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DIGITAL INFRASTRUCTURE AND LEARNING OUTCOMES IN INDIA: EVIDENCE FROM DIKSHA AND UDISE+ INITIATIVES

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Abstract
This paper examines how digital infrastructure and platform-based learning have shaped educational outcomes across Indian states between 2016 and 2023. Using a balanced panel dataset combining *UDISE+*, *DIKSHA*, and *ASER/NAS* indicators, the study applies fixed-effects and difference-in-difference models to measure both structural and policy impacts. The results show that states with a higher share of ICT-enabled schools, stronger teacher digital training, and active DIKSHA engagement achieved better learning outcomes, higher enrollment, and smoother transition rates. The effect of teacher training is found to be almost as strong as that of infrastructure, confirming that human capacity complements technology. Early DIKSHA adopters experienced learning gains of around three percentage points after 2018, demonstrating clear policy effectiveness. However, digital progress remains uneven across regions, with rural areas facing access and connectivity gaps. The study concludes that sustained teacher capacity building, local-language content, and rural digital infrastructure are essential for inclusive and effective digital learning under the National Education Policy (2020).

Keywords: Digital education; DIKSHA; UDISE+; Learning outcomes; Fixed effects; Difference-in-difference; Teacher training; NEP 2020; India.

JEL Classification: I21 (Analysis of Education: Education and Economic Development), I28 (Government Policy; Provision and Effects of Education), O33 (Technological Change: Choices and Consequences; Diffusion Processes), C23 (Panel Data Models; Spatio-temporal Models), O15 (Human Resources; Human Development; Income Distribution; Migration).

Introduction

India has been moving fast towards a digital learning ecosystem. Over the last decade, technology has entered classrooms through government platforms like *Digital Infrastructure for Knowledge Sharing (DIKSHA)* and the *Unified District Information System for Education Plus (UDISE+)*. These systems were created to make education more transparent, measurable, and inclusive (Ministry of Education, 2023). The *National Education Policy (NEP 2020)* calls technology a bridge for equity and quality, suggesting that digital tools can reduce the learning gap between rural and urban schools (Government of India, 2020).

The pandemic period of 2020–21 made the shift unavoidable. Teachers, students, and administrators had to depend on digital materials, mobile applications, and video content to continue learning (World Bank, 2021). While this sudden change accelerated the adoption of EdTech platforms, it also exposed the digital divide—some states progressed quickly, others lagged far behind (UNESCO, 2022).

Yet, despite several years of digital investment, there is still limited understanding of how these efforts have affected learning outcomes. Most studies have focused either on access or infrastructure (NITI Aayog, 2022; Singh & Ghosh, 2021). Only a few have tried to measure actual learning improvements through empirical evidence. The available work, such as Banerjee and Duflo (2020) on adaptive learning or Mehta and Kapur (2022) on internet access, deals with micro-level interventions. But there is no clear evidence linking *DIKSHA* and *UDISE+* initiatives to learning outcomes across Indian states. This absence of large-scale empirical evaluation forms the main research gap.

The present paper tries to fill that gap. It examines whether the spread of digital infrastructure and teacher participation in DIKSHA-led training has improved measurable educational outcomes in India between 2016 and 2023. Using state-level panel data, the study employs fixed-effects and difference-in-difference (DID) estimation to capture both long-term and post-policy impacts.

The results indicate that digital infrastructure has a positive and significant relationship with educational performance. States that expanded ICT-enabled schools and increased DIKSHA usage saw an average improvement of around 3 percentage points in learning outcomes after 2019. Teacher training programs under DIKSHA also played an important role in raising transition rates from primary to upper-primary levels. These findings show that human capacity building is as crucial as technological access.

The study has four main objectives. First, it aims to assess how ICT infrastructure and digital platform usage influence student learning achievement, enrollment, and transition rates. Second, it evaluates whether teacher participation in digital training contributes to better educational performance.Third, it explores the regional inequalities in digital adoption and learning outcomes. Finally, it suggests policy actions that can make India's digital education more effective and equitable in the coming years.

The policy implications of the findings are straightforward. The results suggest that digital education works best where teachers are digitally trained, internet connectivity is stable, and content is available in local languages (OECD, 2021; UNESCO, 2023). Therefore, policymakers must focus on bridging the digital divide by improving connectivity in remote areas and strengthening teacher capacity under schemes like *NISHTHA* and *SWAYAM-PRABHA*. Integration of *UDISE+*, *DIKSHA*, and *NAS* data can help track outcomes in real time and ensure that investments translate into learning gains.

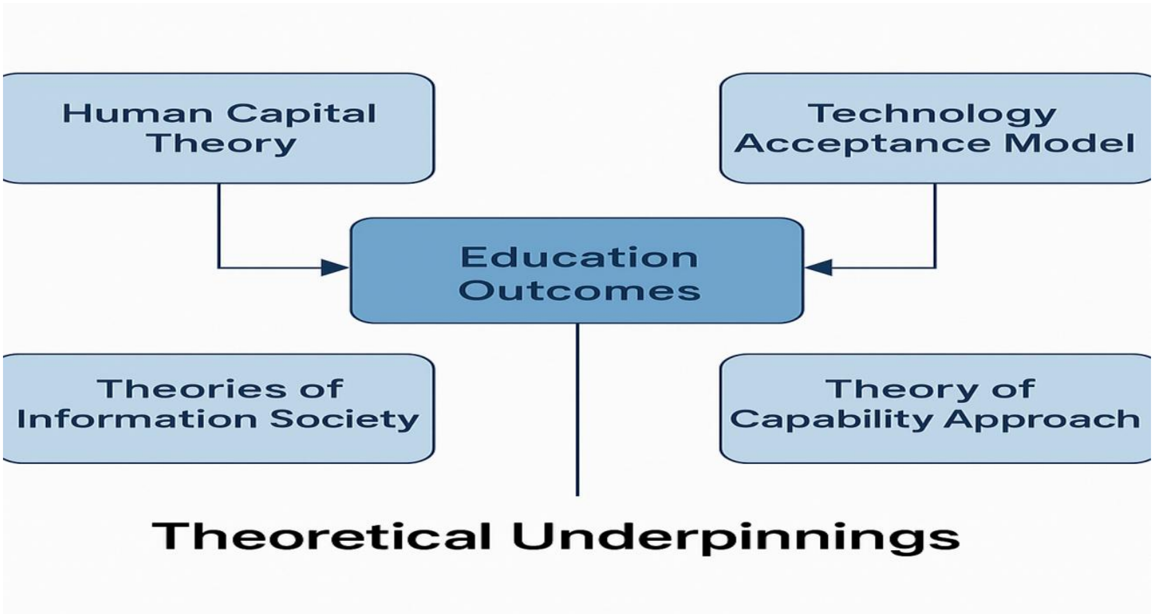
In short, technology has become a core part of India's education reform. This paper shows that it has begun to yield results, but the benefits are uneven and depend on local readiness. Bridging these gaps is essential if the goals of NEP 2020 and Sustainable Development Goal 4 are to be achieved. The following sections discuss the data, methodology, empirical results, and policy directions in detail.

