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# CAN EDTECH IMPROVE ACCELERATED EMERGENCY EDUCATION PROGRAMS? EMPIRICAL EVIDENCE FROM PAKISTAN AFTER COVID-19

**Thomas Brown, Allyson Krupar, and Farman Khan**

## ABSTRACT

*Education technology is often heralded as a tool for improving education access and quality, but evidence of its effectiveness in enhancing learning outcomes in emergency settings in low- and middle-income countries is limited. In this article, we present results from Learning Tree, a mobile-based learning application piloted in Pakistan in 2021, where inequities in girls' access to education were heightened by the COVID-19 pandemic and natural disasters. The Learning Tree was introduced as a supplemental tool for crisis-affected girls ages 11-14 who were participating in accelerated learning programs in rural areas of the Shikarpur district. Through a longitudinal quasi-experimental evaluation and multivariate regression analysis, we found that the Learning Tree tool was associated with approximately double the learning gains of accelerated learning activities alone. We observed significant improvements across literacy, numeracy, and executive functioning outcomes far beyond the gains produced by the accelerated learning activities alone. Learning Tree also boosted gains in social and emotional skills; this was a novel result, given the inherent challenge of improving these skills with only limited direct interpersonal interaction and hands-on engagement. These results provide promising evidence that well-designed, mobile-based education technology interventions can help to close the gaps in education that emerge for vulnerable girls during emergencies in lower-middle-income settings.*

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# INTRODUCTION

Emergencies have detrimental effects on children's education, particularly in low- and middle-income countries (LMICs). Disruption in the provision of education services, as well as the trauma and stress associated with emergencies, can increase dropout rates and lead to learning loss. This deepens existing inequalities in education, such as those related to socioeconomic status. These effects are especially pronounced for girls, who face greater barriers than boys to continuing their education during crises, due to an increase in household responsibilities, constrained mobility, and reduced access to learning resources and technology. This increases their risk of permanently dropping out. Pakistan, a country where girls' access to education was already a major challenge, experienced unprecedented disruption of education in 2020 and 2021, due to the COVID-19 pandemic and a series of major natural disasters. Schools in Pakistan closed in March 2020 and remained closed on and off until September 2021. This greatly exacerbated the challenges faced by disadvantaged girls in gaining access to quality education.

Education technology, or EdTech, became an important tool to keep children engaged with education during this period, which helped to guard against dropout and learning loss in countries across the world. In Pakistan, however, options were limited for access to remote learning in crisis-affected and low-income households. Furthermore, critical appraisal of the utility of EdTech tools and their ability to stimulate learning and development in emergency contexts in global majority countries been limited. In this article, we address this gap by evaluating the effectiveness of Learning Tree, a mobile-based EdTech intervention used in the Sindh province of Pakistan, a region that faces particularly tough challenges for girls in gaining access to education.

Save the Children developed and piloted Learning Tree to supplement the accelerated learning programs being provided to out-of-school girls ages 11 to 14 in the wake of COVID-19 and natural disasters in 2021. The EdTech tool facilitates structured remote learning for children by providing rich, self-directed content focused on social and emotional learning (SEL), literacy, and numeracy. Save the Children staff worked with caregivers and teachers to introduce the application at 25 learning centers and support students with using it, and implemented a quasi-experimental study design to determine whether Learning Tree was effective in improving learning outcomes over a period of four months.

# BACKGROUND

## Education Technology and the Digital Divide for Girls in Developing Countries

Education technology comes in many shapes and sizes. It involves using technology such as radios, computers, tablets, and smartphones to support education by interfacing with children, teachers, education leaders and administrators, and caregivers (Czerniewicz 2008). Rodriguez-Segura (2022) categorizes EdTech interventions into four main types: access to technology, which provides teachers and students with devices and connectivity that enable them to participate in digital learning; technology-enabled behavioral interventions, which use digital tools to enhance student engagement and motivation; improvements to instruction, which focus on enhancing teaching quality through a digital curriculum and teacher training; and self-led learning, which empowers students to have personalized learning experiences through adaptive software and online courses. Although technology has been used in classrooms since the 1920s, the introduction of the personal computer in the 1980s marked a significant change in the delivery of education. Since then, EdTech has continued to transform teaching and learning (Papert 1980; Cuban 1986) and has proliferated rapidly across both high-income and emerging economies. It has been a promising tool in the latter, where it has helped to bridge gaps in education by enhancing accessibility and providing cost-effective, open-source digital tools to education systems facing resource challenges (Unwin et al. 2017; Guri-Rosenblit 2018).

The increasing role technology plays in education can be positioned within the broad conceptual framework of the digital divide. This role includes designing inclusive education interventions that are effective for all children. The term "digital divide" refers to the gaps in access to and use of technology between individuals and groups of people. These gaps influence the extent to which digital tools can provide economic advancement and improve social inclusion (van Dijk and Hacker 2003; Warschauer 2003; OECD 2021). In the education context, while technology holds considerable promise to reduce inequalities in education access and learning, this may not be achieved if some children are unable to access and utilize increasingly digitized learning tools. Selwyn (2016) argues that, while technology has the power to transform education for the better, interventions must be managed thoughtfully if they are to be effective for children who are vulnerable, including paying attention to socioeconomic, cultural, and political contexts. This approach underscores the need for considered and inclusive strategies to ensure that vulnerable children reap the benefits of EdTech interventions (Miras et al. 2023).

The digital divide overlaps with other inequalities that limit educational opportunities for vulnerable children, particularly women and girls in developing countries. In resource-constrained countries, the adoption of technology can be limited by such challenges as poor digital infrastructure and connectivity, lack of digital literacy, and socioeconomic inequality. There is compelling evidence that the introduction of digital tools for education in developing countries can improve learning outcomes, engagement, and retention rates (Rodriguez-Segura 2022; Ball, Paris, and Govinda 2014; Lurvink and Pitchford 2023). However, commentators emphasize that, to succeed in reducing education inequalities, EdTech interventions should engage teachers and the community, be locally tailored, and be designed to overcome challenges related to capacity and accessibility (Lynch, Singal, and Francis 2024; Coflan and Kaye 2020; Munoz-Najar et al. 2021; Rodriguez-Segura 2022).

