Educational Technology, Pedagogical Scaffolding, and 21st-Century Skills: Quasi-Experimental Evidence from Mexico

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Abstract

This article presents evidence on the effects of a program implemented in Mexico by a non-profit organization to improve students' digital and 21st-century skills in public schools. The intervention provides media classrooms, internet connectivity, educational materials, and pedagogical scaffolding for teachers. Based on pre- and post-intervention surveys, the analysis focuses on students' self-reported competencies in digital and 21st century skills like communication, collaboration, creativity, and problem-solving. Results show that this program increases students' digital skills, with the strongest effects among sixth graders. In addition, this program enhanced digital communication, content creation, and online safety, fostering other skills like communication, creativity, and collaboration. These findings highlight the importance of including pedagogical support for teachers implementing educational technology programs, representing one of the few examples of causal evidence available in Mexico on the relationship between the provision of educational technology with pedagogical support and the development of students' skills.

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1 Introduction

For decades, integrating technology into public schools has been a widely supported government policy aimed at improving the quality of education. However, despite significant public and private investments in information and communication technologies in education (ICTE) (Rodriguez-Segura, 2021; Silverman et al., 2025), the empirical evidence on the impacts of school-based technology interventions on student achievement is still mixed (UNESCO, 2023). Furthermore, the adoption of educational technology within school systems remains controversial in many countries due to a limited amount of actionable evidence on how to replicate, adapt, and scale these technologies effectively (Shank, 2019).

The combination of inconsistent evaluation results and difficulties in using existing evidence to design effective ICTE interventions in developing countries raises important questions: What are the main factors facilitating the adequate integration of educational technology in public schools? How do these factors influence students' academic achievement? These questions are particularly relevant for policymakers in developing countries, where longstanding educational inequalities now interact with the effects of digital exclusion and the inadequate design of educational technology programs. (Buabeng-Andoh, 2012; Gottschalk and Weise, 2023; UNESCO, 2023).

This article presents the first quasi-experimental evidence on the effects of the "Programa de Fortalecimiento Escolar" (*School Strengthening Program*). This flagship initiative has been implemented since 2016 by the non-profit organization "Unión de Empresarios para la Tecnología en la Educación" (*Union of Entrepreneurs for Technology in Education*, UNETE), to address the digital divide in Mexican public schools. This program supplies selected schools with media classrooms, internet access, educational materials, and both technical and pedagogical support for teachers and school principals.

To evaluate this program, we use a two-period panel design. Specifically, we estimate treatment effects through a difference-in-differences framework enhanced by a doubly robust estimator. Our empirical analysis relies on detailed survey data collected from students before and after the program's implementation. To assess program outcomes, we focus on composite indices of self-reported perceptions about mastering digital skills and 21st-century competencies. These competencies include communication, collaboration, creativity, and problem-solving. Notably, self-perception is an important aspect of developing capabilities and indicates both exposure to and confidence in using technology.[1]

Our results show that access to educational technology, combined with pedagogical scaf-

[1] As Holenstein et al. (2022) pointed out, self-efficacy is a reliable predictor of academic achievement. Even though self-reported measures may be considered subjective, they may indeed capture individual perceptions of self-efficacy in digital and 21st-century competencies.

folding for teachers, significantly improves students' self-reported digital competencies. The preferred doubly robust difference-in-differences (DR-DiD) estimates indicate an average increase of about 0.11 in the proportion of competencies reported by students. This corresponds to a 10–11 percentage-point improvement relative to the control group. These effects are particularly noticeable among sixth-grade students, who are in the last year of elementary school in Mexico. The improvements are especially clear in areas like digital communication, content creation, and online safety. Additionally, we find positive and statistically significant effects on broader competencies. These effects are strongest in communication, creativity, and collaboration.

This article contributes to three key areas of ICTE literature. First, it presents one of the few causal pieces of evidence available in Mexico on the relationship between the provision of educational technology with pedagogical support and the development of students' competencies. Second, it broadens the international literature on technology and education by assessing a program implemented by a non-profit organization in a middle-income country that faces ongoing structural educational inequalities. Finally, it complements research focusing on traditional learning outcomes by exploring how ICTE programs may impact 21st-century competencies.

The paper is organized as follows: Section 2 covers the institutional context and intervention; Section 3 outlines the quasi-experimental design; Section 4 describes the data and balance checks; Section 5 presents the estimation strategy and main results; Section 6 discusses policy implications for technology-based education.

2 Context and intervention

2.1 Integration of educational technology in public schools

ICTE interventions can improve students' academic achievement in two key ways. Educational technology may increase access to relevant educational content and support autonomous learning. These interventions also provide instructional tools that, when used effectively, enhance teacher effectiveness. The success of these efforts, however, depends on several factors: teachers' ability to integrate technology, the availability of reliable educational technology and connectivity, strong school leadership, and a school community open to innovation and collaboration.

Integrating technology into classrooms is, therefore, a challenging task, especially in areas where significant educational inequalities prevail. Teachers often must significantly adapt their practices, usually lacking adequate support. While addressing the digital divide,

effective technology use in classrooms remains limited due to insufficient teachers´ skills and expertise (Gambi et al., 2025). Limited ICTE use and poor implementation by educators lead to "partial reforms" that disrupt school operations, such as reducing instructional time for non-technological activities. Therefore, identifying key factors or principles behind successful ICTE interventions is crucial for improving academic achievement.

Looking for a response on how to design effective ICTE interventions underscores an expected challenge: producing reliable, valid evidence on how educational technology should be integrated into classrooms and modify instructional activities. A 2015 report found, for instance, that although the educational technology literature is extensive, most studies focus on small-scale interventions and rely primarily on qualitative data from teachers and students to describe short-term effects. Few studies identify statistical connections between classroom technology use and long-term outcomes, such as secondary education assessment success. At that time, the authors also found no longitudinal studies linking digital learning to long-term outcomes (ICF, 2015). Recent experimental research helps close this evidence gap by showing positive effects from ICTE interventions, especially computer-assisted learning (Angrist et al., 2020; Rodriguez-Segura, 2021; Bhatt et al., 2024). This research also shows that expanding access to devices or connectivity alone—a popular policy option—often leads to limited or no learning gains (Shank, 2019). However, this research has two main limitations: a) most studies take place in countries with high technology integration, although recent work in India, Peru, Kenya, Zambia, Malawi, and Tanzania (Rodriguez-Segura, 2021; Muralidharan and Singh, 2025; Aulagnon et al., 2025) reports positive outcomes; and b) there is still insufficient evidence on using technology with key educational inputs, such as teacher professional development (Osorio Vanegas et al., 2025). Overall, these findings support cautious optimism about integrating educational technologies to enhance learning but stress the importance of including pedagogical components in ICTE programs.

The prevailing narrative suggests that access to educational technology can transform instructional practices in schools (López-Navas, 2014; Reimers et al., 2026). However, evidence regarding the relationship between improvements in teachers' practices and students' competency development remains mixed and highly dependent on context, methodological approaches, and program characteristics. For instance, Angrist et al. (2020) examines low-cost "simple technology" (telephone-based) interventions and finds significant gains in learning. However, as Sun et al. (2024) points out, it is necessary to incorporate pedagogical components into such educational technology programs to increase the likelihood of positively impacting students' academic achievement. This condition is supported by systematic reviews of programs promoting access to technology, which conclude that their effects on academic achievement and other learning outcomes have been, at best, mixed (Escueta et al.,

2020).

Overall, this literature recognizes the promise of ICTE for improving school performance but indicates that merely providing access to technology is patently insufficient. Deliberate pedagogical support, such as teacher scaffolding, well-designed and structured materials, and purposeful classroom integration, is essential for achieving meaningful, scalable impact.

2.2 School Strengthening Program

UNETE is a nonprofit organization committed to enhancing educational quality and equity by addressing the digital divide in Mexican public schools. Founded in 1999, it focuses on supporting schools located in rural areas, indigenous communities, and marginalized urban neighborhoods. According to its theory of change, UNETE's primary goal is to assist "children and teachers in public [...] schools in Mexico who lack the fundamental skills and competencies necessary for success in the 21st century,"achieved "through the integration of technology into teaching and learning processes" UNETE (2020).

The organization's main initiative, the "Programa de Fortalecimiento Escolar" ("School Strengthening Program", or SSP), aims to enhance teachers' instructional skills and help students develop digital and 21st-century competencies. The SSP, led by UNETE-trained facilitators, consists of: a) supporting school management; b) providing pedagogical scaffolding in classrooms; c) conducting on-site and virtual professional development activities; d) offering assessment and support; e) training school principals; f) delivering online technical support (connectivity, hardware, software); and g) providing individual teacher training. This article presents quasi-experimental evidence on the program's effects.

Schools participating in the program, ranging from preschool to high school, may be proposed by local educational authorities or selected from a web-based registry database.[2] UNETE's central staff determines the final list of supported schools. During the selection process, UNETE uses general criteria set by the organization, as well as guidelines from agreements with local educational authorities and from private donors. After selecting a school, UNETE facilitators assess its readiness to receive computers and internet access. If any issues arise, the facilitator collaborates with UNETE's central staff, teachers, and school principals to resolve any problem that may hinder the program's initial rollout.

Before UNETE provides any technology input, such as computers, connectivity, or educational materials, or before the SSP implementation begins, parents and school principals must renovate and adapt the classroom or computer lab for final approval by UNETE. Once

[2]UNETE will consider only schools without a media classroom or computer lab. Also, it requires parents' commitment to participate in adapting the media classrooms.

the computer lab is operational, UNETE facilitators are responsible for promoting the adequate instructional use of equipment and educational materials.

During the implementation of the SSP, three key actors interact: teachers, UNETE facilitators, and UNETE coordinators. At each school, the UNETE facilitator conducts a diagnostic assessment to identify teachers' digital competencies and the state of the media classroom. Based on this information, the facilitator co-designs individualized training and coaching plans for teachers, principals, and the school community. Throughout the school year, teachers create several lesson plans aimed at integrating technology into regular instruction, utilizing the media classrooms, with optional in-class support from facilitators. Finally, UNETE coordinators monitor implementation during the school year, provide ongoing feedback and pedagogical support, and track progress against the school and teachers' lesson plans.

A key component of the SSP is teachers' pedagogical scaffolding. This concept, originally described by Wood et al. (1976), includes efforts to support novices in completing tasks beyond their current abilities. Guidance and feedback are thus carefully provided, with support fading gradually as the novice develops new skills. This pedagogical approach is essential for the UNETE program, as it distinguishes this intervention from other ICTE initiatives currently implemented in Mexico, which often rely solely on the provision of computers and Internet connectivity. In contrast to this common approach, the SSP implemented by UNETE not only provides computers and connectivity but also offers curated educational materials, ongoing technical support, pedagogical scaffolding, on-site observation, and constant feedback. By embracing this approach, the SSP aligns with recent evidence highlighting the lack of digital competencies among teachers in Latin America, underscoring the importance of implementing teacher professional development programs that should be "ongoing, contextualized, and focused on practice" Gambi et al. (2025).

