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Inverted advantage: Technology adoption and the achievement paradox in Bangladesh secondary schools during COVID-19

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Abstract

The COVID-19 pandemic forced education to shift from face-to-face learning to digital platforms, which exposed unequal technology access between rural and urban schools in Bangladesh. This raised the question of whether technology adoption or access hindered learning across the phases. This study examines technology utilization, digital learning comfort, and adaptation challenges among 446 secondary school students. The study used a convergent mixed-method design grounded in Fullan's theory, while critical realism was the philosophical orientation. Pre-pandemic, urban students showed better academic performance ($R^2 = 0.196$) compared to rural students ($R^2 = 0.039$). During the pandemic, there was little difference between rural and urban students ($R^2 = 0.097$ vs. 0.091). Technology utilization changed direction: a positive association with performance in rural schools ($B = 0.299$) but a negative association in urban schools ($B = -0.372$). None of the regression models reached statistical significance. After the pandemic, rural students showed a stronger recovery, with $R^2 = 0.152$. The improvement was small among urban students and did not reach the pre-pandemic baseline ($R^2 = 0.111$). The findings suggest that technology access alone cannot improve academic performance. It requires continuous feedback, teacher training, access to resources, and technology and communication support in rural schools, as well as psychosocial counselling in urban schools.

Keywords: Academic performance, Bangladesh, COVID-19, Digital learning, Regression analysis, Rural-urban divide, Secondary education, Technology adoption.

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Contents

1. Introduction **53**
2. Literature Review **53**
3. Methodology **55**
4. Results and Discussion **58**
5. Policy Implications **62**
6. Conclusion **63**
References **64**

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Contribution of this paper to the literature

The contribution of this study is to identify the inequalities between rural and urban learners across the pandemic phases. Students' academic performance does not depend on technology alone. Rather, it depends on several factors, such as continuous feedback, close monitoring, and support. It highlights that policymakers in developing-country education systems should focus on communication and feedback structures and provide guidance to minimize the inequalities.

1. Introduction

The COVID-19 pandemic forced secondary education to move suddenly to digital platforms. It also exposed pre-existing infrastructure and technology gaps within national education systems (UNESCO, 2023). In Bangladesh, this shift happened with longstanding structural inequalities between rural and urban schools. As a result, technology adoption followed different paths in rural and urban schools instead of a single national pattern (Bangladesh Bureau of Educational Information and Statistics (BANBEIS), 2023a; Sarker, Sarkar, Alam, Begum, & Bhandari, 2023). In urban schools, there was greater device availability, more stable internet connectivity, and higher levels of trained teachers. In contrast, rural schools faced numerous barriers, including limited access to technology, high technology costs, electricity disruptions, and limited exposure to online learning tools. Due to these challenges, unequal opportunities for technology adoption and learning continuity were created between the two localities. This study explores technology-related predictors of academic performance across the phases of the pandemic. It uses multiple regression models for rural and urban areas separately instead of combining all students into one model, which allows for a more detailed and accurate comparison between the contexts. This study identifies not only the magnitude of the inequalities but also traces whether the difference has increased or decreased over time. Specifically, it investigates whether the technology-related factors explain academic performance to the same extent over time or become more similar between contexts during the crisis. These issues are treated as empirical questions to be examined in Section 4 rather than as outcomes assumed in advance.

Three research questions guide the study.

RQ1: How did technology use, learning comfort, adaptation challenges, and communication affect students' academic performance in rural and urban secondary schools across phases in the COVID-19 pandemic?

RQ2: Did the new learning methods change the effect of adaptation challenges between the pandemic and post-pandemic periods?

RQ3: To reduce the remaining academic achievement gap, what technology and communication support is needed in rural and urban schools?

According to the Bangladesh Bureau of Educational Information and Statistics (BANBEIS) (2023b), the school closures lasted about two consecutive academic years. To minimize the suffering of students, the Government of Bangladesh launched the "My School at Home" program on national television during this period, while some mobile operators offered lower-cost educational data packages to support learning continuity (Bangladesh Bureau of Educational Information and Statistics (BANBEIS), 2023a; UNESCO, 2023). Unequal digital engagement persisted between rural and urban populations despite these interventions. This study measures that disparity using locality-specific regression models rather than relying only on descriptive comparisons.

Before-, during-, and after-pandemic data for the quantitative strand were collected through a single post-reopening survey administered after schools reopened. Respondents retrospectively rated their technology utilization, learning comfort, adaptation, and communication ability for the before- and during-pandemic phases, while reporting their current status for the post-reopening phase. This approach was adopted because conducting a follow-up study over multiple time points during school closures and reopening was not logistically feasible. However, the retrospective nature of the before- and during-pandemic measures may have introduced recall bias, and this limitation is discussed further in Section 4.8.

This study contributes in four ways. First, this study examines technology utilization as a separate predictor from general digital access, allowing its effect to be compared across pandemic phases and between rural and urban schools. Second, it considers adaptation challenges as a key factor influencing students' readiness and ability to adopt new learning methods rather than as a background variable. Third, it highlights that better technology infrastructure in urban schools did not necessarily lead to stronger academic resilience during the pandemic. Fourth, these findings address whether improving technology infrastructure alone is sufficient to reduce students' performance gap. These contributions would help other low-income countries beyond the Bangladesh context. Other low-income countries took similar initiatives during the pandemic to maintain learning continuity. They assumed that device distribution and improved internet connectivity would automatically ensure the continuation of learning (UNESCO, 2023). The phase-based regression model used in this study provides a practical framework that can be applied in other national contexts. Instead of relying only on combined national statistics, it enables a more detailed assessment to identify important regional differences. Rather than presenting only regression coefficients, the study also highlights the conditions under which these challenges increase or decrease. Section 4 examines the specific patterns observed in Bangladesh.

2. Literature Review

2.1. Digital Learning Adoption and the Technology Access Divide

In Bangladesh, to maintain educational continuity, schools rapidly adopted online and hybrid learning models. However, these approaches were successful only when teachers received essential training and learning activities included instruction–feedback cycles. Without such support, technology alone cannot ensure students' performance (Black & Wiliam, 2010; Clark & Mayer, 2016; Means, Toyama, Murphy, & Baki, 2013). Digital learning and rapid adoption improved participation, outcomes, and interaction, while different studies showed that uneven preparation slowed progress (Helma & Murni, 2021). Though hybrid learning helped recover social interaction and maintain learning continuity despite challenges, its benefits depended solely on stable routines and teachers' feedback (Alkhnbashi, Mohammad, & Bamasoud, 2024; Bangladesh Bureau of Educational Information and Statistics (BANBEIS), 2023b; UNESCO, 2023).

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Low socioeconomic conditions in rural areas and limited access to devices, internet data, and reliable electricity reduced student participation and widened educational inequalities (Ferraro, Ambra, Aruta, & Iavarone, 2020; Saleem, AlNasrallah, Malik, & Rehman, 2022). As a low-income country, Bangladesh could not ensure laptops, internet hotspots, or device support for all students. However, some low-tech alternatives helped student engagement. Due to the lack of support, students struggled to attend classes, submit assignments, and experience a decline in their academic performance (Bangladesh Bureau of Educational Information and Statistics (BANBEIS), 2024; UNESCO, 2023). To reduce educational inequalities and ensure learning continuity during disruptions, there is no alternative to developing infrastructure and inclusive policies (Li, 2024; Saleem et al., 2022).

According to Clark and Mayer (2016), learning outcomes improve only when technology is incorporated into structured practice with regular feedback loops. Technology alone cannot increase student interest or progress. Along with technological access, early detection, training facilities, and stable routines are equally important.

That is partly why this study did not just ask whether students had a device. Technology Utilization was measured by how often, and how seriously, they actually used it for schoolwork.

2.2. Instructional Quality, Interactivity, and Performance Links

Quality of instruction significantly influences the relationship between technology use and learning outcomes. Active learning through well-structured, interactive lessons that use digital tools improves student achievement and knowledge retention, whereas poorly designed instruction hinders learning (Clark & Mayer, 2016; Helma & Murni, 2021). During remote learning, a lack of teacher feedback or presence increased stress and decreased engagement, lowering performance (Ferraro et al., 2020). On the other hand, active learning such as problem-based discussions and multimedia feedback enhanced understanding and confidence (Lavy, 2015; Means et al., 2013).