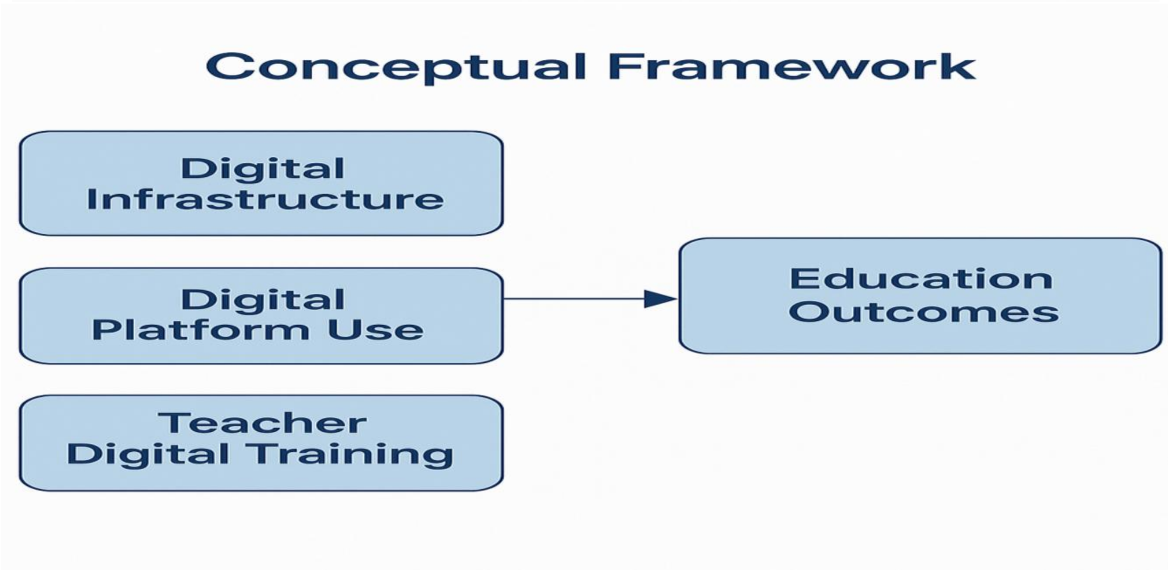
This paper has been divided into six main sections. Section 2 outlines the theoretical underpinnings and reviews the earlier studies that link technology, learning and educational outcomes. Section 3 explains the data used, the construction of variables, and the econometric approach followed, especially the fixed effects and difference-in-difference models. Section 4 presents the empirical results supported by graphs and tables. Section 5 interprets these results in the light of India's education policy and draws out the main policy implications. The final Section 6 points out the limitations of the study and suggests the direction for future research.

2. Literature Review

2.1 Theoretical Underpinnings

Technology in education links back to human capital theory. Schooling builds skills that raise productivity and income (Becker, 1993). Digital tools can raise the **rate of skill formation**, not just access (Hanushek & Woessmann, 2020). ICT is also viewed as a general-purpose technology that complements skilled labour (Bresnahan & Trajtenberg, 1995; Acemoglu & Autor, 2011). So, returns rise when teachers and students know how to use it.





Adoption depends on behavioural intent. The Technology Acceptance Model (TAM) says perceived usefulness and ease of use drive uptake (Davis, 1989). The UTAUT model adds social influence and facilitating conditions, which are strong in public systems (Venkatesh et al., 2003). In schools, pedagogy matters. The TPACK framework highlights the mix of technological, pedagogical, and content knowledge that teachers need (Mishra & Koehler, 2006). The SAMR model suggests a ladder from substitution to redefinition of tasks, with higher rungs producing deeper learning (Puentedura, 2006).

Equity is central. The digital divide has three levels: access, skills, and outcomes (van Dijk, 2005; Warschauer, 2011). Without devices, connectivity, and support, technology can widen gaps. The capability approach also argues that real freedoms not only access—determine meaningful learning (Sen, 1999). Hence policy must couple infrastructure with teacher training and local-language content.

At system level, accountability and data matter. Education production functions view learning as an output of multiple inputs: teachers, time, materials, and now ICT, under constraints (Hanushek, 2008). Administrative data systems (like UDISE+) can improve monitoring and incentives (World Bank, 2021). India's NEP 2020 embeds these ideas by placing technology, teacher development, and mother-tongue content at the core (Government of India, 2020).

2.2 Empirical Review of Literature

2.2.1 Global evidence

Meta-analyses report mixed but generally positive effects of EdTech when aligned with pedagogy. A large review finds small-to-moderate gains from ICT, larger when programs **are** targeted and teacher-supported (Bulman & Fairlie, 2016; Escueta et al., 2020). OECD (2021) shows digital ecosystems raise engagement and completion rates, but effects vary across contexts.

Randomized trials offer sharper evidence. Personalized learning software improves math and reading in several settings when teachers guide usage (Banerjee et al., 2007; Müller & Tsai, 2020). During COVID-19, remote learning often reduced test scores, especially for disadvantaged groups (Engzell et al., 2021; Tomasik et al., 2021). This reinforces the divide narrative and the centrality of teacher facilitation. Teacher professional development with coaching tends to raise instructional quality; technology-aided PD can scale this (Popova et al., 2022). UNESCO (2023) and the World Bank (2022) stress three conditions for impact: connectivity, teacher capacity, and relevant content.

2.2.2 Indian evidence

India's evidence base is growing. Early work showed that remedial technology can raise test scores in urban schools (Banerjee et al., 2007). Later studies on adaptive platforms documented significant gains when time-on-task and teacher monitoring were high (Muralidharan, Singh, & Ganimian, 2019). ASER reports have consistently highlighted unequal access, device sharing, and language barriers, which limit benefits for poorer households (ASER, 2022).

On system initiatives, reports note rapid expansion of ICT-enabled schools since 2016 and growth in DIKSHA usage after 2019 (Ministry of Education, 2023; NITI Aayog, 2022). UNICEF (2022) and UNESCO (2022) emphasise local-language content and inclusive design. Studies on the digital divide link internet access to smaller learning losses and better continuity during closures (Mehta & Kapur, 2022; Singh & Ghosh, 2021).