3 Quasi-Experimental Design and Data Collection

This evaluation follows a quasi-experimental design using a two-period panel of treated and comparison schools, as a randomized controlled trial was not feasible because enrollment in this program was determined by UNETE's operational rules and donor-driven geographical criteria (Section 2.2). Because UNETE implements a non-randomized school selection process, the research team identified a group of comparison schools before baseline data collection, using administrative data from the most recent publicly available National School Census (Format 911), accounting for 16 school characteristics to estimate propensity scores. Our evaluation followed this pre-established design to estimate causal effects using a

difference-in-differences (DiD) framework.[3]

3.1 Construction of the Comparison Group

To ensure evaluation credibility and to approximate a reliable counterfactual, once UNETE staff selected the treatment schools, we identified a comparison group of schools not included in the program but with observable characteristics similar to those of the treatment schools. As previously described, selection relied on the most recent administrative data from the National School Census (School Year 2018–2019) published by the Mexican Secretariat of Public Education. This dataset contains school-level information for all Mexican schools. The 2018–2019 school year was chosen not only for data availability but also for its comparability with the 2024–2025 school year, when the program was implemented. Data from 2020 to 2023 may be atypical, as schooling conditions were strongly affected by the COVID-19 pandemic during those years.

Using these administrative data, we estimated the probability of program participation– interpreted as the propensity score – for each school, based on a set of covariates capturing demographic, infrastructure, and contextual characteristics. The variables captured characteristics of students (e. g., gender ratio, annual students' expenditure on school supplies, proportion of students with special educational needs, proportion of indigenous students), schools (e. g., student–teacher ratio, number of classrooms, number of staff members, total number of teachers), as well as a state identifier.

Estimated propensity scores identified schools with similar likelihoods of program participation, creating a pool of comparison schools as a constructed counterfactual. The final *ex-ante* design included 133 prospective treated schools participating in the 2024–2025 academic year and 381 (potentially) matched comparison schools selected through the aforementioned procedure, including primary, secondary, and high schools, and using propensity score matching with oversampling (Vincenzi et al., 2021). Our research team performed no further matching or reweighting, taking the identified treated and comparison schools to apply a Difference-in-Differences measurement strategy, as described in the following sections. Analysis was restricted to the primary school balanced subsample, comprising 69 treatment

[3]Regarding ethical considerations, the study was conducted under formal collaboration agreements signed between state-level Secretaries of Education, individual schools, and UNETE, which included explicit data-protection provisions. Although the implementer did not formally submit the study to an Institutional Review Board (IRB), all procedures complied with prevailing ethical standards for research involving human subjects. In particular, no minor was included without the explicit authorization of both parents and school authorities, and all participating adults provided informed consent. Participation was entirely voluntary, and all individuals retained the right to decline or withdraw at any time without consequence. This strict adherence to voluntary participation explains the observed variation in response rates and ensures that the data reflect a fully consensual sample.

and 65 comparison schools.[4]

3.2 Evaluation Design and Data Collection

The evaluation leverages this pre-existing matched sample to assess program impacts using a DiD framework. Two rounds of data collection were conducted using online surveys: a baseline prior to program implementation at the beginning of the school year and a follow-up after the completion of the intervention (end of the school year).[5] Both rounds included student-, parent-, and school-level questionnaires, designed to capture relevant information on covariates and measure student outcomes.[6]

Student and teacher questionnaires measured self-reported mastering of digital and 21st-century competencies, covering domains such as communication, collaboration, creativity, problem-solving, and digital literacy. Parent questionnaires gathered information on household demographics, socioeconomic status, and access to digital assets, while principal questionnaires collected data on school infrastructure, technological endowments, and connectivity. These instruments allow for a multidimensional assessment of the program's effects on both students' capabilities and school environments.

3.3 Identification Strategy

The causal identification relies on a standard difference-in-differences (DiD) design, using pre- and post-intervention survey data for the same schools. The key identifying assumption is that, in the absence of treatment, treated and comparison schools would have followed parallel trends in outcomes. While this assumption is not directly testable, it is supported by the fact that the initial school matching process was explicitly designed to ensure comparability in observable characteristics associated with baseline outcomes and their evolution.

All treatment effect estimates correspond to the Average Treatment Effect on the Treated (ATT), which is estimated through a doubly robust DiD estimator (Sant'Anna and Zhao,

[4]The sample size used in the final estimations is attributable to varying response rates across the different instruments, which included questionnaires administered to parents, students, and school principals.

[5]We used a dedicated online survey platform due to cost-efficiency concerns, considering that "online platforms are also suitable for collecting a variety of data, including experimental data, and cross-sectional and longitudinal survey data" (Newman et al., 2021). Questionnaires had been administered via online platforms in previous studies or piloted by the research team with comparable student samples prior to the evaluation.

[6]Parents, students, school principals, and teachers completed a context questionnaire. All adult participants were required to sign an informed consent form. Parents signed an additional informed consent form before any data were collected from students. Students and teachers also responded to questionnaires to capture their perceptions of their digital and 21st-century skills. The data collection process was designed to prevent students from responding to more than one instrument in a single session.

2020). This estimator combines regression adjustment and inverse probability weighting, ensuring consistency provided that either the outcome model or the treatment model is correctly specified. By leveraging both the matched design and the doubly robust estimation approach, our analysis achieves credible causal inference under relatively mild assumptions.[7]

4 Balance checks and summary statistics

A key identifying assumption in our empirical strategy is that, in the absence of treatment, outcomes for treated and control schools would have evolved along parallel trends over time. This *parallel trends assumption* is central to the validity of our difference-in-differences (DiD) estimator (see Section 5.1), as it underlies the causal interpretation of post-treatment differences as program effects. Because the counterfactual evolution of treated units cannot be directly observed, however, the assumption is inherently untestable. We therefore provide indirect evidence on its plausibility by examining whether treated and control schools display similar pre-treatment characteristics across a broad set of observable variables plausibly correlated with outcome trajectories.

Our balance diagnostics draw on two complementary data sources. The first comprises *household and socioeconomic variables* obtained from parent surveys, which capture student background, household composition, and access to digital assets. The second source consists of *school-level characteristics* collected through principal surveys, reflecting differences in infrastructure, technological endowments, and connectivity conditions prior to program implementation. Together, these data allow us to evaluate whether treated and control schools were comparable before the intervention in both socioeconomic composition and institutional capacity.

Tables 1, 2, and 3 report mean values for each covariate in the treatment and control groups during the baseline period, along with standard errors and the normalized difference in means. The normalized difference provides a scale-invariant measure of imbalance, defined as:

$$ND = \frac{\bar{X}_T - \bar{X}_C}{\sqrt{\left(S_T^2 + S_C^2\right)/2}}, \tag{1}$$

where $\bar{X}_T$ and $\bar{X}_C$ denote sample means and S_T^2 and S_C^2 denote sample variances for the treatment and control groups, respectively. We interpret absolute values of $|ND| > 0.20$ as indicative of potentially meaningful imbalance, an approach that is slightly more conservative than (Imbens and Rubin, 2015, Chapter 14), who suggest using $|ND| > 0.25$.

[7] Appendix A presents the details of the power analysis and Minimum Detectable Effect (MDE) calculations for this study.

4.1 Household and Socioeconomic Characteristics

Table 1 presents balance checks for household composition, living conditions, and access to basic assets. Across most variables, normalized differences are below the 0.20 threshold, indicating satisfactory pre-treatment comparability. The average household size, number of working members, and ownership of durable goods such as computers, tablets, and televisions are statistically indistinguishable across groups. A small number of asset-related variables display normalized differences close to this benchmark, with the largest corresponding to streaming services (0.207). These minor imbalances suggest slightly higher asset ownership among treated households and are addressed by conditioning on baseline covariates in the main analysis.

This overall similarity supports the view that treatment assignment did not systematically favor households with distinct socioeconomic profiles. Given that digital exposure and household technology access could influence students' baseline familiarity with ICT, these results strengthen the internal validity of our subsequent estimates.

Table 1: Household Characteristics and Socioeconomic Status

	Control group		Treatment group		Normalized
	Mean	*Std. Dev.*	*Mean*	*Std. Dev.*	Difference
Household size	4.752	1.612	4.681	1.496	-0.046
Employed HH members	1.577	1.070	1.572	0.831	-0.005
Food expenses (MXN/week)	1,291.1	692.8	1,377.9	831.5	0.113
Owner	0.586	0.493	0.608	0.488	0.045
Dirt floor	0.021	0.145	0.040	0.195	0.111
Concrete floor	0.831	0.375	0.753	0.431	-0.193
Covered floor	0.144	0.352	0.192	0.394	0.128
Indigenous language	0.132	0.339	0.111	0.315	-0.064
Disability in HH	0.098	0.298	0.072	0.258	-0.093
Computer	0.280	0.450	0.278	0.448	-0.004
Car	0.271	0.445	0.354	0.478	0.180
Tablet	0.108	0.310	0.144	0.351	0.109
Pay/Sat TV	0.462	0.499	0.505	0.500	0.086
Streaming	0.086	0.281	0.153	0.360	0.207
Game console	0.055	0.229	0.072	0.258	0.070
Internet	0.606	0.489	0.647	0.478	0.085
Scholarship recipient	1.773	12.161	2.920	15.764	0.081
Observations	438		1,438		

This table presents the balance checks for household characteristics and socioeconomic status variables, using data provided by parents. The first column reports the mean and standard deviation for the control group, the second column reports the same for the treatment group, and the third column shows the normalized difference.

4.2 Parental Education and Expectations

Table 2 examines differences in parental education and expectations regarding their children's educational attainment. The distributions of education levels are highly comparable: approximately one-third of parents in both groups have completed middle school, and around 15–17 percent hold a bachelor's degree. The normalized differences are uniformly below 0.20, with the largest value (0.167) corresponding to the share of parents holding a primary school diploma. Likewise, expectations for their children's future education (whether up to high school, bachelor's, or graduate level) are balanced, with normalized differences below 0.15 in absolute value.

Table 2: Education Level and Expectations

	Control group		Treatment group		Normalized
	Mean	*Std. Dev.*	*Mean*	*Std. Dev.*	Difference
Parent:					
No education	0.006	0.078	0.017	0.128	0.104
Primary	0.083	0.276	0.135	0.342	0.167
Lower secondary	0.366	0.482	0.371	0.483	0.010
High School	0.369	0.483	0.291	0.454	-0.166
College	0.148	0.355	0.170	0.376	0.060
Graduate	0.028	0.164	0.016	0.125	-0.082
Expectations for child:					
Up to high school	0.059	0.236	0.091	0.288	0.122
College	0.349	0.477	0.388	0.487	0.081
Graduate	0.592	0.492	0.521	0.500	-0.143
Observations	438		1,438		

This table reports the balance checks for parental education and expectations regarding their child. The first column reports the mean and standard deviation for the control group, the second column reports the same for the treatment group, and the third column shows the normalized difference.

The absence of systematic differences in parental education and aspirations is relevant because these variables often correlate with children's motivation, access to learning resources, and engagement with digital tools. Their balance reduces concerns that unobserved parental factors could drive differences in student outcomes across treatment status.

4.3 School-Level Characteristics

Table 3 reports baseline characteristics of schools, focusing on infrastructure, access to technology, and internet availability. As expected, treated schools display much higher values for variables directly linked to ICTE. This includes the number of computers for teaching

and the presence of a computer lab or media room, reflecting that media classrooms were provided by UNETE before or at the start of the school year.