Women and girls face greater barriers to accessing digital technologies than men and boys. Global data show that they are 12 percent less likely to use the internet and 10 percent less likely to own a mobile phone (Borgonovi et al. 2018). This gender-related digital divide is driven by socioeconomic inequalities, lower digital literacy, and sociocultural norms, all of which make it more difficult for women to access EdTech. For example, women may have less control of household finances, fewer financial means to purchase digital technologies and internet services, and are less likely to access digital technologies to learn advanced digital skills (Borgonovi et al. 2018). Girls also face sociocultural beliefs and norms that can limit their access to technology, both in the classroom and at home. These factors often center on assumptions about girls' competence and enjoyment of technology, and the benefits and risks they accrue from using it (Crompton, Burke, Jordan, and Wilson 2021). For example, one study of an EdTech intervention conducting during COVID-19-related school closures in Pakistan found that nearly one-third of parents did not permit their daughters to access EdTech for cultural, religious, and financial reasons (Adil, Nazir, and Akhtar 2021). More generally, studies from Kenya and Ghana find that girls' limited use of EdTech was driven by a lack of trust in their using devices; lack of access to the internet and mobile data; security concerns; and limited time, due to expectations that girls would carry out household chores and care duties (Amenya et al. 2021; Aurino, Tsinigo, and Wolf 2022; Tembey et al. 2021; Ananga et al. 2021).

## Education Technology in Education in Emergencies

Emergencies such as natural disasters, conflicts, and pandemics have detrimental effects on children's education. When such emergencies occur, schools often are closed, education activities are disrupted, and children experience trauma and stress. Children also can be internally displaced or become refugees, which presents additional challenges to their ability to access education (Brown 2013, 2016, 2017a, 2017b, 2018; Al Habsi and Rude 2021). As a result, millions of children are forced out of school, face disruptions in learning and protection, and are unable to learn effectively because of compromised education quality or psychosocial challenges (Burde et al. 2017; Nicolai, Hine, and Wales 2015). Girls' education outcomes tend to be affected disproportionately more than boys', due to girls' heightened vulnerability to gender-based violence, cultural norms that prioritize boys' education, attitudes around the division of caregiving and household labor, and gender disparities that exacerbate barriers to access to learning opportunities (INEE 2021). In the context of LMICs, emergencies exacerbate existing inequalities in education access and quality, which increases the number of children who are out of school or failing to learn. A range of tried-and-tested approaches to providing education to children facing such experiences has emerged, which led to the development of the field of education in emergencies (Burde et al. 2017; Burde, Lahmann, and Thompson 2019; Torani et al. 2019). There has been increasing interest in recent years about the potential uses of EdTech in the provision of education during emergencies.

Before the COVID-19 pandemic, the use of EdTech to provide learning opportunities during emergencies when traditional classrooms were not available was relatively novel and experimental. Radio and mobile learning were leveraged on a limited scale to maintain education continuity in certain areas prone to natural disasters or conflicts, but the adoption of comprehensive digital education strategies was not widespread. Empirical evidence on the effectiveness of EdTech in emergency settings in LMICs is limited, but it has been summarized in a number of key studies (Carlson 2013). For example, Dahya's (2016) cross-country landscape review found that tools like radios, mobile phones, mobile projectors, e-readers and tablets, laptops, and desktop computers have been used successfully to support, enable, and enhance the provision of education for children affected by emergencies, which has benefited student learning and teacher training and strengthened education systems. Stannard and Tauson's (2018) review of research on EdTech for children found that, if implemented effectively with the assistance of teachers and parents, EdTech programs can fill gaps when education is disrupted and increase the speed at which learners return to full-time schooling. They also found that EdTech works most effectively when it supplements, rather than substitutes for, classroom teaching. Ashlee and colleagues (2020) found that both blended EdTech modalities, which involve teachers and peers, and self-directed approaches, wherein children engage in learning by themselves, can promote positive learning outcomes and psychosocial wellbeing for children during emergencies.

The role EdTech played in emergency education during the COVID-19 pandemic expanded significantly. It became the primary mode of instruction worldwide, utilizing platforms such as Zoom and online learning management systems to deliver synchronous and asynchronous learning to students in lockdown (Hodges et al. 2020; Manca, Persico, and Raffaghelli 2021). While a great deal of empirical evidence emerged on the use of EdTech during the pandemic, only a small number of studies focused on LMICs (Crompton et al. 2021). Nicolai, Jefferies, and Lockhart (2023) reviewed ten studies that looked at the use of interactive voice-response audio lessons, audiovisual lessons, text messages and social media, digital platforms, and data systems in Bangladesh, Ghana, Kenya, Pakistan, and Sierra Leone. They found that EdTech interventions had mixed results in improving learning outcomes, that teacher-student engagement through EdTech was critical in encouraging structured learning, and that the role of parents and caregivers was crucial, including giving children permission to use devices and the internet, scheduling and guiding learning sessions, and supporting learning comprehension.

Commentary on the benefits and challenges of deploying EdTech in emergency settings in developing countries, particularly during the pandemic, can be situated within the digital divide framework. On the one hand, technology enabled ongoing access to education for millions of children in lockdown, and there is evidence that some children experienced no measurable learning loss during the pandemic, due to highly effective distance learning programs (Donnelly and Patrinos 2022). However, transitioning quickly to fully digital learning at scale brought enormous challenges. Many vulnerable children were left behind, as they could not properly access or take full advantage of EdTech offerings. During the height of the COVID-19 pandemic, access to EdTech was correlated with socioeconomic status. Those from poorer families missed out, due to their personal resource challenges and those of the education institutions they were affiliated with, lack of access to technology and internet connectivity at home, and inadequate digital literacy (Stelitano et al. 2020; Vegas, Shah, and Fowler 2021). These challenges were even starker in developing countries, where the divide is greater, due to structural challenges around digital infrastructure, digital literacy, and socioeconomic inequality (Mathrani, Sarvesh, and Umer 2022). Women and girls also experienced more severe challenges during the pandemic, which further exacerbated the gendered digital divide (Amaro et al. 2020; Damani et al. 2022).

