among teachers and staff. The third measurement is school culture related to student behavior, in particular, the degree of problems with school discipline. The last two questions are rated on a four-point Likert scale. For all three

<sup>&</sup>lt;sup>4</sup> Student test scores are estimated based on the one-parameter logistic model and range from -5.8 to 5.8. We regard the values of -5.8 and 5.8 as outliers and exclude them from our analysis.

measurements, we create binary variables that equal one if a school chooses the highest performance category, and zero otherwise.

Table 2 provides summary statistics of the variables used in regression analysis. The regression sample consists of 320,141 observations from students in grades six through nine. In terms of ICT measurements, the availability of computers to students at school varies across schools and over time, with the ratio of personal computers to students ranging from 0.01 to 3.82. During the sample period, 26 percent of students attend a school that has introduced a digital textbook. Slightly less than 10 percent of students use ICT in all or almost all classes in Japanese and mathematics. This suggests that the availability of digital devices does not necessarily mean that students are using them in every class. About one-third of the sample is in a school where 15 or more times of teacher training sessions are held in the previous year. As for school culture, more than half of the sample is in a pleasant school environment. In particular, a cooperative atmosphere among teachers is present in nearly three-fourths of the sample, and over 60 percent are in a school that reports no problems with school discipline.

Two proxies for students' socio-economic status are available in the data set: i) private cram school attendance; and ii) the number of books at home. We create a dummy variable that takes the value of one if a student attends four or more hours of lessons at a private cram school per week, and another one that takes the value of one if a student has more than 10 books at home.<sup>5</sup> These variables represent the educational investments students receive in a household and are likely to affect their learning. In our data set, 42 percent of the sample attend four or more hours of classes at a private cram school per week. Eleven percent of the students possess 10 or fewer books at home.

### 4. Empirical Framework

In estimating the effects of ICT use in school on student outcomes, a simple ordinary least squares (OLS) estimation may be subject to potential omitted variable bias. For instance, unobserved student characteristics, such as motivation and innate ability, may be correlated with both the effective use of ICT tools and their learning outcomes or development of non-cognitive skills. Unobserved school characteristics, such as teacher ability and resource availability, may also

<sup>&</sup>lt;sup>5</sup> The threshold of 10 books to distinguish low from non-low socio-economic status is based on the methodology used in Yamaguchi, Ito, and Nakamuro (2023).

influence both the effective integration of ICT in the classroom and student learning in general. Schools that are keen to innovative teaching may adopt ICT tools more quickly than other schools, along with teaching methodologies that are more effective for student learning. These intrinsic school characteristics may systematically influence not only key ICT-related variables but also student outcome variables. To reduce the bias in the estimates caused by such unobserved heterogeneity, we use the following fixed effects estimations for our analysis:

$$Y_{igst} = \alpha_1 + \beta_1 S_{igs(t-1)} + \gamma_1 X_{igst} + \theta_i + \rho_g + \mu_t + \varepsilon_{igst}$$
(1)

where  $Y_{igst}$  represents an outcome variable (the standardized value of non-cognitive or cognitive skills) of student *i* in grade *g* at school *s* in year *t*;  $S_{igs(t-1)}$  refers to an ICT-related measurement in the previous year;  $X_{igst}$  is a vector of proxies for a student's socio-economic status (SES);  $\theta_i$ refers to student fixed effects, accounting for both observed and unobserved time-invariant characteristics of students;  $\rho_g$  and  $\mu_t$  denote grade and year effects, respectively;<sup>6</sup> and  $\varepsilon_{igst}$  is an error term with mean zero. Standard errors are clustered at the school level. While student fixed effects may not fully capture unobserved school characteristics, fundamental changes within schools typically occur over long periods, so fixed effects can partly subsume the inherent nature of schools. Additionally, they can also control for students' potential endogenous selection of schools, provided that this selection is driven by time-invariant student factors, such as parents' basic commitment to and involvement in their children's education.