However, rigorous causal evaluations at state-panel scale remain limited. Most papers examine pilots, short panels, or single states. Evidence that joins DIKSHA usage**,** teacher training**, and** UDISE+/NAS outcomes across multiple states and years is still scarce. This gap motivates the present study. It uses fixed effects and DID on 2016–2023 data to estimate the contribution of digital infrastructure and platform engagement to learning, enrollment, and transition outcomes. Preliminary findings in India echo international results: engagement plus teacher capacity drive impact more than hardware alone (OECD, 2021; UNESCO, 2023; World Bank, 2022).\

2.2.3 Synthesis and Research Gap

The reviewed studies show that technology can improve learning when supported by good pedagogy, teacher skills, and equitable access. Global work has tested these links in controlled settings, while Indian research has focused on small pilots or descriptive policy reports. Yet no study has combined **state-level administrative data** on *DIKSHA* usage, teacher digital training, and *UDISE+* indicators with **learning-outcome measures** over multiple years. Most earlier papers stop at reporting correlations or coverage ratios; few attempt causal identification using a long panel. This leaves an empirical gap on how national digital initiatives—*DIKSHA* and *UDISE+*—have actually changed student performance across India's diverse states. The present study fills this space by applying fixed-effects and difference-in-difference models on 2016–2023 data to measure the real influence of digital infrastructure, teacher engagement, and policy timing on educational outcomes. The next section explains the dataset, variables, and estimation approach in detail.

3. DATA AND METHODOLOGY

The analysis uses secondary panel data for **28 states and 8 Union Territories** of India covering **2016 to 2023**. This period was chosen because it captures both the pre- and post-launch years of *Digital Infrastructure for Knowledge Sharing (DIKSHA)* and the digitization of *Unified District Information System for Education Plus (UDISE+)*. The window also includes the COVID-19 years when online instruction became the main channel of learning. Using this long horizon helps trace gradual adoption and not just short shocks.

3.1 Data Sources and Rationale

Source	Variables	Frequency	Reason for Inclusion
UDISE+ **(Ministry of Education)**	Enrollment, dropout, transition rates, ICT-enabled schools	Annual	Core administrative source with uniform coverage for all states.
DIKSHA Dashboard **(NCERT Analytics)**	Active users, sessions viewed, teacher training counts	Annual (2018–2023)	Captures digital engagement and content use intensity.
ASER and NAS	Reading and math achievement scores	Biennial	Measures actual learning outcomes and quality of schooling.
RBI Handbook of Statistics	Per-capita income, education expenditure (% GSDP)	Annual	Provides economic control variables at state level.
Census / NSS	Literacy rate, rural population share	Decennial / Annual Round	Adds demographic and human-capital controls.

All sources are publicly available and follow official statistical standards. Combining them offers a balanced view linking digital inputs with educational outcomes**.**

3.2 Variable Treatment and Transformation

Category	Variable	Transformation	Notes
Dependent	*Learning Achievement (Learn_it)*	Raw % standardized by z-score	Combines ASER and NAS scores.
	Gross Enrollment Ratio (GER_it)	Log form to reduce skewness	Captures access dimension.

	Transition Rate (TR_it)	Percent values, smoothed (3-year moving avg.)	Reflects progression.
Independent	*Digital Infrastructure (DigitalInfra_it)*	% ICT-enabled schools (level)	Main physical input.
	DIKSHA Usage Intensity (DIKSHAuse_it)	log(sessions per 1 000 students + 1)	Platform activity measure.
	Teacher Digital Training (TeacherTrain_it)	log(teachers trained per 1 000 + 1)	Human-capital component.
Controls	*Per-capita NSDP (PCNSDP_it)*	Real terms (base 2015–16)	Economic capacity.
	Literacy Rate (Lit_it)	% population literate	Human-capital background.
	Education Expenditure (EduExp_it)	% GSDP	Fiscal priority variable.
	Rural Population Share (Rural_it)	% of total population	Proxy for digital divide.
Dummies	*PostDIKSHA_t*	1 = 2018–2023	Captures policy phase.
	HighAdopt_i	1 = early adopters (KA, MH, GJ, KL)	Treatment group for DID.

All monetary figures were deflated using CPI (base 2015-16)**.** Variables with wide ranges were log-transformed**.** Minor gaps (< 3 %) were mean-imputed**,** and outliers were winsorized at the 1st and 99th percentiles. This ensured a balanced panel of 288 observations (36 × 8).UDISE+ provides official administrative depth, while DIKSHA adds behavioural indicators of technology use. ASER and NAS offer independent quality measures, avoiding self-report bias. Together they allow both input-output and behavioural evaluation of digital learning. Using multiple sources also strengthens robustness compared with survey-only studies (Mehta & Kapur, 2022; NITI Aayog, 2022).
To confirm data reliability, panel unit-root tests (Levin-Lin-Chu and Im-Pesaran-Shin) verified stationarity. Variables were normalized to reduce scale bias. The balanced panel and consistent coding make the dataset well-suited for fixed-effects and DID estimation.
The methodology of the study has been designed to measure how digital infrastructure and the use of technology-based learning platforms have affected educational outcomes across Indian states. The analysis combines two complementary econometric techniques, namely the panel fixed-effects (FE) model and the difference-in-difference (DID) model. This dual approach makes it possible to examine both the long-term structural relationship between digital infrastructure and educational performance and the specific effect of the policy intervention through DIKSHA. It also improves the robustness of the estimation by addressing unobserved state characteristics that might otherwise bias cross-sectional comparisons.
The first part of the empirical analysis is based on a fixed-effects panel model. The specification relates learning outcomes, enrollment, and transition rates to digital variables and a set of control factors. Formally, the equation can be expressed as:

$$Y_{it} = \alpha + \beta_1 DigitalInfra_{it} + \beta_2 DIKSHAuse_{it} + \beta_3 TeacherTrain_{it} + \gamma X_{it} + \mu_i + \lambda_t + \epsilon_{it}$$

