Take-Up, Use, and Effectiveness of Remote Technologies: Pre-Analysis Plan

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1 Introduction

Governments and educational organizations worldwide are adapting to the unprecedented circumstances created by the pandemic by developing or scaling up distance education modalities to continue delivering educational content to students and maintain students' connection to formal education. However, the effectiveness of these tools is largely unknown.

The first known cases of Covid-19 were reported in Bangladesh on March 7, 2020. The country-wide school closures implemented in Bangladesh began on March 17, 2020, with an uncertain end date (as is the case in many countries around the globe), affecting the 24 million students across the country. Over the past year, the government's main priority has been to minimize the disruption of learning as much as possible. The Ministry of Education and Aspire to Innovate (a2i) are working together to use a combination of mass media broadcasting and an online platform to remotely deliver educational content from the school curriculum.

At the end of March 2020, the government-run Sangsad TV channel started broadcasting two 20-minute daily lessons for students in grades 6 through 10, and these lessons are also available on a YouTube channel. a2i has built a parallel platform, Konnect, to host Sangsad TV videos, electronic textbooks, life-skills videos, and other educational materials. Additionally, a2i manages a popular Facebook group, which serves as a meeting point for increasing engagement of students and teachers, and it regularly features educational videos and live video lessons with Q&A capabilities. Non-governmental organizations are also offering educational resources and initiatives to aid remote learning during school closures.

This study evaluates four interventions designed to reduce the barriers to remote education, two targeting information constraints and two targeting price constraints.

This pre-analysis plan describes the sampling frame, randomization, and the methodology to be used for analyzing data collected during the midline survey, conducted in March and April of 2021, and the endline survey, scheduled for May and June 2021. With schools expected to start re-openings in May, midline results will document any intermediate effects of the treatments, as well as descriptively capture the behaviors and intentions of school-going and children and their parents in Bangladesh. The endline analysis will measure impacts after the conclusion of the interventions.

We outline a plan of analysis and hypotheses based on our review of baseline and midline descriptive statistics. We have not looked at any midline results by treatment arm. We will review our midline results after publishing the PAP, and we may refine our hypotheses based on these midline findings. At the stage that the midline PAP is submitted, we have not yet finalized the endline questionnaire. In a future version of the PAP, we may modify the questions, hypothesis and outcomes related to the endline based on the endline pilot. All other parts of the PAP will remain unchanged.

1.1 Research Questions

The broader study will answer the following overarching question: What are the impacts of households' remote education investment decisions?

This overarching question can be subdivided into the following research questions:

- (RQ1) How does educational technology adoption affect (parental) economic and time investments?

- (RQ2) How do changes in relative input costs affect households' decisions?

- (RQ3) What are the short-term (take-up and usage) and medium-term (usage, engagement, re-enrollment, learning and aspirations) impacts of household remote education decisions?

- (RQ4) Is there heterogeneity in the effects on remote educational investments (by parents) and outcomes based on (i) age, (ii) gender, and (iii) household socio-economic status?

The midline survey seeks to capture any changes in household's behavior around the planned re-openings in response to the treatments. We will also descriptively capture the behaviors and intentions of school-going and children and their parents in Bangladesh. The endline survey will capture these same behaviors after the end of the interventions along with measurement of children's learning.

2 Sampling Frame

2.1 Baseline sampling

Because the interventions are useful only to those who have access to the requisite technology, our phone sample consists of 7,576 respondents that have (a) at least one child in grades 6-10 (grades 7-11 in January 2021) and (b) have at least one smartphone in the house. 6,746 agreed to be recontacted and form the sample for our midline and endline surveys.

We recruited households based on numbers obtained from three sources: A sample of numbers obtained through Random Digit Dialing (RDD), a list of numbers of parents of recipients of the government Secondary School Stipend Program, and a list of phone numbers of students who had previously enrolled in the Konnect webpage. The RDD sample is aimed to be broadly representative of all smartphone users in Bangladesh and will require more screening to select eligible households. The second sample (recipients of the Secondary School Stipend) will include more underprivileged households and it is targeted to the age range of interest. The third sample (students enrolled in the Konnect webpage) will likely have slightly higher socioeconomic status (SES) than average, but likely higher smartphone penetration. It includes those households for whom we already know whether they have children eligible for our study (though in higher grades on average).

2.2   Midline sampling

The midline sample is an 89% sample of the full set of baseline respondents, reflecting the full set of those who consented to be recontacted.