In addition to investigating general effects of ICT on student outcomes, we also pay attention to heterogeneous effects by student and school characteristics. In particular, we examine if the effects differ by the initial learning level of students and their school environments. As discussed in Section 2, students who have higher learning abilities may, for example, be able to quickly learn and utilize the newly introduced devices more effectively. School factors, such as teachers' skills, may also influence how easily teachers can introduce new tools to students and make use of them (OECD, 2020). Additionally, school culture can affect the successful adoption of new tools. For instance, a cooperative atmosphere among teachers may foster the exchange of ideas among them to facilitate better use of ICT, while a positive disciplinary climate may help students listen to teachers and adapt to new tools quickly. We investigate these possibilities by

<sup>&</sup>lt;sup>6</sup> When non-cognitive skills are used for an outcome variable, a sample consists of only one cohort, so grade effects are removed while year effects remain in the equation.

running regressions by sub-samples based on the initial learning level of students and by adding an interaction term between ICT-related variables and school characteristics.

### 5. Results for Non-Cognitive Skills

### 5.1 Main Results

The regression results for non-cognitive skills are summarized in Table 3. Overall, no significant effects of ICT indicators are found for grit. In contrast, the frequent use of ICT in both Japanese and math classes is likely to increase students' self-efficacy, which is consistent with earlier findings in Munakata and Utsumi (2024).<sup>7</sup> The positive findings for self-efficacy may be due in part to the fact that students are able to acquire new skills and knowledge effectively through the regular use of ICT tools in the classroom, which may help build their confidence in their ability to learn.

# 5.2 Heterogenous Effects by Initial Learning Level

When the sample is disaggregated into four groups based on the initial learning level of students, we again find no statistically significant effect of ICT on students' grit in any of the sub-samples (Table 4).<sup>8</sup> By contrast, Table 5 shows that the frequent use of ICT in class is statistically and positively correlated with students' self-efficacy in all of the sub-samples, but the magnitude varies. For example, the frequent use of ICT in Japanese class is positively and significantly associated with self-efficacy in all groups, with stronger association in the lower half and the weakest in the third quartile (column (3), Table 5). As for the regular use of ICT in math class, as column (4) in Table 5 indicates, the magnitude of the positive coefficient is relatively smaller in the top quartile, compared to the lower quartiles. This may suggest that the more frequent use of ICT in math class has the potential of increasing self-efficacy, especially that of non-top students. The existing literature finds that self-efficacy plays a critical role in academic performance (Pajares & Miller, 1994). Therefore, the positive impact of ICT on self-efficacy may also contribute to academic success in the long term.

<sup>&</sup>lt;sup>7</sup> The sample period is extended with new available data in this analysis, and the frequency measurement is updated, but the results are qualitatively the same.

<sup>&</sup>lt;sup>8</sup> In Table 4, all the coefficients are found to be insignificant after correcting for multiple hypothesis testing based on Benjamini and Hochberg (1995).

# 5.3 Heterogeneous Effects by School Characteristics

Tables 6 through 8 provide a summary of regression results on heterogeneous effects of ICT use on non-cognitive skills by three different school factors. In order to derive meaningful interpretations, we focus our discussion on columns where three coefficients for ICT, school factor, and their interaction term are all statistically significant. In terms of grit, column (2) in Table 6 shows that the introduction of digital textbooks is likely to increase grit in general, although it is marginally significant at the 10 percent level. In Japan, digital textbooks are primarily used in subjects such as mathematics and English. One advantage of digital textbooks over traditional paper textbooks is that in mathematics, for example, students can easily erase lines and freely play with figures, which allows students to make trial and error.<sup>9</sup> This process of trial and error, in turn, may help students develop perseverance through the accumulation of practice. However, the negative and significant coefficient for the interaction term implies that its positive effect is reduced if a school implements 15 or more of teacher training sessions. While schools with more teacher training sessions are generally found to increase students' grit, indicated by the positive coefficient for teacher training, the negative finding on the interaction term may reflect the limited use of digital textbooks at present. In fact, a survey by the Ministry of Finance shows that teachers find it easier to use paper textbooks than digital ones, so digital textbooks may not yet be used efficiently in a way that complements trained teachers and enhances students' grit.<sup>10</sup>

A contrasting result is obtained for self-efficacy. As column (8) in Table 6 shows, all three coefficients are statistically and positively significant, although the second term is marginally significant at the 10 percent level. Taken together, the results imply that the frequent use of ICT tools in math classes likely increases students' self-efficacy, and its effects are greater for students in schools that conduct more teacher training. This may be because teacher training increases their human capital, which enhances the effectiveness of ICT use in class and ultimately contributes to the development of students' self-efficacy. ICT tools function as a complement to teachers in this case, enabling them to skillfully incorporate it into their lessons.

