

Organizational Behavior and Technology Adoption in Primary Education: Budgetary Trade-Offs and Economic Implications of iPad Purchases



Walter L. Rosado¹ , Theodore J. Albright² 

¹The Citadel, Tommy and Victoria Baker School of Business,
South Carolina, United States of America
wrosado@citadel.edu

²Thiel College, Greenville, Pennsylvania, United States of America
talbright@thiel.edu

Citation: Rosado, W. L., & Albright, T. J. (2026). Organizational behavior and technology adoption in primary education: Budgetary trade-offs and economic implications of iPad purchases. *Theoretical and Practical Research in Economic Fields*, 17(3), 913–922. [https://doi.org/10.14505/tpref.v17.3\(39\).20](https://doi.org/10.14505/tpref.v17.3(39).20)

Article info: Received 30 April 2026;
Received in revised form 28 June 2026;
Accepted 7 August 2026;
Published 30 September 2026.

Abstract: A one-to-one device program does more than place hardware in classrooms; it converts a purchase decision into a multiyear operating commitment. This article examines whether school districts absorb that commitment through new capacity, displacement of existing services, or both. Financial, enrollment, demographic, procurement, and assessment records from 610 Pennsylvania and Ohio districts provide 3,000 district-year financial observations and 1,175,000 student-years. Treatment begins when a district crosses a prespecified threshold for large-scale iPad deployment. Because implementation occurs in different years, the primary analysis estimates cohort- and time-specific effects using Callaway and Sant’Anna’s approach, with district-clustered inference; conventional two-way fixed-effects estimates and Goodman-Bacon diagnostics serve as transparency checks. Adoption reduced instructional spending by 1.85 percentage points and teacher compensation by \$280.40 per pupil while increasing information-technology operating cost by \$145.80 and capital expenditure by \$310.20 per pupil. Mathematics achievement declined by 0.045 standard deviations, attendance fell by 0.35 percentage points, and suspensions increased by 0.42 percentage points. The reading estimate was small and statistically imprecise. Robustness estimates were directionally stable, and joint pre-trend tests did not reject parallel pre-adoption trends. The findings support a capacity-centered account of educational technology: returns depend not simply on device access, but on whether districts can finance recurring obligations, adapt work systems, and preserve core instructional inputs during implementation.

Keywords: organizational capacity; fiscal displacement; educational technology; staggered adoption; school finance; implementation resilience.

JEL Classification: H52; I21; I22; I28; C23.

Copyright© 2026 The Author(s). Published by ASERS Publishing 2026. This is an open access article distributed under the terms of [CC-BY 4.0 license](https://creativecommons.org/licenses/by/4.0/).

Introduction

A school board can approve a device purchase in one meeting, but the organization must absorb the decision for years. District-wide iPad deployment creates new work: devices must be configured, secured, repaired, supported, integrated into lessons, replaced, and financed. The economic question is therefore not only whether technology improves learning. It is whether the district can carry these obligations without weakening the instructional system the devices are intended to improve. Existing research finds that educational technology can support learning but returns vary substantially with implementation quality and context (Bulman and Fairlie 2016; Escueta *et al.* 2020).

This article examines three linked margins: fiscal absorption, organizational adaptation, and student response. It asks whether iPad adoption changes the mix of district expenditures, whether those changes reveal displacement of core services, and whether achievement responds during the same implementation cycle. The design combines financial and academic outcomes in a staggered-adoption framework. Its distinctive contribution is a capacity-centered model in which adoption unfolds through commitment, absorption, and renewal rather than a simple before-and-after purchase event.

1. From Device Acquisition to Organizational Absorption

Research on classroom technology distinguishes access from effective use. Hardware alone does not determine learning; teacher knowledge, curricular alignment, professional development, classroom routines, leadership, and technical reliability shape whether a device becomes productive instructional capital (Hershkovitz, Merceron, and Shamaly 2019; Krumsvik *et al.* 2021; Reis-Andersson 2023). Studies of one-to-one initiatives also document uneven implementation and equity effects, particularly when schools differ in staff capacity and complementary resources (Hull and Duch 2017; Kirkpatrick *et al.* 2017; Licwinko 2020; O'Rourke, Main, and Hill 2017). Meta-level economic reviews therefore caution against treating device provision as a uniform intervention (Bulman and Fairlie 2016; Escueta *et al.* 2020).

The fiscal literature provides a complementary lens. Additional school spending can improve educational and longer-run outcomes, but the productivity of spending depends on its use (Jackson, Johnson, and Persico 2016). A district that commits resources to devices gives up alternative uses such as personnel, tutoring, instructional materials, or student support. The relevant economic quantity is therefore not the invoice price but total cost of ownership (TCO): acquisition, deployment, infrastructure, software, security, support, training, repair, replacement, disposal, and financing over the usable life of the program. This lifecycle perspective broadens the analysis from acquisition price to the recurring organizational and financial obligations associated with technology adoption.