3   Treatment arms

For the study participants, we have two information treatments and two treatments that reduce the price of educational inputs.

Information treatments:

- **Treatment 1** – Remote learning information: Information and reminders about government remote learning initiatives that follow the national curriculum. We split the information salience treatment into two sub-treatments:

     1A – **"TV"**: Information/reminders about Sangsad TV lessons

     1B – **"TV + Internet"**: Information/reminders about Sangsad TV lessons and internet lessons (Sangsad TV YouTube)

- **Treatment 2** – **"Adaptive learning"**: Information about an adaptive learning internet resource (Robi 10-minute school).

Cost reduction treatments:

- **Treatment 3** – **"Data subsidy"**: Reduce costs of using internet remote learning technologies by providing a free 1-month data package for 10 GB.

- **Treatment 4** – **"Teacher support"**: Pair students with a teacher who will provide weekly check-ins and support.

The information treatments will be delivered by automated voice call and/or SMS messaging.

Individuals selected for Treatment 3 will receive a text message offering them the opportunity to avail of a 10GB data package, allowing them to opt-out if they do not wish to participate. We coordinated with a large mobile provider to activate the package (or enable the package on the respondent's mobile phone through a different vendor), which had a 30-day validity.

Individuals selected for Treatment 4 were matched with an a2i partner teacher from a pool of 70 teachers recruited for the study. These recruited teachers provided a weekly, 30-minute phone check-in with 7 assigned students, and filled out a short weekly log. They received a modest stipend to cover their associated phone charges.

4   Randomization

The entire sample was cross-randomized in evenly sized cells across Treatment 1 (information and reminders about remote TV lessons and online platforms) and Treatment 2 (adaptive learning).

Table 1: TREATMENT ARM DISTRIBUTION, INFORMATION AND ADAPTIVE LEARNING

	Control	2. Adaptive learning
Control	1/4	1/4
1a: TV	1/8	1/8
1b: TV + internet	1/8	1/8

Treatment arm 3 (data subsidy) was cross randomized equally across Treatments 2 and 1b. Treatment arm 4 was initially cross-randomized to 1/4 of students (teacher support) across Treatments 1a and 1b (TV only and TV + internet only), though we increased the share assigned to treatment in response to substantial treatment attrition, described in more detail below.

Randomization was done in office by a computer and was conducted at the household level[1]. We stratified by the following factors:

- Household income (5 categories).

- Sample source: whether sample was drawn from Konnect, Secondary School Stipend or RDD databases (3 categories).

- Child gender: Whether households had only male, only female, or both male and female children in grades 6-10 (3 categories).

- Internet: Whether the household had access to at least one smartphone with an active internet connection (2 categories).

For the teacher support intervention, we initially assigned 473 students to 70 teachers in groups of approximately 6-7 students per teacher, roughly matched in terms of grade levels. Durin the first week of the intervention, teachers were not able to reach all students, primarily because some had discontinued their studies (marriage), parents refused to consent, or because female students were not comfortable speaking with male teachers over the phone. To address these issues, we re-sampled 355 more students, of which teachers were able to reach about 80%. In the second round of sampling, we tried to loosely match teachers and students in terms of their gender as well as grade levels.

4.1 Extended list of treatments (12 arms)

Below, we provide an exhaustive list of treatment arms that arise from the cross-randomizing each of the main treatment arms.

0 Control

1a TV

1b TV + internet

2a Adaptive learning

2b Adaptive learning + TV

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[1]See `treatment_ 03Jan.do`.

2c Adaptive learning + TV + internet

3a Data subsidy + TV + internet

3b Data subsidy + Adaptive learning

3c Data subsidy + Adaptive learning + TV

3d Data subsidy + Adaptive learning + TV + internet

4a Teacher support + TV

4b Teacher support + TV + internet

4c Teacher support + Data subsidy + TV + internet

Randomization and assignment to treatment occurred at the household level among the set of 7,576 baseline respondents.