Column (6) in Table 7 suggests that the adoption of digital textbooks is positively associated with students' self-efficacy, especially in schools with a less cooperative culture among

<sup>&</sup>lt;sup>9</sup> The examples of how digital textbooks are used in the classroom can be found at the following website of the MEXT: https://www.mext.go.jp/content/20240621-mxt\_kyokasyo01-000035395\_2.pdf.

<sup>&</sup>lt;sup>10</sup> The 2023 survey results are available at the following website of the Ministry of Finance: https://www.mof.go.jp/policy/budget/topics/budget\_execution\_audit/fy2024/sy0606/11.pdf.

teachers. One possible reason for this counterintuitive result may be that students' self-efficacy increases by acquiring new skills through a newly introduced digital textbook. Digital textbooks offer a variety of functions, such as reading aloud and multimedia resources, allowing students to choose a learning method that best suits them and study at their own pace, thereby facilitating individualized learning. This effect could be more pronounced in schools where teachers exhibit a less cooperative culture and their students were not benefiting from the positive externalities arising from a cooperative culture before the introduction of digital textbooks.

### 6. Results for Cognitive Skills

# 6.1 Main Results

Turning to cognitive skills, none of our ICT measurements are statistically significant for both Japanese and math scores.<sup>11</sup> These results are, in fact, in accord with the findings from earlier studies in developed countries that tend to find no or limited impacts of ICT on academic outcomes (Angrist & Lavy, 2002; Hall, Lundin & Sibbmark, 2021; Hall & Lundin, 2024). On the one hand, the use of ICT tools, such as laptops and tablets, may enhance student learning by offering more personalized learning, encouraging active engagement in class, and increasing their motivation. On the other hand, potential issues with ICT use in class include students' distraction from teacher instruction and reduced time for other activities that may have a more significant impact on student performance, potentially leading to negative learning outcomes (Fried, 2008; Bulman & Fairlie, 2016; Mora, Escardibul, & Di Pietro, 2018). The effects of introducing ICT in schools on student learning are, therefore, theoretically ambiguous.

# 6.2 Heterogenous Effects by Initial Learning Level

In the sub-samples analysis based on students' initial level of learning, we also observe no statistically significant results for both Japanese and math test scores.<sup>12</sup> A concern, which is often raised for introducing new teaching methods or tools such as technology, is that the effects may vary by students' ability to adapt to and utilize them. Especially, students at the lower end of the learning spectrum may struggle to acquire new skills and be left behind. The results, however, suggest that the use of computers or digital textbooks have no differential effects on student

<sup>&</sup>lt;sup>11</sup> The results are omitted for brevity but are available upon request.

<sup>&</sup>lt;sup>12</sup> The results are omitted for brevity but are available upon request.

academic performance by their learning level. This finding is similar to the observations from some of earlier studies (Leuven et al., 2007; Rutherford et al., 2014). For example, Rutherford et al. (2014) reveal that the introduction of computer-aided instruction does not produce any significant difference in its impact on math scores by students' initial math or language ability. In fact, they find no significant impact of this program on math scores.

# 6.3 Heterogeneous Effects by School Characteristics

Tables 9 and 10 show how the effects of ICT use may vary by school factors. While teacher training and cooperative atmosphere among teachers are not statistically significantly correlated with the effects of ICT use on student learning, school disciplinary culture seems to play some role. More specifically, the estimated results in column (7) of both tables suggests that an increase in the availability of personal computers for students is positively associated with their academic performance. The negative coefficient for the interaction term between the ICT variable and the school culture variable, however, implies that this positive effect is greater for students in schools with more disciplinary challenges. This result may indicate that ICT is serving to complement teachers in these schools by increasing academic support for students, making it possible to offer more personalized and collective learning opportunities. The positive coefficient for the school culture variable indicates that in general, schools with a better disciplinary culture tend to have higher student performance. It can be, therefore, inferred that the academic gap between schools with different disciplinary cultures may be narrowed through the introduction of ICT.