Despite these differences, other aspects of the school environment remain broadly comparable. Indicators of power stability and internet access for support staff show moderate differences, with normalized values ranging from 0.10 to 0.40. These are not large enough to suggest structural disparities beyond the program's targeting criteria. By contrast, administrative ICT use—measured by the availability of computers for administrative purposes—shows a near-zero normalized difference (−0.039). This indicates a high balance between treatment and control schools. Importantly, our analysis confirmed that none of the variables related to school size, socioeconomic composition, or management autonomy show statistically significant differences between groups. [8]

Table 3: School Characteristics

	Control group		Treatment group		Normalized
	Mean	*Std. Dev.*	*Mean*	*Std. Dev.*	Difference
Days with power outages	1.811	4.124	3.529	8.413	0.259
Computers for teaching	0.466	0.502	0.921	0.271	1.128
Computers for admin use	0.877	0.331	0.864	0.344	-0.039
Internet access for students	0.311	0.466	0.644	0.481	0.703
Internet access for teachers	0.534	0.502	0.735	0.443	0.425
Internet access for supp staff	0.622	0.488	0.676	0.470	0.113
Has computer lab/media room	0.542	0.502	0.961	0.194	1.101
Observations	65		69		

This table presents balance checks for key primary school characteristics, based on responses from the school principal. The first column reports the mean and standard deviation for the control group, the second column reports the same for the treatment group, and the third column shows the normalized difference.

Overall, the pattern of results indicates that treatment and control schools are balanced across key socioeconomic and demographic dimensions, with imbalances concentrated in variables directly associated with program targeting. To account for these differences and reduce residual bias, all school-level covariates with $|ND| > 0.20$ are included as controls in our DiD and DR-DiD estimations, as detailed in Section 5.

4.4 Discussion on Balance

Taken together, the evidence suggests that treated and control schools were highly comparable prior to the intervention, particularly in terms of students' household background and

[8] Estimations were conducted using complementary administrative data, available upon request.

parental education. Observable differences at the school level primarily reflect the program's eligibility criteria rather than unobserved selection. This reinforces the plausibility of the conditional parallel trends assumption once covariates are included.

While balance on observables does not guarantee balance on unobservables, the extensive similarity across socioeconomic, educational, and infrastructural characteristics provides reassurance that potential bias from differential pre-trends is limited. In addition, the magnitude and direction of any residual imbalance, mainly favoring slightly better-resourced schools, suggest that our estimated treatment effects may represent a conservative lower bound of the true impact.

These diagnostic exercises, therefore, support the internal validity of the empirical design and provide a transparent basis for interpreting the causal estimates presented in Section 5.2.

5 Estimation

5.1 Estimation Strategy

Our outcome variable, Y, is a composite index representing students' self-reported digital and 21st-Century competencies, constructed as the average of several binary indicators measuring abilities related to technology use, internet navigation, and digital tasks. By construction, Y ranges from 0 to 1, reflecting the proportion of competencies each student reports being able to perform.[9] Given the 2×2 Difference-in-Differences design –two periods, $t = 1, 2$, and two groups, $D = 0, 1$– and the balanced panel structure of our data, we start by estimating the average treatment effect on the treated using a canonical specification as follows

$$Y_{it} = \beta_0 + \beta_1 \mathbf{1}\{D_i = 1\} + \beta_2 \mathbf{1}\{t = 2\} + \tau \mathbf{1}\{D_i = 1\} \times \mathbf{1}\{t = 2\} + \varepsilon_{it}, \tag{2}$$

where Y_{it} is the outcome variable for student i in period t and D_i is a binary treatment indicator. The parameter of interest is τ, which represents the average treatment effect on the treated (ATT). Identification of τ relies on the standard parallel trends assumption, namely that, in the absence of treatment, the average change in outcomes over time would have been the same for treated and comparison students. Formally, this assumption requires that

$$\mathbb{E}[Y_{i2}(0) - Y_{i1}(0) \mid D_i = 1] = \mathbb{E}[Y_{i2}(0) - Y_{i1}(0) \mid D_i = 0].$$

Given the bounded nature of Y, we interpret the coefficient τ as the average change in

[9] Appendix B presents the questions included in each of the two main questionnaires used to construct the indices.

the proportion of competencies acquired due to the intervention. This specification allows us to evaluate whether providing computer labs and internet access leads to a measurable improvement in students' self-reported digital competencies relative to the comparison group.

As explained in Section 3, the intervention in schools was not truly random, which casts some doubt on the identification assumptions underlying the regression specified in equation 2, in particular the unconditional parallel trends assumption. Fortunately, we can leverage rich information on pre-treatment covariates and incorporate it into the analysis by checking for balance in variables expected to influence Y_{it} and by conditioning on these baseline characteristics in the main estimates. We therefore begin by estimating a two-way fixed effects (TWFE) specification of the form

$$Y_{it} = \theta_t + \eta_i + \tau D_{it} + \boldsymbol{X}_i \beta + \varepsilon_{it} \tag{3}$$

where $\boldsymbol{X}_i$ denotes a vector of observed baseline (pre-treatment) covariates, θ_t captures time fixed effects, and η_i denotes individual fixed effects. The parameter of interest is τ.

However, several critical issues are associated with the TWFE estimator in equation (3). First, identification relies on a conditional parallel trends assumption given baseline covariates, whose plausibility depends on the choice of $\boldsymbol{X}_i$. Second, including post-treatment or endogenous controls may bias the estimated ATT (Baker et al., 2025). For example, if the intervention affects school infrastructure, conditioning on such variables, or on their evolution over time, would constitute bad control bias. Third, even when a valid set of baseline covariates exists, recent work by Caetano and Callaway (2024) shows that τ does not generally correspond to a simple convex average of conditional treatment effects, but instead reflects a weighted average that may involve negative weights and additional bias components arising from functional form assumptions.

To address the limitations of the TWFE estimator, we adopt recent alternative estimators for the ATT that explicitly condition on baseline covariates. In particular, we consider the following estimand:

$$ATT = \mathbb{E}\left\{\Delta Y_{i,t=2}(1) \mid D_i = 1\right\} - \mathbb{E}\left\{\mathbb{E}\left[\Delta Y_{i,t=2}(0) \mid D_i = 0, \boldsymbol{X}_i\right] \mid D_i = 1\right\}, \tag{4}$$

where $\boldsymbol{X}_i$ denotes the same vector of baseline covariates defined above. Conditioning exclusively on pre-treatment characteristics avoids post-treatment bias and ensures that the identifying assumptions of the difference-in-differences framework are formulated in terms of conditional parallel trends given baseline information.

The first term in equation 4 is estimated using the observed average outcome change among treated units. The second term can be obtained either through a regression-adjustment

difference-in-differences (RA DiD) approach or by modeling the propensity score and applying an inverse probability weighted (IPW) DiD estimator (Abadie, 2005). In our preferred specification, we employ the doubly robust difference-in-differences (DR DiD) estimator proposed by Sant'Anna and Zhao (2020), which combines both approaches and is consistent provided that at least one of the auxiliary models, the outcome regression or the propensity score, is correctly specified.[10]

5.2 Estimation Results

Tables 4–7 present the estimated effects of the program on the self-reported digital and 21st-century competencies of students. The specifications in columns (1)–(3) of each table correspond to alternative linear probability model (OLS) estimations, with varying inclusion of student and school covariates and fixed effects. Point estimates are consistently positive and of comparable magnitude, which—together with school-clustered standard errors—supports the internal robustness of the findings. Nevertheless, we focus on the specifications in column (4), which employ the Doubly Robust Difference-in-Differences (DR DiD) estimator and are considered our preferred specifications. Sample sizes differ across columns for two reasons. First, from column (1) to columns (2) and (3), the differences are attributable to item non-response and the inclusion of covariates. Second, in column (4), the difference arises because double-robust estimation involves trimming units that fall outside the common-support region of the propensity score, in addition to the missing values resulting from the inclusion of covariates. Nevertheless, the qualitative conclusions remain unchanged.

[10] See Baker et al. (2025) for a recent and comprehensive guide to DiD-type estimators.

Table 4: Estimated Overall Effect on Students' Digital Competencies

	(1)	(2)	(3)	(4)
4th to 6th grade	0.0866***	0.0800**	0.111***	0.107***
	(0.0251)	(0.0309)	(0.0212)	(0.0268)
Observations	3,129	2,438	2,250	1618
4th grade	0.0625	0.0464	0.0879**	0.0409
	(0.0463)	(0.0595)	(0.0396)	(0.0435)
Observations	904	687	637	436
5th grade	0.0759**	0.0874**	0.131***	0.0928***
	(0.0330)	(0.0391)	(0.0251)	(0.0337)
Observations	1,167	905	841	610
6th grade	0.123***	0.0895*	0.0955***	0.228***
	(0.0442)	(0.0481)	(0.0289)	(0.0474)
Observations	1,058	846	772	572
Time Fixed Effects	Yes	Yes	Yes	NA
Student Fixed Effects	Yes	Yes	No	NA
Background Covariates	No	Yes	Yes	Yes
School Covariates	No	No	Yes	Yes

This table presents the estimated overall Average Treatment Effect on the Treated (ATT) for students' digital competencies. Specifications in columns (1), (2), and (3) are estimated using a linear probability model (OLS), whereas column (4) employs the Doubly Robust DiD estimator. Clustered standard errors at school level are reported in parentheses. Significance levels: * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

As shown in Table 4, the DR DiD estimates indicate that the program significantly increases students' overall digital competencies. For the full sample of 4th–6th graders, the estimated ATT is 0.107 (SE = 0.027, $p < 0.01$), implying a roughly 10-percentage point increase in the proportion of competencies reported by students. The effect is largest for 6th graders (ATT = 0.228, SE = 0.047, $p < 0.01$), suggesting that older students benefit most from the evaluated program, a pattern that may be explained by age or cumulative learning. Effects for 4th and 5th graders are smaller but remain positive and significant for 5th graders. This grade pattern is consistent with a "readiness and exposure" mechanism: older students may (i) leverage lab time more productively, (ii) require less basic onboarding, and (iii) be closer to transition grades where digital tasks are more salient in daily coursework. It also aligns with the view that technology gains materialize when hardware is paired with pedagogical guidance, as emphasized in Sun et al. (2024).