5 Data Collection

5.1 Baseline data collection

During the baseline survey, we conducted 20- to 25-minute phone surveys with our phone sample to collect the following baseline variables:

- Student demographics (age, gender, and number of siblings)

- Measures related to the family socioeconomic status (parent's occupation/earnings, self-reported opportunity costs)

- Parental perceptions of the student's ability and academic standing

- Parent assessment of student baseline ability

- Current student educational activities

    Number of days/hours engaged in learning activities

    Type of learning activities

    Support received from family, teachers, tutors

- Educational expectations and aspirations

5.2 Midline data collection

In March 2021, the Ministry of Education announced that schools would open beginning March 30. In late March, the MoE released an updated plan that included a start date of May 22. The opening of schools for in-person instruction, even partially, may influence how parents invest in their children's education. We anticipate that parents' time and monetary investments may also be affected by the teacher outreach and data subsidy treatments, which create exogenous variation in their costs of intervention. In order to isolate these two factors, we conducted a midline survey with parents from mid-March to mid-April 2021 in order to gather information on the impact of our interventions on parental behavior prior to school re-openings. Specifically, we measured the impact of our interventions on the following short-run outcomes:

- Parental behaviors:

    o Time investment in children's education

    o Economic investment in children's education

- Parental beliefs and expectations:

    o Expectations on school completion

    o Beliefs on children's learning/achievement

- Student behavior:

    o Use of learning resources

    o Effort/engagement in learning activities

    o Outside options – time spent working for pay by students

5.3 Endline data collection

We will conduct an endline survey from May - June 2021 with our baseline survey respondents, regardless of whether they participated in the midline survey. We will re-assess the same set of outcomes as above, and we will also measure student learning and student educational perceptions:

- Student learning

    o Performance on series of adaptive math questions

    o Performance on series of adaptive Bangla questions

- Student perceptions

    o Use of learning resources

    o Student engagement

    o Student educational aspirations and expectations

    o Parental support

6 Outcome variables

We have categorized the outcomes into the following 7 domains. Domains 1 through 5 will be collected at midline and at endline. The question numbers below correspond to the midline survey instrument. The questions will not change at endline. Domains 6 and 7 will only be collected at endline. The instrument for these latter domains has not yet been finalized. We will write questions on the items below, and pilot them during the first week of May 2021. We may make some adjustments to the questions based on the pilot results.

6.1 Domain 1: Parental Time Investment in Education

We will measure parents' time and effort invested in helping the student in the educational activities during the month of March (midline) or May (endline), using the variables below:

- Number of days reminded student to study in past week (CR25)

- Number of hours other family helped the student to study in typical week (CR27)

- Number of hours parent helped in typical week (CR28)

Related to this domain, but presented as a separate table, is whether each type of help is provided (CR29: 1/0):

- Explain or clarify materials and concepts

- Help with assignments or specific problems

- Watch videos or TV with student

- Help find additional resources

- Provide encouragement and support

- Provide supervision to help student stay on task

6.2 Domain 2: Parental Monetary Investment in Education

We will measure parents' financial investment in educational activities using the variables below:

- Whether the student received private tutoring in past 30 days (CR05)

- Money spent on tutoring in March/May (midline/endline), unconditional on any tutoring (CR07)

- Money spent on any learning activities, unconditional on any educational activities (CR18)

6.3 Domain 3: Take-up and Utilization of technology-dependent learning resources

To capture the extent to which students utilize the various technology-dependent learning resources that might be available to them, we will ask about the use of the following, at both 1) the extensive margin (that is, *any* use, CR09), as well as at 2) the intensive margin (that is, the number of hours spent on each of these activities in a typical week in the month of March/May (midline/endline), CR10. We classify the following activities as those that require technology use:

- Watched video lessons on a smartphone or other device

- Used Robi platform

- Used other internet resources

- Met with a teacher remotely: by phone or internet

- Attended remote school classes

Within this domain, we also ask whether students used any of the following devices for learning that may rely on internet (CR13), and we ask about and data/internet usage for learning activities during the month of March (midline) (CR14 and CR15) and May (endline):

- Used smart phone for educational activities (CR13.3)

- Used pre-paid internet package for learning activities (CR14)

- Amount used in GB in month of March (midline) (CR15) and May (endline)

6.4 Domain 4: Take-up and Utilization of non technology-dependent learning resources

To capture the extent to which students utilize non technology-dependent learning resources, we will ask about the use of the following, at both 1) the extensive margin (that is, *any* use, CR09), as well as at 2) the intensive margin (that is, *the number of hours spent on each of these activities in a typical week in the month of March (midline), CR10, or May (endline)*). We classify the following activities as those that do not require technology use:

- Read textbooks/school books

- Worked in exercise books

- Met with a teacher in person

- Attended in-person school classes (while closures persist)

6.5 Domain 5: Student Time Investment

- Days per week any schoolwork is done by the student in the month of March/May (midline/endline) (CR03)

- Hours per week that school work done by the student in March/May (midline/endline) (CR04)

6.6 Domain 6: Student Learning (endline only)

- Math achievement based on assessment

- Bangla achievement based on assessment

6.7 Domain 7: Student Engagement, motivation, and re-enrollment (endline only)

If schools are open partially or fully for in-person enrollment, we will ask if students are attending in-person schooling. Otherwise, we will ask only if students are enrolled in school.