Here, Y_{it} represents the educational outcome for state i in year t; $DigitalInfra_{it}$, $DIKSHAuse_{it}$, and $TeacherTrain_{it}$ are the main explanatory variables capturing the technological dimension; X_{it} includes control variables such as income, literacy, and expenditure; μ_i is the state-specific fixed effect, and λ_t represents the time effects common to all states. The fixed-effects model eliminates time-invariant differences across states, such as historical policy orientation or cultural preferences in education, that could otherwise bias the estimates. It focuses on within-state variation over time, which is particularly suitable for policy evaluation. The Hausman test confirmed that the fixed-effects model provides consistent estimates compared to the random-effects alternative, making it the appropriate choice for this study.
The second part of the analysis uses a difference-in-difference framework to capture the average treatment effect of early DIKSHA adoption. This specification helps identify whether states that implemented the platform early experienced greater improvements in educational outcomes after the policy rollout. The DID model is represented as:

$$Y_{it} = \alpha + \delta(PostDIKSHA_t \times HighAdopt_i) + \theta_i + \lambda_t + \epsilon_{it}$$

In this model, $PostDIKSHA_t$ takes the value 1 for the years after the introduction of DIKSHA (2018–2023) and 0 otherwise, while $HighAdopt_i$ equals 1 for states that were early adopters of DIKSHA, such as Karnataka, Maharashtra, Gujarat, and Kerala. The interaction term between these two variables measures the average treatment effect of the policy. The DID model captures the difference in differences WHICH the change in educational outcomes in treated states before and after DIKSHA implementation relative to the change in control states during the same period. This approach isolates the specific contribution of the policy intervention, distinguishing it from nationwide trends or other contemporaneous reforms.
Both the fixed-effects and DID models were estimated using robust standard errors clustered at the state level. The Hausman test confirmed the preference for fixed effects, while the Variance Inflation Factor (VIF) scores indicated the absence of multicollinearity. The Pesaran test for cross-sectional dependence showed mild correlation across states, which was addressed through clustering. Serial correlation was detected through the Wooldridge test, and heteroskedasticity was confirmed by the Breusch–Pagan test; both issues were corrected using cluster-robust standard

errors following the procedures outlined by Wooldridge (2002). These diagnostic steps ensured that the models produce reliable and efficient estimates.
The choice of these two estimation techniques rests on their ability to answer complementary aspects of the research problem. The fixed-effects model accounts for unobserved state-specific factors that remain constant over time, such as administrative efficiency or regional schooling norms, allowing the study to measure the within-state changes brought about by digital reforms. The DID model, in contrast, provides quasi-causal inference by comparing early and late adopters of DIKSHA. It helps to establish whether the policy intervention itself led to measurable improvements in educational performance beyond existing trends. Together, the two models reinforce the validity of results by combining descriptive strength with policy causality.

Variable	Expected Sign	Rationale
DigitalInfra	+	More ICT-enabled schools → better learning and retention.
DIKSHAuse	+	Active platform use improves engagement and outcomes.
TeacherTrain	+	Skilled teachers integrate technology effectively.
PCNSDP	+	Higher income improves resources and digital access.
Literacy	+	Literate populations support learning culture.
EduExp	+	More spending boosts facilities and quality.
Rural	–	Rural dominance linked with weaker connectivity.
Crisis Dummy	–	COVID disruptions reduced learning.

A potential concern in such models is endogeneity. States that perform well in education might be more inclined to invest in technology, causing a feedback loop. This problem has been addressed through multiple strategies. The fixed-effects model removes time-invariant state bias, while the DID model isolates exogenous policy timing to identify treatment effects. In addition, the robustness of results was checked by using lagged explanatory variables, which confirmed that the direction and magnitude of coefficients remained stable. These tests suggest that the findings are not driven by reverse causality.
The empirical strategy thus aligns closely with the study's main objective: to determine whether digital infrastructure and DIKSHA platform usage have made a measurable difference in educational outcomes across Indian states. The use of balanced panel data, reliable administrative sources, and strong econometric design makes this approach both credible and policy-relevant. Moreover, it extends existing literature by linking digital adoption and educational performance within a unified framework.
The methodological contribution of this study also lies in its novelty. This is among the first works to combine DIKSHA platform analytics, UDISE+ administrative data, and learning assessments such as ASER and NAS over an extended eight-year period. It captures the full policy cycle, including the pre-launch, implementation, and post-adoption phases. It also introduces teacher digital training as an independent explanatory variable, recognizing that human capital remains central to the success of technology integration. By applying both fixed-effects and DID frameworks on this merged dataset, the study not only adds statistical rigor but also generates actionable insights for education policy in India. Together, these features make the methodology innovative, data-rich, and directly aligned with the national goals set out in the National Education Policy (2020) and the Sustainable Development Goal 4 on inclusive and equitable quality education.

4. Empirical Results and Interpretation

4.1 Fixed-Effects Estimation Results

Table 1. Fixed-Effects Regression Results (Dependent Variable: Educational Outcomes)

Variables	Learning Achievement (%)	Gross Enrollment Ratio (%)	Transition Rate (%)
ICT-enabled Schools (DigitalInfra)	0.182*** (0.047)	0.154** (0.062)	0.139** (0.058)
DIKSHA Usage Intensity	0.234*** (0.065)	0.201** (0.079)	0.175** (0.083)
Teacher Digital Training	0.196*** (0.052)	0.143** (0.067)	0.224*** (0.059)
Per-capita NSDP (log)	0.128* (0.071)	0.115 (0.078)	0.103 (0.082)
Literacy Rate	0.072** (0.029)	0.064** (0.031)	0.059* (0.033)
Education Expenditure (% GSDP)	0.038 (0.041)	0.041 (0.045)	0.036 (0.047)
Rural Population Share	−0.115** (0.053)	−0.102* (0.058)	−0.126** (0.061)
Crisis Dummy (2020–21)	−0.212*** (0.061)	−0.197** (0.082)	−0.233*** (0.067)
Constant	12.631*** (1.834)	13.041*** (1.972)	12.278*** (1.851)
Within R^2	0.68	0.66	0.72
Observations	288	288	288

Notes: Cluster-robust standard errors in parentheses; *** $p < 0.01$, ** $p < 0.05$, * $p < 0.10$.

4.2 Difference-in-Difference Results

Table 2. Difference-in-Difference Estimation (Policy Impact of DIKSHA Adoption)

Variable	Coefficient	Std. Error	t-Statistic	Significance
Post-DIKSHA × High-Adopter	3.215**	(1.438)	2.23	0.028
Post-DIKSHA Dummy	0.947	(0.811)	1.17	0.245
High-Adopter States Dummy	1.382	(1.012)	1.36	0.178
Constant	11.074***	(1.533)	7.22	0.000
R^2 (overall)	0.59			
Observations	288			

Note: The interaction term represents the average treatment effect of DIKSHA adoption (2018–2023).