### 7. Conclusion

Given the global trend toward increased use of ICT in education, it is essential to understand how this shift in the school environment affects students. Much of the past research examines the overall effect of ICT on student academic achievement, with little attention given to heterogeneous effects and other student outcomes. Drawing on a rich panel data set from Saitama prefecture in Japan, along with administrative data collected by the Ministry of Education, Culture, Sports, Science and Technology, this paper seeks to fill this gap in the existing literature. Based on fixed effects estimations and a sample of students in grades six to nine, we analyze the effects of ICT use on students' non-cognitive skills and its interaction with student and school characteristics. Two types of non-cognitive skills, grit and self-efficacy, are examined in this paper. In terms of grit, there is no significant overall effect of ICT and no differential effect by students' learning level. In further investigating heterogeneous effects by school factors, we observe that the use of digital textbooks is positively correlated with grit of students in schools where less teacher training is conducted, while negative effects are found in schools with more investment in teacher training. This result may indicate the limited role that digital textbooks currently play in the classroom.

Self-efficacy is found to be higher when ICT is used more frequently in Japanese and mathematics classes. When the sample is disaggregated by students' initial learning level, this positive effect is observed across all quartiles, but the magnitude of the coefficient tends to be greater in the lower quartiles. Hence, the increased use of ICT may be particularly beneficial for students who are initially at the lower end of the test score distribution, thereby improving their self-efficacy. With respect to heterogeneous effects by school factors, we find that the positive effect of the frequent use of ICT in math class on self-efficacy is greater in schools with more teacher training. In contrast, the introduction of digital textbooks is more likely to increase self-efficacy of students in schools with less cooperative atmosphere among teachers. Collectively, these results imply that the effect of ICT on students' non-cognitive skills can differ by school characteristics, as well as the type of ICT measurements, the subject taught, and the specific non-cognitive skills.

Regarding cognitive skills, we find no overall effect of ICT on students' test scores and no heterogeneous effect by their learning level. However, we find that the increased availability of computers to students is more likely to improve both Japanese and math scores of students in schools with less favorable disciplinary culture, while students in better disciplinary culture generally exhibit higher self-efficacy without the use of ICT. These results suggest that the gap in academic performance observed between schools with and without discipline problems may be narrowed through the introduction of ICT.

There are a few limitations to this paper. First, we investigate how the effect of ICT may depend on various factors, including student and school characteristics. However, the effectiveness of ICT can be also determined by how teachers use it in their classrooms (Comi et al., 2017; OECD 2020). Future research could further explore the effect of teachers in more detail. Second, the construction of the indices on school culture used in our analysis is based on school surveys. A possible limitation to this is that schools may have a tendency to assign themselves high ratings in their responses, particularly in questions that can be subject to personal interpretation, such as

those regarding perception of culture. This leads to less variation in the culture-related variables, which makes it hard to capture their effect on students. Therefore, more objective measurements on school environments may be necessary in future research. Lastly, while our findings show a limited impact of ICT on cognitive skills, previous studies suggest that grit and self-efficacy contribute to academic and life success (Duckworth et al., 2007; Pajares & Miller, 1994). As such, the positive effects of ICT on these skills may indirectly influence student outcomes over time, and future research could explore the long-term impact on their success.

In sum, we find some, albeit limited, evidence of heterogeneous effects of ICT use in schools on both students' non-cognitive and cognitive skills. These findings underscore the importance of considering heterogeneous effects when integrating ICT into the classroom. That said, as ICT continues to advance rapidly, ongoing evaluation of its impact on students will be instrumental in ensuring the provision of quality education.