- Student engagement index: We will create an index from a subset of questions of the RAPS questionnaire on the "Ongoing Engagement" subdomain.

- Student educational aspirations and expectations

- Student enrollment and/or likelihood of re-enrollment once schools reopen (wording dependent on piloting)

- Student currently attending in-person classes at least part time

7 Testable hypotheses

7.1 Midline and Endline

- **(H1)** T1 and T2, which broadly provide information about (1) government-led remote learning initiatives, and (2) about an adaptive learning resource, will increase take up and use of these specific educational products (CR09.1-CR09.3).

  (H1A) Increased take-up of these specific educational products induced by T1 and T2 will affect parents' investment in their children's education, measured primarily through money spent on tutoring (Domain 1) and/or parental time investment (Domain 2). If these educational products are a substitute for parental investment, we would expect a reduction in measured investments across these outcomes. If they are a complement, then we would expect an increase.

  (H1B) Increased take-up of these specific educational products induced by T1 and T2 will weakly increase student time spent on educational activities (Domain 5).

- **(H2)** T3 (data subsidy) will increase the take up and use of technology-dependent learning resources for the duration of the intervention. (Domain 3).

  (H2A) If T3 (data subsidy) increases the take-up and usage of educational resources that rely on the internet, this in turn may affect the usage of non technology-based learning resources (Domain 4). There will be a decrease in non technology-based learning resources if they are substitutes to technology-based resources, or there will be an increase if they are complements.

  (H2B) If T3 increases the take-up and usage of technology-based learning resources, this in turn will impact parental monetary investments (Domain 1) and parental time investment (Domain 2). There will be a decrease in monetary investment (time investment) if it is a substitute for technology-based learning resources. There will be an increase if they are complements.

- **(H3)** T4 (teacher support) will increase student time spent on educational activities (Domain 5).

  (H3B): Regardless of *whether* students increase their time spent on educational activities, T4 (teacher support) affect what educational learning resources student use (Domains 3 and 4). If the other learning resources are a substitute for teacher support, their usage will decrease. There will be an increase if they are complements.

  (H3C): T4 (teacher support) will impact parental monetary investment (Domain 1) and parental time investment (Domain 2). There will be a decrease in tutoring (parental time investment) if it is a substitute of teacher support. There will be an increase if it is a complement.

We will also explore some secondary hypotheses that are not essential to our research questions, but which can provide additional context to interpret the above results:

- If any or all interventions increase student or parental educational investment, this investment may crowd out other student activities, such as working or caring for household members (Domain 6).

7.2 Endline only

- **(H4)** These educational interventions will increase student learning (Domain 6). We will test interventions individually.

- **(H5)** These educational interventions will increase student engagement, motivation, and re-enrollment (Domain 7). We will test interventions individually.

8 Covariates for balance checks and main specifications

We test for balance in treatment assignment along baseline covariates. Because our main specifications are at the child level, we conduct our balance tests at the child level as well, clustering standard errors at the household level. For all included covariates, we predict each covariate with dummy variable indicators for each treatment arm, and test for the joint significance of these treatment arms using randomization inference. We also include stratification-cell fixed effects. We test the joint significance of our baseline covariates by predicting treatment assignment for each arm against the control group, using seemingly unrelated regression estimates. Any variables with missing values will be excluded from the individual-covariate tests. For the joint tests, these missing values recoded as zero with a flag added to the joint test.

8.0.1 Covariates for balance checks

We will test for balance along the following covariates. We will also include any covariates selected through our LASSO selection process outlined below that are not already in this list.

- Household size

- Number of children in grades 6-10

- TV with satellite

- Respondent is mother of child in grade 6-10

- Respondent is father of child in grade 6-10

- Mother's highest level of education

- Father's highest level of education

- Mother income, past 30 days

- Father income, past 30 days

We also include the following baseline child-level covariates:

- Number of days did schoolwork in past week

- Number of days did school work in April

- Received private tutoring

- Worked for pay

9 Empirical Specifications

Our main empirical specifications will estimate intention-to-treat effects, reflecting the causal impact of assignment to each treatment arm on our outcomes of interest.