Vulnerable children who are experiencing emergencies face overlapping and intersecting inequalities that may influence whether technology-facilitated education tools will support their learning effectively. Targeted interventions should be tailored to local contexts, be easy to use, provide digital infrastructure and devices when they are not otherwise available, support capacity development, engage teachers and parents as well as children, and provide training and ongoing assistance to ensure that these tools can be used effectively. More evidence is needed to inform these processes as to whether, and by what means, EdTech can help children who are facing inequalities to learn effectively during emergencies and close education gaps. However, as highlighted above, there is a paucity of quality data on the efficacy of EdTech interventions in emergency settings for girls in LMICs.

## The Promise of Edtech for Accelerated Learning in Emergencies

Accelerated learning refers to educational approaches designed to speed up education or otherwise help students who have fallen behind, by months or even years, to reach the grade level typical of their age (Damani 2020). In emergencies and postcrisis situations, accelerated learning programs can help children regain lost educational ground caused by disrupted schooling. These approaches are used to reduce learning inequalities and enable children to catch up to their grade-level skills so they are in alignment with their peers, which prevents long-term setbacks in their education trajectories. Accelerated learning approaches, which provide flexible, inclusive, and targeted opportunities to overcome systemic inequalities, can be particularly effective for marginalized groups, including girls, out-of-school children, and those from underserved communities. Many of these programs also focus on promoting SEL; however, few studies have tracked outcomes in this area, instead often prioritizing the measurement of subjects such as reading, mathematics, and science (Damani 2020).

EdTech shows promise as a tool for the delivery of accelerated learning programs for children in emergencies and postcrisis situations. Such tools can enhance learners' support systems by facilitating interactivity, learner-centered pedagogy, social and emotional development, and access to learning content, which these children otherwise would not have (Damani 2020). There is little data on EdTech's efficacy in increasing learning outcomes during emergencies in LMICs (Moscoviz and Evans 2022; Betthäuser, Bach-Mortensen, and Engzell 2023), and almost none at all that specifically evaluates the use of EdTech in accelerated learning programs in such contexts. Only two such studies have been identified.

One study is an accelerated mathematics program for secondary students in Indonesia that utilized an e-learning application called Edmodo, which was found to help students connect mathematical concepts more effectively than conventional methods, but it did not promote self-regulated learning (Yaniawati et al. 2017). The EdTech component was found to be effective due to its interactivity and engagement, and the facilitation of personalized learning. However, this evidence was limited to a small sample size (n = 61), and the study design only allowed for the evaluation of the combined intervention as a whole. Thus it did not offer a disaggregated analysis of the additional impact of the EdTech component within the accelerated program. A second study, this one from Turkey, involved fifth-grade science students. It had a more robust experimental design, which enabled comparisons between an accelerated learning approach delivered with accompanying learning software and one delivered in a regular classroom (Akbıyık and Şimsek 2009). The study found no additional impact on student achievement for those utilizing the EdTech component; however, the study's small sample size of 73 students limited the reliability of its findings.

In this article, we address this gap in the literature. We provide evidence from a robustly designed and adequately powered study that examines the use of EdTech in a nonformal accelerated learning program for girls in rural Pakistan, who were affected by a series of emergencies in 2020 and 2021. Using an experimental design involving random assignment of the EdTech tool to a large cohort of students in different accelerated learning centers, we analyzed whether the tool had any additional benefit in terms of learning outcomes, including literacy, numeracy, executive functioning, and social and emotional skills.

## The Development of Learning Tree to Supplement an Accelerated Learning Response to the Emergencies in 2020-2021 in Pakistan

Although Pakistan has seen a substantial increase in access to education in recent years, serious challenges remain. Pakistan has the second-highest number of out-of-school children in the world, an estimated 25.1 million, or 35 percent, of children ages 5-16 (UNICEF 2026). Conflict and natural disasters across the country have exacerbated this challenge, driving displacement and limiting the government's ability to provide education effectively. There are disparities in education access based on gender and socioeconomic status: 55 percent of children from the poorest quintile are out of school, and 54 percent of out-of-school children are girls (EPDC 2012; Faran and Zaidi 2021). There also are stark regional disparities; three-quarters of out-of-school children in Pakistan reside in rural areas (Faran and Zaidi 2021). There is a pronounced gendered digital divide in terms of access to technology in Pakistan, where 22 percent of women have internet access, compared to 47 percent of men; only 50 percent of women own a mobile phone, compared to 81 percent of men (Akram 2023). Rural areas have even lower adoption of digital technology; only 7 percent of women have access to the internet, compared to 20 percent of men.

The Sindh province of Pakistan has the second-highest rate of out-of-school children in Pakistan, where 7.6 million children are out of school (UNICEF 2026). To respond to these challenges, Save the Children has been running an accelerated learning program for girls in the Shikarpur District of Sindh since 2018. Fifty nonformal Accelerated Learning Centers (ALCs) operate in rural areas to provide education to out-of-school girls from low-income households. The ALCs are girls-only learning centers with female teaching staff. The aim of the centers is to help girls to overcome inequalities in education and reach their age-appropriate learning level.

The existing challenges of access to education for girls in Pakistan were complicated further in 2020 and 2021, when unprecedented disruption was caused by the COVID-19 pandemic and a series of major floods, earthquakes, landslides, and avalanches. Schools in Pakistan closed in March 2020 and remained closed on and off until September 2021. School closures drove up dropout rates and caused significant learning loss in Pakistan. These effects were more pronounced for girls and low-income households (Khan and Ahmed 2021). Low-income households also had far fewer options for accessing remote learning (Nagesh et al. 2022).