During the pandemic, incorporating digital platforms such as Google, Zoom, Messenger, and WhatsApp improved online and hybrid learning. These platforms increased student engagement, interaction, feedback mechanisms, and multimedia learning experiences when they were aligned with regular teaching practice (Jarrah & Alkhasawneh, 2023). Though improvements were seen during the digital learning period, poor implementation could lead to distraction rather than learning, especially when teachers lacked digital skills or the curriculum was not aligned with the technology (Clark & Mayer, 2016).

Academic achievement is influenced by feedback frequency. It shapes how effectively students learn through digital platforms by determining how often they receive feedback, opportunities for brainstorming, and corrective support. Feedback is most effective when it is provided immediately after a learning activity (Hattie & Timperley, 2007). Students' learning is negatively affected by delayed or absent feedback. Timely feedback depends on platform design, infrastructure, reliable internet, and teachers' skills. Slow teacher responses, poor connectivity, or delays in any of these areas can reduce the benefits of technology-based learning. During the pandemic, these challenges became prominent across contexts. It was also found that feedback quality and local infrastructure played a vital role in learning outcomes.

Timely feedback really matters. In this study, learning comfort was measured not as screen time but according to whether students found online or hybrid classes manageable in their daily routines.

2.3. Self-Regulation, Communication, and the Contextual Divide

Self-regulation and autonomy are key factors for academic success. The shift to online learning transferred greater responsibility from teachers to learners. Maintaining a dependable routine, focus, and independent motivation became essential because online learning provided little face-to-face supervision (Pham & Le, 2021). Many students faced challenges in adapting to online learning due to distractions and delays in completing tasks. However, students with stronger self-discipline demonstrated greater persistence and academic stability (Clark & Mayer, 2016).

Urban students benefited from stable internet connectivity, timely feedback, and the consistent use of digital learning platforms. In contrast, rural students faced challenges such as shared devices, unreliable electricity, and limited learning support (Bangladesh Bureau of Educational Information and Statistics (BANBEIS), 2023b; Hossain et al., 2021; UNESCO, 2023). In localities with weak digital access, low-tech solutions such as notice boards, printed learning packets, and regular teacher check-ins helped maintain learning continuity (Bangladesh Bureau of Educational Information and Statistics (BANBEIS), 2023b; UNESCO, 2023).

Rural and urban students benefited differently. Rural students relied on offline materials, whereas urban schools were supported by stable internet connectivity and consistent communication (UNESCO, 2023). Unequal access between localities in South Asia aligned closely with this study (Hossain et al., 2021). According to UNESCO's global comparison, communication predictability is emphasized as the key mechanism influencing learning outcomes. However, in South Asia, infrastructure gaps were the main hindrance rather than technology alone. Though most studies focused on device and connectivity gaps, the joint evidence suggests that communication gaps have a greater influence on learning across different localities.

Since it seemed to be communication, not infrastructure, that separated rural and urban outcomes in these studies, Communication Ability was measured by how easily a student could get help from a teacher or peers when stuck.

2.4. Innovation Interest and Communicative Structure

Interest in innovation motivated students to adopt new learning methods even with limited facilities. Their willingness played a vital role in exploring and experimenting with digital technologies rather than simply meeting basic learning needs. The Diffusion of Innovations theory (Rogers, 2003) suggests that people are more willing to use digital learning when they see it as beneficial and compatible with their daily routines. Though this theory was not made for school students specifically, the same idea should apply: when students feel confident, find the technology easy, and see some benefit in it, they are likely to respond the same way. User-friendly technology increases users' confidence in using it and encourages technology adoption (Deci & Ryan, 2000; Nielsen, 1993). When students have different levels of confidence and digital literacy, communication becomes even more important. Instead of becoming demotivated, students with better communication skills are more likely to ask for help, understand expectations, and explore new ideas.

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Studies argue over how communication ability affects learning. Some find it a strong factor in how well students adapt, while others support the view that its effect depends heavily on local context. For this reason, this study looks at rural and urban students separately, rather than assuming communication works the same way in both settings.

In this study, adaptation was treated as a matter of mindset, not a technology problem. Students were simply asked how easily they adopted new methods of learning.

2.5. Theoretical Framework

This study uses Fullan (2020) theory of educational change through three dimensions: capacity, equity, and alignment. The ability to learn independently, the availability of learning tools, and the skills of teachers denote capacity. Meanwhile, access to devices, internet data, and reliable electricity measures equity. Consistency between platform selection, classroom routines, and feedback delivery describes alignment. When these three are linked together, a small change can bring meaningful outcomes. Conversely, when these connections are disconnected, negative effects can increase over time (Fullan, 2020; Lavy, 2015). As a philosophical orientation, critical realism (Bhaskar, 1975) provides the foundation by viewing both visible and invisible factors. These factors operate differently across rural and urban settings within social and spatial contexts.

In this framework, capacity and alignment shape how technology is used. Technology does not have a fixed role; rather, its role changes according to the surrounding conditions. The same device can support learning in different ways depending on how it is used (Clark & Mayer, 2016; Means et al., 2013). During a crisis, the effects of the same technology differ across settings. This contrast in the findings is discussed in the following part of this study.

According to self-determination theory (Deci & Ryan, 2000), some students adapted to technology with ease during technological disruption, while others struggled. Students who were supported through stable connectivity or alternative communication methods overcame the challenges instead of withdrawing (Chang, Gaines, & Mosley, 2022).

3. Methodology

3.1. Research Design

This study used a convergent mixed-methods design, with multiple regression analyses conducted across different phases. As the study followed the philosophical orientation of critical realism, the semi-structured interviews and qualitative questionnaires were designed to explore both the visible and underlying causes of disruption. Rural and urban samples were analysed separately throughout the study and across all phases. This was done to identify the different causes of the challenges in each locality (Bangladesh Bureau of Educational Information and Statistics (BANBEIS), 2023a; Sarker et al., 2023).

The convergent method was chosen because it allows the comparison of quantitative and qualitative data at the same time. After the analysis, the two sets of findings were compared to identify similarities and differences, rather than using only the qualitative findings to explain the quantitative results (Creswell & Plano Clark, 2018). This approach was important because some of the statistical models did not produce significant results. In several phases and localities, the statistical tests alone could not provide clear interpretations. However, the qualitative findings helped explain the quantitative results and reduced uncertainty where the statistical findings were inconclusive.

3.2. Sample Size

The study locations were selected from officially declared COVID-19 red zones in 2020. The rural model draws on 235 secondary school students, and the urban model draws on 211 students from six secondary schools in four districts (Institute of Epidemiology Disease Control and Research (IEDCR), 2020; Zayeef, 2020), supported by national media reports (AA News Desk, 2020; Nafiu, 2020; Star Online Report, 2020).

The three rural schools were Ramrayel Shaheed Dhirendranath High School, a government public secondary school in Basudev Union, Brahmanbaria Sadar Upazila, Brahmanbaria District; Saint Nicholas Boys' High School, a Catholic missionary secondary school in Nagori village, Kaliganj Union, Gazipur District; and Brahmangaon High School, a government public secondary school in Louhajang Upazila, Munshiganj District. The three urban schools were Narinda Government Boys' High School, a public secondary institution under Dhaka South City Corporation; Playpen School, an English-medium private secondary school in Bashundhara, under Dhaka North City Corporation; and Motijheel Government Girls' High School, a public secondary institution under Dhaka South City Corporation. The selected schools purposely included government, missionary, and private English-medium schools. Across the localities, they also represented boys', girls', and co-educational schools to capture differences in curriculum and teaching methods. The independent variables were Learning Comfort (X_1), Technology Utilization (X_2), Adaptation Challenges (X_3), and Communication Ability (X_4), while Academic Performance was the dependent variable. The variables were measured using either a five-point Likert scale (1 = Excellent to 5 = Poor) or a binary scale (1 = Yes; 2 = No). Figure 1 shows the locations of the six selected schools, and Figure 2 presents the sample characteristics by locality. It also displays pre-pandemic training, learning comfort, and adaptation challenges using a heatmap for easy comparison.

Figure 3 portrays an early idea of the findings, which are later discussed in Section 4. Rural students faced more challenges during online learning compared with urban students (11.5%; 57.8%). Difficulties accounted for 74.5% and 43.6%, respectively, among rural and urban learners. None of the rural learners claimed that remote learning was easy, while around 19.0% of urban students found it easy to adopt hybrid lessons. The findings revealed that a smoother transition was completely absent in the rural sample.