Organizational behavior connects these literatures through the concept of absorption capacity: the ability to incorporate a new operating demand without degrading existing services. Adoption changes work design, decision rights, training demands, communication patterns, and expectations for instructional practice. The process has three phases. Commitment includes procurement and deployment. Absorption includes support, professional learning, curricular redesign, and near-term disruption. Renewal includes replacement, contract escalation, security updates, and the decision to continue or exit. Districts with slack resources may add capacity; constrained districts may finance the same obligations by displacing personnel, materials, or student services. This conditional mechanism, not a presumed “iPad effect”, organizes the empirical analysis.

Table 1. The Commitment–Absorption–Renewal Framework

Lifecycle phase	Organizational demand	Empirical signal
Commitment	Procurement, device preparation, network readiness, initial contracts	Capital outlay and first-year IT costs
Absorption	Technical support, teacher learning, workflow redesign, classroom integration	Operating IT, professional learning, utilization, short-run achievement
Displacement risk	Recurring obligations financed by reductions elsewhere	Instructional share, staffing, materials, and student-support spending
Renewal	Replacement, license escalation, cybersecurity, contract continuation or exit	Three- and five-year cost, debt service, refresh-cycle exposure
Educational response	Instructional change after the organization stabilizes	Dynamic mathematics, reading, attendance, and discipline effects

Source: Authors' framework

2. Method

2.1 Research Design and Unit of Analysis

The study uses a district-year panel and a staggered-adoption difference-in-differences design. Fiscal outcomes are analyzed at the district-year level. Academic outcomes are district-grade-year aggregates; the student-year counts represent the enrolled students underlying those aggregates rather than longitudinal individual-student records. Treatment begins in the first fiscal year in which an elementary-serving district deploys Apple iPads at a device-to-student ratio of at least 50% across enrolled students in grades 3–5. Districts using only non-Apple tablets are excluded from treatment. Never-treated and not-yet-treated districts provide comparison observations, subject to common-support and overlap checks.

The underlying financial and academic panel extends from 2017 through 2024 so that the 2020 adoption cohort has a pre-treatment reference year and earlier trend observations. The primary outcome-reporting window covers academic and fiscal years 2020 through 2024, corresponding to school years 2019–2020 through 2023–2024. It includes 185 adopting districts and 425 never- or not-yet-treated comparison districts. Within that reporting window, the financial estimation sample is an unbalanced panel of 610 unique districts and 3,000 district-year observations; 50 otherwise

possible district-year records were unavailable or unusable. The linked academic aggregates represent 235,000 enrolled students and 1,175,000 student-year exposures.

2.2 Data Sources and Sample Construction

Financial variables are drawn from audited district reports and state education finance files for Pennsylvania and Ohio, supplemented with National Center for Education Statistics fiscal and enrollment data. Adoption timing and program scale are established from board minutes, procurement records, contract awards, capital plans, and vendor documentation using a documented coding protocol. Assessment outcomes cover grades 3–5 mathematics and reading and are standardized within state, grade, subject, and year. District demographics include enrollment, free- or reduced-price lunch eligibility, English-learner share, special-education share, urbanicity, revenue composition, local unemployment, and median household income. Dollar measures are expressed in constant 2020 dollars using the NCES State Elementary and Secondary Education Finance Price Index (SEFPI).

Adoption dates were independently coded from historical board minutes, procurement records, vendor contracts, and other available district documentation. For the 2020 cohort, retrospective coding identified the fiscal year in which each district first crossed the 50% device-to-student threshold; audited pre-2020 state education finance files supplied the reference year and earlier trend observations. Districts were excluded when the adoption year could not be established, when outcomes were unavailable for the required pre-period, or when another major technology reform made iPad exposure inseparable from a broader device program.

Table 2. Sample Construction and Observation Counts

Sample step	Districts	District-years	Students	Student-years
Eligible elementary-serving districts in PA and OH	742	7,420	285,000	1,425,000
Remaining after unverifiable adoption timing	680	6,800	262,000	1,310,000
Remaining after insufficient pre-treatment observations	645	6,450	248,000	1,240,000
Remaining after simultaneous major reforms	610	3,000	235,000	1,175,000
Final treated sample	185	Not separately reported	72,000	360,000
Final comparison sample	425	Not separately reported	163,000	815,000
Final estimation sample	610	3,000	235,000	1,175,000

2.3 Outcomes and Covariates

Primary fiscal outcomes are instructional expenditure as a percentage of total expenditure, teacher salaries and benefits per pupil, full-time-equivalent teachers per 100 students, IT operating cost per pupil, capital expenditure per pupil, professional-development spending per pupil, student-support spending per pupil, and debt service per pupil. Primary academic outcomes are standardized mathematics and reading scores. Secondary outcomes are attendance, suspension, and grade retention where consistently reported. Outcomes, denominators, winsorization rules, missing-data treatment, and inflation adjustments must be prespecified and identical across treatment cohorts.