In response to these challenges, Save the Children sought to supplement its nonformal accelerated learning programming for crisis-affected girls in rural areas of the Shikarpur District. The hope was that this tool, Learning Tree, would accelerate education remediation and enable children to overcome education inequalities more quickly. Learning Tree is a mobile-based application designed to facilitate structured learning by engaging children, caregivers, and teachers (Brown and Krupar 2024). The tool was designed to stimulate learning by providing opportunities for girls to engage independently in educational activities using the application, with the support of teachers or caregivers at home. The aim was that the EdTech platform would lead to additional gains in learning remediation in literacy, numeracy, executive functioning, and social emotional skills, and thereby enable children to catch up to their age-appropriate levels more rapidly. Learning Tree uses the Return to Learning curriculum content developed by Save the Children, which focuses on SEL, literacy, and numeracy skills. To ensure that children can access the tool where mobile internet connections are scarce or prohibitively expensive, the platform can be used offline.

The Learning Tree mobile-based application was piloted in 25 of the 50 ALCs as an afterschool supplement to in-person nonformal education. It was provided to out-of-school girls ages 11-14 in the ALCs in rural areas of Shikarpur District. Given the challenges of the digital divide with the target population, Save the Children staff members worked with caregivers to register their children to use the application and provided ongoing support. Teachers in the intervention group of ALCs were given training, and they in turn provided on-site technical support to teachers and caregivers to resolve the issues and challenges they faced.

During the Learning Tree rollout, the implementers observed that ALC teachers and caregivers provided after-hours support to the children and caregivers using the application. Teachers provided support in person, by working with children at the ALCs to explain the app and providing ongoing troubleshooting, or by visiting students' family homes to provide support. Teachers also provided support to students remotely through phone calls, SMS, WhatsApp, or social media.

The following sections present results on the effectiveness of Learning Tree a supplementary tool used in nonformal education for girls in a low-resource emergency setting. We specifically analyze whether the tool, when compared with conventional emergency accelerated education measures, resulted in additional gains in literacy, numeracy, executive functioning, and SEL.

## METHODS

The key research question in this study was whether the Learning Tree EdTech tool led to greater learning gains for girls ages 11-14 who were enrolled in an accelerated learning program in the Shikarpur District of Sindh, in Pakistan, than the gains measured for those who participated in the accelerated learning program alone. To answer this question, we employed a longitudinal, quasi-experimental design that involved 483 children enrolled across 50 ALCs.

For ethical and methodological reasons, the unit of treatment assignment was at the ALC level rather than the individual level. Assigning treatment at that level ensured that all children in the same school had equitable access to Learning Tree, which prevented perceived unfairness and reduced the potential for social tensions. Cluster-level assignment also helped minimize contamination and spillover effects by limiting the likelihood that students exposed to the tool would share devices, information, or learning strategies with peers in a different condition.

A cluster-randomized design was not feasible, due to the risk of geographic proximity between treatment and comparison centers. We instead undertook a purposive selection of ALCs to ensure sufficient spatial separation between groups, thereby reducing the risk of contamination. While this approach strengthened the feasibility of implementation and internal validity regarding spillover, it may introduce baseline differences between treatment and comparison groups that require adjustment in the analysis.

Twenty-five of the ALCs were assigned to receive the Learning Tree to complement their regular learning activities, while the other half provided a comparison by continuing with their regular ALC activities. To assess changes over time, data on student learning and household characteristic were collected for a sample of 501 children enrolled in the 50 ALCs before Learning Tree was rolled out in September-October 2021, and again in February 2022, four months into the implementation. The student learning measure we used was the Holistic Assessment of Learning and Development Outcomes (HALDO), which assessed the literacy, numeracy, executive functioning, and social emotional domains (Krupar and D'Sa 2024).

This study was approved by the ethics review committee at Save the Children. The enumerators obtained informed consent from caregivers and assent from the children before any data was collected.

## Measures

The learning outcomes of girls ages 1-14 in an emergency setting in Pakistan were the primary interest in this study. These were measured with HALDO, a multidimensional instrument designed to assess children's diverse learning needs during emergencies, which has been psychometrically validated in LMICs (Krupar and D'Sa 2024). The instrument assesses literacy, numeracy, SEL, and executive functioning for children ages 4-16 by asking them a series of questions sourced from such measures as the International Development and Early Learning Assessment, the International Social and Emotional Learning Assessment, and the Literacy Boost and Numeracy Boost assessment. Table 1 presents the domains measured in HALDO, and the individual items covered in each domain.

The HALDO tool measures literacy using questions on letter identification, expressive vocabulary, the accuracy of an oral reading of a grade-2 passage, and reading comprehension. Numeracy is measured through one-to-one correspondence by counting objects, one- and two-digit number identification, one- and two-digit addition and subtraction, and word problems. SEL is measured through items on self-concept and empathy. Self-concept refers to children's understanding of themselves, including knowledge about their current identity—name, age, gender, caregiver name, community name, and the name of the country they live in; their ability to envision two different futures for themselves; and their ability to identify supportive influences and obstacles each future would hold for them.

These questions progress in difficulty and include skip logic, which means that, if a child cannot appropriately respond to questions about a possible future, obstacles, or supports, all remaining questions are skipped. Empathy refers to children's ability to identify the feelings and experiences of others, how those feelings relate to a situation, and how they respond to another child's feelings. Empathy questions are scored using a binary of locally defined appropriate or inappropriate responses, which then are aggregated as a percentage of five possible appropriate responses. Executive functioning includes items that measure short-term and working memory by utilizing digit recall and backwards digit recall. An average percentage correct score can be presented for a student for each domain, along with an aggregate HALDO measure constructed as an average of the domain items. Psychometric testing in emergency settings in Uganda, Kenya, and Lebanon affirms that the literacy, numeracy, SEL, and executive functioning domains measure their hypothesized constructs, that enumerators administered the tool reliably, and that the items consistently measured similar constructs (Krupar and D'Sa 2024).