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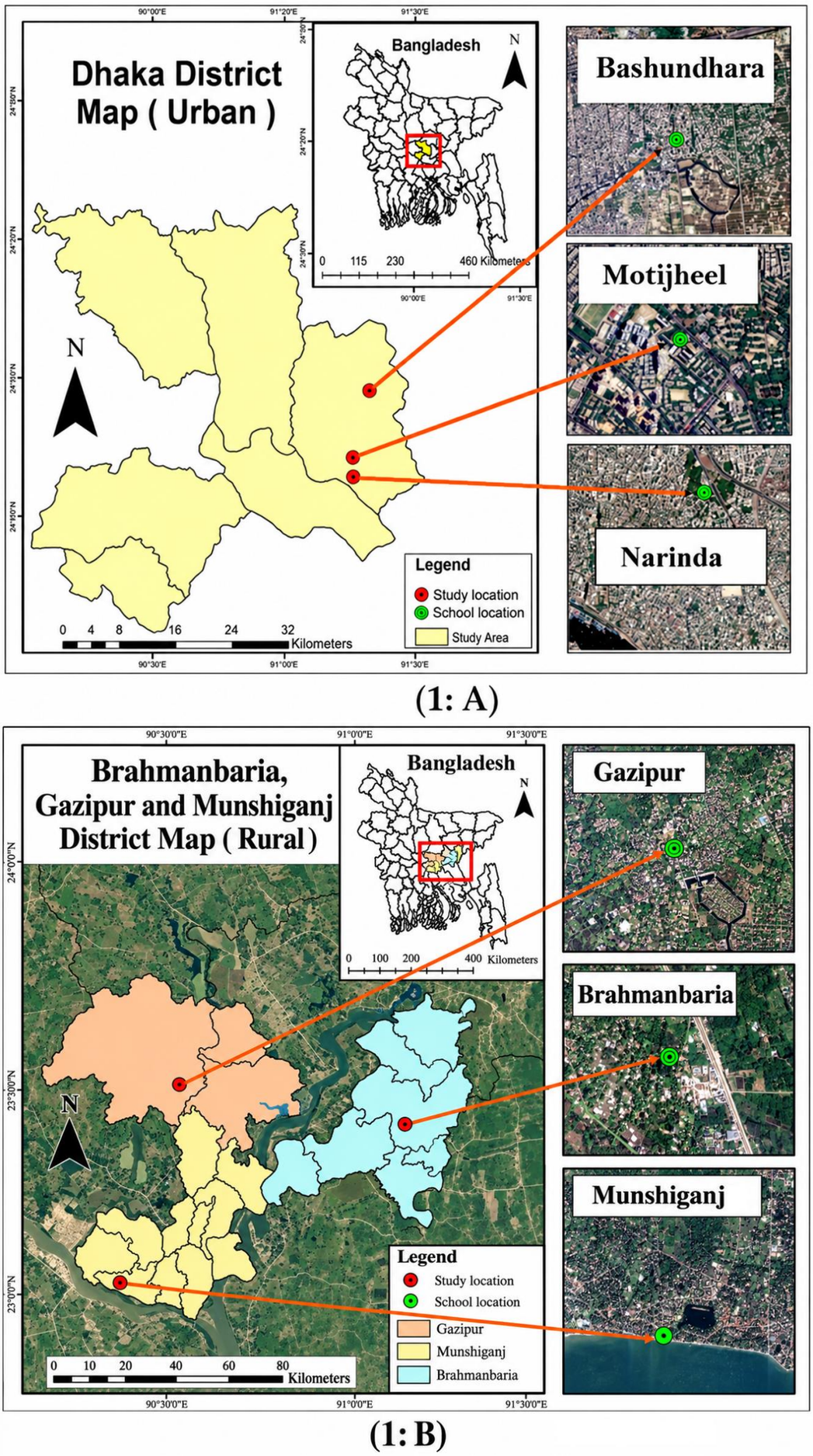
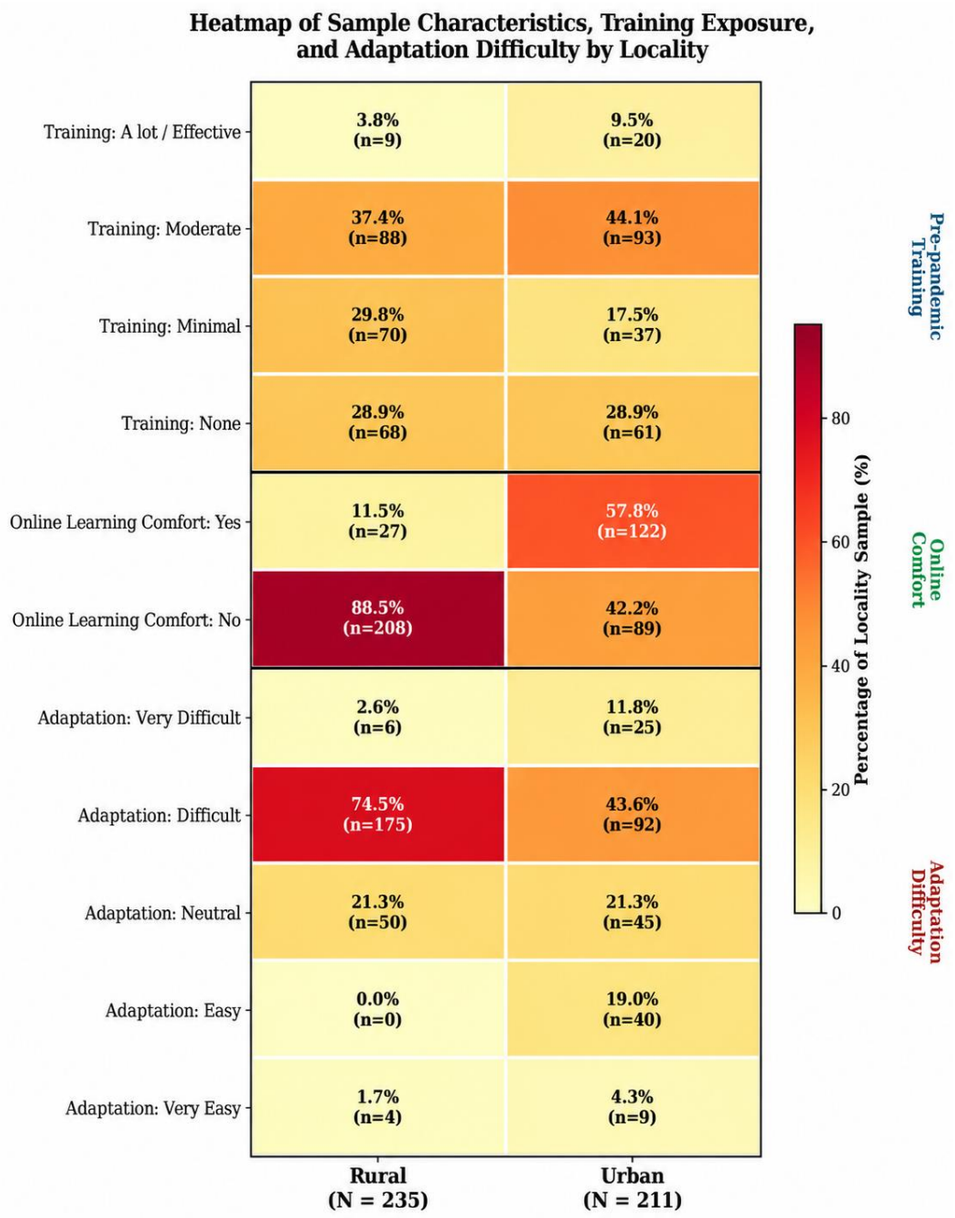


Figure 1. Study areas and school locations. (1: A) Urban study area map (Dhaka); (1: B) Rural study area map (Gazipur, Munshiganj, Brahmanbaria).

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Note: Each cell represents the percentage of the sample (n) across localities.

Figure 2. Sample characteristics, training exposure, and adaptation difficulty (Rural vs Urban).

3.3. Analytical Approach

The analytical strategies included reporting unstandardized coefficients (B) with 95% confidence intervals (CI), along with R^2, adjusted R^2, Cohen's f^2, and ANOVA statistics. Pearson's correlation (Akoglu, 2018), independent-samples t-tests, chi-square tests (McHugh, 2013), and Cramer's V were used to examine relationships between variables and to compare the rural and urban groups. Effect sizes were interpreted according to Cohen (1988) guidelines (Ferguson, 2009), where 0.02 indicates a small effect, 0.15 a medium effect, and 0.35 a large effect.

