Educational Technology and Cognition

PISA 2018 Evidence on Technology Use and Student Performance

Harper Stephens

University of Louisville

Abstract

This paper estimates how technology use in school is associated with student cognitive achievement using PISA 2018 plausible values and survey weights in a sequential regression framework. I estimate sequential regressions on a constant sample of 9,313 students across 48 education systems for reading, mathematics, and science. I find a significant negative association between broad school technology use and cognitive achievement across all subjects tested that is present across all models, while technology use for instructional practices has a moderately significant association in mathematics only. Associations found have different ranges of effects on different subjects. Household digital resources also display concavity through a negative quadratic term. The results do not imply that technology is inherently beneficial or detrimental; they indicate that associations depend on how technology is integrated into instructional settings and how intensively it is used.

Keywords: Human Capital, Technology in Education, PISA, Diminishing Returns

1 Introduction

The relationship between technology adoption, human capital formation, and long-run growth is a pillar of modern growth theory, yet the role of technology within education remains contested. While digital development has transformed labor markets by increasing returns to productive workers (Rubinstein and Tsiddon 2000), its integration into schooling has produced mixed evidence.

The correlation between cognitive performance and productivity is central. As argued by Barro (2013), human capital is a key mechanism of economic growth, and cognitive skills are robust predictors of national income (Hanushek and Woessmann 2008; Boman 2022). If certain forms of educational technology reduce cognitive performance, they may imply macroeconomic opportunity costs through the formation of human capital.

Prior studies are often single-country or intervention-specific, making common associations harder to assess. This paper uses a constant sample across 48 educational systems to separate school-based, instructional, and non-school technology use, showing that school-based technology use is negatively associated with reading, mathematical, and scientific cognitive skills across all model specifications.

2 Literature Review

The theoretical link between schooling and growth is grounded in Mincer's framework, where education is an investment in productivity across the life cycle (Mincer 1958, 1974). Later work incorporates technological change and skill-biased demand (Mincer 1989; Rubinstein and Tsiddon 2000; Autor, Katz, and Krueger 1998), based on the perspective that technology can increase returns to skill in labor markets.

2.1 Digital Technology Productivity Paradox

Empirical results vary by implementation context. Early causal studies found that adding computers within classrooms did not consistently raise performance and could reduce learning under certain settings (Angrist and Lavy 2002; Rouse and Krueger 2004). Evidence on the accessibility of home computers shows that unstructured access often yields little or negative effects on educational subjects, even when technological skills improve (Fairlie and Robinson 2013; Malamud and Pop-Eleches 2011; Beuermann et al. 2015). Similarly, related studies indicate that expanding access to technology is not equivalent to improving educational achievement alone. Internet subsidy expansions increased connectivity within schools but did not directly translate to measured achievement gains (Goolsbee and Guryan 2006). Advancements in infrastructure and instructional methods are distinctly separate, which is central to interpreting technological variables.

2.2 Integration and Design

Recent studies emphasize methods of implementation and intensity of technology use. Technology access can reduce academic performance through increasing distractions or substituting for traditional instruction (Beland and Murphy 2016; Carter, Greenberg, and Walker 2017). At the same time, well-targeted technological implementation can produce large learning growth, especially when technology complements instruction and is aligned to students (Muralidharan, Singh, and Ganimian 2019; Oreopoulos, Rosinger, and Jue 2019). This is further supported by evidence on educator training, showing that progression depends on instructional integration and not the device itself (Oreopoulos et al. 2024).

There are also findings on non-linear returns from technology. Evidence indicates that low-to-moderate levels of instructional technology use can be beneficial, while more substantial substitutions from traditional instruction may cause weak or costly marginal returns (Bettinger et al. 2020; Ma et al. 2020).

2.3 Global and Development Patterns

Some developing-country contexts report positive effects under student resource constraints (Nganga and al. 2022; Bianchi, Lu, and Song 2020). By contrast, evidence in high-income settings often finds weak or negative average effects from broad technology exposure (Hall and Lundin 2021; Husøy and Mignon 2021). More generally, the consensus is that technology is not universally beneficial, with implementation methods, students, and circumstances determining whether the effects are beneficial or costly (Escueta et al. 2017; Bulman and Fairlie 2016).

3 Data

My analysis uses student-level data from PISA 2018 (OECD 2019a, 2019b). The sample is built by merging student questionnaire responses with cognitive outcomes for Booklets 1, 30, 31, and 36.

To ensure comparability across specifications, the analysis is restricted to a constant sample of $N = 9{,}313$ students with complete responses for the technology, control, and identification variables used in the most specified model (Model 5). The constant sample includes 48 education systems in North and South America, Europe, and Asia (B). African and Oceanic countries are excluded due to limited representation in the sample and insufficient cross-continent comparability.

3.1 PISA Estimation, WLE Variables, and Construction Inputs

PISA outcomes are represented by plausible values, and inference should account for complex survey design and weighting (OECD 2020; Rubin 1987). I therefore use the `intsvy` package to calculate individual scores (Caro and Biecek 2017). As Jerrim, Micklewright, and Micklewright (2016) note, plausible values and sampling weights are necessary to avoid biased ability estimates and incorrect uncertainty.

For easier comprehension, A provides official PISA variable names and the redefined names as used in this paper. Technology factors used in this study are PISA index variables reported on the WLE scale from the optional ICT questionnaire (OECD 2020, 2019b, 2019c; Mang et al. 2023). Higher values indicate higher levels of the underlying construct, resources or frequency of use, and indices are standardized within the OECD reference metric, with an approximate mean of 0 and standard deviation of 1. Coefficients should be interpreted as score differences associated with one standard deviation and not as a raw questionnaire item. Negative values therefore indicate that a student is below the OECD-reference average on that latent construct, while positive values indicate above-average levels. As a result, negative values are expected and do not imply impossible quantities of a specific index.