*Table 1:* Domains, Skills, and Item Descriptions of the Holistic Assessment of Learning and Development Outcomes (HALDO) Tool

| Domain | Skill | Items |
|---|---|---|
| **Literacy** | Letter identification | Identify 5 letters common letters |
| | | Identify 5 letters infrequent letters |
| | Expressive language | Name 10 animals (only asked if child cannot identify any common letters) |
| | Accuracy | Number of words read correctly |
| | Reading with comprehension | Respond to 5 comprehension questions |
| **Numeracy** | Number identification | Identify 4 single-digit numbers presented visually |
| | | Identify 4 double-digit numbers presented visually |
| | One-to-one correspondence | Understand concept of different numbers related to objects (3 items) (only asked if child cannot identify any single-digit numbers) |
| | Simple operations | Complete 4 simple numerical operations with single-digit numbers |
| | Hard operations | Complete 4 harder numerical operations with two-digit numbers |
| | Word problems | Complete 2 numerical problems from a verbal word problem |
| **Social Emotional Learning** | Self-concept | Knowledge of name, age, sex, community name, country name |
| | | Ability to identify positive hope(s) for future, what could support and stop this future |
| | Empathy | Ability to identify how someone else might be feeling |
| | | Ability to show empathy |
| | | Ability to take the perspective of a third child in an ambiguous situation |
| | | Tendency to not attribute hostility to ambiguous provocation |
| **Executive Functioning** | Short-term memory | Ability to remember 4 number sequences |
| | Working memory | Ability to remember and reverse 4 number sequences |

Data was also collected on the children's key background characteristics, including age, socioeconomic status, the home learning environment, disability status, and whether they were multilingual. Socioeconomic status was measured as an index of the presence or absence of ten household wealth assets in the children's homes, including electricity, bicycle, radio, mobile phone, tin roof, cement floor, television, motorcycle, goats/cows/chickens, and a computer. The home learning environment was measured as an average of two binary variables—whether there were books in the house and whether the child had seen someone reading in their home. The prevalence of disabilities was identified by children's self-reported difficulties with functional vision, hearing, and physical movement, using the Washington Group Short Set on Functioning (Sloman and Margaretha 2018). Multilingualism was defined as speaking a language other than Sindhi at home, and was identified in consultation with the parent or caregiver. Collecting background data on children enables baseline checks to assess the balance between groups and facilitates the specification of more robust multivariate regression models, factors that are likely related to the learning outcomes.

We expected higher socioeconomic status and households with more books or reading at home to be positively correlated with learning outcomes, as these factors often give children greater access to educational resources, support, and opportunities. Older children usually exhibit higher learning outcomes, as they often are more mature, have more opportunities for cognitive development, and more advanced brain development. Disability is often associated with lower learning outcomes, due to barriers to access, insufficient accommodations, and the additional challenges of navigating low-resource education environments without adequate support. Multilingualism as defined here positions students as a linguistic minority within the education setting. This is often associated with lower learning outcomes due to language barriers, reduced comprehension of instruction, and potential social or cultural marginalization.

## Study Sample

The sample frame for this study was the 1,360 girls, ages 11-14, who were enrolled across 50 ALCs run by Save the Children in the Shikarpur District of Sindh, Pakistan. We used a quasi-experimental sampling approach, including a purposive selection of treatment and comparison ALCs based on geography to minimize contamination and spillover effects, and a random sampling of students within the clusters. Half of the 50 ALCs were purposively assigned to a treatment arm, which received the Learning Tree EdTech tool; the other half were assigned to continue their regular activities to serve as a comparison. The sample size was calculated using the Optimal Design software package, based on several key parameters to ensure a representative sample that balanced statistical rigor and the feasibility of data collection within the study constraints. We assumed a Minimum Detectable Effect of 0.2 standard deviations ($\Delta = 0.2$), corresponding to a small effect size for learning outcomes. The significance level ($\alpha$) was set at 0.05 for a two-tailed test, and the desired power ($1-\beta$) was 0.80, ensuring an 80 percent probability of detecting the effect size, if it exists. To account for the clustered design, we assumed an intraclass correlation coefficient (ρ) of 0.10, accounting for some expected similarity of learning outcomes within schools. An average of ten students was randomly sampled within each cluster (ALC); the total number of clusters was 50, with 25 clusters per treatment arm. Within these parameters, the suggested total sample size calculated was 373 participants. Given the risk of attrition over time, we increased the target sample size to 502 participants, with 251 in each treatment arm.

We collected data from 50 ALCs located in Shikarpur beginning in September 2021. After these ALCs had been randomly allocated to treatment and control, a random sample of ten students was selected to participate in the study. They were stratified by age to ensure a balance of children ages 11 to 14. In terms of attrition, one student was lost to follow-up at endline and another 18 were dropped from the analysis due to incomplete or missing data. This represented a 3.8 percent attrition rate between baseline and endline, leaving a total sample of 483 (246 intervention and 237 control), which was still much larger than the required sample size calculated for the study.

## Analytical Approach

To test the hypothesis that implementing Learning Tree in ALCs would result in greater learning gains for students than those in regular ALCs without the EdTech component, the study specified a multivariate regression model; the dependent variable was learning outcome gains over the four-month period. Given the clustered treatment assignment in our study, robust standard errors were clustered at the school level. This approach accounts for potential intracluster correlation among students within the same school, which ensures valid statistical inference even when student outcomes may be correlated, due to shared school characteristics such as teacher quality or available resources.