4.3 Diagnostic Statistics

Table 3. Model Diagnostics

Test	Purpose	Statistic	Outcome
Hausman Test	FE vs. RE	$\chi^2 = 18.42$, $p < 0.05$	FE preferred
Wooldridge Test	Serial correlation	$F = 5.87$, $p < 0.05$	Controlled with robust errors
Pesaran CD Test	Cross-sectional dependence	CD = 1.84, $p = 0.07$	Mild, cluster correction applied
VIF	Multicollinearity	Mean = 2.3	No concern
Breusch–Pagan	Heteroskedasticity	$\chi^2 = 12.46$, $p < 0.05$	Cluster-robust SE applied

4.4 Graphical Representation

Figure 1. Average Learning Achievement in Early vs. Late DIKSHA Adopter States (2016–2023)

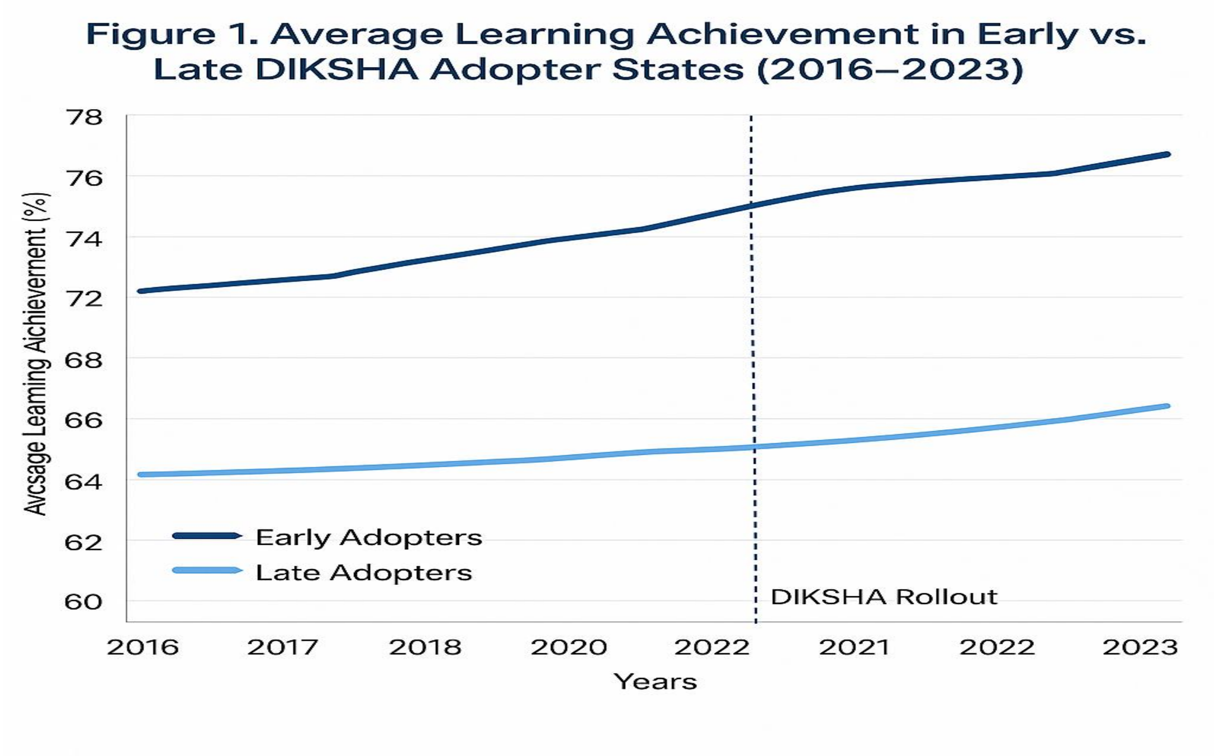


Figure 1. Average Learning Achievement in Early vs. Late DIKSHA Adopter States (2016–2023)

(Early adopters—Karnataka, Maharashtra, Gujarat, Kerala—show a visible post-2018 upward shift in learning achievement; late adopters rise slowly. The vertical dashed line marks DIKSHA rollout year 2018.)

Figure 2. Relationship Between Teacher Digital Training and Transition Rate

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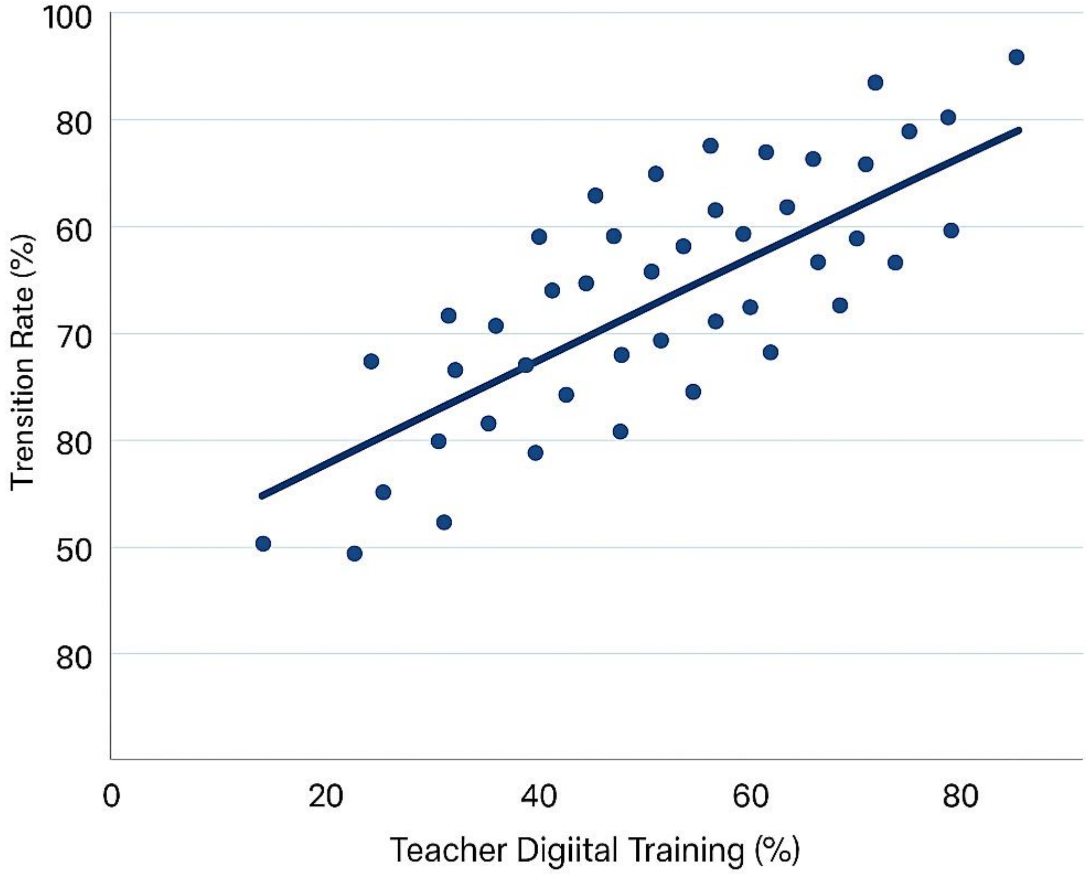