Technology resources at home captures digital access and device availability in the household, based on responses regarding internet connectivity, and availability of computers, tablets, smartphones, e-readers, and educational software. I include the linear term and a squared term such that the models can assess marginal associations as household access increases.

The remaining indices describe the context and use. Technology use at school reflects broad school-based digital activity in common academic tasks; no leisure or distraction responses are used. Technology use in lessons captures the use of instructional activity within class. Technology use for homework reflects school-based tasks performed at home, ranging from homework, communication, and school materials. Technology use for leisure captures non-instructional digital activity. Technology use outside of school captures subject-related use beyond formal class time. By separating digital activities, the analysis can distinguish structured use from non-instructional.

3.2 Descriptive Statistics

Table 1 presents descriptive statistics for the regression sample.

Table 1: Summary Statistics

Variable	Mean / %	Std. Dev.	Min	Max	N
Outcome Scores					
Reading Score	510.710	97.620	–	–	9,313
Mathematics Score	491.570	89.450	–	–	9,313
Science Score	500.280	91.520	–	–	9,313
Continuous Predictors					
Tech Resources at Home	-0.168	0.968	-3.768	3.601	9,313
Tech Usage at School	0.002	0.991	-2.513	3.348	9,313
Tech Usage in Lessons	-0.059	0.999	-1.219	2.439	9,313
Tech Usage for Leisure	0.062	1.044	-3.594	4.314	9,313
Tech Usage for Homework	0.083	0.989	-2.698	3.315	9,313
Tech Usage Outside School	0.030	1.009	-1.305	2.497	9,313
Continuous Controls					
Socioeconomic Status	-0.080	0.999	-3.773	3.216	9,313
Grade Level	-0.099	0.555	-4.000	3.000	9,313
Learning Time (Weekly Mins)	1664.583	417.514	100.000	3000.000	9,313
Categorical Controls	%				**N**
Gender					
Female	50.81	–	–	–	4,732
Male	49.19	–	–	–	4,581
Immigration Status					
Native	89.20	–	–	–	8,307
Second-Generation	6.50	–	–	–	605
First-Generation	4.31	–	–	–	401
OECD Status					
OECD Member	66.34	–	–	–	6,178
Non-OECD Country	33.66	–	–	–	3,135

Note: Only students with complete technology responses are included. Negative values for technology variables and socioeconomic status reflect standardized scales using OECD-average as the reference group. Grade is coded relative to the country's grade system.

3.3 Outlier and Support Checks

The observed minimum and maximum of learning time are 100 and 3,000 minutes per week. In the constant sample ($N = 9{,}313$), these values are not typographical errors in the cleaned file; they are outlier observations. The 1st percentile is 540 minutes, the median is 1,600 minutes, and the 99th percentile is 2,925 minutes. Only 7 observations are at or below 200 minutes and 199 observations are at or above 2,800 minutes. PISA includes questions regarding reported absences, ranging from missing one class to multiple months of all courses, supporting the plausibility of extremely minimal reported time. The maximum value of 3,000 minutes appears in multiple education systems. The upper value corresponds to 50 hours per week and is an extreme but feasible reported value. I retain these observations in the baseline and report this support check for transparency.

4 Methodology

4.1 Technology–Cognition Estimation Strategy

I estimate the relationship between technology use and cognition using:

$$C_{is} = \alpha + \eta_1 T_i + \eta_2 T_i^2 + \boldsymbol{\gamma}\mathbf{S}_i + \boldsymbol{\sigma}\mathbf{E}_i + \boldsymbol{\Lambda}\mathbf{Z}_i + \tau_c + \epsilon_{is} \tag{1}$$

where C_{is} is student i's score in subject s; T_i is home technology resources; $\mathbf{S}_i$ captures school technology use; $\mathbf{E}_i$ captures non-school technology use; $\mathbf{Z}_i$ is the control vector; and τ_c are country fixed effects. The term T_i^2 is the squared home-technology term, not a marginal-return variable itself. It is included to study the marginal effect of home technology:

$$\frac{\partial C_{is}}{\partial T_i} = \eta_1 + 2\eta_2 T_i \tag{2}$$

to calculate the turning-point for each subject:

$$T_i^* = -\frac{\eta_1}{2\eta_2} \tag{3}$$

Sequential models M1–M6 are estimated on the same sample. OECD is included in M4 to capture the OECD/non-OECD status differential, and omitted in M5–M6 because it is country-invariant under country fixed effects.

5 Results

5.1 Diagnostics

Figure 1 reports predictor correlations. Table 2 reports the variance inflation factors. All remain below the concern thresholds, supporting the interpretation of stable coefficients. The VIF is calculated from the predictor set used in Model 4 (all covariates jointly, excluding country fixed effects) rather than pairwise two-variable checks.

The correlation between household technology resources and socioeconomic status is the highest, supporting the decision to keep socioeconomic status as a control variable.

The correlation between technology usage at school and technology usage in lessons is modest. This is expected because the school-use index captures broad school digital activity while the lesson-use index captures reported instructional time during specific subjects only. The two variables are related but are not designed to measure the same behavior.

5.2 Sequential Regressions

Tables 3, 4, and 5 show the regression results for all subjects tested.