Instead of using a single combined regression model with a locality interaction term, separate regression models were estimated for the rural and urban samples at each pandemic phase. This approach helped identify the factors affecting rural and urban learners separately. Because of differences in infrastructure, teacher training, and access to household resources, rural and urban schools in Bangladesh were affected differently. Therefore, they were treated as two separate educational contexts rather than as parts of a single national education system (Bangladesh Bureau of Educational Information and Statistics (BANBEIS), 2023a; UNESCO, 2023).

Some models included different predictor variables because complete data were not available across all settings, not because of a research decision. These differences are clearly explained in the Results section. Qualitative interviews and focus groups were conducted at the same time as the quantitative survey with teachers, parents, head teachers, district education officials, and school inspectors from both localities. They were conducted to support the statistical findings and enable comparison with them (Creswell & Plano Clark, 2018).

3.4. Data Collection Procedures

Between February and August 2025, quantitative and qualitative data were collected following the phased reopening of the sampled schools. Eligible student participants were those enrolled in secondary grades at one of the six sampled schools. They had been continuously enrolled from before the school closures until the data collection period, allowing them to report on all three pandemic phases. Teachers, head teachers, parents, district education officials, and school inspectors were eligible if they held their respective roles at a sampled school or in the relevant administrative position during the school closure period. Written informed consent was obtained from the parents or guardians and the school authorities for all student participants below the age of 18. Adult participants (teachers, parents, head teachers, district education officials, and school inspectors) provided written informed consent before

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interviews or focus groups. The study protocol, consent procedures, and data handling plan were reviewed and approved by the supervisor and the department chairman before data collection.

The student questionnaire was completed in paper form under the supervision of a trained research assistant at each school. It was administered in Bengali, the participants' first language, and later translated into English for analysis and reporting. The research supervisor independently checked a sample of the translated responses to ensure consistency of meaning, as he was fluent in both Bengali and English. As noted in Section 1, the before- and during-pandemic items were collected retrospectively using a single post-reopening questionnaire. Participants rated their learning comfort, technology utilization, adaptation, and communication ability based on their memories of each earlier phase, while the after-pandemic items reflected their current situation. This retrospective approach may have introduced recall bias, which is discussed as a limitation in Section 4.8. Semi-structured interviews and focus groups with teachers, parents, head teachers, district education officials, and school inspectors were conducted in Bengali by trained interviewers using a common set of open-ended questions based on the same four predictor areas. Each session lasted about 30 to 45 minutes and was audio-recorded with participant consent. Later, the recordings were transcribed in Bengali, translated into English, and coded by the researcher using a coding scheme reviewed and approved by the supervisor before analysis. If there were any disagreements, the coding decision was confirmed by consulting with the supervisor.

Quantitative data were analysed in IBM SPSS Statistics (v.26). Qualitative transcripts were organised and coded using manual matrix coding. Missing data were handled by listwise deletion within each phase–locality regression model. This is the main reason that predictor sets differ across phases for a given locality. When any predictor showed no meaningful variation, it was removed for that phase and so could not be estimated. Accordingly, Communication Ability was omitted from the rural pre-pandemic model, as nearly all students in rural settings used to communicate with their teacher face-to-face, leaving minor variation to model. This avoided introducing artificial precision into a retrospectively measured variable. Because the predictor sets, degrees of freedom, and model specifications differ across phases, the R^2 values reported in Table 1 are not directly comparable across phases. Each R^2 value should be interpreted only for the phase in which it was estimated. Comparisons across phases should be viewed as indicating general trends rather than as statistically equivalent comparisons.

4. Results and Discussion

Results are presented together with their interpretation in each subsection below. This follows the recommendation that regression results should be considered alongside their theoretical implications rather than reported as separate numerical findings. Table 1 provides an overview of the model fit statistics for all six locality-phase combinations before the detailed phase-by-phase analysis.

None of the overall regression models in Table 1 reached the conventional level of statistical significance ($p < 0.05$), including the urban after-pandemic model ($p = 0.051$). The coefficient patterns discussed below are therefore reported as descriptive trends rather than confirmed predictors. Any statistically significant result is identified explicitly where it occurs.

Table 1. Multi-phase regression model fit summary by locality (N = 446).

Phase	Locality	R^2	Adj. R^2	f^2	ANOVA F (df)	p-value
Before	Rural	0.039	-0.054	0.040	F(3,231)=0.422	0.738
Before	Urban	0.196	0.089	0.244	F(4,206)=1.831	0.149
During	Rural	0.097	-0.023	0.107	F(4,230)=0.810	0.529
During	Urban	0.091	-0.030	0.010	F(4,206)=0.750	0.566
After	Rural	0.152	0.039	0.179	F(4,230)=1.341	0.278
After	Urban	0.111	0.084	0.124	F(1,209)=4.118	0.051

Note: DV = Academic Performance. R^2 = explained variance; predictors vary across phases.
Source: Questionnaire Survey (2025).

4.1. Structural Difference (Pre-Pandemic)

Before the pandemic, the urban model explained more variation ($R^2 = 0.196$, $f^2 = 0.244$) than the rural model ($R^2 = 0.039$, $f^2 = 0.040$), although neither overall model was statistically significant. Although the confidence interval crossed zero in the urban model, Communication Ability had the largest coefficient (B = -0.574). In the rural model, all predictors had very small coefficients, and their confidence intervals also crossed zero, indicating that none of the predictors showed a statistically significant association with the outcome. During the pre-pandemic phase, the regression equation in rural schools was:

$$Y = 1.132 + 0.062X_1 + 0.036X_2 + 0.194X_3 \quad (1)$$

The equation suggests that none of the predictors was statistically significant in explaining students' performance in the rural setting. The urban f^2 of 0.244 approaches a medium-to-large effect, and the urban R^2 is about five times higher than the rural value. However, because the urban model was not statistically significant, this difference is reported as a descriptive comparison rather than a confirmed difference between the two localities. In normal times, the school lacked the structures needed to engage and motivate students (Rural teacher).

This difference in explained variance may reflect different structural conditions before the pandemic, although it should be treated as a descriptive finding because neither model was statistically significant. An urban teacher described students as generally responding positively to new learning methods. In contrast, a rural parent explained that when new activities required extra resources, those resources could not be provided. These qualitative accounts provide context for the quantitative findings rather than confirming them independently. The near-zero explanatory power of the rural pre-pandemic model may be consistent with the absence of conditions needed for technology-related predictors to have a measurable influence (Bhaskar, 1975). This is an interpretation rather than a statistically confirmed finding. The weak rural model indicates that the predictors had not yet become meaningful factors influencing change, rather than suggesting student indifference. However, this is a theoretical interpretation of a non-significant result rather than a confirmed finding.

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Training exposure data corroborate this divergence. Before the pandemic, 88 rural and 93 urban students reported moderate promotion and some training. Effective preparation was more common in urban areas (20 students) than in rural areas (9 students), while no training was reported by 68 rural students and 61 urban students. A rural head teacher described limited use of digital tools in schools. A rural governing body member added that there had been no initiatives to promote technology and that rural children were often neglected in this regard. An urban governing body member also acknowledged that budgets for digital resources had not been allocated, with very few efforts made to equip classrooms. This suggests that the urban advantage, although present, was smaller than access statistics alone might indicate.

4.2. New Method Adoption and Adaptation Challenges

New Method Adoption is examined using Adaptation Challenges (X) as the sole predictor. The rural model covers only the during-pandemic phase (N = 235), and the urban model spans the during- and after-pandemic phases (N = 211).