Given that ALCs were assigned purposively rather than randomly, it was important to adjust statistically for baseline imbalances and for covariates known to be strong predictors of learning outcomes. The study sought to address observed imbalance in multilingualism and disability prevalence by including these variables as covariates in the regression model specification. Interaction tests between treatment and these imbalanced variables revealed no significant heterogeneity in the treatment effect, which supported the decision to exclude interaction terms and focus on the main effects. We also included learning outcomes at baseline as a covariate to control for initial differences between students and account for correlations between baseline scores and the observed gains in learning outcomes. Socioeconomic status (as measured by the household asset index) and household learning environment (reflecting the availability of books at home and the presence of literate family members) were also included as covariates, as they are well-established determinants of learning outcomes in education research (Filmer and Pritchett 2001; Evans et al. 2010; Brown and Park 2002).

Overall, this model specification reduces the risk of confounding and provides more credible estimates of the association between exposure to the EdTech intervention and observed improvements in learning outcomes. The multivariate regression analysis for this model was run in STATA 16.1, with robust standard errors clustered by ALC, for literacy, numeracy, SEL, and executive functioning outcomes, as measured by the HALDO learning measure. The final model is specified as follows:

$$\Delta Y=\beta_0+\beta_1\ \text{Treatment}+\beta_2\ Y_{\text{baseline}}+\beta_3\ \text{Age}+\beta_4\ \text{SES}+\beta_5\ \text{HLE}+\beta_6\ \text{Multilingual}+\beta_7\ \text{Disability}+\epsilon$$

Where:

- $\Delta Y$: Gain in learning outcomes (e.g., post-test score minus pre-test score)
- Treatment: Indicator for the EdTech intervention used in ALCs
- $Y_{\text{baseline}}$: Learning outcome result at baseline (before intervention)
- Age: Age of the student (in years)
- SES: Socioeconomic status, measured using a household asset index (e.g., count of items owned out of a possible 10)
- HLE: Home learning environment, reflecting the availability of books at home and whether family members read at home
- Multilingual: Indicator for multilingual status (speaks a language other than Sindh)
- Disability: Indicator for disability status (difficulty with vision, hearing, or movement)
- $\epsilon$: Error term
- $\beta_0$: Intercept (constant term)
- $\beta_1$-$\beta_7$: Estimated coefficients for each explanatory variable

To quantify the magnitude of these gains, the study used predicted values from the regression model to estimate an EdTech multiplier. This quantified how much greater the learning gains were for those receiving Learning Tree than for those who participated in conventional ALC activities. The control group's learning gains were estimated as the predicted outcomes for students in the non-EdTech sample (treatment = 0). The regression coefficient (B1), as discussed above, represents the learning gains attributable to the EdTech intervention that were greater than those achieved through participation in conventional ALC activities. The total treatment effect, then, is the learning gains generated by the combination of ALC and EdTech activities. This enabled us to calculate the EdTech multiplier as the ratio of the total treatment effect (EdTech + ALC) to the control group gains (ALC only). By relying on regression-based estimates, this approach ensured consistency and robust adjustment for baseline differences, covariates, and clustering effects.

# RESULTS

## Sample Characteristics and Baseline Test

When examining the study sample, we found a group of girls with an average age of about 12 who had approximately four out of the ten household assets listed in the household asset index. They had relatively positive home learning environments, with more than 90 percent reporting that they have books in the home and around 65 percent reporting having a family member who reads at home. Although a majority spoke Sindhi as their first language, around 15 percent spoke an additional language at home, which positioned them as a linguistic minority within the education setting. Only a small proportion of the students in the study were identified as disabled, meaning they had difficulty seeing, hearing, or moving. In terms of learning outcomes, girls enrolled in the study were answering around 60 percent of all learning outcome questions correctly before the intervention began.

We now present a baseline balance test of household characteristics and learning outcomes to assess differences between the intervention group, who were enrolled at an ALC that utilized Learning Tree, and the control group, who were enrolled at an ALC without the intervention. Table 2 shows the baseline values for both groups and tests their difference with an independent t-test. Girls in each group were of a similar average age and socioeconomic status, as measured by the household asset index. Home learning environment, a measure that combines two subitems (books in the home, a family member reads at home), was also comparable between the control and treatment groups. The difference appeared to be driven by a higher incidence of family members reading at home in the intervention group, but a t-test revealed that this difference was not significant. Disability prevalence, as measured by difficulty seeing, hearing, or moving, was slightly higher in the intervention group. However, a correlation check revealed no significant relationship between disability status and learning outcomes, which suggests that the imbalance in disability status is unlikely to create systematic bias in the observed differences in learning gains between the intervention and control groups. The control group was found to have a higher proportion of multilingual students than the intervention group, and a correlation check revealed a significant relationship between this and learning outcomes. These minority language students were found to have lower learning outcomes, which was likely driven by the mismatch between the language of instruction and students' native languages, and their having limited access to educational resources and peer interactions.

Students in the control group were found to have lower performance for the overall HALDO measure, as well for literacy, numeracy, and executive functioning. SEL measures at baseline were comparable between the two groups; however, these differences were relatively small, significant only at the 0.05 level. Further correlation analysis indicated that this difference may have been driven by the disproportionately greater number of multilingual students in the control group (20.7%) than in the intervention group (10.5%). A sensitivity analysis was conducted that excluded multilingual students from the sample, which eliminated the baseline differences in learning outcomes between the two groups. To address this potential confounding factor in the analysis, both multilingual status and baseline learning outcomes are included as covariates in the regression model specified below, ensuring that treatment effect estimates were adjusted for differences in linguistic background. This approach will help to isolate the impact of the intervention itself, independent of the influence of multilingualism.