Model 5 shows a stable negative coefficient on general school technology use across all three subjects. In the preferred country fixed-effects model (M5), a one-standard deviation increase in general school technology use is associated with lower scores in reading, mathe-

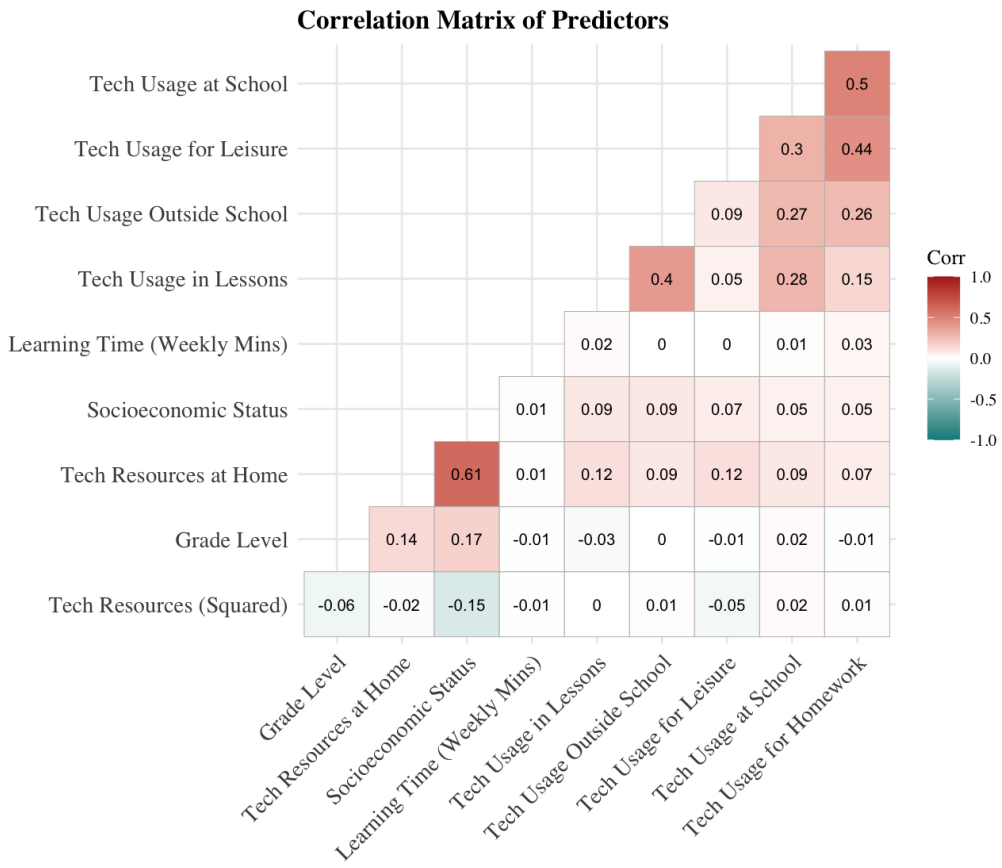


Figure 1: Correlation Matrix of Predictors and Controls

Table 2: Variance Inflation Factors

Variable	**VIF**	**Variable**	**VIF**
Tech Resources at Home	1.308	Tech Usage Outside School	1.129
Tech Resources (Squared)	1.022	Socioeconomic Status	1.295
Tech Usage at School	1.206	Female	1.014
Tech Usage in Lessons	1.124	Grade Level	1.034
Tech Usage for Leisure	1.140	OECD Country	1.059
Tech Usage for Homework	1.258	Learning Time (Weekly Mins)	1.002
Immigration Status	1.005	–	–

Table 3: Sequential Regression Results: Reading Performance

Variable	**M1**	**M2**	**M3**	**M4**	**M5**	**M6**
Tech Resources at Home	29.480***	29.812***	29.545***	-1.939	-4.083	-4.200
	(2.950)	(2.902)	(2.896)	(3.032)	(3.182)	(3.180)
Tech Resources (Squared)	-6.912***	-6.808***	-6.628***	-2.948**	-2.960**	-2.903**
	(1.191)	(1.186)	(1.202)	(0.971)	(0.967)	(0.967)
Tech Usage at School	–	-7.275**	-8.461***	-10.260***	-10.559***	-10.625***
		(2.401)	(2.504)	(2.257)	(2.411)	(2.416)
Tech Usage in Lessons	–	4.176	3.167	1.256	0.985	0.950
		(2.790)	(2.851)	(2.706)	(2.955)	(2.958)
Tech Usage for Leisure	–	–	1.814	6.339*	6.750**	6.816**
			(3.120)	(2.494)	(2.330)	(2.341)
Tech Usage for Homework	–	–	-0.333	-1.171	-0.220	-0.261
			(3.309)	(2.918)	(2.956)	(2.957)
Tech Usage Outside School	–	–	3.713	2.061	2.564	2.621
			(2.793)	(2.586)	(2.743)	(2.755)
Socioeconomic Status	–	–	–	37.047***	36.243***	36.230***
				(3.514)	(3.629)	(3.600)
Female	–	–	–	18.284***	17.527***	17.535***
				(4.991)	(5.036)	(5.010)
Grade Level	–	–	–	34.767***	37.121***	37.011***
				(3.993)	(4.336)	(4.335)
OECD Country	–	–	–	27.364***	–	–
				(4.538)		
Second-Gen Immigrant	–	–	–	19.497·	13.399	13.648
				(10.415)	(11.176)	(11.185)
First-Gen Immigrant	–	–	–	-16.111	-22.256	-22.586
				(21.925)	(22.274)	(22.282)
Learning Time (Weekly Mins)	–	–	–	0.002	0.000	–
				(0.007)	(0.007)	
Log(Learning Time)	–	–	–	–	–	8.854
						(8.836)
Country Fixed Effects	No	No	No	No	Yes	Yes
Observations	9,313	9,313	9,313	9,313	9,313	9,313
R^2	0.142	0.148	0.149	0.312	0.339	0.340
ΔR^2	0.142	0.005	0.002	0.163	0.027	0.001

Standard errors in parentheses. $^{\cdot}p < 0.10$, $^{*}p < 0.05$, $^{**}p < 0.01$, $^{***}p < 0.001$.