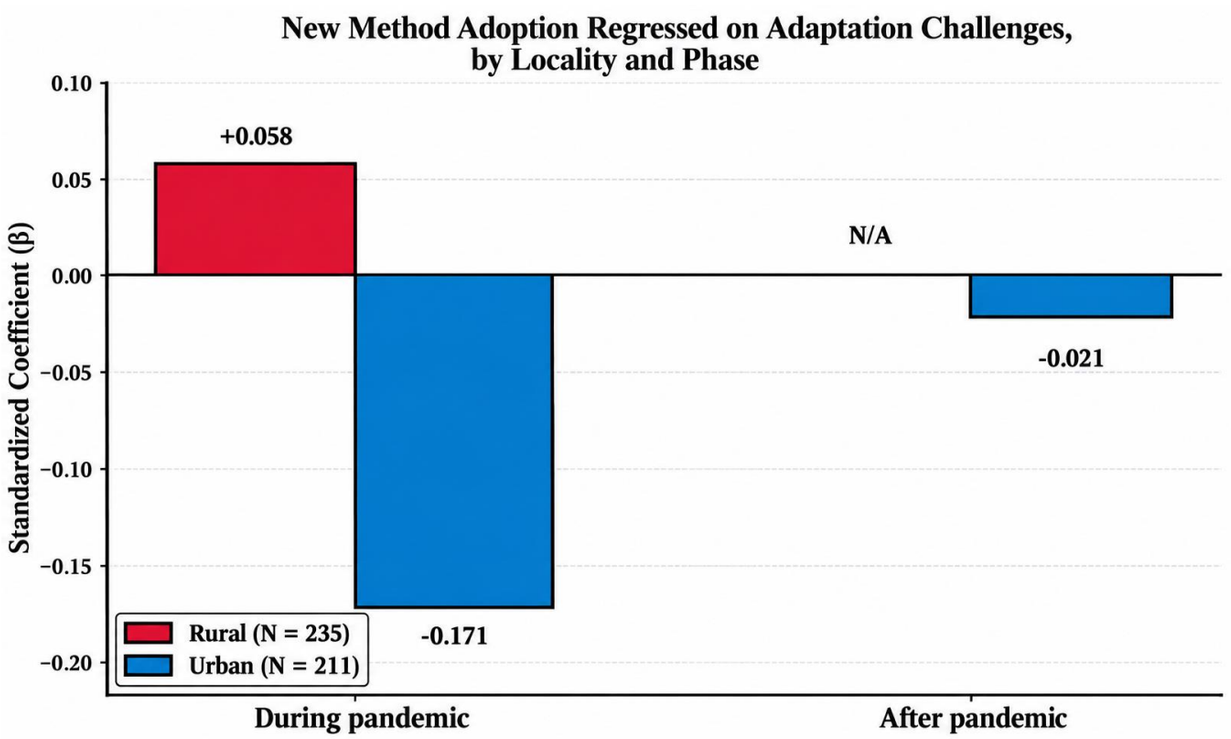
The rural during-pandemic model is statistically negligible ($R^2 = 0.003$, $f^2 = 0.003$, $F(1, 233) = 0.111$, $p = 0.741$). The urban during-pandemic model similarly underperforms ($R^2 = 0.029$, $f^2 = 0.030$, $F(1, 209) = 0.999$, $p = 0.325$). Despite non-significance, the directional contrast is theoretically meaningful. Rural students show a positive association ($B = 0.026$, $\beta = +0.058$).

$$Y = 1.282 + 0.026X \quad (2)$$

Though the coefficient did not reach significance, it may reflect necessity-driven compliance. Urban students show a negative association ($B = -0.110$, $\beta = -0.171$).

$$Y = 1.658 - 0.110X \quad (3)$$

It suggests that students with stronger prior resources showed greater adoption of new methods, though the association did not reach significance.



Note: Rural during-pandemic model, N = 235 ($R^2 = 0.003$, $p = 0.741$); rural after-pandemic data were not collected. Urban during-pandemic model, N = 211 ($R^2 = 0.029$, $p = 0.325$); urban after-pandemic model, N = 211 ($R^2 = 0.000$, $p = 0.906$). All models were non-significant at conventional thresholds.
Source: Questionnaire Survey (2025).

Figure 3. Adoption coefficients by locality and phase. Standardised beta coefficients.

A rural parent expressed cautious gratitude.

"We are thankful to the school. Despite the resource constraints, the school did its best, and our children did not feel lost" (rural parent).

Figure 3 shows the urban standardized coefficient shifting from $\beta = -0.171$ during the pandemic to $\beta = -0.021$ after, an eightfold reduction in magnitude. The urban after-pandemic model yields $R^2 = 0.000$, $F(1, 209) = 0.014$, $p = 0.906$. This trend may align with Fullan (2020) institutionalization stage. It suggests that successful changes become part of everyday practice. As the p-value ($p = 0.906$) does not reach the level of significance, this is offered as a theoretical interpretation rather than a confirmed pattern.

4.3. Crisis Convergence and Predictor Polarity Reversal

None of the underlying models reaches statistical significance; they produce a convergence in explained variance between localities. The rural during-pandemic model yields $R^2 = 0.097$, Adjusted $R^2 = -0.023$ (negative), $f^2 = 0.107$, $F(4, 230) = 0.810$, $p = 0.529$. The urban during-pandemic model yields $R^2 = 0.091$, Adjusted $R^2 = -0.030$ (negative), $f^2 = 0.010$, $F(4, 206) = 0.750$, $p = 0.566$. This is the only phase where rural and urban explained variance converge ($R^2 = 0.097$ vs. 0.091), reflecting a crisis-induced levelling effect whereby pandemic disruption collapsed the urban structural advantage. A striking polarity reversal characterises the predictor dynamics. In the rural model,

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Technology Utilization carries the largest positive coefficient (B = 0.299; CI: −0.221 to 0.819) while it turns strongly negative in the urban model (B = −0.372; CI: −0.951 to 0.206).

The urban regression equation.

$$Y = 3.955 + 0.016X_1 - 0.372X_2 - 0.212X_3 + 0.378X_4 \quad (4)$$

Though neither model reaches statistical significance, it may reflect a structural inversion where greater technology engagement is associated with poorer outcomes. This may be because urban technology use was characterised by non-academic screen use or poorly mediated online instruction.

A rural district head of education conveyed the institutional failure with evident frustration.

"There was no budget allocation for digital resources for teaching. So, the whole effort was a bottomless basket" (Rural district head of education)

Rural teachers confirmed the void of institutional guidance.

"During the pandemic, there were no clear guidelines for us, but we were asked to use digital platforms in teaching." (Rural teacher).

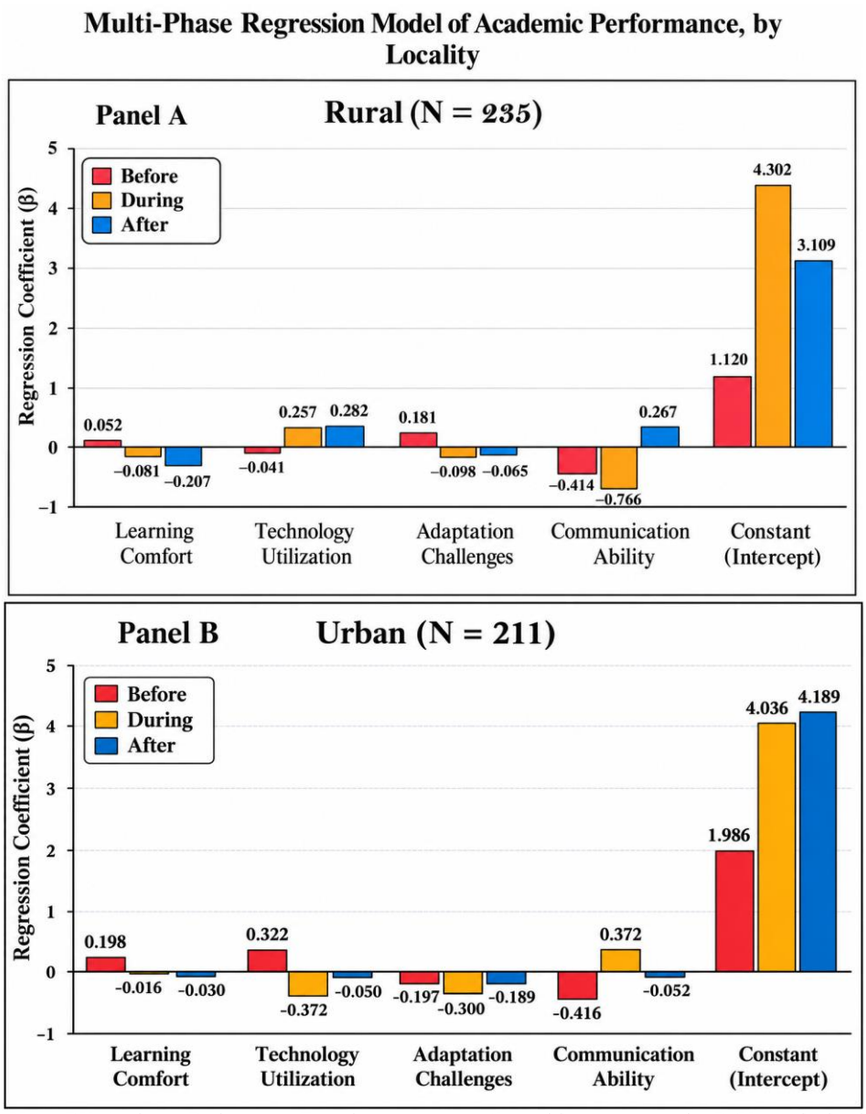
Urban teachers described a contrasting and more structured experience.