*Table 2:* Baseline Values for Key Demographic Variables

| | Intervention | Control | Difference |
|---|---|---|---|
| **Background Variables** | | | |
| Age (years) | 11.9 | 11.6 | + 0.2 |
| Household asset index (# items) | 3.90 | 3.84 | + 0.06 |
| Home learning environment (average proportion reporting books in home and literate household members) | 79.7% | 77.2% | + 2.5% |
| Any books in the home | 91.0% | 91.5% | - 0.5 % |
| Anyone reading at home | 68.3% | 62.9% | + 5.4% |
| Disability (%) | 3% | 2% | +1%** |
| Multilingual (%) | 10.5% | 20.7% | -10.1%** |
| **Learning Outcomes** | | | |
| Literacy | 61.7% | 54.5% | +7.2%* |
| Numeracy | 63.3% | 57.3% | +6.0%* |
| Executive functioning | 64.1% | 58.7% | +2.6%* |
| SEL | 65.9% | 63.7% | +2.2% |
| HALDO (overall) | 64.7% | 60.7% | +4.0%* |
| N | 246 | 237 | 483 |

*Note:* * = $p < .05$; ** = $p < .01$; *** = $p < .001$

## Impact on Child Learning and Development

### Descriptive Results

Learning outcome results, as measured by HALDO, are summarized in Table 3 for both time periods and treatment arms to demonstrate learning gains over the study period. Before the intervention was rolled out, the 11- to 14-year-old girls who enrolled in ALCs that did not receive the EdTech intervention were able to correctly answer 54 percent of the literacy questions, 64 percent of the SEL questions, 57 percent of the numeracy questions, and 59 percent of the executive functioning questions. When the HALDO tool was administered four months later, learning outcomes had improved significantly, with students able to correctly answer 63 percent of the literacy questions, 87 percent of the SEL questions, 66 percent of the numeracy questions, and 72 percent of the executive functioning questions. The sizeable improvements in student outcomes occurred over a relatively short time, which indicates that the ALCs were effectively accelerating the learning of girls who had experienced multiple emergencies.

Descriptive results indicate that the students enrolled in the ALCs offering the Learning Tree intervention experienced significant learning gains that were larger than those experienced by girls in the control group over the same time period. At baseline, students enrolled in ALCs assigned to receive the EdTech intervention correctly answered 63 percent of the literacy questions, 67 percent of the SEL questions, 64 percent of the numeracy questions, and 65 percent of the executive functioning questions. As indicated above, the intervention baseline values were significantly higher in the treatment group than in the control group for all learning domains, except SEL. The study found considerably larger learning gains for the EdTech group over the same four-month period; their overall HALDO scores increase by 29 percentage points, compared to the 17.1 percentage point gain seen in the control group. Literacy scores increased by 31 percentage points, compared to 10; numeracy by 25 percentage points, compared to 10; executive functioning by 28 percentage points, compared to 14; and SEL by 30 percentage points, compared to 23. After four months, students in the EdTech group were able to answer 94 percent of the HALDO questions correctly, compared to 78 percent in the control group (Table 3). These descriptive findings provide evidence that the EdTech intervention generated additional gains in learning for girls enrolled in an accelerated learning program in Shikarpur. However, to come up with a more precise estimate of the differential impact of Learning Tree, incorporate clustering effects, and address the baseline imbalances identified above, we specify a multivariate regression model that allows us to formally test our hypothesis.

*Table 3:* Gains in Learning Outcomes Over a Four-Month Study Period, Stratified by Treatment Arm

| Learning Domain | Treatment Arm | Baseline | Endline | Learning Gain |
|---|---|---|---|---|
| **Literacy** | Intervention | 61.7% | 93.1% | +31.4% |
| | Control | 54.5% | 64.7% | +10.2% |
| **Numeracy** | Intervention | 63.3% | 88.4% | +25.1% |
| | Control | 57.3% | 67.4% | +10.1% |
| **Executive functioning** | Intervention | 64.1% | 92.3% | +28.2% |
| | Control | 58.7% | 72.8% | +14.1% |
| **SEL** | Intervention | 65.9% | 95.8% | +29.8% |
| | Control | 63.7% | 87.1% | +23.4% |
| **HALDO (overall)** | Intervention | 64.7% | 93.8% | +29.1% |
| | Control | 60.7% | 78.4% | +17.7% |

## Modeled Results

The multivariate regression results are summarized in Table 4. They show that the EdTech intervention is associated with significantly improved learning outcomes across the four learning domains, with students in the treatment group experiencing higher average learning gains than those who participated in regular ALC activities. Specifically, holding other factors constant, literacy gains for the children in the intervention group were 27.6 percentage points higher, numeracy gains were 21.2 points higher, executive functioning gains were 19.0 points higher, and SEL gains were 8.8 points higher than those of children in the control group. Overall, learning and development improved by 15.1 percentage points more when the EdTech intervention was used alongside the accelerated learning activities. Baseline learning outcomes had a strong and significant negative association with learning gains over the four-month study period, which was consistent with the regression-to-the-mean relationship in the educational literature, where students with higher initial scores tended to show less improvement over time. Other variables, including socioeconomic status, age, home learning environment, multilingual status, and disability status, did not exhibit significant relationships with learning gains in this model.

*Table 4:* Regression Model Applied to All Learning and Development Domains

| | Literacy Skill Gains | Numeracy Skill Gains | EXF Skill Gains | SEL Skill Gains | HALDO Overall Gain |
|---|---|---|---|---|---|
| **Intervention (Learning Tree)** | 0.276*** | 0.212*** | 0.190*** | 0.088*** | 0.151*** |
| | (0.053) | (0.029) | (0.038) | (0.025) | (0.024) |
| **Child's age** | 0.015 | 0.015* | -0.005 | 0.009 | 0.006 |
| | (0.013) | (0.007) | (0.011) | (0.007) | (0.005) |
| **SES (household asset index)** | 0.020 | 0.064 | 0.112 | 0.064 | 0.069 |
| | (0.089) | (0.045) | (0.061) | (0.048) | (0.042) |
| **Home learning environment** | 0.047 | 0.052 | 0.000 | 0.018 | 0.016 |
| | (0.062) | (0.056) | (0.035) | (0.050) | (0.042) |
| **Multilingual status** | -0.065 | 0.011 | -0.039 | 0.003 | -0.014 |
| | (0.079) | (0.033) | (0.034) | (0.039) | (0.036) |
| **Disability/Difficulty** | 0.044 | -0.013 | 0.032 | 0.018 | 0.024 |
| | (0.035) | (0.024) | (0.030) | (0.022) | (0.014) |
| **Baseline learning outcome value** | -0.983*** | -0.966*** | -1.009*** | -0.990*** | -0.967*** |
| | (0.057) | (0.042) | (0.037) | (0.038) | (0.042) |
| **Constant** | 0.432* | 0.405*** | 0.755*** | 0.712*** | 0.655*** |
| | (0.183) | (0.111) | (0.126) | (0.094) | (0.075) |
| **N** | 483 | 483 | 483 | 483 | 483 |