Table 4: Sequential Regression Results: Mathematics Performance

Variable	**M1**	**M2**	**M3**	**M4**	**M5**	**M6**
Tech Resources at Home	26.467***	26.592***	26.428***	0.091	-2.007	-2.126
	(2.256)	(2.199)	(2.210)	(2.677)	(2.869)	(2.867)
Tech Resources (Squared)	-8.062***	-7.948***	-7.842***	-4.278***	-3.198***	-3.141**
	(1.046)	(1.028)	(1.039)	(0.960)	(0.964)	(0.963)
Tech Usage at School	–	-7.938***	-8.187***	-10.098***	-8.422***	-8.479***
		(2.186)	(2.347)	(2.238)	(2.378)	(2.379)
Tech Usage in Lessons	–	6.118*	6.134*	4.788*	4.167·	4.123·
		(2.483)	(2.444)	(2.252)	(2.402)	(2.411)
Tech Usage for Leisure	–	–	2.736	4.261*	2.750	2.796
			(2.267)	(1.930)	(1.833)	(1.833)
Tech Usage for Homework	–	–	-1.629	-1.557	0.035	-0.008
			(2.949)	(2.779)	(2.891)	(2.891)
Tech Usage Outside School	–	–	0.558	-1.507	0.481	0.548
			(2.568)	(2.314)	(2.340)	(2.350)
Socioeconomic Status	–	–	–	31.757***	32.222***	32.187***
				(2.822)	(3.132)	(3.101)
Female	–	–	–	-16.037***	-16.481***	-16.462***
				(4.848)	(4.818)	(4.798)
Grade Level	–	–	–	32.090***	33.029***	32.891***
				(3.617)	(3.715)	(3.737)
OECD Country	–	–	–	15.597***	–	–
				(4.175)		
Second-Gen Immigrant	–	–	–	8.094	8.422	8.630
				(9.498)	(10.132)	(10.124)
First-Gen Immigrant	–	–	–	-11.302	-14.627	-14.960
				(17.619)	(17.627)	(17.636)
Learning Time (Weekly Mins)	–	–	–	0.002	0.002	–
				(0.006)	(0.006)	
Log(Learning Time)	–	–	–	–	–	10.850
						(8.065)
Country Fixed Effects	No	No	No	No	Yes	Yes
Observations	9,313	9,313	9,313	9,313	9,313	9,313
R^2	0.153	0.162	0.163	0.302	0.340	0.341
ΔR^2	0.153	0.009	0.001	0.139	0.038	0.001

Standard errors in parentheses. $^{\cdot}p < 0.10$, $^{*}p < 0.05$, $^{**}p < 0.01$, $^{***}p < 0.001$.

Table 5: Sequential Regression Results: Science Performance

Variable	**M1**	**M2**	**M3**	**M4**	**M5**	**M6**
Tech Resources at Home	26.792***	26.796***	26.700***	-0.582	-3.066	-3.160
	(2.366)	(2.355)	(2.405)	(3.102)	(3.277)	(3.278)
Tech Resources (Squared)	-6.792***	-6.682***	-6.628***	-3.190**	-3.108**	-3.061**
	(1.203)	(1.192)	(1.210)	(1.148)	(1.183)	(1.185)
Tech Usage at School	–	-7.632**	-7.466**	-9.069***	-9.226***	-9.283***
		(2.381)	(2.524)	(2.448)	(2.555)	(2.554)
Tech Usage in Lessons	–	6.643*	6.313*	4.431	3.330	3.305
		(2.848)	(2.815)	(2.706)	(2.931)	(2.936)
Tech Usage for Leisure	–	–	1.168	3.483	3.503	3.564
			(2.949)	(2.493)	(2.388)	(2.407)
Tech Usage for Homework	–	–	-1.686	-1.759	-0.745	-0.778
			(3.232)	(3.039)	(3.063)	(3.057)
Tech Usage Outside School	–	–	1.290	-0.297	0.991	1.033
			(2.581)	(2.449)	(2.562)	(2.568)
Socioeconomic Status	–	–	–	32.735***	32.859***	32.856***
				(3.347)	(3.535)	(3.492)
Female	–	–	–	-7.212	-7.815	-7.813
				(5.079)	(5.115)	(5.103)
Grade Level	–	–	–	27.879***	28.876***	28.798***
				(4.150)	(4.682)	(4.713)
OECD Country	–	–	–	23.375***	–	–
				(4.312)		
Second-Gen Immigrant	–	–	–	8.564	3.373	3.589
				(9.627)	(9.943)	(9.973)
First-Gen Immigrant	–	–	–	-22.383	-27.747	-28.013
				(21.004)	(21.353)	(21.414)
Learning Time (Weekly Mins)	–	–	–	0.003	0.000	–
				(0.007)	(0.007)	
Log(Learning Time)	–	–	–	–	–	6.453
						(8.759)
Country Fixed Effects	No	No	No	No	Yes	Yes
Observations	9,313	9,313	9,313	9,313	9,313	9,313
R^2	0.138	0.147	0.147	0.278	0.308	0.308
ΔR^2	0.138	0.009	0.001	0.131	0.030	0.000

Standard errors in parentheses. $^{\cdot}p < 0.10$, $^{*}p < 0.05$, $^{**}p < 0.01$, $^{***}p < 0.001$.

matics, and science. Because the technology indices are WLE-standardized, these estimates are interpreted as score differences associated with a one-standard deviation increase in the latent technology-use construct.

The non-linear household technology term remains negative and significant across all subjects, supporting diminishing marginal effects. The linear household resource term is large and positive in early models (M1–M3), but becomes small or negative after adding socioeconomic controls and country fixed effects, indicating that earlier models weren't accounting for the association between household technology and background covariates.