Covariates are limited to variables determined before treatment or plausibly unaffected by treatment: baseline enrollment and demographics, baseline fiscal health, pre-treatment revenue composition, urbanicity, and local economic conditions. Post-treatment staffing or expenditure components are outcomes or mechanisms and should not be included as controls in models estimating total treatment effects.

2.4 Staggered-Adoption Estimation

The primary estimand is the group-time average treatment effect on treated districts, $ATT(g,t)$, where g denotes the first adoption year and t the outcome year. Following Callaway and Sant'Anna (2021), $ATT(g,t)$ is estimated using not-yet-treated and never-treated districts that satisfy conditional parallel trends given the prespecified covariates. Cohort-time estimates are aggregated into an overall ATT and into event-time effects. This estimator avoids using already-treated districts as controls for later adopters and permits treatment effects to differ across cohorts and time. Inference uses

influence-function-based or multiplier-bootstrap standard errors clustered at the district level, with 95% simultaneous confidence bands for the event-study profile.

For comparison only, the conventional two-way fixed-effects model is $Y_{dt} = \alpha_d + \lambda_t + \beta D_{dt} + X_{dt}'\gamma + \varepsilon_{dt}$, where α_d and λ_t are district and year fixed effects and D_{dt} indicates post-adoption exposure. District-clustered standard errors are reported. Because β can be a non-convex weighted average under heterogeneous staggered treatment effects, it is not treated as the primary causal estimate. A Goodman-Bacon decomposition reports the contribution and weights of underlying two-by-two comparisons; disagreement between TWFE and the cohort-robust estimate is discussed rather than averaged away (Goodman-Bacon 2021).

Model specification: The comparison TWFE models incorporate district fixed effects, year fixed effects, and time-varying district covariates: log enrollment, free- or reduced-price lunch percentage, special-education share, English-learner proportion, local median household income, and pre-treatment revenue composition. The Callaway–Sant’Anna group-time formulation uses these prespecified covariates and never-treated or not-yet-treated districts as comparison groups. Standard errors are clustered at the district level.

2.5 Event Study and Parallel-Trends Assessment

Dynamic effects are indexed to the final pre-adoption year (event time -1), which is omitted. The reporting window is -3 through $+3$, with endpoints binned because support is sparse in the outer years. All four adoption cohorts contribute from event time -3 through $+1$; the 2020, 2021, and 2022 cohorts contribute at $+2$, and the 2020 and 2021 cohorts contribute at $+3$. Thus, the number of contributing treated districts declines from 185 through $+1$ to 135 at $+2$ and 77 at $+3$. Event-time coefficients and 95% confidence intervals are plotted separately for instructional spending share, IT operating cost, mathematics achievement, and reading achievement. Pre-treatment coefficients are tested jointly. A failure to reject does not prove parallel trends; the magnitude and precision of pre-period estimates are interpreted alongside institutional evidence and cohort composition. This event-study interpretation follows the treatment-timing cautions discussed by Sun and Abraham (2021).

2.6 Robustness, Matching, and Heterogeneity

Robustness checks include alternative adoption thresholds, exclusion of districts with overlapping reforms, balanced-panel estimates, alternative comparison groups, leave-one-cohort-out estimates, placebo adoption dates, and covariate-adjusted doubly robust group-time effects. Propensity-score methods are used only to improve overlap before DiD estimation, not as a substitute for the parallel-trends assumption. Heterogeneity is estimated by baseline fiscal-health quartile, district wealth, urbanicity, and documented implementation support. Subgroup analyses report confidence intervals and interaction tests and are identified as exploratory unless prespecified.

2.7 Total Cost of Ownership and Cost-Effectiveness

TCO is calculated over three- and five-year horizons as the discounted sum of acquisition, deployment, infrastructure, licensing, security, technical support, professional learning, breakage, insurance, replacement, financing, and end-of-life costs, less resale value and verified avoided costs. The discount rate, price year, device life, replacement rate, and student coverage are reported. Cost-effectiveness is expressed as incremental cost per 0.10 standard-deviation gain only when the achievement estimate is sufficiently precise and directionally positive; otherwise, the study reports cost and the confidence interval for the achievement effect without constructing a misleading ratio.