Table 5: Estimated Effects on Students' Digital Competencies by Category (Indices according to Appendix B.1)

	(1)	(2)	(3)	(4)
1. Info. and Data Literacy	0.0609**	0.0561	0.100***	0.104**
	(0.0281)	(0.0374)	(0.0240)	(0.0415)
Observations	3283	2559	2369	1616
2. Comm. and Collab.	0.0922***	0.0818**	0.117***	0.111***
	(0.0249)	(0.0312)	(0.0219)	(0.0310)
Observations	3283	2559	2369	1616
3. Digital Content Creation	0.0957***	0.0913**	0.115***	0.124***
	(0.0272)	(0.0351)	(0.0233)	(0.0341)
Obsservations	3282	2559	2369	1616
4. Safety	0.0861***	0.0911**	0.120***	0.125***
	(0.0282)	(0.0382)	(0.0225)	(0.0284)
Observations	3285	2561	2371	1618
5. Problem Solving	0.0860**	0.0727*	0.1000***	0.0684**
	(0.0366)	(0.0422)	(0.0267)	(0.0300)
Observations	3281	2558	2368	1612
Time Fixed Effects	Yes	Yes	Yes	NA
Student Fixed Effects	Yes	Yes	No	NA
Background Covariates	No	Yes	Yes	Yes
School Covariates	No	No	Yes	Yes

This table presents the estimated Average Treatment Effect on the Treated (ATT) on students' digital competencies by category. Specifications in columns (1), (2), and (3) are estimated using a linear probability model (OLS), whereas column (4) employs the Doubly Robust DiD estimator. Clustered standard errors at school level are reported in parentheses. Significance levels: * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

Table 5 shows that the intervention has statistically significant positive effects across all digital competency categories for the full sample of 4th–6th graders (see Appendix B.1 for more details on the constructed digital competency indices). Notably, "Communication and Collaboration" (ATT = 0.111, SE = 0.031, $p < 0.01$), "Digital Content Creation" (ATT = 0.124, SE = 0.034, $p < 0.01$), "Safety" (ATT = 0.125, SE = 0.028, $p < 0.01$), and "Information and Data Literacy" (ATT = 0.104, SE = 0.042, $p < 0.05$) exhibit large improvements among students enrolled in treatment schools. "Problem Solving", in turn, shows a smaller but still significant effect (ATT = 0.068, SE = 0.030, $p < 0.05$). These results suggest that the intervention broadly enhances students' digital competencies, particularly in areas requiring interaction and creation. The concentration of effects in communication, creation, and safety is intuitive: these domains map closely to the guided activities implemented in

media classrooms (e. g., messaging etiquette, document/presentation production, safe navigation), whereas problem-solving requires broader transfer across subjects and thus shows more modest gains. Back-of-the-envelope, these effect sizes represent nontrivial movements in binary indices, suggesting meaningful shifts in the share of students who report performing core digital tasks.[11]

Turning to broader self-reported 21st-century competencies (Table 6), the DR DiD estimates reveal a significant overall effect (ATT = 0.0676, SE = 0.0283, $p < 0.05$) for the combined 4th–6th grade sample. The effect is particularly strong for 5th graders (ATT = 0.122, SE = 0.039, $p < 0.01$), whereas estimates for 4th and 6th graders are not statistically significant, highlighting potential grade-specific differences in responsiveness. One conjectural interpretation is that competencies such as collaboration and creativity, which are often developed through project-based work, peak in the middle grades, when students have sufficient digital fluency to collaborate but before end-of-cycle academic priorities reallocate time away from cross-curricular projects. The imprecise and negative point estimate for 6th grade suggests limited power and/or shorter exposure rather than adverse effects, given the strong positive gains observed for digital competencies in that cohort.

As reported in Table 7, the intervention significantly improves several specific competencies (see Appendix B.2 for more details on the constructed 21st-century competencies indices). There are large gains observed in "Critical Thinking" (ATT = 0.148, SE = 0.048, $p < 0.01$), "Collaboration" (ATT = 0.142, SE = 0.044, $p < 0.01$), "Communication" (ATT = 0.164, SE = 0.044, $p < 0.01$), and "Creativity" (ATT = 0.139, SE = 0.072, $p < 0.05$) suggesting meaningful gains in students' higher-order analytical and reasoning skills. Positive effects also emerge for "Problem Solving" (ATT = 0.144, SE = 0.056, $p < 0.01$), "Data Management" (ATT = 0.098, $p < 0.05$), "'Content Integration" (ATT = 0.128, $p < 0.10$), and "IP & Licenses" (ATT = 0.162, $p < 0.05$), indicating gains in the organization of information and in understanding basic digital citizenship. Competencies such as "Information Literacy" and "Technical Literacy" show negative but non-significant estimates, which likely reflects that search/evaluation routines and device-level troubleshooting received less explicit instructional time in the first implementation cycle. Future iterations might therefore strengthen modules on evidence vetting and responsible sourcing to complement the observed gains in creation and communication.[12]

[11] Table 12 in Appendix C presents the estimation results for each individual question of the questionnaire Digital Competencies administered to students. For reference, Table 10 in Appendix B.1 provides the full English translations of the original Spanish questions.

[12] Table 13 in Appendix C presents the estimation results for each individual question of the questionnaire 21st Century Competencies administered to students. For reference, Table 11 in Appendix B.2 provides the full English translations of the original Spanish questions.

Table 6: Estimated Overall Effect on Students' 21st-Century Competencies

	(1)	(2)	(3)	(4)
4th to 6th grade	0.0508	0.0582	0.0650	0.0676**
	(0.0516)	(0.0804)	(0.0451)	(0.0283)
Observations	3,091	2,422	2,241	1,616
4th grade	0.0436	0.0725	0.0727	0.0255
	(0.0583)	(0.1050)	(0.0507)	(0.0371)
Observations	974	749	693	492
5th grade	0.0391	0.0668	0.0575	0.122***
	(0.0417)	(0.0625)	(0.0418)	(0.0388)
Observations	1246	972	910	664
6th grade	0.0668	0.0344	0.0361	-0.148
	(0.0701)	(0.0906)	(0.0566)	(0.188)
Observations	1183	940	868	652
Time Fixed Effects	Yes	Yes	Yes	NA
Student Fixed Effects	Yes	Yes	No	NA
Background Covariates	No	Yes	Yes	Yes
School Covariates	No	No	Yes	Yes

This table presents the estimated overall Average Treatment Effect on the Treated (ATT) on students' 21st-century competencies. Specifications in columns (1), (2), and (3) are estimated using a linear probability model (OLS), whereas column (4) employs the Doubly Robust DiD estimator. Clustered standard errors at school level are reported in parentheses. Significance levels: * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

Table 7: Estimated Effects on Students' 21st-Century Competencies by Category (Indices according to Appendix B.2)

	(1)		(2)		(3)		(4)	
Critical Thinking	0.0752	(0.0815)	0.0847	(0.135)	0.0816	(0.0738)	0.148***	(0.0476)
Obs.	3475		2718		2526		1808	
Collaboration	0.0547	(0.0880)	0.0794	(0.150)	0.0643	(0.0796)	0.164***	(0.0442)
Obs.	3474		2717		2525		1806	
Communication	0.0763	(0.0867)	0.0996	(0.146)	0.0887	(0.0776)	0.147***	(0.0481)
Obs.	3471		2714		2523		1804	
Creativity	0.0636	(0.0793)	0.0919	(0.126)	0.0736	(0.0700)	0.139*	(0.0716)
Obs.	3475		2718		2526		1808	
Info Literacy	0.0105	(0.0530)	-0.00458	(0.0787)	-0.0219	(0.0424)	-0.0658	(0.0545)
Obs.	3467		2711		2520		1804	
Tech Literacy	-0.000321	(0.0379)	0.0213	(0.0487)	0.00315	(0.0349)	-0.0480	(0.0432)
Obs.	3466		2712		2522		1802	
Problem Solving	0.0416	(0.0638)	0.0621	(0.0974)	0.0856	(0.0523)	0.144***	(0.0555)
Obs.	3465		2709		2519		1798	
Data Management	0.0623**	(0.0243)	0.0850**	(0.0348)	0.0841***	(0.0228)	0.0981**	(0.0400)
Obs.	3477		2720		2528		1808	
Search & Filter (Info)	0.0443	(0.0462)	0.101	(0.0682)	0.0826**	(0.0345)	0.0419	(0.0631)
Obs.	3477		2720		2528		1808	
Evaluate Content (Info)	0.0955**	(0.0427)	0.0724	(0.0597)	0.0847**	(0.0351	-0.0133	(0.0658)
Obs.	3477		2720		2528		1808	
Content Creation	0.0530*	(0.0311)	0.0549	(0.0470)	0.0696**	(0.0287)	0.0580	(0.0516)
Obs.	3477		2720		2528		1808	
Content Management	0.00481	(0.0232)	0.00718	(0.0320)	0.00145	(0.0181)	0.0378	(0.0331)
Obs.	3477		2720		2528		1808	
Content Integration	0.0787	(0.0476)	0.0817	(0.0708)	0.0841*	(0.0463)	0.128*	(0.0653)
Obs.	3477		2720		2528		1808	
IP & Licenses	0.118**	(0.0471)	0.0827	(0.0598)	0.128***	(0.0401)	0.162**	(0.0654)
Obs.	3477		2720		2528		1808	
Time Fixed Effects	Yes		Yes		Yes		NA	
Student Fixed Effects	Yes		Yes		No		NA	
Background Covariates	No		Yes		Yes		Yes	
School Covariates	No		No		Yes		Yes	

This table presents the estimated Average Treatment Effect on the Treated (ATT) on students' 21st-century competencies by category. Specifications in columns (1), (2), and (3) are estimated using a linear probability model (OLS), whereas column (4) employs the Doubly Robust DiD estimator. Clustered standard errors at school level are reported in parentheses. Significance levels: * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

Overall, our results indicate that the implementation of the School Strengthening Program (SSP) substantially increased students' self-reported digital and 21st-century competencies, with the strongest effects in areas involving communication, creation, collaboration, and problem-solving. For the main overall competency indices, statistically significant effects range from approximately 7 to 11 percentage points, as shown in Tables 4 and 6. In

addition, meaningful effects, on the order of about 7 to 13 percentage points, are observed for specific sub-dimensions of digital competencies, such as digital content creation, problem solving and related category-level indices reported in Table 5. The magnitude of effects therefore spans moderate to large gains, demonstrates both statistical and practical significance. Taken together, the pattern supports a mechanism in which technology access plus structured pedagogical scaffolding shifts day-to-day classroom practice toward interactive production and safer online behavior, while more research-oriented literacies may require longer exposure and explicit instruction. Policy-wise, the results suggest that targeted digital investments coupled with teacher-centered coaching can yield efficiency and equity gains at scale, while highlighting specific domains (information and technical literacy) where complementary training would likely raise returns.

Finally, as an additional empirical exercise, which can be interpreted as a partial robustness check, Tables 14 and 15 in Appendix C report estimation results based on pooled cross-sectional specifications, rather than the balanced panel framework used in the main analyses. In this setting, treated and control observations across periods do not necessarily correspond to the same students, and therefore the estimates rely on weaker identifying assumptions than those underlying the panel DiD approach. While some specifications in this robustness check estimation yield smaller and, in some cases, statistically insignificant estimates (for example, for 6th graders' digital skills), the direction of the estimated effects remains broadly consistent with the main results previously described, and several coefficients preserve their sign and, in some cases, statistical significance. The comparison between panel-based and pooled cross-sectional estimates thus provides complementary evidence: although the latter should be interpreted with caution, the observed attenuation of effects is consistent with the presence of persistent unobserved heterogeneity that is better controlled for in the panel specification.

6 Final comments and policy implications

Information and Communication Technology in Education programs play a crucial role in equipping teachers and students in developing countries with essential competencies. These programs can impact not only immediate learning outcomes but also long-term educational benefits and labor-market preparedness. Therefore, it is important to quantify the effects of these interventions to understand how investments in educational technology and pedagogical support may contribute to educational effectiveness and improve equity conditions in public schools. Since used technologies, pedagogical approaches, and implementation strategies vary significantly, a challenge for researchers and practitioners arises to inform decision-

makers promoting the integration of technologies in schools about "which tools to use, when to introduce them, and how to align them with specific educational goals" (Forsström and et al., 2025). Addressing these questions remains an essential goal in creating cost-effective, scalable designs for such interventions.

Based on the experience of UNETE's School Strengthening Program (SSP), we estimated various effects of providing educational technology to school communities, along with the pedagogical support needed to facilitate the integration of these new technologies into teaching practices, both in media-focused settings and in regular classrooms. Our results highlight the importance of incorporating effective pedagogical support for teachers into the design of ICTE interventions. Furthermore, this evidence demonstrated significant variations across grade/age and competency domains, offering valuable guidance for designing teacher-centered, technology-enabled interventions tailored for different age groups or school grades. Our findings also confirm that, for any decision-maker or stakeholder seeking to integrate educational technology, it is crucial to recognize that the effective use of ICTE does not emerge naturally with technological progress; rather, it depends on intentional and sustained efforts to prepare and support teachers (Siyam et al., 2025; Gambi et al., 2025).