Other technology-use variables are less stable. Technology use in lessons is positive for mathematics in the more saturated specifications, while non-school technology variables are generally imprecise and inconsistent across subjects. This pattern supports the interpretation that broad school-wide technology use and instructional technology use are empirically distinct.

As controls are added, model fit increases from M1 to M5 across subjects (R^2 rising from about 0.14–0.15 to 0.31–0.34). Model 6, which replaces weekly learning time with log(Learning Time), yields nearly identical coefficients and fit, supporting functional-form robustness.

5.3 Singular School Technology Specification

To isolate the main variable of interest, I also estimate a chary specification that includes general school-based technology use as the only technology regressor, with the same control sets as M4 and M5 (Table 6). This check addresses whether the negative association is robust when other technology-use indices are excluded. M6 is included as an additional robustness check.

Table 6: Sequential Regressions: Tech Usage at School Only (M4–M6)

Domain	**M4-Style**	**M5-Style**	**M6-Style**
Reading	-8.426***	-7.720***	-7.783***
	(2.057)	(2.222)	(2.228)
Mathematics	-9.197***	-6.595**	-6.655**
	(1.997)	(2.136)	(2.138)
Science	-8.184***	-7.631**	-7.681**
	(2.238)	(2.348)	(2.350)
Country Fixed Effects	No	Yes	Yes
Observations	9,313	9,313	9,313
R^2 (Reading)	0.303	0.328	0.329
ΔR^2 (Reading)	0.303	0.025	0.001
R^2 (Mathematics)	0.287	0.331	0.332
ΔR^2 (Mathematics)	0.287	0.044	0.001
R^2 (Science)	0.268	0.298	0.299
ΔR^2 (Science)	0.268	0.031	0.001

Standard errors in parentheses. $^{\cdot}p < 0.10$, $^{*}p < 0.05$, $^{**}p < 0.01$, $^{***}p < 0.001$.

5.4 Learning-Time Outlier Sensitivity

As an additional check, I remove the 1st and 99th percentiles of learning time and re-estimate the M5 specification for each subject. The school-based technology use coefficients remain negative and statistically significant, with only slight change relative to the baseline estimates.

Table 7: M5 Sensitivity to Outlier-Removed Learning-Time

Domain	**Baseline M5**	**Outlier-Removed M5**	**Δ (Outlier-Removed - Baseline)**
Reading	-10.559***	-10.016***	0.543
	(2.411)	(2.500)	
Mathematics	-8.422***	-7.717**	0.706
	(2.378)	(2.450)	
Science	-9.226***	-8.679**	0.547
	(2.555)	(2.642)	
Country Fixed Effects	Yes	Yes	–
Observations	9,313	9,142	–
Countries	48	48	–
R^2 (Reading)	0.339	0.334	–
ΔR^2 (Reading)	–	–	-0.005
R^2 (Mathematics)	0.340	0.336	–
ΔR^2 (Mathematics)	–	–	-0.004
R^2 (Science)	0.308	0.306	–
ΔR^2 (Science)	–	–	-0.002

Standard errors in parentheses. $^{\cdot}p < 0.10$, $^{*}p < 0.05$, $^{**}p < 0.01$, $^{***}p < 0.001$. Outlier-removed model uses cuts 1st–99th percentile of learning time respondents.