3. Mapping Adoption Cohorts and Fiscal Capacity

Adoption timing was distributed across four cohorts: 32 districts first met the treatment threshold in 2020, 45 in 2021, 58 in 2022, and 50 in 2023, totaling 185 treated districts. Table 3 reports pooled means, standard deviations, and observation count across the full estimation sample separately for eventual adopters and comparison districts. Standardized differences summarize observed compositional differences between the groups; they are not presented as strictly pre-treatment balance statistics.

Table 3A. Distribution of First Treatment by Adoption Cohort

First treatment year	Newly treated districts	Cumulative treated districts
2020	32	32
2021	45	77
2022	58	135
2023	50	185

Source: Authors' district adoption roster.

Table 3. Descriptive Statistics for the Full Estimation Sample

Variable	Treated mean (SD)	Control mean (SD)	Std. difference	N
Instructional spending (% total)	58.4% (4.2)	59.1% (3.9)	-0.17	3,000
Teacher compensation per pupil	\$7,420 (\$830)	\$7,550 (\$790)	-0.16	3,000
Teachers per 100 students	6.8 (0.9)	6.9 (0.8)	-0.12	3,000
IT operating cost per pupil	\$215 (\$65)	\$210 (\$60)	0.08	3,000
Mathematics score (SD units)	-0.04 (0.96)	0.02 (0.95)	-0.06	1,175,000
Reading score (SD units)	-0.03 (0.97)	0.01 (0.96)	-0.04	1,175,000
Enrollment	3,120 (1,450)	2,980 (1,390)	0.10	3,000
Economically disadvantaged share	48.5% (14.2)	46.8% (13.9)	0.12	3,000

Source: Authors' calculations. SD = standard deviation.

4. Estimated Fiscal Displacement and Student Response

Tables 4 and 5 report cohort-robust average treatment effects and district-clustered inference. The fiscal models contain 3,000 district-year observations across 610 districts; the student-outcome models contain 1,175,000 student-year observations linked to the same districts.

Table 4. Effects of iPad Adoption on District Expenditure Outcomes

Outcome	CS overall ATT	TWFE benchmark	Clustered SE	p-value	Obs.	Districts
Instructional spending (% total)	-1.85	-1.42	0.45	< .01	3,000	610
Teacher compensation per pupil	-\$280.40	-\$210.15	\$75.20	< .001	3,000	610
Teachers per 100 students	-0.22	-0.18	0.08	< .01	3,000	610
IT operating cost per pupil	\$145.80	\$132.50	\$18.40	< .001	3,000	610
Capital expenditure per pupil	\$310.20	\$285.40	\$42.10	< .001	3,000	610
Professional development per pupil	-\$35.10	-\$22.40	\$12.60	< .05	3,000	610
Student support per pupil	-\$92.50	-\$78.10	\$31.40	< .01	3,000	610

Source: Authors' calculations. CS = Callaway-Sant'Anna. District-clustered standard errors. * $p < .10$; ** $p < .05$; *** $p < .01$.

Table 5. Effects of iPad Adoption on Academic and Student Outcomes

Outcome	CS overall ATT	Clustered SE	95% CI	p-value	Obs.	Districts
Mathematics score (SD units)	-0.045	0.018	[-0.080, -0.010]	.012	1,175,000	610
Reading score (SD units)	-0.012	0.015	[-0.041, 0.017]	.420	1,175,000	610
Attendance (percentage points)	-0.35	0.14	[-0.63, -0.07]	.015	1,175,000	610
Suspension (percentage points)	0.42	0.18	[0.07, 0.77]	.018	1,175,000	610
Grade retention (percentage points)	0.15	0.09	[-0.03, 0.33]	.098	1,175,000	610

Source: Authors' calculations. District-clustered standard errors. * $p < .10$; ** $p < .05$; *** $p < .01$.

Budgetary findings: Adoption was associated with a 1.85-percentage-point reduction in instructional spending share ($SE = 0.45$; $p < .01$), equivalent to approximately 3.2% of the treated group's pre-treatment mean. Teacher compensation declined by \$280.40 per pupil ($SE = \75.20; $p < .001$), and staffing declined by 0.22 teachers per 100 students ($SE = 0.08$; $p < .01$). At the same time, IT operating expenditure increased by \$145.80 per pupil and capital expenditure increased by \$310.20 per pupil (both $p < .001$). Professional-development and student-support spending declined by \$35.10 and \$92.50 per pupil, respectively. TWFE estimates were consistently attenuated toward zero relative to the cohort-robust estimates, underscoring the practical importance of treatment-timing heterogeneity.