Evidence from our study can inform decision-makers interested in adopting educational technology by prompting reflection on the importance of designing and providing adequate educational materials and teaching support.

The main goal of this study was to develop new evidence to help address barriers linked to the adoption and implementation of ICTE programs in developing countries, stemming from limited knowledge of the factors or components that can maximize the likelihood of transforming instructional practices and, consequently, enhancing student learning outcomes. Generating further reliable evidence on the impact of ICTE programs in developing countries is crucial because, as Rodriguez-Segura (2021) highlights, policymakers and education stakeholders must understand which ICTE interventions have proven most effective across various outcomes, target groups, and contexts. Furthermore, promoting the consistent use of up-to-date evidence is essential to avoid the risks of digital exclusion posed by interventions focused solely on the provision of technology and connectivity. This is a relevant aspect to consider, since, as noted by Shank (2019), the impact of educational technologies mainly depends on the design, implementation, and accessibility, factors that can either help to reduce or deepen longstanding educational inequalities.

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Declaration of generative AI and AI-assisted technologies in the manuscript preparation process

During the preparation of this work, the authors used the following tools:

a) "Grammarly" to verify spelling, punctuation, and grammar since we are non-native English speakers.

b) "Refine" in order to identify potential errors.

After using these services, all the authors reviewed and edited the content as needed. We take full responsibility for the content of the published article.

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A Power Analysis

This appendix presents the analytical expression used to compute the Minimum Detectable Effect (MDE) in a two-period, two-group Difference-in-Differences (DiD) design with treatment assigned at the cluster level (schools). The derivation follows standard power calculation frameworks for cluster-randomized trials adapted to DiD settings (see, for example, Bloom, 1995; Schochet, 2008; McKenzie, 2012; Burlig et al., 2020).

We assume the data are generated according to the following model:

$$Y_{it} = \theta_t + \eta_i + \tau D_{it} + \boldsymbol{X}_{it}\beta + \varepsilon_{it},$$

where ε_{it} is an idiosyncratic error term distributed as $\mathcal{N}(0, \sigma^2)$. Table 8 shows the notation used in the equations from this appendix.

Table 8: Notation

J_T	Number of treatment clusters (i.e., treated schools)
J_C	Number of control clusters (i.e., comparison schools)
m	Average number of individual observations per cluster and period
σ^2	Individual-level outcome variance within a period
ρ	Intra-cluster correlation (ICC) within a period
ϕ	Serial correlation of the outcome over time
$\mathbf{X}$	Vector of pre-specified baseline controls included in the regression
R_X^2	Fraction of outcome variance explained by covariates $\mathbf{X}$
α	Significance level
$1-\kappa$	Desired statistical power
$t_{1-\alpha/2}$	Critical value of the t-distribution associated with the probability of a Type I error in a two-sided test against the null hypothesis $\tau = 0$
$t_{1-\kappa}$	Critical value associated with the probability of correctly rejecting a false null hypothesis

The MDE is defined as:

$$\text{MDE} = (t_{1-\alpha/2} + t_{1-\kappa})\sqrt{\text{Var}(\widehat{\tau} \mid \mathbf{X})},$$

where $\text{Var}(\widehat{\tau} \mid \mathbf{X})$ is the finite-sample variance of the DiD estimator of the treatment effect, conditional on covariates $\mathbf{X}$.

Role of Covariates

Conditioning on covariates $\mathbf{X}$ reduces the residual variance used in power calculations. Let σ^2_{res} denote the residual variance of the outcome after projecting out $\mathbf{X}$ (and any fixed effects included). There are two equivalent ways to represent this adjustment:

1. **Direct residual variance:** Estimate σ^2_{res} as the sample variance of the regression residuals from

$$Y_{it} = \theta_t + \eta_i + \boldsymbol{X}_{it}\gamma + u_{it},$$

   using baseline (pre-treatment) data or pooled pre/post data (excluding the treatment indicator). In this case, σ^2_{res} replaces σ^2 in the formulas below.

2. R^2 **adjustment:** Define R^2_X as the fraction of the unconditional variance explained by $\mathbf{X}$ (and any fixed effects included before treatment). Then

$$\sigma^2_{\text{res}} = (1 - R^2_X)\,\sigma^2,$$

   and one can substitute σ^2_{res} for σ^2 in the MDE expressions.

Panel Data Structure and Estimator

Although the outcome model is written at the individual level and motivates the analysis using within-individual variation, the power calculations are based on the canonical Difference-in-Differences estimator constructed from cluster–period means. Specifically, outcomes are first averaged at the school–period level, and the treatment effect is obtained by comparing changes over time between treated and control schools. Under a balanced panel and standard assumptions, this aggregated DiD estimator is algebraically equivalent to an individual-level fixed-effects DiD estimator, while delivering a transparent variance expression commonly used in power calculations.

For a balanced panel (i.e., the same individuals observed before and after treatment), differencing outcomes over time at the cluster level reduces the variance by a factor approximately equal to $(1 - \phi)$, where ϕ captures the serial correlation of outcomes across periods. Replacing the unconditional variance with the residual variance after conditioning on covariates, the approximate variance of the DiD estimator is:

$$\text{Var}(\widehat{\tau} \mid \mathbf{X}) \approx 2(1-\phi)\,\sigma^2_{\text{res}} \left(\rho + \frac{1-\rho}{m}\right)\left(\frac{1}{J_T} + \frac{1}{J_C}\right).$$

Substituting $\sigma^2_{\text{res}} = (1 - R^2_X)\sigma^2$ yields:

$$\text{Var}(\widehat{\tau} \mid \mathbf{X}) \approx 2(1-\phi)(1-R^2_X)\,\sigma^2 \left(\rho + \frac{1-\rho}{m}\right)\left(\frac{1}{J_T} + \frac{1}{J_C}\right).$$

Minimum Detectable Effect (MDE)

Using the variance above, the MDE that achieves a two-sided significance level α and power $1-\kappa$ is:

$$\text{MDE} = (t_{1-\alpha/2} + t_{1-\kappa})\sqrt{2(1-\phi)\,\sigma^2_{\text{res}}\left(\rho + \frac{1-\rho}{m}\right)\left(\frac{1}{J_T} + \frac{1}{J_C}\right)}.$$

Using the parameter values summarized in Table 9, the Minimum Detectable Effect (MDE) was computed following the previous expression. Under a two-period, two-group DiD design with treatment assigned at the school level, balanced panel data (same students observed before and after treatment), and conditioning on covariates that explain $R^2_X = 0.20$ of the unconditional variance, the resulting detectable effect size at a 5% significance level and 80% power is MDE = 0.0666.

Table 9: Parameters for Power Calculation

σ^2	Maximum variance for a binary outcome variable	0.25
m	Average number of students per class	30
$t_{0.975}$	t critical value for significance tests	1.96
$t_{0.80}$	t critical value for power calculation	0.84
ϕ	Autocorrelation	0.5
ρ	Intra-cluster correlation (ICC)	0.1
J_C	Number of control schools	85
J_T	Number of treated schools	100
R^2_X	Fraction of unconditional variance explained by $\mathbf{X}$	0.2

Given the assumed intra-cluster correlation ($\rho = 0.10$), autocorrelation over time ($\phi = 0.5$), and number of clusters per group ($J_T = 100$, $J_C = 85$), the study design yields sufficient statistical power to detect an average treatment effect of approximately 0.067. Because the outcome variable is binary, this value corresponds to approximately 7-percentage-point change in the probability of the outcome.

B Questionnaires and Category Composition

B.1 Students' Digital Competencies

The questionnaire used to measure students' perceptions of their digital competencies in this study is based on the European Digital Competence Framework for Citizens (DigCompSAT) (see Clifford et al., 2020, p. 154). Table 10 lists all the items in the questionnaire, and each item belongs to one of the following categories:

1. **Information and Data Literacy:** It reflects students' confidence to find, evaluate, and manage digital information effectively.
2. **Communication and Collaboration:** It reflects students' confidence in communicating and collaborating through digital platforms.
3. **Digital Content Creation:** It reflects students' confidence to create and edit digital content, including multimedia.
4. **Safety:** It reflects students' awareness and practices regarding online safety, privacy, and responsible behavior.
5. **Problem Solving:** It reflects students' confidence in identifying digital problems and effectively using technology to solve them.

Included items are designed with a 4-point Likert scale, where higher values indicate greater mastery in the respective skill domain. These responses are transformed into binary values by assigning 1 when the response corresponds to the highest scale point and 0 otherwise. An index is computed for each category as the mean of the corresponding binary item values for that category.

Table 10: English translation of Digital Competencies items

Q.	English translation	Category
8	I know that different search engines may give different search results, because they are influenced by commercial factors.	Information and Data Literacy
9	I know which words to use in order to find what I need quickly (e.g., to search online or within a document).	
10	When I use a search engine, I can take advantage of its advanced features.	
11	I know how to find a website I have visited before.	

Continued on next page

Q.	English translation	Category
12	I know how to differentiate promoted content from other content I find or receive online (e.g., recognizing an advert on social media or search engines).	
13	I know how to identify the purpose of an online information source (e.g., to inform, influence, entertain, or sell).	
14	I critically check if the information I find online is reliable.	
15	I know that some information on the Internet is false (e.g., fake news).	
16	I know about different storage media (e.g., internal or external hard disk, USB memory, pen drive, memory card).	
17	I know how to organize digital content (e.g., documents, images, videos) using folders or tagging to find them back later.	
18	I know how to copy and move files (e.g., documents, images, videos) between folders, devices, or on the cloud.	
19	I know how to manage and analyze data using software (e.g., sorting, filtering, calculations).	
20	I know how to send, reply, and forward e-mails.	Communication and Collaboration
21	I know that many communication services and social media are free of charge because they are paid for by advertising.	
22	I know how to use advanced videoconferencing features (e.g., moderating, recording audio and video).	
23	I know which communication tools and services (e.g., phone, email, video conference, text message) are appropriate to use in different circumstances.	
24	I am open towards sharing digital content that I think might be interesting and useful to others.	
25	I know how to use cloud services (e.g., Google Drive, Dropbox, and OneDrive) to share my files.	
26	I know how to change who I share content with (e.g., friends, friends of friends, everyone).	
27	I know how to reference the source of documents (e.g., the author or web address) that I found online.	
28	I know how to apply for a job using a digital platform (e.g., fill in a form, upload my CV and photo).	
29	I know that many public services are available on the Internet (e.g., booking a health visit, submitting a tax declaration, requesting birth, marriage, residence, and other certificates).	
30	I know how to pay for goods and services that I buy online (e.g., using direct bank transfer, credit/debit cards, other online payment systems).	
31	It matters to me to debate social or political issues online (e.g., in online forums, news sites, Facebook, Twitter).	