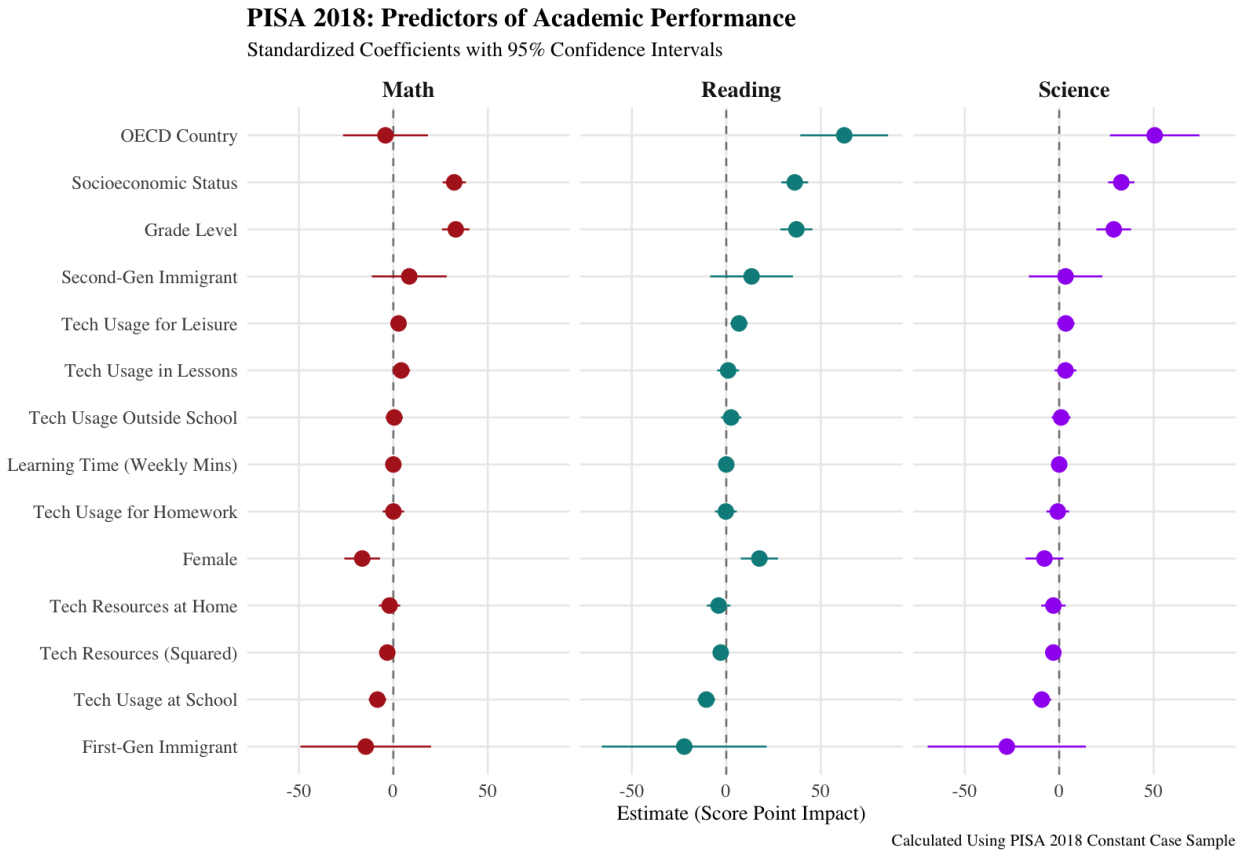


Figure 2: Model 5 Coefficient Estimates with 95% Confidence Intervals

5.5 Digital Ceiling

Figure 3 and Table 8 show a significant negative quadratic term for home technology resources in all subjects, consistent with diminishing marginal effects. In preferred controlled models (M4–M6), the linear home-technology term is small or negative while the squared term is negative and significant; therefore, the visual should be interpreted as concave (declining marginal effect). The turning points implied by Model 5 occur within the observed support of the constant sample and indicate where the estimated marginal effect crosses zero in each subject-specific model.

Table 8: Optimal Digital Technology Resource Levels

Domain	Peak (WLE Units)	Sample Percentile	Resource Description
Reading	-0.69	25.10	Below OECD-reference average access
Mathematics	-0.31	44.31	Below OECD-reference average access
Science	-0.49	34.27	Below OECD-reference average access

Note: Turning points computed from M5 coefficients ($-\hat{\eta}_1/(2\hat{\eta}_2)$) and mapped to empirical percentiles of the constant-sample household technological resource distribution.

6 Discussion

I find a significant negative association between broad school technology use and cognitive achievement across all subjects tested that is pattern is present across controls, country fixed effects, additional models, and outlier-removed learning-time checks. This strengthens the interpretation that the school-wide technology association is not driven by one specific model choice.

The coefficients for technology use in lessons indicate that methods of technological implementation matter. In mathematics, lesson-linked technology remains weakly positive while broad school technology use remains negative, suggesting that instructional integration and general exposure capture different channels.

The non-linearity of household resources also supports this interpretation. Access to

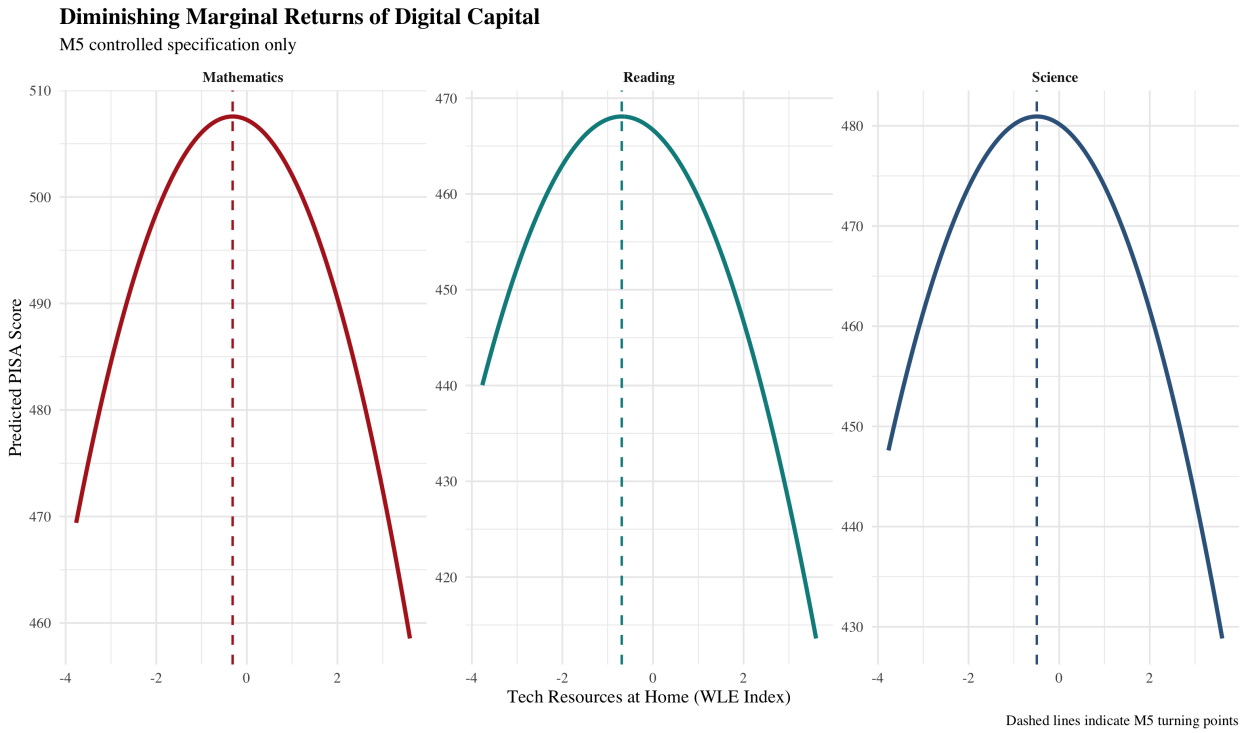


Figure 3: Diminishing Marginal Returns of Digital Capital

technology can be beneficial at some levels, but the negative quadratic term indicates declining marginal effects as resource intensity rises. At the same time, the constant-sample restriction improves comparability across specifications but limits direct generalization to all PISA participants.