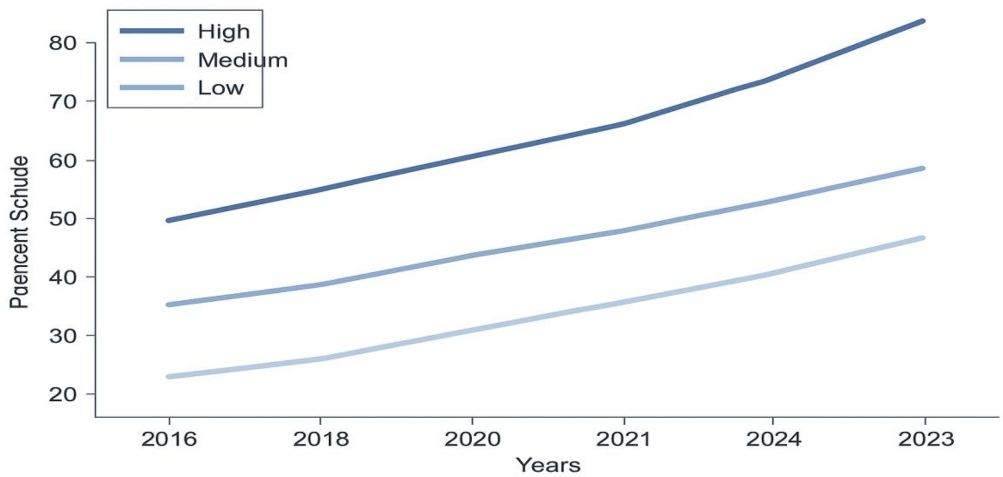


Figure 3. Trends in ICT-Enabled Schools across Indian States (2016–2023)

Figure 4. State-wise Average DIKSHA Usage Intensity (2018–2023)