Continued on next page

Q.	English translation	Category
32	I understand the benefits of remote collaboration (e.g., reduced commuting time).	
33	I know how to edit a shared, online document.	
34	I know how to invite others and give appropriate permissions to collaborate on a shared document.	
35	I am aware that I should ask permission from a person before publishing or sharing photos about them.	
36	I know how to recognize online messages and behaviors that attack certain groups or individuals (e.g., hate speech).	
37	I can take the right measures if someone is doing the wrong thing online (e.g., an offensive comment, threats).	
38	I know how to behave online according to the situation (e.g., formal vs informal).	
39	I know my digital identity is everything that identifies me in online environments (e.g., usernames, likes and posts on social media, petitions signed online)	
40	I know how to create a profile in digital environments for personal or professional purposes.	
41	I know about the "right to be forgotten" and why it is important (e.g., removing private information from the internet).	
42	I know how to configure the settings in my Internet browser to prevent or limit cookies.	
43	I know how to create and edit digital text files (e.g., Word, OpenDocument, Google Docs).	Digital Content Creation
44	I know how to express myself by creating digital content on the Internet (e.g., blog post, video on YouTube).	
45	I know how to produce a multimedia presentation with text, images, audio, and video elements.	
46	I am careful to choose the right type of digital media depending on the audience and my aim (e.g., using social media to promote a project).	
47	I am keen to create new digital content by mixing and modifying existing digital resources (e.g., a presentation with photos and a soundtrack found on the Internet)	
48	I know that some digital content can be reused and reworked legally (e.g., public domain or with Creative Commons licenses).	
49	I know how to edit or make changes to digital content that others have created (e.g., insert text into an image, edit a wiki).	
50	I know how to create something new by mixing different types of content (e.g., text and images).	
51	I am careful to follow the rules about copyrights and licenses of digital content that I find.	

Continued on next page

Q.	English translation	Category
52	I know that downloading or sharing digital content (e.g., music, software, films) may have ethical or legal consequences.	
53	I can detect when digital content is made available illegally (e.g. software, movies, music, books, TV).	
54	I know which different types of licences apply to the use of digital content (e.g. Creative Commons licences).	
55	I am interested in understanding how a task can be broken down into steps so that it can be automated, for example, in software or by a robot	
56	I know that programming languages (e.g., Python, Visual Basic, Java) are used to provide a digital device instructions to carry out a task.	
57	I can write scripts, macros, and simple applications to automate the execution of a task.	
58	I know that there could be different algorithmic solutions to accomplish a specific computational task (e.g., sorting and searching).	
59	I understand the benefits and also the safety risks when using Internet-connected devices or systems (e.g., smart watches, smart home devices).	Safety
60	I know about the importance of keeping the operating system, antivirus, and other software up-to-date in order to prevent security issues.	
61	I know how to configure the settings of a firewall on different devices.	
62	I know how to recover digital information and other content (e.g., photos, contacts) from a backup.	
63	I know how to restrict or refuse access to my geographical location.	
64	I know how to identify suspicious e-mail messages that try to obtain my personal data.	
65	I know how to check that the website where I am asked to provide personal data is secure (e.g., https sites, safety logo or certificate).	
66	I know which personal data I should not share and display online (e.g., on social media).	
67	I am careful about checking the privacy policies of the digital services that I use.	
68	I am aware that I should manage the time I spend on my digital devices.	
69	I know how to protect myself from unwanted and malicious online encounters and materials (e.g., spam messages, identity theft emails).	
70	I know about digital tools that can help older people or people with special needs.	
71	I seek out ways in which digital technologies could help me to live and consume in a more environmentally friendly way.	
72	I know that old digital devices and consumables (e.g., computers, smartphones, batteries) must be appropriately disposed of to minimize their environmental impact.	

Continued on next page

Q.	English translation	Category
73	I know how to reduce the energy consumption of my devices (e.g., change settings, close apps, turn off wifi).	
74	I know 'green' behaviors to follow when buying or using digital devices (e.g., purchase devices with Eco-label, refrain from unnecessary printing of digital files, do not leave mobile phones and laptop chargers connected without the device).	
75	When I face a technical problem, I try step-by-step to identify the problem.	Problem Solving
76	I know some reasons why a digital device may fail to connect online (e.g., wrong wifi password, airplane mode on).	
77	When I face a technical problem, I am able to find solutions on the Internet.	
78	I am able to edit the configurations of the operating system of my digital devices to solve technical problems (e.g., automatic stop/start of services, modify registry keys).	
79	I usually try to find out if there is a technology solution that might help me address a personal or professional need.	
80	I know the main functions of the most common digital devices (computer, tablet, smartphone).	
81	I know how to select the right tool, device, or service to perform a given task (e.g., select a smartphone for my needs, choose a tool for a professional video call).	
82	I know technical solutions that can improve the access and use of digital tools such as language translation, magnification, or zoom and text-to-voice functionality.	
83	I know that digital technology can be used as a powerful tool to innovate processes and products.	
84	I am willing to take part in challenges and contests, aimed at solving intellectual, social, or practical problems through digital technologies.	
85	I can use data tools (e. g., databases, data mining, and analysis software) that manage and organize complex information to make decisions and solve problems.	
86	I am willing to help people in my community improve their digital skills.	
87	I am curious about new digital devices and applications, and I am keen to experiment with them whenever I find the opportunity.	
88	I know how to use online learning tools to improve my digital skills (e.g., video tutorials, online courses).	
89	I know about new trends in the digital world and how they impact on my personal or professional life.	

B.2 Students' 21st-Century Competencies

The questionnaire used to measure students' perceptions of their 21st-century competencies in this study is partially adapted from an instrument developed by (Kelley et al., 2019, Table 5). Table 11 lists all the items in the questionnaire, and each item belongs to one of the following categories:

1. **Critical Thinking:** It reflects students' confidence to analyze, reason, and make informed decisions.
2. **Collaboration:** It reflects students' confidence to work effectively in teams.
3. **Communication:** It reflects students' confidence in expressing ideas clearly in multiple formats.
4. **Creativity:** It reflects students' confidence to generate innovative ideas and solutions.
5. **Information Literacy:** It reflects students' confidence to locate, evaluate, and use information effectively.
6. **Technology Literacy:** It reflects students' confidence in using digital tools and technology.
7. **Problem Solving:** It reflects students' confidence to identify challenges and develop solutions.
8. **Data Management (Information):** It measures students' knowledge for the organization and management of digital files and information.
9. **Search & Filter (Information):** It measures students' knowledge about how to use advanced features of a web browser.
10. **Evaluate Content (Information):** It measures students' knowledge about how to evaluate the reliability and quality of information found on the web.
11. **Content Creation:** It measures students' knowledge about how to produce and manage digital content for effective communication.
12. **Content Management:** It measures students' knowledge about how to organize, store, and manage created digital content.
13. **Content Integration:** It measures students' knowledge about how to combine information and content from different sources effectively.

14. **Intellectual Property & Licenses:** It measures students' awareness of the appropriate use of intellectual property and licensing rules.

Items 8 to 52 consider a 5-point Likert scale, where higher values indicate greater mastery in the respective skill domain. Responses were transformed into binary values by assigning 1 when the response corresponds to one of the two highest scale points and 0 otherwise. Items 53 to 62 are multiple-choice questions, whose responses are transformed into binary values by assigning 1 when the response is correct and 0 otherwise. An index is computed for each category as the mean of the corresponding binary item values for that category.

Table 11: English Translation of 21st-Century Competencies Items

Q.	**English translation**	**Category**
8	I am confident in my ability to review a written text and suggest evidence-based changes.	Critical Thinking
9	I am confident in my ability to suggest questions that help expand or deepen a search.	
11	I am confident in my ability to clearly identify what I need to know to answer a research question.	
12	I am confident in my ability to evaluate the reasoning and evidence someone uses to support an argument.	
14	I am confident in my ability to ask questions that help me understand what someone wants or needs.	
16	I am confident in my ability to understand questions related to critical thinking.	
17	I am confident in my ability to justify the criteria I use to evaluate something.	
18	I am confident in my ability to obtain relevant and sufficient information from different sources.	
33	I am confident in my ability to understand how acquired knowledge or learning can be applied in different contexts.	
19	I am confident in my ability to be polite and courteous with members of a work team.	Collaboration
20	I am confident in my ability to recognize and respect others' perspectives.	
21	I am confident in my ability to follow the rules agreed upon for team meetings.	
22	I am confident in my ability to ensure that everyone's ideas in a team are valued equally.	
23	I am confident in my ability to offer help to others when they need it.	
24	I am confident in my ability to improve my work after receiving feedback or suggestions.	

Continued on next page

Table 11 – continued from previous page

Q.	English translation	Category
26	I am confident in my ability to be mentally and physically prepared each day.	
27	I am confident in my ability to follow the agreed-upon rules for team decision-making.	
28	I am confident in my ability to coordinate meetings and manage team time effectively.	
30	I am confident in my ability to monitor my team's progress toward goals and deadlines.	
31	I am confident in my ability to complete assigned tasks without being reminded.	
35	I am confident in my ability to help my team solve problems and manage conflicts.	
25	I am confident in my ability to use appropriate body language when giving a presentation.	Communication
29	I am confident in my ability to organize available information appropriately.	
32	I am confident in my ability to present all available information clearly, concisely, and logically.	
36	I am confident in my ability to adapt my communication style to the purpose of a meeting or task.	
10	I am confident in my ability to create new things that are unique and impressive.	Creativity
13	I am confident in my ability to generate ideas that are useful to a specific person.	
15	I am confident in my ability to combine existing elements or resources and turn them into a new product.	
34	I am confident in my ability to find sources of information or inspiration that others overlook.	
37	I am confident in my ability to deepen and improve ideas.	
38	When browsing the internet, I have the skills to distinguish an academic research source from other types of texts.	Information Literacy
39	I have the skills to quickly find statistics and relevant information online for school research.	
40	I have the skills to evaluate the credibility and relevance of online information sources.	
41	When browsing the internet, I have the skills to distinguish between fake and real news.	
42	When browsing the internet, I have the skills to identify the social, economic, and political implications of the information I consult.	

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Table 11 – continued from previous page

Q.	English translation	Category
43	I am confident in my ability to access and use the internet.	Technology Literacy
44	I am confident in my ability to send and receive emails.	
45	I am confident in my ability to use word processors.	
46	I am confident in my ability to use databases on a computer.	
47	I am confident in my ability to download and use computer programs.	
48	Please indicate how often you do the following: when I face a problem, I try to identify all its causes.	Problem Solving
49	Please indicate how often you do the following: when I face a problem, I assess all the facts before trying to solve it.	
50	Please indicate how often you do the following: when I face a problem, I consider all possible solutions.	
51	Please indicate how often you do the following: when I face a problem, I consider the perspectives of the people around me.	
52	Please indicate how often you do the following: when I face a problem, I assess all possible consequences of each solution.	
53	True or False: Cloud drives are used to store and share files that can only be accessed from our own computer.	Data Management
54	True or False: Web links saved in a computer's favorites folder can be accessed from any computer.	
55	What happens if we press CTRL+V in a file explorer window?	
56	True or False: Browser extensions or add-ons are programs that add features and improvements to browsers — for example, taking screenshots, downloading videos, or translating text on a webpage. Extensions are installed through the browser's extension store or gallery, adding a small button to the toolbar to activate the new feature.	Search & Filter
57	Is the information found on the internet reliable?	Evaluate Content
58	Which of the following options indicates the file type and its specific properties?: The file maganer, the name, the software, or the extension.	Content Creation
59	The benefits of using infographics are: They allow files to be organized more efficiently; They improve a website's download speed; They make it easier to visually understand complex data; They incorporate a lot of text, since this type of content is the most appealing; They promote use by groups with visual disabilities; They make usage easier, since this type of content is freely licensed and can be used without restrictions; They increase image quality; or They graphically explain processes, comparisons, timelines, product components, instructions, etc.	
60	When I need to find a file or folder, in which of the following storage media could I look? (Select all that apply): Hard drive, USB drive, RAM memory, Google Drive, or ROM memory.	Content Management