These results identify robust patterns in the observed data, but they do not establish causal effects of technology use on cognitive achievement.

7 Conclusion

This paper estimates the relationship between different technology uses and student cognitive achievement using 2018 PISA plausible values and survey weights in a sequential regression framework. General technology use in school is negatively associated with reading, mathematics, and science in preferred specifications with country fixed effects.

Household technology resources show a concave profile through a negative quadratic term. Taken together, the findings do not imply that technology is inherently beneficial or detrimental; they indicate that associations depend on how technology is integrated into instructional settings and how intensively it is used.

Policymakers should be aware that integrating technology into education is not the entire solution. Expanding access alone is unlikely to be sufficient; implementation quality, instructional design, and teacher support are central for converting technology into learning gains.

Future research should extend the analysis to broader samples and designs that better identify mechanisms, including where effects are concentrated across school systems and how specific forms of technological advancement shape cognitive outcomes.

A Variable Definitions

Variable definitions are provided in Table 9.

B Countries Sampled

The list of specific educational systems within the same are mentioned in Table 10.

References

Angrist, Joshua D., and Victor Lavy. 2002. "New Evidence on Classroom Computers and Pupil Learning." *The Economic Journal* 112 (482): 735–765. https://doi.org/10.1111/1468-0297.00068.

Table 9: PISA Variable Definitions and Refined Names

Refined Name	**Original Name**	**Description**
Tech Resources at Home	ICTRES	Index of household digital assets (WLE).
Tech Resources (Squared)	ICTRES2	Quadratic term for diminishing returns.
Tech Usage at School	USESCH	General frequency of digital technology use at school (WLE).
Tech Usage in Lessons	ICTCLASS	Subject-related digital technology use during instruction (WLE).
Tech Usage for Leisure	ENTUSE	Digital device use for leisure activities (WLE).
Tech Usage for Homework	HOMESCH	Digital device use for school tasks at home (WLE).
Tech Usage Outside School	ICTOUTSIDE	Subject-related digital technology use outside school hours (WLE).
Socioeconomic Status	ESCS	Index of economic, social, and cultural status.
Female	ST004D01T	Student gender indicator recoded as female dummy.
Grade Level	GRADE	Student grade relative to modal country grade.
OECD Country	OECD	Included in M4; omitted in M5–M6 due to collinearity with country fixed effects.
Learning Time (Weekly Mins)	TMINS	Total weekly instructional time in minutes.
Log(Learning Time)	Log_TMINS	Log-transformed instructional time (M6 robustness).
Second-Gen Immigrant	IMMIG2	Dummy for second-generation immigrant status.
First-Gen Immigrant	IMMIG3	Dummy for first-generation immigrant status.
Country Fixed Effects	CNT	Country identifier used for fixed effects.

Table 10: Countries and Education Systems Included in the Constant Sample

Europe	**Asia**	**Americas**	**Transcontinental / Regional Units**
Albania, Belgium, Bulgaria, Switzerland, Czech Republic, Denmark, Spain, Estonia, Finland, France, United Kingdom, Greece, Croatia, Hungary, Ireland, Iceland, Italy, Lithuania, Luxembourg, Latvia, Malta, Poland, Serbia, Slovak Republic, Slovenia, Sweden	Brunei Darussalam, Israel, Kazakhstan, Korea, Singapore, Thailand	Brazil, Chile, Costa Rica, Dominican Republic, Mexico, Panama, Uruguay, United States	Hong Kong (China), Macao (China), Chinese Taipei, Georgia, Turkey, Russian Federation, Moscow Region (RUS), Tatarstan (RUS)

Note: Total $N = 48$ education systems in the constant-sample estimation set.

Autor, David H., Lawrence F. Katz, and Alan B. Krueger. 1998. "Computing Inequality: Have Computers Changed the Labor Market?" *The Quarterly Journal of Economics* 113 (4): 1169–1213. https://doi.org/10.1162/003355398555874.

Barro, Robert J. 2013. "Human Capital and Growth." *American Economic Review* 91 (2): 12–17.

Beland, Louis-Philippe, and Richard Murphy. 2016. "Ill Communication: Technology, Distraction & Student Performance." *Labour Economics* 41:61–76. https://doi.org/10.1016/j.labeco.2016.04.004.

Bettinger, Eric, Robert W. Fairlie, Anastasia Kapuza, Elena Kardanova, Prashant Loyalka, and Andrey Zakharov. 2020. *Diminishing Marginal Returns to Computer-Assisted Learning.* Working Paper 26967. National Bureau of Economic Research. https://doi.org/10.3386/w26967.

Beuermann, Diether W., Julian Cristia, Santiago Cueto, Ofer Malamud, and Yyannu Cruz-Aguayo. 2015. "One Laptop per Child at Home: Short-Term Impacts from a Randomized Experiment in Peru." *American Economic Journal: Applied Economics* 7 (2): 53–80. https://doi.org/10.1257/app.20130267.

Bianchi, Nicola, Yi Lu, and Hong Song. 2020. *The Effect of Computer-Assisted Learning on Students' Long-Term Development.* Working Paper 28180. National Bureau of Economic Research. https://doi.org/10.3386/w28180.

Boman, Björn. 2022. "Cognitive skills and economic growth in the twenty-first century: Evidence from PISA and cognitive ability studies." *Heliyon* 8 (4). https://doi.org/10.1016/j.heliyon.2022.e09307.

Bulman, George, and Robert W. Fairlie. 2016. *Technology and Education: Computers, Software, and the Internet.* Working Paper 22237. National Bureau of Economic Research. https://doi.org/10.3386/w22237.