"Along with the digital platform incorporated into teaching, we used different models and PowerPoint presentations to engage and motivate our students" (Urban teacher).

According to Fullan (2020) implementation dip stage, this pattern has a theoretical basis for context-specific distortions rather than uniform effects, though this remains an interpretation given the non-significant models.

4.4. Multi-Phase Regression Models of Academic Performance

Figure 4 (Panels A and B) presents the complete multi-phase regression structure for both urban and rural samples. It displays unstandardized coefficients with 95% confidence intervals across all three pandemic phases in a single combined figure. Visual inspection of Figure 4 shows that the urban Communication Ability coefficient changed from a negative value before the pandemic (B = −0.574) to a positive value during the crisis (B = 0.378). After schools reopened, it was no longer retained as a predictor in the regression model. None of the three overall regression models reached conventional statistical significance across these phases. Therefore, this change should be interpreted as a descriptive pattern rather than a statistically established shift in the role of communication ability.



Note: DV: Academic Performance. Error bars represent 95% confidence intervals for B (Unstandardized coefficients). Dependent variable: Academic Performance (1 = Excellent, 5 = Poor). All six omnibus ANOVA models are non-significant at $p < 0.05$ (Closest: Urban after-pandemic, $p = 0.051$). N/A = Predictor not estimated or not retained in that phase's final model.

Source: Questionnaire Survey (2025).

Figure 4. (Panel A and B): Multi-phase regression model of academic performance, rural (N = 235) and urban (N = 211).

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The rural panel in Figure 4 shows a different pattern. Communication Ability could not be estimated in the rural pre-pandemic model because there was no variation in this predictor within the sample. During the crisis, it had a negative coefficient (B = −0.436, 95% CI: −1.153 to 0.281). After schools reopened, it became the largest positive coefficient in the rural model (B = 0.347), although the overall regression model was not statistically significant (p = 0.278). This pattern is described for comparison only and may suggest that communication became more important in rural schools after students gained greater familiarity with digital learning during the pandemic.

4.5. Asymmetric Recovery and Residual Vulnerability

The post-pandemic phase produces the strongest rural model performance and a paradoxical narrowing in the urban context.

The rural post-pandemic model achieves $R^2 = 0.152$, adjusted $R^2 = 0.039$, $f^2 = 0.179$, $F(4, 230) = 1.341$, $p = 0.278$, representing the highest R^2 achieved by the rural sample across all three phases.

Communication Ability carries the largest coefficient (B = 0.347; CI: −0.426 to 1.120), followed by Technology Utilization (B = 0.282; CI: −0.197 to 0.761), though the overall model does not reach statistical significance.

$$Y = 3.019 - 0.267X_1 + 0.282X_2 - 0.035X_3 + 0.347X_4 \quad (5)$$

After the crisis, better communication skills and technology skills were linked to recovery, which matches (Fullan, 2020) idea of "recapturing." However, this is only a pattern observed in the data and should be interpreted with caution, as the statistical model was not significant.

The urban after-pandemic model yields $R^2 = 0.111$, Adjusted $R^2 = 0.084$, $f^2 = 0.124$, $F(1, 209) = 4.118$, $p = 0.051$, with the predictor structure collapsing entirely to,

$$Y = 3.890 - 0.329X_3 \quad (6)$$

The only predictor left in this model is Adaptation Challenges. The overall test does not reach the usual level of significance (p = 0.051). Its negative direction may suggest that urban students who continued to find adaptation difficult reported lower academic performance. Still, this result is borderline and remains unconfirmed.

Table 2. Summarises R^2 and f^2 trajectories for direct comparison.

Phase	Rural R^2	Urban R^2	Rural f^2	Urban f^2
Before	0.039	0.196	0.040	0.244
During	0.097	0.091	0.107	0.010
After	0.152	0.111	0.179	0.124

Note: R^2 = coefficient of determination; f^2 = Cohen's effect size. Rural and urban models employ multiple linear regression across three pandemic phases. Before pandemic: Rural ANOVA $F(3, 231) = 0.422$, $p = 0.738$; urban ANOVA $F(4, 206) = 1.831$, $p = 0.149$. During the pandemic: rural ANOVA $F(4, 230) = 0.810$, $p = 0.529$; urban ANOVA $F(4, 206) = 0.750$, $p = 0.566$. After pandemic: rural ANOVA $F(4, 230) = 1.341$, $p = 0.278$; urban ANOVA $F(1, 209) = 4.118$, $p = 0.051$. Effect size interpretation follows Cohen (1988): $f^2 = 0.02$ small, 0.15 medium, 0.35 large.
Source: Questionnaire Survey (2025).

A rural district head of education confirmed that the absence of digital promotion curtailed student progress.

"There were almost no initiatives to promote the online platforms, which hindered students' progress drastically." (Rural district head of education).

An urban teacher pointed to a mismatch between curriculum content and student readiness.

"The curriculum does not match their level of understanding" (Urban teacher).

The rural model exhibits a monotonic increase in R^2 (0.039 to 0.097 to 0.152), reflecting progressive psychosocial structuration of academic outcomes. The urban model follows an inverted trajectory: $R^2 = 0.196$ before the pandemic, then collapses to 0.091 during the crisis and partially recovers to 0.111 after, never returning to its baseline level.

4.6. Technology Utilization and Digital Learning Impact: The Study's One Significant Result

Technology Utilization is examined with Digital Learning Impact (X) as the sole predictor across the During and After phases (Figure 5) in both rural (N = 235) and urban (N = 211) contexts.

During the pandemic, both models are statistically negligible. An urban inspector captured the structural disconnect between resource provision and genuine learning outcomes:

"Installing a digital lab does not mean innovation as long as the teachers do not know how to use it" (Urban inspector).

This reflects Means et al. (2013) distinction between technology access and technology-enabled learning outcomes. Urban teachers nonetheless demonstrated creative engagement:

"Tools and PPT helped with engagement" (Urban teacher).

The after-pandemic phase produces the most dramatic rural-urban divergence in the entire analysis. The urban after-pandemic model yields an adjusted $R^2 = 0.098$, $f^2 = 0.143$, $F(1, 209) = 4.708$, and $p = 0.037$; the equation is:

$$Y = 2.135 + 0.374X \quad (7)$$

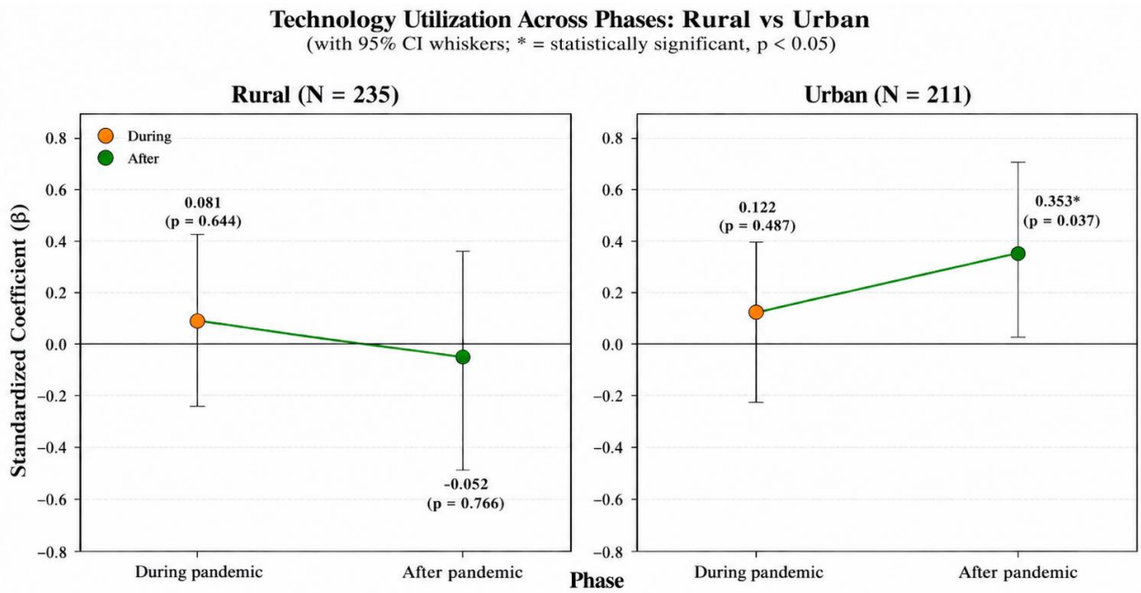
This is the only statistically significant ANOVA result across both figures and both phases, marking the early stages of Fullan (2020) institutionalization phase in urban education. By contrast, the rural after-pandemic model yields the equation $Y = 3.284 - 0.039X$, with β declining from +0.081 during the pandemic to −0.052 after. Though the rural coefficient itself is not statistically significant, this pattern may suggest that rural digital infrastructure did not consolidate into a stable institutional feature of education after the crisis.