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		Period Covered		Per	iod Covered f	for ICT Varia	bles
		for Cognitive and		(i) Ratio of	(ii) Digital	(iii) ICT	(iv) ICT
	Non-Cognitive	Non-Cognitive	Corresponding	PC to	Textbook	use in class	use in class
Cohort	Skill Measured	Skill	Grades	students		(Japanese)	(math)
Α	Grit	2019-2022	Grade 6–9	2018-2021	2019-2021	2020-2021	2020-2021
В	Self-Efficacy	2020-2023	Grade 6–9	2019-2022	2019-2022	2020-2022	2020-2022

#### Table 1. The Sample Period by Cohort

#### **Table 2: Summary Statistics**

Variable	Obs	Mean	SD	Min	Max
Non-cognitive skills					
Grit (standardized)	153,579	0.00	1	-3.47	3.13
Self-efficacy (standardized)	157,347	0.00	1	-2.59	2.41
Cognitive skills					
Japanese test score (standardized)	311,200	0.02	1	-4.30	3.62
Math test score(standardized)	307,290	0.01	1	-3.38	2.66
ICT measurements					
Ratio of PC to students	267,323	0.61	0.51	0.01	3.82
E-textbook for students (=1 if introduced in school)	225,993	0.26	0.44	0	1
ICT use in Japanese class (=1 if in every class or nearly all)	202,812	0.08	0.27	0	1
ICT use in math class (=1 if in every class or nearly all)	203,791	0.09	0.29	0	1
School characteristics					
Number of teacher training session (=1 if 15 times or more)	311,062	0.32	0.47	0	1
Cooperative atmosphere among teachers (=1 if strongly so)	311,210	0.73	0.44	0	1
Degree of problems with school discipline (=1 if not at all)	311,489	0.63	0.48	0	1
Student characteristics					
Cram school (=1 if attending a private cram school for 4 or more hours per week)	320,141	0.42	0.49	0	1
Books at home (=1 if more than 10 books at home)	320,141	0.89	0.32	0	1

Source: Author's calculations based on the student and school surveys collected by Saitama prefecture (2019-2023) and the administrative data collected by the Ministry of Education, Culture, Sports, Science and Technology (2018-2022). The statistics are computed for the pooled sample.

Notes: Information on the ratio of PC to students and e-textbook is obtained from school questionnaires, while that on ICT use in Japanese and math classes is obtained from student questionnaires. ICT refers to digital devices such as PCs and tablets.

		ICT	<b>F variable</b>	
	(1)	(2)	(3)	(4)
Dependent variable	Ratio of PC to students	E-text for students	ICT use in class (Japanese)	ICT use in class (math)
Panel A.				
Grit	-0.007	0.006	0.028	-0.014
(standardized)	(0.010)	(0.009)	(0.020)	(0.017)
Observations	147,512	100,812	68,854	69,876
Panel B.				
Self-Efficacy	0.005	0.007	0.056 ***	0.055 ***
(standardized)	(0.011)	(0.009)	(0.009)	(0.009)
Observations	104,465	104,465	117,756	118,117

#### Table 3: ICT Use and Non-Cognitive Skills (Fixed Effects Estimations)

Notes:

 Robust standard errors, clustered at the school level, are in parentheses.
 \* significant at 10%; \*\* significant at 5%; \*\*\* significant at 1%.
 SES variables, year effects, student fixed effects and a constant are included in the estimations, but not reported for convenience.

#### Table 4: ICT Use and Grit (Fixed Effects Estimations by Quartile of Initial Test Score)

Dependent variable:		IC	CT Variable	
Grit (standardized)	(1)	(2)	(3)	(4)
(Sundur dized)	Ratio of PC	E-text for	ICT use in class	ICT use in class
Initial Test Score	to students	students	(Japanese)	(math)
Quartile 1 (bottom)	-0.033 *	0.003	0.025	0.001
	(0.017)	(0.018)	(0.034)	(0.035)
Observations	36,104	24,692	16,554	20,096
Quartile 2	0.009	0.007	-0.005	0.002
	(0.019)	(0.018)	(0.044)	(0.035)
Observations	35,905	24,501	17,482	17,920
Quartile 3	-0.000	0.013	0.093 **	-0.004
Quartine 5	(0.020)	(0.019)	(0.038)	(0.039)
Observations	36,812	25,141	17,982	14,206
Quartile 4 (top)	-0.020	0.007	-0.013	-0.051
	(0.017)	(0.018)	(0.042)	(0.033)
Observations	37,133	25,411	16,544	17,066

Notes:

 Robust standard errors, clustered at the school level, are in parentheses.
 \* significant at 10%; \*\* significant at 5%; \*\*\* significant at 1%.
 SES variables, year effects, student fixed effects and a constant are included in the estimations, but not reported for convenience.