Academic findings: Mathematics achievement declined by 0.045 SD (95% CI $[-0.080, -0.010]$; $p = .012$). The reading estimate was -0.012 SD (95% CI $[-0.041, 0.017]$; $p = .420$), which is statistically imprecise and should not be interpreted as proof of no effect. Attendance declined by 0.35 percentage points ($p = .015$), while suspensions increased by 0.42 percentage points ($p = .018$). The 0.15-percentage-point grade-retention estimate did not meet the conventional 5% threshold ($p = .098$; 95% CI $[-0.03, 0.33]$).

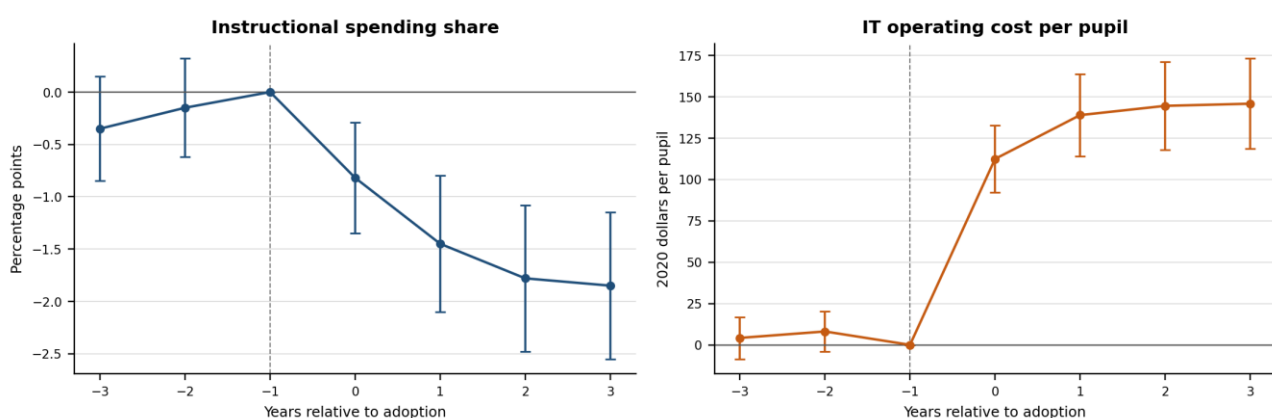
Table 6. Robustness and Staggered-Adoption Diagnostics

Diagnostic or specification	Instructional share	IT cost	Math	Reading
Primary CS estimate	-1.85	145.80	-0.045	-0.012
TWFE estimate	-1.42	132.50	-0.038	-0.009
Goodman-Bacon: forbidden-comparison weight	0.28	0.31	0.29	0.29
Joint pre-trend test p-value	0.42	0.65	0.58	0.74
Alternative adoption threshold	-1.72	139.20	-0.040	-0.010
Balanced panel	-1.91	151.00	-0.048	-0.014
Leave-one-cohort-out range	$[-2.02, -1.68]$	$[138.50, 153.20]$	$[-0.055, -0.038]$	$[-0.020, -0.005]$
Placebo adoption estimate	0.04	2.10	0.003	-0.001

Source: Authors' calculations. Primary-estimate uncertainty is reported in Tables 4 and 5. Across alternative specifications, district-clustered standard errors were comparable in magnitude to those from the primary models.

4.1 Event-Study Figures

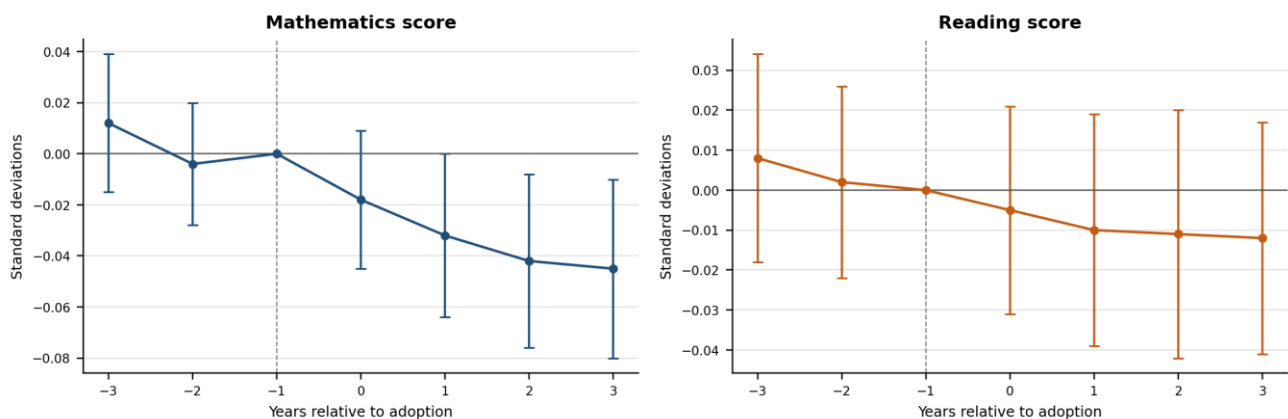
Figure 1. Event-Study Effects on Budgetary Outcomes