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Table 11 – continued from previous page

Q.	English translation	Category
61	What does “format text” mean?	Content Integration
62	Internet resources published by third parties can be used personally with complete freedom simply because they are shared online.	IP & Licenses

C Additional Tables

Table 12: Estimated Effects for Individual Questions on Students' Digital Competencies

	(1)		(2)		(3)		(4)	
	Coef.	SE	Coef.	SE	Coef.	SE	Coef.	SE
Question 8	0.0464	(0.0420)	0.0329	(0.0634)	0.0766	(0.0314)	0.0317	(0.0520)
Question 9	0.0789	(0.0546)	0.0755	(0.0733)	0.145	(0.0493)	0.157	(0.0889)
Question 10	0.0459	(0.0476)	0.0482	(0.0688)	0.0686	(0.0372)	0.0547	(0.0841)
Question 11	0.0814	(0.0498)	0.117	(0.0781)	0.183	(0.0407)	0.160	(0.0857)
Question 12	0.0899	(0.0556)	0.104	(0.0705)	0.128	(0.0419)	0.235	(0.0919)
Question 13	0.0431	(0.0523)	0.0960	(0.0748)	0.114	(0.0411)	0.200	(0.0659)
Question 14	0.0517	(0.0502)	0.0488	(0.0753)	0.0457	(0.0461)	0.0928	(0.102)
Question 15	0.0493	(0.0527)	0.0211	(0.0659)	0.106	(0.0457)	0.126	(0.0694)
Question 16	0.0666	(0.0507)	-0.00428	(0.0577)	0.0924	(0.0438)	0.0427	(0.0737)
Question 17	0.0917	(0.0595)	0.0936	(0.0616)	0.101	(0.0360)	0.148	(0.0848)
Question 18	0.0318	(0.0523)	0.0207	(0.0783)	0.0517	(0.0437)	0.0245	(0.0507)
Question 19	0.0626	(0.0398)	0.0315	(0.0624)	0.0728	(0.0282)	-0.00499	(0.0610)
Question 20	0.0788	(0.0370)	0.0691	(0.0506)	0.0989	(0.0319)	0.0937	(0.0632)
Question 21	0.0722	(0.0502)	0.0611	(0.0621)	0.132	(0.0473)	0.0265	(0.0566)
Question 22	0.0706	(0.0383)	0.0588	(0.0548)	0.0946	(0.0302)	0.0645	(0.0504)
Question 23	0.111	(0.0541)	0.0745	(0.0716)	0.126	(0.0461)	0.0291	(0.0619)
Question 24	0.117	(0.0700)	0.0922	(0.0710)	0.128	(0.0479)	0.0962	(0.0933)
Question 25	0.0607	(0.0384)	0.0618	(0.0528)	0.0930	(0.0312)	0.126	(0.0487)
Question 26	0.121	(0.0492)	0.105	(0.0708)	0.182	(0.0385)	0.168	(0.0892)
Question 27	0.101	(0.0423)	0.106	(0.0632)	0.121	(0.0363)	0.0392	(0.0616)
Question 28	0.149	(0.0398)	0.0993	(0.0500)	0.133	(0.0312)	0.132	(0.0328)
Question 29	0.131	(0.0434)	0.101	(0.0603)	0.137	(0.0367)	0.161	(0.0651)
Question 30	0.0711	(0.0395)	0.0462	(0.0522)	0.0645	(0.0279)	0.117	(0.0603)
Question 31	0.1000	(0.0461)	0.111	(0.0598)	0.0917	(0.0349)	0.101	(0.0886)
Question 32	0.125	(0.0457)	0.112	(0.0597)	0.143	(0.0346)	0.156	(0.0421)
Question 33	0.0820	(0.0400)	0.0970	(0.0524)	0.125	(0.0306)	0.182	(0.0569)
Question 34	0.0821	(0.0399)	0.0661	(0.0535)	0.0877	(0.0306)	0.153	(0.0482)
Question 35	0.0701	(0.0425)	0.0736	(0.0671)	0.111	(0.0371)	0.162	(0.100)
Question 36	0.0893	(0.0423)	0.109	(0.0513)	0.143	(0.0279)	0.0856	(0.0814)
Question 37	0.0893	(0.0411)	0.0951	(0.0649)	0.130	(0.0412)	0.225	(0.0851)
Question 38	0.0520	(0.0515)	0.0167	(0.0716)	0.0992	(0.0462)	0.00307	(0.0737)
Question 39	0.0751	(0.0432)	0.0638	(0.0664)	0.111	(0.0373)	0.0891	(0.0766)

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Table 12 – continued from previous page

	(1)		(2)		(3)		(4)	
	Coef.	SE	Coef.	SE	Coef.	SE	Coef.	SE
Question 40	0.125	(0.0457)	0.112	(0.0624)	0.146	(0.0322)	0.114	(0.0527)
Question 41	0.0794	(0.0385)	0.0771	(0.0489)	0.103	(0.0289)	0.0709	(0.0686)
Question 42	0.0674	(0.0402)	0.0542	(0.0533)	0.0841	(0.0322)	0.130	(0.0489)
Question 43	0.118	(0.0651)	0.0919	(0.0920)	0.127	(0.0504)	0.115	(0.0511)
Question 44	0.114	(0.0428)	0.0822	(0.0496)	0.136	(0.0290)	0.136	(0.0467)
Question 45	0.100	(0.0401)	0.117	(0.0690)	0.145	(0.0390)	0.229	(0.0704)
Question 46	0.104	(0.0557)	0.0844	(0.0777)	0.142	(0.0394)	0.0600	(0.0795)
Question 47	0.114	(0.0579)	0.0695	(0.0710)	0.108	(0.0430)	0.140	(0.0969)
Question 48	0.0736	(0.0354)	0.0706	(0.0518)	0.105	(0.0281)	0.120	(0.0315)
Question 49	0.0915	(0.0391)	0.0926	(0.0503)	0.113	(0.0328)	0.0905	(0.0449)
Question 50	0.0940	(0.0463)	0.122	(0.0665)	0.149	(0.0356)	0.238	(0.0723)
Question 51	0.0702	(0.0522)	0.0937	(0.0887)	0.0981	(0.0416)	0.0188	(0.102)
Question 52	0.0521	(0.0559)	0.0729	(0.0608)	0.0928	(0.0329)	0.127	(0.0603)
Question 53	0.0907	(0.0369)	0.0947	(0.0585)	0.102	(0.0310)	0.191	(0.0491)
Question 54	0.0950	(0.0385)	0.0686	(0.0490)	0.0854	(0.0256)	0.0644	(0.0478)
Question 55	0.116	(0.0642)	0.113	(0.0810)	0.126	(0.0461)	0.135	(0.115)
Question 56	0.0998	(0.0465)	0.0840	(0.0492)	0.0987	(0.0356)	0.100	(0.0560)
Question 57	0.0915	(0.0418)	0.0820	(0.0564)	0.106	(0.0341)	0.0874	(0.0548)
Question 58	0.108	(0.0358)	0.106	(0.0484)	0.112	(0.0301)	0.0612	(0.0435)
Question 59	0.0752	(0.0355)	0.0723	(0.0528)	0.124	(0.0270)	0.220	(0.0553)
Question 60	0.0895	(0.0468)	0.123	(0.0678)	0.157	(0.0398)	0.187	(0.0538)
Question 61	0.0641	(0.0407)	0.0438	(0.0556)	0.0649	(0.0288)	0.0596	(0.0455)
Question 62	0.122	(0.0411)	0.131	(0.0618)	0.145	(0.0343)	0.135	(0.0494)
Question 63	0.0487	(0.0504)	0.0792	(0.0626)	0.0830	(0.0323)	0.0497	(0.0510)
Question 64	0.108	(0.0414)	0.145	(0.0594)	0.176	(0.0322)	0.217	(0.0644)
Question 65	0.114	(0.0451)	0.144	(0.0592)	0.131	(0.0316)	0.139	(0.0498)
Question 66	0.0556	(0.0470)	0.0483	(0.0673)	0.133	(0.0338)	0.158	(0.0699)
Question 67	0.0472	(0.0618)	0.0126	(0.0903)	0.0762	(0.0491)	0.0649	(0.0931)
Question 68	0.0337	(0.0547)	0.0529	(0.0980)	0.0474	(0.0472)	-0.0962	(0.0817)
Question 69	0.0907	(0.0380)	0.104	(0.0552)	0.152	(0.0271)	0.0963	(0.0682)
Question 70	0.0884	(0.0562)	0.0674	(0.0636)	0.103	(0.0386)	0.0949	(0.0537)
Question 71	0.0699	(0.0578)	0.0569	(0.0844)	0.0939	(0.0419)	0.0955	(0.113)
Question 72	0.0993	(0.0569)	0.129	(0.0822)	0.125	(0.0452)	0.147	(0.0652)
Question 73	0.150	(0.0498)	0.139	(0.0703)	0.205	(0.0342)	0.267	(0.0569)
Question 74	0.0991	(0.0442)	0.0915	(0.0626)	0.103	(0.0383)	0.101	(0.0746)

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Table 12 – continued from previous page

	(1)		(2)		(3)		(4)	
	Coef.	SE	Coef.	SE	Coef.	SE	Coef.	SE
Question 75	0.0825	(0.0689)	0.0651	(0.103)	0.0931	(0.0393)	-0.0687	(0.0756)
Question 76	0.0896	(0.0531)	0.0659	(0.0772)	0.106	(0.0427)	0.0408	(0.102)
Question 77	0.0900	(0.0422)	0.0398	(0.0586)	0.109	(0.0324)	-0.0220	(0.0757)
Question 78	0.0977	(0.0401)	0.105	(0.0608)	0.114	(0.0242)	0.129	(0.0344)
Question 79	0.113	(0.0474)	0.0537	(0.0728)	0.0844	(0.0387)	0.126	(0.0859)
Question 80	0.0831	(0.0428)	0.101	(0.0608)	0.143	(0.0356)	0.0948	(0.0744)
Question 81	0.0657	(0.0487)	0.0448	(0.0662)	0.0975	(0.0418)	0.126	(0.0666)
Question 82	0.0978	(0.0465)	0.0954	(0.0672)	0.114	(0.0382)	0.0678	(0.0647)
Question 83	0.0873	(0.0496)	0.0872	(0.0733)	0.0890	(0.0432)	0.118	(0.0652)
Question 84	0.0549	(0.0851)	0.0613	(0.127)	0.0265	(0.0562)	0.0640	(0.0918)
Question 85	0.0963	(0.0389)	0.122	(0.0516)	0.122	(0.0260)	0.129	(0.0395)
Question 86	0.00289	(0.112)	-0.0489	(0.162)	-0.0217	(0.0837)	-0.0227	(0.107)
Question 87	0.0721	(0.0676)	0.00213	(0.0812)	0.0740	(0.0473)	-0.114	(0.0942)
Question 88	0.123	(0.0504)	0.121	(0.0692)	0.183	(0.0365)	0.172	(0.0574)
Question 89	0.127	(0.0446)	0.138	(0.0548)	0.160	(0.0297)	0.152	(0.0517)

This table presents the estimated Average Treatment Effect on the Treated (ATT) for each digital competencies question considered individually. Table 10 in Appendix B presents the full text of each question, translated from Spanish. Similarly to the main estimations in the paper, specifications in columns (1)–(3) are estimated using a linear probability model (OLS), while column (4) employs the Doubly Robust Difference-in-Differences (DiD) estimator. The same controls are included, corresponding to the main estimation results presented in the text. Clustered standard errors at the school level are reported in parentheses. Due to outcome-specific missingness, the number of observations varies across specifications. Sample sizes range from 3,241 to 3,280 in column (1), from 2,526 to 2,557 in column (2), from 2,337 to 2,363 in column (3), and from 1,570 to 1,614 in column (4).