Viewed together, Figures 1-5 and Tables 1-2 show a descriptive pattern across the three pandemic phases. This pattern is based mainly on non-significant models and is reported as directional trends rather than confirmed findings, with one exception. Before the crisis, the urban model showed a higher R^2 associated with Technology Utilization and prior training exposure, whereas the rural model showed very little explanatory power. During the crisis, the Technology Utilization coefficient differed in direction between the two localities. It was positive in the rural model and negative in the urban model.

The variance was close in both contexts. As soon as the pandemic was over, disparities emerged again in both localities. Although the value of the rural model reached the highest level, it was still non-significant, with a low R^2, and Communication Ability had the largest coefficient. The urban model retained only Adaptation Challenges, but it was also non-significant. After the pandemic, Technology Utilization was significantly associated with Digital

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Learning Impact in the urban setting (p = 0.037). In the dataset, this was the only statistically significant result. This descriptive pattern and the single significant finding form the main contribution of the study, while the other results consist of non-significant models that require further testing.



	During	After
R^2	0.007	0.003
f^2	0.007	0.003
F(1, 233)	0.217	0.090
p	0.644	0.766
β [95% CI]	0.063 [–0.213, 0.339]	–0.039 [–0.305, 0.277]

	During	After
R^2	0.015	0.125
f^2	0.015	0.143
F(1, 209)	0.495	4.708*
p	0.487	0.037*
β [95% CI]	0.078 [–0.148, 0.304]	0.374 [0.023, 0.724]

Note: * Indicates a statistically significant result at p < 0.05.
Rural, During pandemic:
Y = 2.545 + 0.063X
Rural, after the pandemic:
Y = 3.284 - 0.039X
Urban, during the pandemic: Y = 3.275 + 0.078X
After pandemic: Y = 2.135 + 0.374X
Indicators: Tech Utilization: 1=High promotion/Training → 4=none. Digital Learning Impact: 1=Very effective → 5=Not effective.
Source: Questionnaire Survey (2025).

Figure 5. Standardized coefficients for technology utilization regressed on digital learning impact, by locality and phase.

4.7. Theoretical Contribution

The descriptive patterns of this study are interpreted through (Fullan, 2020) educational change model by targeting its components of capacity, equity, and alignment. This model suggests that access becomes meaningful when timely feedback and stable routines are incorporated. Rather than being viewed as fixed spatial differences, rural–urban differences are viewed as variations in the strength of this chain. Most of the quantitative results are non-significant. Hence, it is supported by qualitative evidence rather than statistical values.

Another theoretical contribution of this study is that the effects of the predictors changed during periods of major disruption. Regression studies generally assume that predictor effects remain stable over time. However, the findings suggest that the same predictor can show opposite directions across the different phases of the pandemic. As most of the models are non-significant, these shifts should be interpreted in light of the qualitative findings. These non-significant results are consistent with Bhaskar (1975) idea of differential activation of generative mechanisms, which suggests that capacity, equity, and alignment may vary depending on the surrounding conditions. This interpretation should be treated as a hypothesis for future studies rather than as a confirmed finding.

4.8. Limitations

The limitations of this study include the small sample size and the absence of post-pandemic rural data for New Method Adoption and Innovation Interest. Due to these limitations, a large number of non-significant results were produced. Because of the absence of post-pandemic data in the rural setting, comparisons with the urban findings could not be made. Rural schools may have returned to traditional methods of learning, although this could not be verified. Students' academic performance was measured using a Likert scale, which may have overestimated or underestimated actual performance. The study areas were selected based on the red zone criteria, so the findings may not represent the entire secondary education system across the country. The qualitative sample was also small, which may have limited the ability to capture the full picture. Future research should include longitudinal studies with larger datasets to provide a more comprehensive understanding of educational disruption at the secondary level.

5. Policy Implications

5.1. Prioritize Rural Schools: Communication and Technology Consolidation

Rural schools should be supported to improve communication and adopt technology. Institutional support, regular feedback, and communication among teachers, students, and parents should be strengthened. Data plans and digital devices should be provided so that hybrid learning does not become a financial burden on parents. At the same time, offline learning options should continue to be available during any future crisis.

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5.2. Psychosocial Support for Urban Schools

After the pandemic, urban schools should focus on supporting students' adjustment. Learning gaps should be addressed before students move to higher grade levels. Psychological support should be prioritised according to students' needs. Hybrid learning should also be incorporated into regular teaching practices.

5.3. System Enhancement

In both rural and urban settings, teachers should receive training in digital teaching methods. Technology alone cannot improve learning quality unless teachers know how to use it effectively. Therefore, the government should introduce regular digital pedagogy training as part of teachers' professional development rather than treating it as an optional skill.

5.4. Targeted Roadmap to 2030

In light of Sustainable Development Goal 4, a three-tier policy roadmap is proposed to improve the use of technology in secondary education by 2030.

5.5. Tier 1: Immediate Priority for Rural Students

The highest priority is to improve internet access in rural schools through subsidised data plans and offline learning options. Rural teachers should also receive proper training so that they can provide immediate feedback after each lesson. Schools should focus on improving the quality of learning rather than relying on automatic promotion.

5.6. Tier 2: Medium-Term Priority for Urban Students

Urban schools should provide in-house counselling services and adjust the curriculum according to students' current learning levels instead of assuming that they are academically prepared.

5.7. Tier 3: Long-Term National Education Policy

The long-term priority is to make capacity, equity, and alignment a permanent part of the national education system. Communication, technology use, and students' adaptation in both rural and urban schools should be monitored regularly at the district level. This will help identify problems at an early stage and enable timely action to address future educational disruptions.

5.8. Implementation

Strong cooperation and coordination among the Ministry of Education, telecommunication authorities, the Ministry of Health, and local school management committees are essential to reduce vulnerability in the education system during future crises. Infrastructure development should be prioritised in the annual national budget. In-house psychological counselling services should be established with support from the Ministry of Health to help students recover and prevent further educational and emotional challenges. A pilot project could be implemented in the same six schools and three divisions included in this study. The results could then be evaluated to determine whether these interventions reduce the differences between rural and urban schools over time.

6. Conclusion

This study shows how technology use during COVID-19 followed different paths in rural and urban Bangladesh, instead of just different levels of sample patterns. The overall findings show that students in both settings adapted technology in different ways, which in turn led to different educational outcomes. This approach is important because the same technology variable can change under surrounding conditions; a single pooled, cross-sectional model would fail to capture this dynamic variation. Most of these patterns are descriptive rather than statistically confirmed. In this study, only Technology Utilization was significantly associated with Digital Learning Impact in urban schools after the pandemic ($p = 0.037$).

Although urban schools generally had better access to technology, it became unreliable during the crisis. As a result, the gap between rural and urban students became smaller, and after the pandemic was over, technology use could not ensure stronger academic performance in urban schools. However, it was significantly associated with perceived learning impact. Rural schools always lacked access to technology, but over time, they became more resilient through better communication, and the rate of technology use increased and became a part of their education out of necessity. In rural settings, there was variance across all three phases without meeting the significance level.