Notes: Points are cohort-robust event-time ATTs; vertical bars are 95% confidence intervals. Event time -1 is the reference period. Window: -3 to +3, binned at endpoints. Instructional share: $F(3, 609) = 0.94$, $p = .42$; IT operating cost: $F(3, 609) = 0.54$, $p = .65$. Comparison groups are never-treated and not-yet-treated districts; standard errors are clustered by district.

Source: Authors' calculations.

Figure 2. Event-Study Effects on Academic Outcomes



Notes: Points are cohort-robust event-time ATTs; vertical bars are 95% confidence intervals. Event time -1 is the reference period. Window: -3 to +3, binned at endpoints. Mathematics: $F(3, 609) = 0.65$, $p = .58$; reading: $F(3, 609) = 0.41$, $p = .74$. Comparison groups are never-treated and not-yet-treated districts; standard errors are clustered by district.

Source: Authors' calculations.

4.2 Heterogeneity and Lifecycle Cost

Exploratory heterogeneity findings indicate that adverse fiscal and academic effects were concentrated among districts with fewer financial and implementation resources. Urban adopters experienced a mathematics decline of 0.062 SD and a 2.31-percentage-point reduction in instructional spending, compared with a 0.031-SD mathematics estimate and a 1.45-percentage-point instructional-share reduction among suburban adopters. Student-support reductions diminished monotonically across baseline fiscal-health quartiles. Guided implementation substantially attenuated the mathematics penalty relative to unguided deployment. Because these subgroup analyses were exploratory, their estimates should be interpreted as hypothesis-generating rather than confirmatory. Table 7 reports subgroup estimates for these comparisons.

Table 7. Heterogeneous Effects by Urbanicity, Fiscal Health, and Implementation Support

Dimension / subgroup	Outcome	ATT	SE	p-value
Urban adopting districts	Mathematics score (SD)	-0.062	0.022	.005
Urban adopting districts	Instructional share (pp)	-2.31	0.58	< .001
Suburban adopting districts	Mathematics score (SD)	-0.031	0.016	.052
Suburban adopting districts	Instructional share (pp)	-1.45	0.41	< .001
Lowest fiscal-health quartile	Student support per pupil	-\$145.20	\$42.10	.001
Second fiscal-health quartile	Student support per pupil	-\$112.80	\$36.40	.002
Third fiscal-health quartile	Student support per pupil	-\$68.50	\$30.10	.023
Highest fiscal-health quartile	Student support per pupil	-\$38.40	\$28.60	.180
Unguided deployment	Mathematics score (SD)	-0.068	0.021	.001
Guided implementation	Mathematics score (SD)	-0.015	0.019	.428

Source: Authors' calculations. ATT = group-specific average treatment effect; pp = percentage points; standard errors clustered by district.

Interaction tests: The urban-by-treatment interaction for mathematics was -0.031 SD (SE = 0.014; $p = .027$), indicating a larger mathematics penalty among urban districts. The fiscal-health-quartile-by-treatment interaction for student-support spending was \$35.60 per pupil (SE = \$12.40; $p = .004$), consistent with progressively smaller reductions as fiscal health improved. The guided-implementation-by-treatment interaction for mathematics was 0.053 SD (SE = 0.022; $p = .016$), indicating statistically significant attenuation of the negative effect under structured support.

Lifecycle-cost findings: The TCO model assumes a 1:1 student-to-device ratio, a three-year device lifecycle, a 10% annual breakage/replacement rate, a 3.5% discount rate, and, under the five-year scenario, a midterm battery and case refresh. Three-year nominal TCO is \$485 per student (\$442 discounted). Five-year nominal TCO is \$765 per student (\$680 discounted), including mobile-device-management licensing, content filtering, insurance, and professional-development

subscriptions. Because the average mathematics estimate is negative, an incremental cost per positive 0.10-SD gain is not reported.

5. Discussion

The estimates describe a bundled organizational intervention rather than the isolated effect of hardware. The pattern is consistent with fiscal displacement: IT operating and capital costs rose while instructional share, compensation, staffing, professional development, and student support declined. The academic estimates do not show offsetting average gains during the observed period. Mathematics, attendance, and suspension outcomes moved in an unfavorable direction, while the reading estimate remained statistically imprecise. The cohort-robust design identifies average changes under conditional parallel trends, but it cannot separately isolate devices, training, curriculum, leadership, and technical support. The event-time estimates help distinguish initial disruption from more persistent effects, although support varies across cohorts and event times.