Caro, Daniel H., and Przemysław Biecek. 2017. "intsvy: An R Package for Analyzing International Large-Scale Assessment Data." *Journal of Statistical Software* 81 (7): 1–44. https://doi.org/10.18637/jss.v081.i07.

Carter, Samuel P., Kyle Greenberg, and Michael S. Walker. 2017. "The Impact of Computer Usage on Academic Performance: Evidence from a Randomized Trial at the United States Military Academy." *Economics of Education Review* 56:118–132. https://doi.org/10.1016/j.econedurev.2016.12.005.

Escueta, Maya, Vincent Quan, Andre Joshua Nickow, and Philip Oreopoulos. 2017. *Education Technology: An Evidence-Based Review.* Working Paper 23744. National Bureau of Economic Research. https://doi.org/10.3386/w23744.

Fairlie, Robert W., and Jonathan Robinson. 2013. "Experimental Evidence on the Effects of Home Computers on Academic Achievement among Schoolchildren." *American Economic Journal: Applied Economics* 5 (3): 211–240. https://doi.org/10.1257/app.5.3.211.

Goolsbee, Austan, and Jonathan Guryan. 2006. "The Impact of Internet Subsidies in Public Schools." *The Review of Economics and Statistics* 88 (2): 336–347. https://doi.org/10.1162/rest.88.2.336.

Hall, J., and M. Lundin. 2021. "Technology in the classroom: Personal computers and learning outcomes in primary school." *Economics of Education Review* 84.

Hanushek, Eric A., and Ludger Woessmann. 2008. "The Role of Cognitive Skills in Economic Development." *Journal of Economic Literature* 46 (3): 607–668. https://doi.org/10.1257/jel.46.3.607.

Husøy, K., and S. Mignon. 2021. "Well-being and technology: The effect of individual laptops in high school." *Journal of Public Economics* 202.

Jerrim, John, John Micklewright, and J. Micklewright. 2016. "What happens when econometrics and psychometrics collide? An example using the PISA data." *Economics of Education Review* 52:197–213.

Ma, Yue, Robert W. Fairlie, Prashant Loyalka, and Scott Rozelle. 2020. *Isolating the "Tech" from EdTech: Experimental Evidence on Computer Assisted Learning in China.* Working Paper 26953. National Bureau of Economic Research. https://doi.org/10.3386/w26953.

Malamud, Ofer, and Cristian Pop-Eleches. 2011. "Home Computer Use and the Development of Human Capital." *The Quarterly Journal of Economics* 126 (2): 987–1027. https://doi.org/10.1093/qje/qjr008.

Mang, Julia, Ludwig Seidl, Anja Schiepe-Tiska, Ana Tupac-Yupanqui, Lisa Ziernwald, Anastasia Doroganova, Mirjam Weis, et al. 2023. *PISA 2018 Skalenhandbuch: Dokumentation der Erhebungsinstrumente.* 2nd ed. Münster and New York: Waxmann. Accessed April 22, 2026. https://doi.org/10.31244/9783830919964. https://doi.org/10.31244/9783830919964.

Mincer, Jacob. 1958. "Investment in Human Capital and Personal Income Distribution." *Journal of Political Economy* 66 (4): 281–302.

———. 1974. "The Production of Human Capital and the Life Cycle of Earnings." *Journal of Political Economy* 82 (2): S1–S26.

———. 1989. "Human Capital Responses to Technological Change in the Labor Market." *NBER Working Paper,* no. 3207.

Muralidharan, Karthik, Abhijeet Singh, and Alejandro J. Ganimian. 2019. "Disrupting Education? Experimental Evidence on Technology-Aided Instruction in India." *American Economic Review* 109 (4): 1426–1460. https://doi.org/10.1257/aer.20171112.

Nganga, S., and et al. 2022. "Smart classrooms and education outcomes: Evidence from Rwanda." *International Journal of Educational Research* 114.

OECD. 2019a. "PISA 2018 Database." Accessed April 16, 2026. https://www.oecd.org/pisa/data/2018database/.

———. 2019b. *PISA 2018 Results (Volume I): What Students Know and Can Do.* Paris: OECD Publishing. https://doi.org/10.1787/5f07c754-en.

———. 2019c. *PISA 2018 Results (Volume II): Where All Students Can Succeed.* Paris: OECD Publishing. https://doi.org/10.1787/b5fd1b8f-en.

———. 2020. "PISA 2018 Technical Report." Accessed April 16, 2026. https://www.oecd.org/pisa/data/pisa-2018-technical-report/.

Oreopoulos, Philip, Chloe Gibbs, Michael Jensen, and Joseph Price. 2024. *Teaching Teachers To Use Computer Assisted Learning Effectively: Experimental and Quasi-Experimental Evidence.* Working Paper 32388. National Bureau of Economic Research. https://doi.org/10.3386/w32388.

Oreopoulos, Philip, Andre Rosinger, and Nadiya Jue. 2019. *How In-School Supervised Ed-Tech Support Produces Massive Learning Gains: A Khan Academy Field Experiment in India.* Working Paper 25796. National Bureau of Economic Research.

Rouse, Cecilia E., and Alan B. Krueger. 2004. *Putting Computerized Instruction to the Test: A Randomized Evaluation of a "Scientifically-based" Reading Program.* Working Paper 10315. National Bureau of Economic Research. https://doi.org/10.3386/w10315.

Rubin, Donald B. 1987. *Multiple Imputation for Nonresponse in Surveys.* New York: John Wiley & Sons.

Rubinstein, Yona, and Daniel Tsiddon. 2000. "Coping with Technological Change: The Role of Ability in Making Inequality so Persistent." *Journal of Economic Growth* 5 (4): 341–361.