The vital point of this study's findings is that technology infrastructure alone was not enough to improve learning. The study identified that, though urban schools had better technology before the pandemic, they could not perform well during the crisis. In contrast, rural schools lacked resources but showed improvement after the pandemic. The findings indicate that technology alone was not enough to improve students' performance; communication, regular feedback, and positive learning habits are equally important. This claim is not proven by statistical effects but is drawn mainly from non-significant models and qualitative evidence. It aligns with Fullan's educational model as a theoretical interpretation rather than a statistically confirmed finding. According to the model, when capacity, equity, and alignment work together, even small improvements can produce significant results. But when any one of these is missing, technology investment alone cannot reduce the achievement gap.

The tables and figures in this study provide a clear framework for these findings. Figure 1 provides the study areas, and Figure 2 describes the characteristics of the participants and differences in training facilities. Table 1 compares the results across localities and phases, and Table 2 shows the proportion of variance explained (R^2) and effect size (f^2) for academic performance across localities and phases. The remaining figures highlight how each predictor affected learning across the pandemic phases.

The findings suggest that education policies should focus not only on digital access but also on improving communication, feedback, and student support systems. For South Asian countries, including Bangladesh, education policies should be designed according to local needs. While rural schools need stronger communication systems and

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continued support for technology, urban schools need more psychosocial support to reduce the effects of the pandemic. In both settings, teachers should receive regular training in digital teaching methods.

As Bangladesh works toward achieving Sustainable Development Goal 4 by 2030, education technology policies should go beyond increasing access; they should also address the root causes that prevent technology from improving learning. Policymakers and researchers can use this approach to identify the root causes of educational disruptions.

References

AA News Desk. (2020). Wari prepares for lockdown. *The Asian Age*. Retrieved from https://dailyasianage.com/news/234233/wari-prepares-for-lockdown

Akoglu, H. (2018). User's guide to correlation coefficients. *Turkish Journal of Emergency Medicine, 18*(3), 91-93. https://doi.org/10.1016/j.tjem.2018.08.001

Alkhnbashi, O. S., Mohammad, R., & Bamasoud, D. M. (2024). Education in transition: Adapting and thriving in a post-COVID world. *Systems, 12*(10), 402. https://doi.org/10.3390/systems12100402

Bangladesh Bureau of Educational Information and Statistics (BANBEIS). (2023a). *Bangladesh education statistics 2022*. Dhaka, Bangladesh: BANBEIS.

Bangladesh Bureau of Educational Information and Statistics (BANBEIS). (2023b). *Bangladesh education statistics 2023*. Dhaka, Bangladesh: BANBEIS.

Bangladesh Bureau of Educational Information and Statistics (BANBEIS). (2024). *Bangladesh education statistics 2023* Dhaka, Bangladesh: Secondary & Higher Education Division.

Bhaskar, R. (1975). *A realist theory of science*. Leeds, England: Leeds Books.

Black, P., & Wiliam, D. (2010). Inside the black box: Raising standards through classroom assessment. *Phi Delta Kappan, 92*(1), 81-90. https://doi.org/10.1177/003172171009200119

Chang, M.-L., Gaines, R. E., & Mosley, K. C. (2022). Effects of autonomy support and emotion regulation on teacher burnout in the era of the COVID-19 pandemic. *Frontiers in Psychology, 13*, 846290. https://doi.org/10.3389/fpsyg.2022.846290

Clark, R. C., & Mayer, R. E. (2016). *e-Learning and the science of instruction: Proven guidelines for consumers and designers of multimedia learning* (4th ed.). Hoboken, NJ: Wiley.

Cohen, J. (1988). *Statistical power analysis for the behavioral sciences* (2nd ed.). Hillsdale, NJ: Lawrence Erlbaum Associates.

Creswell, J. W., & Plano Clark, V. L. (2018). *Designing and conducting mixed methods research* (3rd ed.). Thousand Oaks, CA: SAGE.

Deci, E. L., & Ryan, R. M. (2000). The "what" and "why" of goal pursuits: Human needs and the self-determination of behavior. *Psychological Inquiry, 11*(4), 227-268. https://doi.org/10.1207/S15327965PLI1104_01

Ferguson, C. J. (2009). An effect size primer: A guide for clinicians and researchers. *Professional Psychology: Research and Practice, 40*(5), 532-538. https://doi.org/10.1037/a0015808

Ferraro, F. V., Ambra, F. I., Aruta, L., & Iavarone, M. L. (2020). Distance learning in the COVID-19 era: Perceptions in Southern Italy. *Education Sciences, 10*(12), 355. https://doi.org/10.3390/educsci10120355

Fullan, M. (2020). *Leading in a culture of change* (2nd ed.). Hoboken, NJ: Jossey-Bass.

Hattie, J., & Timperley, H. (2007). The power of feedback. *Review of Educational Research, 77*(1), 81-112. https://doi.org/10.3102/003465430298487

Helma, H., & Murni, D. (2021). Study of factors affecting student learning outcomes in real analysis lectures during the Covid-19 pandemic. *Journal of Physics: Conference Series, 1742*(1), 012039. https://doi.org/10.1088/1742-6596/1742/1/012039

Hossain, M. M., Rahman, M., Trisha, N. F., Tasnim, S., Nuzhath, T., Hasan, N. T., . . . Ma, P. (2021). Prevalence of anxiety and depression in South Asia during COVID-19: A systematic review and meta-analysis. *Heliyon, 7*(4), e06677. https://doi.org/10.1016/j.heliyon.2021.e06677

Institute of Epidemiology Disease Control and Research (IEDCR). (2020). *List of outbreak investigations done by IEDCR in 2020*. Retrieved from https://iedcr.gov.bd/pages/static-pages/6922df42933eb65569e20e97

Jarrah, H. Y., & Alkhasawneh, T. (2023). The impact continuous adaptation of augmented reality after Covid-19 in United Arab Emirates. *International Journal of Instruction, 16*(2), 719-734.

Lavy, V. (2015). Do differences in schools' instruction time explain international achievement gaps? Evidence from developed and developing countries. *The Economic Journal, 125*(588), F397-F424. https://doi.org/10.1111/ecoj.12233

Li, L. (2024). Reskilling and upskilling the future-ready workforce for industry 4.0 and beyond. *Information Systems Frontiers, 26*(5), 1697-1712. https://doi.org/10.1007/s10796-022-10308-y

McHugh, M. L. (2013). The chi-square test of independence. *Biochemia Medica, 23*(2), 143-149. https://doi.org/10.11613/BM.2013.018

Means, B., Toyama, Y., Murphy, R., & Baki, M. (2013). The effectiveness of online and blended learning: A meta-analysis of the empirical literature. *Teachers College Record, 115*(3), 1-47. https://doi.org/10.1177/016146811311500307

Nafiu, R. F. (2020). *COVID-19: Most areas of Dhaka, Chittagong, Gazipur, Narayanganj in red zone. Dhaka Tribune*. Dhaka, Bangladesh: Dhaka Tribune.

Nielsen, J. (1993). *Usability engineering*. Boston, MA: Academic Press.

Pham, H. H., & Le, Q. A. (2021). Self-regulation in online learning: Insights from Vietnamese university students during the COVID-19 pandemic. *Frontiers in Education, 6*, 674825.

Rogers, E. M. (2003). *Diffusion of innovations* (5th ed.). New York, NY: Free Press.

Saleem, F., AlNasrallah, W., Malik, M. I., & Rehman, S. U. (2022). Factors affecting the quality of online learning during COVID-19: Evidence from a developing economy. *Frontiers in Education, 7*, 847571. https://doi.org/10.3389/feduc.2022.847571

Sarker, M. R., Sarkar, M. A. R., Alam, M. J., Begum, I. A., & Bhandari, H. (2023). Systems thinking on the gendered impacts of COVID-19 in Bangladesh: A systematic review. *Heliyon, 9*(2), e13773. https://doi.org/10.1016/j.heliyon.2023.e13773

Star Online Report. (2020). Coronavirus: Govt forms 17-member nat'l technical advisory committee. *The Daily Star*. Retrieved from https://www.thedailystar.net/coronavirus-outbreak-tackle-govt-forms-17-member-natl-technical-advisory-committee-1894579

UNESCO. (2023). *Education: From disruption to recovery*. Retrieved from https://www.unesco.org/en/covid-19/education-disruption-recovery

Zayeef, A. (2020). *COVID-19: Half of Dhaka city's locked down houses in Wari. Prothom Alo*. Retrieved from https://en.prothomalo.com/bangladesh/covid-19-half-of-dhaka-citys-locked-down-houses-in-wari-3

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