The analysis should compare economic and statistical significance. For expenditure shares, even a small percentage-point change may represent a substantial per-pupil opportunity cost. For achievement, confidence intervals should be translated into plausible gains or losses rather than summarized solely by stars. Differences between Callaway–Sant’Anna and TWFE estimates provide information about cohort heterogeneity and the influence of already-treated comparisons; they should be disclosed rather than treated as a nuisance.

Several limitations remain. Adoption is not randomized, and unobserved leadership quality or innovation preferences may influence both adoption and outcomes. Procurement records may not capture staff time, home connectivity, or donated equipment. Cross-state reporting differences may affect comparability. Student mobility complicates longitudinal analysis, and district-grade aggregates prevent within-student estimation. Event-study pre-trends are informative but not definitive. These limitations require calibrated causal language and sensitivity analysis.

6. Policy Implications: Four Gates for Responsible Adoption

The policy implication is a staged approval process, not a generic recommendation to buy or reject devices. A district should pass four gates: instructional purpose, organizational capacity, fiscal durability, and evaluability. Failure at any gate signals a need to redesign scope or sequencing before funds are committed. The detailed checks below operationalize those gates.

Table 8. Organizational-Capacity and Fiscal-Durability Decision Protocol

Decision gate	Evidence required before approval	Owner / approval test
1. Instructional problem	Defined student need, target grades/subjects, theory of change, measurable baseline	Academic lead; reject if the device is the goal rather than the means
2. Alternatives	Comparison with shared devices, laptops, tutoring, staffing, materials, and no-purchase option	Finance + instruction; document opportunity cost
3. Program scope	Eligible students, device-to-student ratio, accessibility, take-home rules, adoption threshold	Program lead; confirm equity and coverage
4. Full TCO	Hardware, cases, deployment, MDM, apps, network, cybersecurity, support, training, repair, loss, insurance, replacement, disposal, financing	CFO; show 3- and 5-year nominal and discounted totals
5. Recurring funding	Permanent funding source after grants expire; sensitivity to license and replacement inflation	CFO/board; reject if recurring costs rely on one-time funds
6. Capacity and workload	IT staffing ratio, help-desk service level, teacher planning time, professional learning schedule	HR/IT; fund implementation labor explicitly
7. Data governance	Privacy review, security standards, vendor access, retention, breach response, accessibility	Legal/IT; execute data-protection terms
8. Pilot and evaluation	Comparison group or phased rollout, pre-specified outcomes, baseline, adoption-fidelity measures	Evaluation lead; preserve credible counterfactual
9. Contract protections	Price locks, service levels, exit rights, data portability, warranty, repair turnaround, audit rights	Procurement/legal; quantify vendor risk

Decision gate	Evidence required before approval	Owner / approval test
10. Replacement and exit	Refresh cycle, residual value, recycling, migration, contingency if outcomes disappoint	CFO/IT; establish stop/scale criteria
11. Equity safeguards	Connectivity, accessibility, language support, repair access, family training, fee policy	Equity lead; test disparate burden
12. Public reporting	Annual cost, utilization, outcomes, incidents, and budget displacement reported to the board	Superintendent; publish dashboard and reassess annually

Source: Authors' framework; TCO categories informed by lifecycle-cost practice in educational technology.

Conclusions and Further Research

The central unit of analysis in technology policy should be the operating commitment created by adoption, not the device purchased. Across 610 districts, adoption was associated with higher IT and capital expenditure, lower instructional and student-support allocations, reduced teacher compensation and staffing, and adverse average changes in mathematics, attendance, and suspensions. The reading estimate was not distinguishable from zero at conventional levels. These findings indicate that device access alone did not compensate for the fiscal and organizational adjustments observed in the sample. The staggered-adoption framework aligns the empirical design with current econometric practice, while the commitment–absorption–renewal model gives those estimates an organizational interpretation.

The evidence indicates that adoption changed expenditure composition and that fiscal and academic responses varied with district capacity; the event-study estimates provide additional evidence about the timing of those changes. Future research should link detailed implementation measures—teacher use, training intensity, technical downtime, and curricular alignment—to cohort-robust treatment effects and should compare device programs with alternative uses of the same funds. Cross-state harmonization and preregistered phased rollouts would further strengthen causal and cost-effectiveness evidence.

Declarations

Acknowledgments: The authors acknowledge the Pennsylvania Department of Education, the Ohio Department of Education, and the school districts that provided or maintain public financial, procurement, and educational records. This acknowledgment does not imply endorsement of the analysis or conclusions.