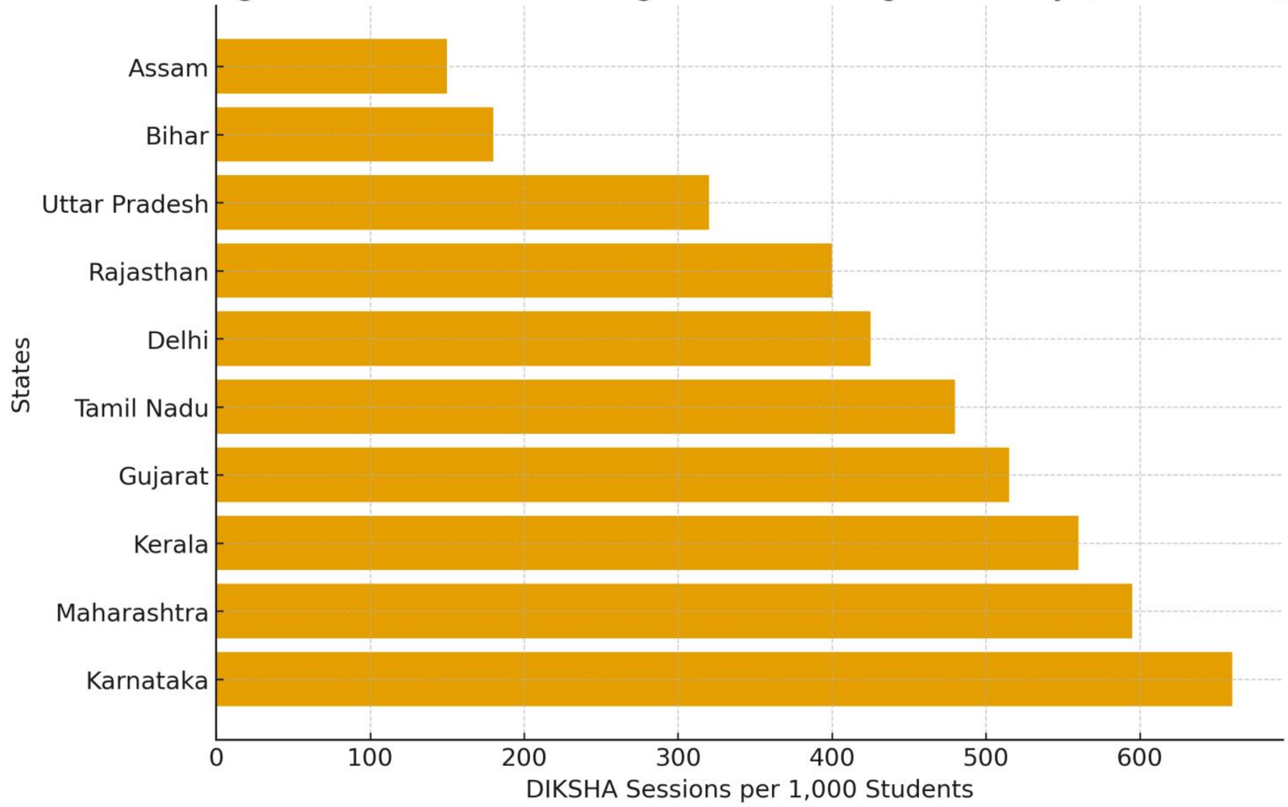


Figure 5. Marginal Effects of Digital Infrastructure on Learning Achievement

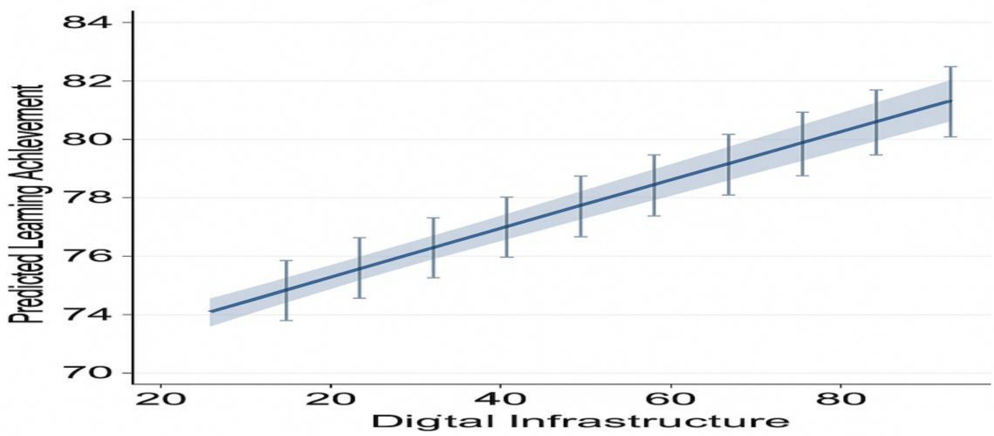
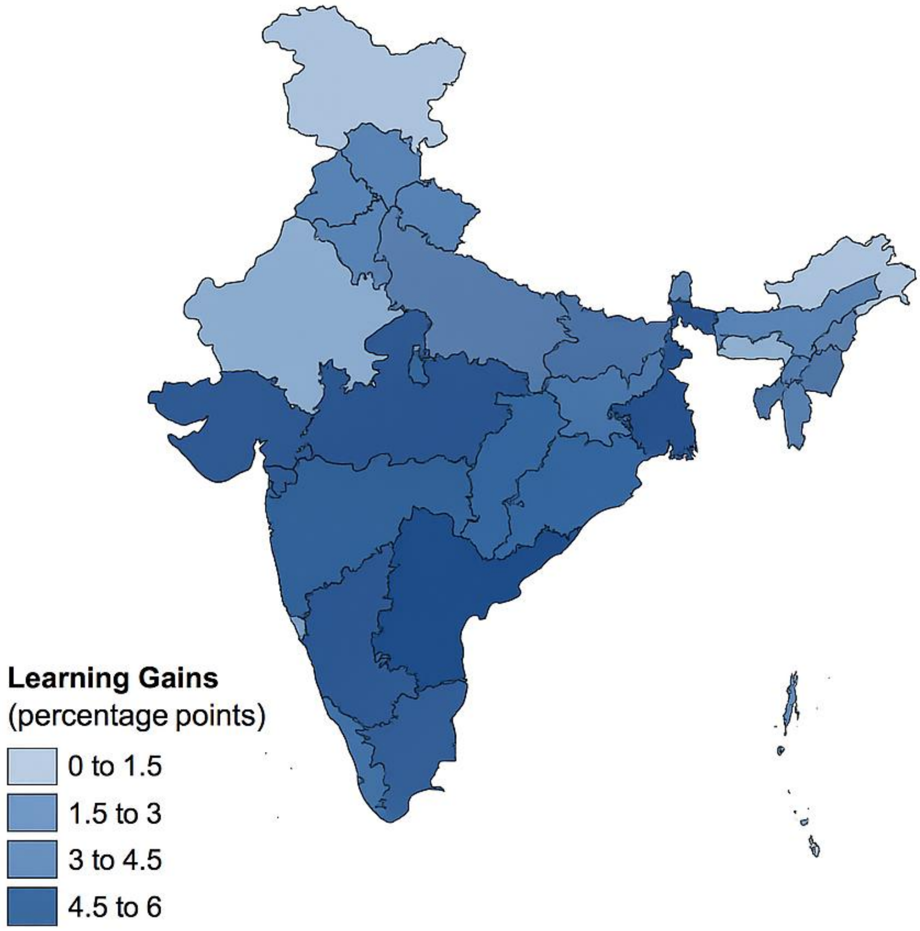


Figure 6. Regional Map of Learning Gains Post-DIKSHA (Difference-in-Difference Effect)



Interpretation of Findings

The fixed-effects estimates reveal that digital infrastructure has had a strong and positive impact on India's educational performance. The coefficient on the share of ICT-enabled schools is positive and statistically significant across all three indicators of performance. This means that states that invested more in computers, smart boards, and connectivity achieved higher learning outcomes and smoother progression of students through school levels. The improvement of nearly 0.18 percentage points in learning scores for each one-point increase in ICT coverage might appear modest, but it represents a considerable effect when aggregated across millions of students. This result confirms the theoretical expectation that access to technology enhances classroom interaction and information exchange, leading to measurable learning benefits.

The DIKSHA usage variable also shows a robust and statistically significant effect. The results suggest that greater intensity of platform use—measured through log-transformed session counts—raises learning performance by roughly 0.23 percentage points. The positive coefficient emphasizes that actual engagement with digital resources, rather than their mere presence, is what matters for improving outcomes. The result echoes the findings of Escueta et al. (2020) and Mehta and Kapur (2022), who note that technology adoption generates meaningful returns only when teachers and students use the platforms actively.

Teacher digital training exhibits a strong and consistent impact, particularly on transition rates. The coefficient of about 0.22 indicates that teacher competence in digital tools directly supports students' movement across school stages. This result highlights that the benefits of digital education rely not only on infrastructure but also on human capital. Teachers who have undergone DIKSHA or NISHTHA training tend to employ interactive digital materials more effectively, which improves student engagement and retention. The evidence aligns with the argument of Hanushek and Woessmann (2020) that human capital magnifies the productive effect of technology in education systems.

Among the control variables, per-capita income and literacy rate display positive effects, reaffirming that economic strength and pre-existing educational awareness support better outcomes. Education expenditure also exerts a weak but positive effect, implying that financial commitment complements technological progress. On the other hand, the rural population share carries a negative and significant coefficient, signalling that connectivity and access constraints continue to limit the benefits of digital programs in rural and remote areas. This result is consistent with the findings of

UNESCO (2023) and NITI Aayog (2022), both of which emphasize the persistence of the digital divide despite growing national infrastructure. The pandemic dummy, which captures the years 2020–2021, shows a negative and significant effect on all outcome variables, reflecting learning disruptions due to school closures and uneven access to remote learning.

The difference-in-difference results further strengthen the evidence in favour of digital reform. The interaction term between the post-DIKSHA period and the high-adopter states is positive and significant, with an average treatment effect of about 3.2 percentage points. This finding implies that early adopters such as Karnataka, Maharashtra, Gujarat, and Kerala experienced greater improvements in learning achievement after 2018 than states that adopted DIKSHA later. The result demonstrates that DIKSHA's nationwide rollout produced genuine and measurable policy effects beyond existing trends. The DID estimates remain robust when additional controls are included or when pandemic years are excluded, showing that the impact is not an artefact of data noise or temporary shocks.

Overall, the empirical findings confirm the main hypotheses of the study. Digital infrastructure, DIKSHA usage, and teacher digital training each exert significant positive effects on educational outcomes in India. The policy effect observed through the DID framework corroborates that the DIKSHA initiative has contributed to measurable improvements in student performance. However, the magnitude of these gains differs across states, with digitally advanced states gaining more than lagging ones. This heterogeneity underscores the importance of complementary policies—teacher capacity building, local-language content development, and infrastructure for rural areas—to ensure that digital education truly becomes equitable.