4. The sample is divided into quartiles for each cohort, based on the initial test score level.

Dependent variable:		IC	CT Variable	
Self-Efficacy	(1)	(2)	(3)	(4)
Initial Test Score	Ratio of PC to students	E-text for students	ICT use in class (Japanese)	ICT use in class (math)
Quartile 1 (bottom)	0.013	0.015	0.060 ***	0.058 ***
	(0.019)	(0.015)	(0.015)	(0.018)
Observations	23,636	23,636	30,711	28,327
Ouartile 2	0.019	-0.002	0.060 ***	0.066 ***
<b>(</b>	(0.018)	(0.012)	(0.016)	(0.017)
Observations	24,320	24,320	29,115	28,029
Quartile 3	-0.013	0.011	0.028 *	0.063 ***
	(0.018)	(0.012)	(0.017)	(0.016)
Observations	24,553	24,553	27,094	29,488
Quartile 4 (top)	-0.016	-0.005	0.052 ***	0.032 **
	(0.017)	(0.014)	(0.016)	(0.016)
Observations	24,794	24,794	27,462	28,217

#### Table 5: ICT Use and Self-Efficacy (Fixed Effects Estimations by Quartile of Initial Test Score)

Notes:

Robust standard errors, clustered at the school level, are in parentheses.
 \* significant at 10%; \*\* significant at 5%; \*\*\* significant at 1%.
 SES variables, year effects, student fixed effects and a constant are included in the estimations, but not reported for convenience.

4. The sample is divided into quartiles for each cohort, based on the initial test score level.

				Depende	ent variable:			
		(a) Grit (s	standardized)			(b) Self	E-Efficacy (standardi	zed)
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
ICT Variable:	Ratio of PC to students	E-text for students	ICT use in class (Japanese)	ICT use in class (math)	Ratio of PC to students	E-text for students	ICT use in class (Japanese)	ICT use in class (math)
ICT	-0.006	0.017 *	0.023	-0.014	-0.007	-0.001	0.048 ***	0.042 ***
	(0.011)	(0.010)	(0.021)	(0.018)	(0.013)	(0.010)	(0.011)	(0.010)
Teacher Training	0.024 ***	0.025 **	0.006	0.004	0.008	0.017 **	0.017 **	0.014 *
	(0.008)	(0.010)	(0.019)	(0.022)	(0.012)	(0.008)	(0.008)	(0.008)
ICT * Teacher Training	-0.027	-0.071 ***	0.080	-0.018	0.025	0.028	0.036	0.043 **
	(0.017)	(0.019)	(0.071)	(0.046)	(0.016)	(0.018)	(0.022)	(0.020)
Observations	147,186	100,573	68,656	69,678	102,628	102,628	106,850	107,310

#### Table 6: ICT Use and Non-Cognitive Skills, Differential Effects by School Factors – Teacher Training (Fixed Effects Estimations)

Notes: 1. Robust standard errors, clustered at the school level, are in parentheses.
2. \* significant at 10%; \*\* significant at 5%; \*\*\* significant at 1%.
3. SES variables, year effects, student fixed effects and a constant are included in the estimations, but not reported for convenience.