Our main specification will pool smaller treatment arms, specifically the TV and TV + internet arms, for which we do not expect substantial differences in treatment impacts. However, we will disaggregate these treatment arms for the subset of hypotheses about any differences in the effects of information about the TV program only vs. TV and internet resources.

Our main outcomes are estimated at the child level, while treatment assignment is randomized at the household level. Because some households have more than one child in grades 6-10, we estimate our models at the child level and cluster our standard errors at the household level to reflect the level of randomization Abadie et al. (2017).

We will estimate equations of the following general form:

$$y_{hc} = \alpha + \beta_1 Info_h + \beta_2 Adaptive_h + \beta_3 Data_h + \beta_4 Teacher_h + \beta_5 Info_h * Adaptive_h +$$
$$\beta_6 Info_h * Data_h + \beta_7 Adaptive_h * Data_h + \beta_8 * Info_h * Adaptive_h * Data_h +$$
$$X'_{hc}\gamma + f_s + g_w + h_j \epsilon_{hc}$$

where y_{hc} is our outcome variable of interest measured at the *household-child* level. $Info_h$ is a binary variable equal to 1 if the household receives information about TV or TV + internet (treatments 1a and 1b); $Adaptive_h$ is a binary variable equal to 1 if the household receives information about adaptive learning platforms (treatment 2); $Data_h$ is assignment to the data subsidy treatment (treatment 3), and $Teacher_h$ is assignment to the teacher support intervention (treatment 4).

We also include a vector of household- and child-level covariates, X, as well as stratification-cell fixed effects (f_s), survey-week fixed effects (g_w) and enumerator fixed effects (h_j).

We follow Jones et al. (2019) to select covariates. The first set will include our set of stratification cell fixed effects only, which effectively control for those variables. The second set will include those fixed effects along with baseline variables that are good predictors of the outcome variable. We will estimate a LASSO regression with five-fold cross validation, including all variables from our baseline data. We will present a table that shows how our results compare across the two specifications, and we will choose one as our preferred specification going forward.

9.1 Heterogeneous Effects

We expect to see heterogeneous effects based on the following student-level and household-level characteristics:

- Gender and age: We will split our sample at the median age overall and create four cells for analysis: girls with below-median age, boys with below-median age, girls with above-median age, and boys with above-median age.

- Socioeconomic status of the household: We will use the first principal component of the following household SES measures collected at baseline: home ownership, whether members have bank account,

household asset ownership (20 items), fuel and water sources (binary indicators for each type), electricity, number of rooms for sleeping, latrine type (binary indicators for each type), and room for kitchen. We will also test the robustness of our results to alternative reasonable measures.

- How close the student is to the cutoff for the nearest standardized (national) high-stakes examination: We will calculate the number of years away from the nearest exam and interact that with our treatment indicators. We will also conduct a robustness test using a binary indicator for being in the immediate year before the exam.[2]

10   Multiple Hypothesis Testing

We will use a domains-based approach based on Kling et al. (2007), and each of the outcome variable categories (domains) listed in Section 6. Furthermore, we will also control the FWER within domains using a method such as Romano and Wolf (2005).

11   Missing values and outliers

We will exclude any of the previously mentioned outcome variables if it is missing for a large share of our sample.

In the case of missing control values, we will create a dummy variable flag, code missing values as zero, and include the dummy variable in our specifications.

In the case of outliers, we will winsorize continuous outcome variables at the 99th percentile.

12   Differential attrition

We will test for differential midline and endline attrition rates based on treatment assignment. In the event of differential attrition, we will also bound our treatment effects using a method such as Lee bounds.

13   Research Team

The principal investigators for this evaluation include Dr. Emily Beam, Assistant Professor (University of Vermont); Dr. Priya Mukherjee, Assistant Professor (University of Wisconsin-Madison); and Dr. Laia Navarro-Sola, Assistant Professor (Stockholm University). Additionally, the team also comprises of Mohammad Ashraful Haque, Country Director (IPA Bangladesh); Sohini Chaparala, Research Manager (IPA Bangladesh); Tanzila Tabassum, Research Analyst (IPA Bangladesh); Sathia Chakrapani, Research Associate (IPA Bangladesh); Zaima Promy, Associate Research Analyst (IPA Bangladesh); and Sukriti Ahmed, Senior Research Analyst (IPA Bangladesh).

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[2]Note that the high stakes national examinations relevant for our student population are (1) the Junior Secondary Certificate (JSC), which is held at the end of grade 8, and (2) the Senior Secondary Certificate (SSC), which is held at the end of grade 10.

References

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