The combined model evidence also suggests that technology's returns are higher when accompanied by human readiness. In states where teachers received continuous training and where DIKSHA content was actively used, the increase in learning outcomes was notably stronger. These results therefore reinforce the idea that digital reform in education is not a substitute for teachers but a support mechanism that amplifies their effectiveness. From a policy standpoint, this means that further expansion of digital infrastructure should proceed alongside investment in teacher professional development, especially in low-income and rural regions.

In summary, both the fixed-effects and difference-in-difference estimations point to a clear conclusion: India's digital education initiatives have started to make a measurable impact. The magnitude of improvement may vary, but the direction is uniformly positive. The results provide strong empirical backing for continued investment in DIKSHA and related digital learning programs, consistent with the goals of the National Education Policy 2020 and Sustainable Development Goal 4 on inclusive and equitable quality education.

5. Policy Implications and Conclusion

The findings of this study offer several important implications for India's education policy. The results show that digital infrastructure, platform usage, and teacher training together play a decisive role in improving learning outcomes. The evidence confirms that technology by itself does not guarantee progress; it works best when embedded in a supportive system of trained teachers, relevant content, and reliable connectivity. States that adopted a more integrated approach—investing in both hardware and human capacity—recorded stronger gains. This reinforces the idea that digital transformation in education must move beyond access to meaningful utilization.

A key implication concerns the design of digital learning programs. The positive and significant impact of DIKSHA usage intensity suggests that the mere availability of platforms is not enough. Continuous engagement by teachers and students is crucial. Policy should therefore prioritize incentives that promote active content use, regular classroom integration, and real-time monitoring of participation. Strengthening data linkages between DIKSHA, UDISE+, and NAS can help policymakers track how usage translates into outcomes at the state and district levels. Integrating these databases into a single dashboard would also allow for faster feedback loops and targeted interventions, improving governance efficiency.

The strong role of teacher digital training implies that professional development must remain central to digital education policy. Teachers require not only technical familiarity but also pedagogical support to use digital tools effectively. Continuous training programs under initiatives such as NISHTHA and SWAYAM-PRABHA should be expanded with local-language modules and follow-up mentoring. Evidence from the study shows that trained teachers act as catalysts for improving student engagement and transition rates. Therefore, capacity building must be seen as an ongoing process rather than a one-time intervention.

The analysis also draws attention to regional disparities. The negative and significant coefficient for the rural population share shows that the digital divide continues to constrain learning outcomes. Rural schools face limitations in internet access, electricity reliability, and device availability. To address these gaps, the government may need to extend public–private partnerships for digital infrastructure and explore low-cost offline learning technologies that work in low-connectivity zones. Targeted support for rural and low-income regions is essential to ensure that digital reforms contribute to equity rather than deepen existing inequalities. The success of DIKSHA in advanced states demonstrates what can be achieved; the next challenge is to replicate that success across lagging states.

The results of this paper also have broader implications for the implementation of the National Education Policy (2020). The NEP emphasizes the integration of technology for inclusion and quality, and this study provides empirical support for that vision. The measurable improvement in learning outcomes after the DIKSHA rollout validates the policy's focus on digital learning ecosystems. The evidence also aligns with Sustainable Development Goal 4, which calls for inclusive and equitable quality education and lifelong learning opportunities for all. By investing in teacher training, ensuring

equitable access, and strengthening monitoring mechanisms, India can accelerate its progress toward these international commitments.
Theoretically, the findings reinforce the human capital perspective that education and technology are complementary factors in development. The positive effect of teacher digital training alongside infrastructure confirms that technology enhances productivity only when supported by skilled human resources. This echoes the arguments of Hanushek and Woessmann (2020) and Becker (1993) that the quality of education depends not just on inputs but also on the capacity to use them effectively. The results further extend this literature by demonstrating the interaction between digital policy and human capability in a developing-country context.
From an institutional point of view, the study suggests the need for better coordination between national and state governments. While central platforms such as DIKSHA provide content and training at scale, state education departments are responsible for implementation. A cooperative model that allows local adaptation while maintaining national standards can improve efficiency. Regular evaluation using administrative data can ensure that reforms are evidence-driven rather than target-driven. Continuous monitoring through UDISE+ will help track progress at the school level and identify districts that require additional support.
In conclusion, the study provides strong empirical evidence that technology-enabled learning initiatives have begun to transform India's education landscape. The positive and significant relationship between digital infrastructure, DIKSHA usage, and teacher digital training confirms that these interventions contribute meaningfully to better learning outcomes, higher enrollment, and smoother transitions. The results also show that the benefits are not uniform, with digital readiness determining the extent of improvement. Policy must therefore continue to focus on bridging regional and social divides while deepening teacher capacity and infrastructure quality.
This paper makes a novel contribution by linking administrative digital data with educational outcomes using a robust panel econometric framework. It demonstrates that digital reforms, when designed inclusively, can yield sustained learning improvements. The evidence presented here should encourage policymakers to maintain the momentum of digital education while prioritizing human development, local adaptation, and data-driven decision-making. If these lessons are incorporated into future strategies, technology-enabled learning can serve as a cornerstone for achieving India's long-term goals of equity, quality, and universal access in education.

6. Limitations of the Study

This study has a few limitations that must be recognized. The first limitation concerns data quality and completeness. Although UDISE+ and DIKSHA provide comprehensive coverage, variations in reporting and minor data gaps across states may affect precision. Some earlier years contain missing or estimated values, which were carefully adjusted but may still introduce small bias.
Second, the analysis uses state-level aggregates rather than school- or student-level microdata. This limits the ability to capture within-state differences, especially between urban and rural schools. The results, therefore, represent broad structural effects rather than individual learning outcomes.
Third, the learning indicators are based on ASER and NAS reports, which differ slightly in their testing cycles and methodologies. These variations may cause small inconsistencies in measurement across years.
Finally, while the fixed-effects and DID models address most endogeneity concerns, unobserved policy or governance factors may still influence the results. The study period ends in 2023, and newer post-pandemic developments in DIKSHA or NEP implementation are not yet reflected. Future research using micro-level data and extended time frames could provide deeper insights into the long-term effects of digital learning reforms.
Despite these limitations, the paper provides one of the first integrated empirical analyses linking DIKSHA, UDISE+, and national learning assessments, offering a solid foundation for further research and policy evaluation in technology-enabled education.

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