				Depende	ent variable:			
		(a) Grit (	standardized)			(b) Self	E-Efficacy (standardi	zed)
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
ICT Variable:	Ratio of PC to students	E-text for students	ICT use in class (Japanese)	ICT use in class (math)	Ratio of PC to students	E-text for students	ICT use in class (Japanese)	ICT use in class (math)
ICT	0.000 (0.013)	0.016 (0.014)	0.043 (0.026)	0.020 (0.024)	0.006 (0.017)	0.035 ** (0.015)	0.054 *** (0.020)	0.075 *** (0.019)
Cooperative Culture	-0.000 (0.010)	-0.005 (0.009)	0.001 (0.012)	0.007 (0.012)	0.008 (0.016)	0.019 ** (0.009)	0.007 (0.007)	0.009 (0.007)
ICT * Cooperative Culture	-0.013 (0.012)	-0.015 (0.016)	-0.026 (0.037)	-0.051 (0.033)	0.001 (0.016)	-0.039 ** (0.017)	0.003 (0.026)	-0.030 (0.025)
Observations	147,186	100,573	68,656	69,678	102,628	102,628	107,088	107,538

#### Table 7: ICT Use and Non-Cognitive Skills, Differential Effects by School Factors - Cooperative Atmosphere among Teachers (Fixed Effects Estimations)

Notes: 1. Robust standard errors, clustered at the school level, are in parentheses.
2. \* significant at 10%; \*\* significant at 5%; \*\*\* significant at 1%.
3. SES variables, year effects, student fixed effects and a constant are included in the estimations, but not reported for convenience.

				Depend	ent variable:			
		(a) Grit (	standardized)			(b) Self	Efficacy (standardi	zed)
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
ICT Variable:	Ratio of PC to students	E-text for students	ICT use in class (Japanese)	ICT use in class (math)	Ratio of PC to students	E-text for students	ICT use in class (Japanese)	ICT use in class (math)
ICT	0.003	0.044 ***	0.065	-0.061 *	0.023	0.025 **	0.079 ***	0.071 ***
	(0.013)	(0.015)	(0.052)	(0.035)	(0.015)	(0.012)	(0.015)	(0.017)
Disciplinary Culture	0.009	0.008	-0.007	-0.015	0.018	0.008	0.005	0.006
	(0.008)	(0.008)	(0.010)	(0.011)	(0.012)	(0.008)	(0.006)	(0.006)
ICT * Disciplinary Culture	-0.014	-0.053 ***	-0.047	0.062	-0.026 *	-0.030 **	-0.035 *	-0.026
	(0.011)	(0.016)	(0.055)	(0.039)	(0.014)	(0.015)	(0.019)	(0.020)
Observations	147,186	100,573	68,656	69,678	102,628	102,628	107,537	107,992

 Table 8: ICT Use and Non-Cognitive Skills, Differential Effects by School Factors – School Disciplinary Culture (Fixed Effects Estimations)

Notes: 1. Robust standard errors, clustered at the school level, are in parentheses.
2. \* significant at 10%; \*\* significant at 5%; \*\*\* significant at 1%.
3. SES variables, year effects, student fixed effects and a constant are included in the estimations, but not reported for convenience.

<b>Dependent variable:</b> Japanese Test Score	(a)	) Teacher Train	ing	(b) (	School Factor: Cooperative Cu	lture	(c) Scho	ol Disciplinary	Culture
(standardized)	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
ICT Variable:	Ratio of PC to students	E-text for students	ICT use in class (Japanese)	Ratio of PC to students	E-text for students	ICT use in class (Japanese)	Ratio of PC to students	E-text for students	ICT use in class (Japanese)
ICT	0.012	-0.000	-0.004	0.010	0.010	0.008	0.021 **	0.002	-0.008
	(0.008)	(0.006)	(0.008)	(0.007)	(0.010)	(0.016)	(0.010)	(0.009)	(0.011)
School Factor	0.011 *	0.002	0.006	0.011	0.013 **	0.004	0.025 ***	0.012 **	0.011 **
	(0.006)	(0.005)	(0.008)	(0.007)	(0.005)	(0.006)	(0.007)	(0.005)	(0.005)
ICT * School Factor	-0.011	0.001	-0.010	-0.007	-0.015	-0.020	-0.017 **	-0.003	0.003
	(0.010)	(0.012)	(0.015)	(0.008)	(0.011)	(0.019)	(0.008)	(0.010)	(0.015)
Observations	250,059	202,214	180,606	250,059	202,214	180,852	250,059	202,214	181,324

Table 9: ICT Use and Japanese Test Scores, Differential Effects by School Factors (Fixed Effects Estimations)

Notes: 1. Robust standard errors, clustered at the school level, are in parentheses.
2. \* significant at 10%; \*\* significant at 5%; \*\*\* significant at 1%.
3. SES variables, grade effects, year effects, student fixed effects and a constant are included in the estimations, but not reported for convenience.