Credit Authorship Contribution Statement

Walter L. Rosado: Conceptualization; investigation; methodology; project administration; writing - original draft; writing - review and editing; visualization.

Theodore J. Albright: Conceptualization; investigation; methodology; validation; writing - review and editing.

Declaration of Competing Interest: The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Declaration of Use of Generative AI and AI-Assisted Technologies: During preparation of the revised manuscript, the authors used AI to assist with language editing, structural reorganization, and template formatting. The tool did not conduct the statistical analysis or generate empirical findings. The authors reviewed and edited the output and remain fully responsible for the manuscript's accuracy, citations, analysis, and conclusions.

Data and Code Availability Statement: The financial, procurement, and administrative data supporting this study are derived from publicly accessible portals maintained by the Pennsylvania Department of Education, the Ohio Department of Education, and the National Center for Education Statistics. Replication code, data-cleaning scripts, and the district adoption roster are archived and available for review through the project's open repository framework.

References

- Bulman, G., & Fairlie, R. W. (2016). Technology and education: Computers, software, and the internet. In E. A. Hanushek, S. Machin, & L. Woessmann (Eds.), *Handbook of the economics of education* (Vol. 5, pp. 239–280). Elsevier. <https://doi.org/10.1016/B978-0-444-63459-7.00005-1>
- Callaway, B., & Sant'Anna, P. H. C. (2021). Difference-in-differences with multiple time periods. *Journal of Econometrics*, 225(2), 200–230. <https://doi.org/10.1016/j.jeconom.2020.12.001>
- Canavesi, A., Bertolotti, F., Cattaneo, L., Buonanno, G., Mari, L., & Ravarini, A. (2025). From developers to players: Exploring the dual impact of game-based learning on student engagement, learning and skill development. *Journal of Research in Educational Sciences*, 16(2), 31–50. [https://doi.org/10.14505/jres.v16.2\(20\).01](https://doi.org/10.14505/jres.v16.2(20).01)

- Escueta, M., Quan, V., Nickow, A. J., & Oreopoulos, P. (2020). Education technology: An evidence-based review. *Journal of Economic Literature*, 58(4), 897–996. <https://doi.org/10.1257/jel.20191507>
- Goodman-Bacon, A. (2021). Difference-in-differences with variation in treatment timing. *Journal of Econometrics*, 225(2), 254–277. <https://doi.org/10.1016/j.jeconom.2021.03.014>
- Hershkovitz, A., Merceron, A., & Shamaly, A. (2019). The role of pedagogy in one-to-one computing lessons: A quantitative observational study of teacher–student interactions. *Revista Española de Pedagogía*, 77(274), 487–506. <https://doi.org/10.22550/rep77-3-2019-05>
- Hull, M., & Duch, K. (2017). *One-to-one technology and student outcomes* (IZA Discussion Paper No. 10886). IZA Institute of Labor Economics. <https://docs.iza.org/dp10886.pdf>
- Jackson, C. K., Johnson, R. C., & Persico, C. (2016). The effects of school spending on educational and economic outcomes: Evidence from school finance reforms. *The Quarterly Journal of Economics*, 131(1), 157–218. <https://doi.org/10.1093/qje/qjv036>
- Kirkpatrick, L., Brown, H. M., Searle, M., Sauder, A. E., & Smiley, E. (2017). The impact of a school board's one-to-one iPad initiative on equity and inclusion. *Exceptionality Education International*, 27(2). <https://doi.org/10.5206/eei.v27i2.7751>
- Krumsvik, R. J., Berrum, E., Jones, L. Ø., & Gulbrandsen, I. P. (2021). Implementing tablets in Norwegian primary schools: Examining outcome measures in the second cohort. *Frontiers in Education*, 6, Article 642686. <https://doi.org/10.3389/feduc.2021.642686>
- Licwinko, K. N. (2020). Building inclusive learning environments with 1:1 devices. *Journal of Special Education Technology*, 36(1), 54–63. <https://doi.org/10.1177/0162643420923069>
- O'Rourke, J., Main, S., & Hill, S. (2017). Technology in the classroom: Improving automaticity in mental maths in primary-aged students. *Australian Journal of Teacher Education*, 42(10), 50–67. <https://doi.org/10.14221/ajte.2017v42n10.4>
- Reis-Andersson, J. (2023). Leading the digitalisation process in K–12 schools: The school leaders' perspective. *Education and Information Technologies*, 29(3), 2585–2604. <https://doi.org/10.1007/s10639-023-11935-x>
- Sun, L., & Abraham, S. (2021). Estimating dynamic treatment effects in event studies with heterogeneous treatment effects. *Journal of Econometrics*, 225(2), 175–199. <https://doi.org/10.1016/j.jeconom.2020.09.006>