Table 13: Estimated Effects for Individual Questions on Students' 21st-Century Competencies

	(1)		(2)		(3)		(4)	
	Coef.	SE	Coef.	SE	Coef.	SE	Coef.	SE
Question 8	0.0489	(0.0816)	0.0389	(0.123)	0.0358	(0.0683)	0.189	(0.0735)
Question 9	0.0474	(0.0805)	0.0499	(0.122)	0.0327	(0.0699)	0.0917	(0.0711)
Question 10	0.0644	(0.0781)	0.106	(0.121)	0.0736	(0.0697)	0.154	(0.0959)
Question 11	0.113	(0.0845)	0.132	(0.143)	0.129	(0.0772)	0.192	(0.0779)
Question 12	0.0467	(0.0885)	0.0404	(0.140)	0.0421	(0.0738)	0.120	(0.0992)
Question 13	0.0690	(0.0782)	0.106	(0.118)	0.0936	(0.0660)	0.121	(0.109)
Question 14	0.0435	(0.0896)	0.0798	(0.143)	0.0639	(0.0758)	0.181	(0.0745)
Question 15	0.0492	(0.0761)	0.0486	(0.131)	0.0360	(0.0718)	0.0536	(0.0782)
Question 16	0.0621	(0.0905)	0.0593	(0.154)	0.0806	(0.0855)	0.0907	(0.0881)
Question 17	0.124	(0.0916)	0.0998	(0.154)	0.122	(0.0847)	0.125	(0.0838)
Question 18	0.0943	(0.100)	0.133	(0.163)	0.124	(0.0888)	0.147	(0.0999)
Question 19	0.0232	(0.0921)	0.0274	(0.165)	0.0247	(0.0821)	0.0299	(0.0536)
Question 20	0.0551	(0.0875)	0.0802	(0.152)	0.0754	(0.0819)	0.151	(0.0525)
Question 21	0.0738	(0.0914)	0.0941	(0.151)	0.0696	(0.0780)	0.159	(0.0508)
Question 22	0.0778	(0.0940)	0.0656	(0.158)	0.0837	(0.0811)	0.194	(0.0692)
Question 23	0.0359	(0.0927)	0.0592	(0.158)	0.0316	(0.0829)	0.0566	(0.0563)
Question 24	0.0714	(0.0908)	0.0726	(0.162)	0.0813	(0.0823)	0.171	(0.0638)
Question 25	0.0843	(0.0900)	0.0826	(0.165)	0.0851	(0.0834)	0.175	(0.0562)
Question 26	0.0342	(0.0900)	0.0359	(0.159)	0.0356	(0.0807)	0.132	(0.0659)
Question 27	0.0597	(0.0998)	0.0942	(0.163)	0.0712	(0.0871)	0.216	(0.0652)
Question 28	0.0609	(0.0952)	0.103	(0.154)	0.0660	(0.0798)	0.246	(0.0730)
Question 29	0.0731	(0.0837)	0.100	(0.138)	0.109	(0.0743)	0.0864	(0.0701)
Question 30	0.0659	(0.0910)	0.125	(0.146)	0.0814	(0.0802)	0.181	(0.0737)
Question 31	0.0427	(0.0966)	0.0973	(0.155)	0.0651	(0.0864)	0.229	(0.0768)
Question 32	0.0764	(0.0899)	0.0938	(0.146)	0.0798	(0.0757)	0.191	(0.0650)
Question 33	0.0952	(0.0889)	0.126	(0.147)	0.0974	(0.0803)	0.221	(0.0825)
Question 34	0.0718	(0.0935)	0.0764	(0.143)	0.0730	(0.0807)	0.152	(0.105)
Question 35	0.0475	(0.100)	0.0966	(0.171)	0.0791	(0.0874)	0.194	(0.0697)
Question 36	0.0632	(0.0981)	0.109	(0.147)	0.0687	(0.0881)	0.143	(0.0823)
Question 37	0.0662	(0.0935)	0.113	(0.146)	0.0825	(0.0804)	0.200	(0.0760)
Question 38	0.0523	(0.0687)	0.0428	(0.0975)	0.00417	(0.0547)	-0.0795	(0.0828)
Question 39	-0.0158	(0.0650)	0.0130	(0.0857)	-0.0518	(0.0520)	0.0207	(0.0874)
Question 40	0.00259	(0.0718)	-0.0278	(0.114)	-0.0215	(0.0630)	-0.0898	(0.0901)

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Table 13 – continued from previous page

	(1)		(2)		(3)		(4)	
	Coef.	SE	Coef.	SE	Coef.	SE	Coef.	SE
Question 41	0.0126	(0.0597)	-0.0321	(0.0889)	-0.00746	(0.0453)	-0.146	(0.0779)
Question 42	0.00242	(0.0583)	-0.0198	(0.0827)	-0.0334	(0.0437)	-0.0258	(0.0958)
Question 43	-0.00061	(0.0528)	0.0159	(0.0762)	0.0103	(0.0464)	-0.128	(0.0614)
Question 44	-0.0157	(0.0520)	0.0125	(0.0701)	-0.0320	(0.0429)	-0.0694	(0.0704)
Question 45	-0.0213	(0.0509)	0.0106	(0.0690)	-0.00773	(0.0415)	-0.0115	(0.0709)
Question 46	-0.00512	(0.0502)	0.0301	(0.0644)	0.00127	(0.0420)	-0.0286	(0.0594)
Question 47	0.0420	(0.0436)	0.0399	(0.0661)	0.0457	(0.0421)	0.00256	(0.0780)
Question 48	0.0613	(0.0693)	0.0855	(0.112)	0.0914	(0.0598)	0.294	(0.0710)
Question 49	0.0654	(0.0744)	0.0593	(0.122)	0.0836	(0.0634)	0.114	(0.0921)
Question 50	0.0286	(0.0787)	0.0473	(0.121)	0.0764	(0.0642)	0.199	(0.0895)
Question 51	0.0312	(0.0647)	0.0663	(0.0926)	0.0717	(0.0504)	0.0428	(0.0716)
Question 52	0.0136	(0.0705)	0.0471	(0.0924)	0.107	(0.0505)	0.0840	(0.0849)
Question 53	0.0483	(0.0435)	0.0610	(0.0667)	0.0668	(0.0391)	0.0218	(0.0718)
Question 54	0.0351	(0.0481)	0.0807	(0.0720)	0.0694	(0.0479)	0.0949	(0.0454)
Question 55	0.107	(0.0382)	0.118	(0.0497)	0.119	(0.0342)	0.182	(0.0657)
Question 56	0.0443	(0.0462)	0.101	(0.0682)	0.0826	(0.0345)	0.0419	(0.0631)
Question 57	0.0955	(0.0427)	0.0724	(0.0597)	0.0847	(0.0351)	-0.0133	(0.0658)
Question 58	0.0268	(0.0300)	0.0191	(0.0468)	0.0218	(0.0270)	-0.0172	(0.0548)
Question 59	0.0781	(0.0426)	0.0896	(0.0653)	0.117	(0.0392)	0.132	(0.0695)
Q. 60 (drive)	-0.00150	(0.0467)	-0.0185	(0.0737)	-0.0117	(0.0391)	0.0360	(0.0629)
Q. 60 (ram)	-0.0204	(0.0677)	-0.0197	(0.0885)	-0.0378	(0.0469)	0.0582	(0.0635)
Q. 60 (usb)	-0.0116	(0.0582)	0.00782	(0.0775)	-0.0133	(0.0425)	0.0430	(0.101)
Q. 60 (rom)	0.0233	(0.0383)	0.0382	(0.0698)	0.0533	(0.0383)	0.0524	(0.0437)
Q. 60 (disco)	0.0341	(0.0535)	0.0281	(0.0808)	0.0168	(0.0476)	-0.00079	(0.0675)
Question 61	0.0787	(0.0476)	0.0817	(0.0708)	0.0841	(0.0463)	0.128	(0.0653)
Question 62	0.118	(0.0471)	0.0827	(0.0598)	0.128	(0.0401)	0.162	(0.0654)

This table presents the estimated Average Treatment Effect on the Treated (ATT) for each 21st-Century Competencies question considered individually. Table 11 in Appendix B presents the full text of each question, translated from Spanish. Similarly to the main estimations in the paper, specifications in columns (1)–(3) are estimated using a linear probability model (OLS), while column (4) employs the Doubly Robust Difference-in-Differences (DiD) estimator. The same controls are included, corresponding to the main estimation results presented in the text. Clustered standard errors at school level are reported in parentheses. Due to item-specific nonresponse, the number of observations varies across outcomes. Sample sizes range from 3,437 to 3,477 in column (1), from 2,684 to 2,720 in column (2), from 2,496 to 2,528 in column (3), and from 1,766 to 1,808 in column (4).

Table 14: Pooled Cross Section: Estimated Overall Effect on Students' Digital Competencies

	(1)	(2)	(3)
4th to 6th grade	0.083***	0.087***	0.087***
	(0.020)	(0.022)	(0.025)
Observations	6,102	4,779	4,281
4th grade	0.038	0.065*	0.071*
	(0.029)	(0.036)	(0.036)
Observations	1,470	1,104	1,001
5th grade	0.050*	0.066**	0.084***
	(0.029)	(0.031)	(0.032)
Observations	1,690	1,258	1,131
6th grade	0.028	0.014	0.023
	(0.033)	(0.040)	(0.037)
Observations	1,607	1,251	1,110
Time Fixed Effects	Yes	Yes	Yes
Background Covariates	No	Yes	Yes
School Covariates	No	No	Yes

This table reports the estimated overall Average Treatment Effect on the Treated (ATT) for students' digital competencies using a pooled cross-sectional specification. All models are estimated using a linear probability model (OLS). Differences in the number of observations across specifications arise from missing values in different sets of covariates. Standard errors clustered at the school level are reported in parentheses. Significance levels: * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

Table 15: Pooled Cross Section: Estimated Overall Effect on Students' 21st-Century Competencies

	(1)	(2)	(3)
4th to 6th grade	0.049	0.062	0.023
	(0.067)	(0.108)	(0.026)
Observations	6,629	5,193	4,616
4th grade	0.044	0.073	0.051
	(0.076)	(0.136)	(0.031)
Observations	1,656	1,252	1,112
5th grade	0.039	0.067	0.036
	(0.050)	(0.074)	(0.029)
Observations	1,831	1,361	1,222
6th grade	0.067	0.034	-0.015
	(0.086)	(0.110)	(0.035)
Observations	1,803	1,402	1,230
Time Fixed Effects	Yes	Yes	Yes
Background Covariates	No	Yes	Yes
School Covariates	No	No	Yes

This table presents the estimated overall Average Treatment Effect on the Treated (ATT) on students' 21st-century competencies using a pooled cross-sectional specification. All models are estimated using a linear probability model (OLS). Differences in the number of observations across specifications arise from missing values in different sets of covariates. Standard errors clustered at the school level are reported in parentheses. Significance levels: * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.