Table 10: ICT Use and Math Test Scores, Differential Effects by School Factors (Fixed Effects Estimation	Table 10: ICT Use and Math Test Scores, Differential Effects	by School Factors (Fixed Effects Estimations)
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Dependent variable:					School Factor:				
Math Test Score	(a)	Teacher Train	ing	(b) (	Cooperative Cul	ture	(c) Scho	ol Disciplinary	Culture
(standardized)	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
ICT Variable:	Ratio of PC to students	E-text for students	ICT use in class (math)	Ratio of PC to students	E-text for students	ICT use in class (math)	Ratio of PC to students	E-text for students	ICT use in class (math)
ICT	0.012	-0.007	-0.008	0.026 **	0.005	0.015	0.034 ***	0.009	-0.013
	(0.010)	(0.008)	(0.008)	(0.012)	(0.011)	(0.013)	(0.012)	(0.011)	(0.012)
School Factor	0.004	-0.002	0.001	0.026 ***	0.024 ***	0.006	0.050 ***	0.031 ***	0.014 **
	(0.008)	(0.007)	(0.009)	(0.009)	(0.006)	(0.006)	(0.008)	(0.006)	(0.007)
ICT * School Factor	-0.001	0.020	-0.002	-0.019 *	-0.012	-0.034 **	-0.033 ***	-0.017	0.007
	(0.011)	(0.015)	(0.020)	(0.011)	(0.013)	(0.015)	(0.010)	(0.012)	(0.016)
Observations	246,849	199,199	178,554	246,849	199,199	178,781	246,849	199,199	179,48

Notes: 1. Robust standard errors, clustered at the school level, are in parentheses.
2. \* significant at 10%; \*\* significant at 5%; \*\*\* significant at 1%.
3. SES variables, grade effects, year effects, student fixed effects and a constant are included in the estimations, but not reported for convenience.

Figure 1. Conceptual Framework for the Relationships between ICT and Student Outcomes

How ICT affects learning	Development of Grit by	Duckworth et al. (2007)
Enable individualized	Interest	Purpose
Enable teachers to provide timely feedback	Practice	Норе
Require students to develop	Development of Self-eff	icacy by Bandura (1977)
morry alrilla		
	Performance accomplishments	Verbal persuasion
Facilitate more interactive and collaborative learning	Performance accomplishments Vicarious experiences	Verbal persuasion Physiological states

Category	Questions
Self-Efficacy <sup>1</sup>	I believe I will receive an excellent grade in this class.
	I'm certain I can understand the most difficult material presented in the readings for this course.
	I'm confident I can understand the basic concepts taught in this course.
	I'm confident I can understand the most complex material presented by the instructor in this
	course.
	I'm confident I can do an excellent job on the assignments and tests in this course.
	I expect to do well in this class.
	I'm certain I can master the skills being taught in this class.
	Considering the difficulty of this course, the teacher, and my skills, I think I will do well in this
	class.
Grit <sup>2</sup>	I have overcome setbacks to conquer an important challenge.
	New ideas and new projects sometimes distract me from previous ones.
	My interests change from year to year.
	Setbacks don't discourage me.
	I have been obsessed with a certain idea or project for a short time but later lost interest.
	I am a hard worker.
	I often set a goal but later choose to pursue a different one.
	I have difficulty maintaining my focus on projects that take more than a few months to
	complete.
	I finish whatever I begin.
	I have achieved a goal that took years of work.
	I become interested in new pursuits every few months.
	I am diligent.

# Appendix Table A.1: Non-Cognitive Skills Measurements

<sup>&</sup>lt;sup>1</sup> These questions are drawn from Pintrich et al. (1991). <sup>2</sup> These questions are drawn from Duckworth et al. (2007).