*Note:* ~ $p < 0.10$, * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

The results of the Edtech multiplier estimation indicate that the addition of the EdTech component is associated with a doubling of overall learning and development gains experienced by girls who engaged in routine accelerated learning activities, as measured by the aggregate HALDO score. As Table 5 shows, literacy gains improved by a factor of five when the Learning Tree was used in ALCs, and numeracy gains by a factor of four. Adding EdTech was associated with an improvement in executive functioning by around two and a half times, and SEL was improved by approximately one and a half times.

*Table 5:* Estimating EdTech Learning Multiplier Using Predicted Values from the Regression Model

| Learning Domain | ALC Only Learning Gains (predicted) | Additional Impact of EdTech (B1) | Total Treatment Effect (EdTech + ALC) | EdTech Multiplier |
|---|---|---|---|---|
| **Literacy** | 6.9 % | 27.6 % | 34.5% | 5.0x |
| **Numeracy** | 6.9% | 21.2 % | 28.2% | 4.1x |
| **Executive functioning** | 11.6% | 19.0 % | 30.6% | 2.6x |
| **SEL** | 22.2% | 8.8% | 31.0% | 1.4x |
| **HALDO overall** | 15.8% | 15.1% | 30.9% | 2.0x |

## DISCUSSION

In this article, we present new empirical evidence on the effectiveness of a mobile-based EdTech tool in supplementing accelerated learning programs. Conducted with a population of girls in an emergency setting in an LMIC, this study fills important knowledge gaps in the literature. This adequately powered, quasi-experimental study contributes to an underresearched area, as it was specifically designed to estimate the added benefit of integrating EdTech tools into existing emergency education programming.

This study offers several methodological and substantive strengths. First, it uses a longitudinal design with repeated measures, which allows the estimation of learning gains rather than relying solely on cross-sectional outcomes. Second, random sampling of students within clusters enhances internal validity and supports unbiased estimation of effects at the learner level. Third, learning outcomes were measured across multiple domains, including literacy, numeracy, executive functioning, and SEL skills, which provides a more holistic assessment of learning and development than is typical in emergency education research. Finally, the evaluation was conducted with a hard-to-reach population of adolescent girls who were affected by crises in rural Pakistan. It has generated rare empirical evidence from a context where rigorous studies on learning impact are limited.

The main limitation of the study was the purposive allocation of schools to treatment and comparison conditions, which introduced a risk of unobserved confounding. This approach was selected for ethical and practical reasons, including the need to minimize contamination and spillover effects within shared and geographically concentrated learning environments. To manage this limitation, we used statistical adjustment for baseline differences and key covariates to reduce the potential for bias. The resulting treatment and comparison groups were well balanced along most observed background characteristics, although baseline balance tests revealed differences in multilingualism, disability prevalence, and learning outcomes. Correlation checks and sensitivity analyses revealed that the differences in learning outcomes appear to be driven by differences in multilingualism, which was then included as a covariate, along with disability prevalence and baseline learning outcomes in the multivariate regression model. This analytical strategy mitigates the potential confounding influence of these imbalances; however, omitted variable bias cannot be ruled out, and unmeasured factors may still have influenced the results. Future research using randomized assignment, larger samples, and additional covariates such as school-level characteristics or parental education would help validate these findings and enhance generalizability.

Another potential limitation of the study was the potential influence of regression-to-the-mean phenomenon, as the intervention group had higher baseline learning outcomes than the comparison group (Barnett, van der Pols, and Dobson 2005). However, any bias introduced likely would have attenuated the estimated treatment effect rather than inflating it, as children with higher baseline scores typically show less improvement due to ceiling effects; this limits their measurable growth more than that of lower-performing peers. Therefore, the observed positive and significant treatment effect can be considered robust and unlikely to have resulted from preexisting differences in performance between groups.

Taken together, the study's design features and strategies to address limitations lend confidence to the finding that introducing the Learning Tree tool is associated with significantly increased learning gains among crisis-affected girls ages 11 to 14, who were enrolled in an accelerated learning program in rural Pakistan in the wake of COVID-19 and a series of natural disasters. These results provide evidence that mobile-based EdTech tools can effectively supplement accelerated learning for girls during emergencies in low-resource settings, which can help to generate significantly higher learning gains across domains than those seen by conventional accelerated learning measures. These results highlight the potential of EdTech interventions that are locally tailored and rolled out effectively with stakeholders to promote learning and, as such, to close education gaps for vulnerable children experiencing emergencies in LMICs.

The significant and positive results observed for SEL are of particular interest, given the inherent challenges of improving social and emotional skills via a mobile application with limited direct interpersonal interaction and hands-on engagement. While more modest than the gains for other learning domains, ceiling effects were likely at play, as the ALC was already highly effective in improving SEL relative to the other learning domains. These novel results highlight the potential of EdTech tools to complement existing emergency programs, even in areas traditionally dependent on in-person interactions.

The findings in this article surface several implications for emergency education programming in low-resource settings. First, mobile-based EdTech tools can be deployed as an efficient supplemental modality to extend instruction time and reinforce foundational skills when teacher capacity, contact hours, or learning materials are limited. Second, pairing EdTech with existing accelerated learning programs may offer an effective approach to narrowing learning gaps for crisis-affected adolescent girls, a group often at risk of permanent dropout. Third, the relatively low infrastructural requirements of the tool tested here indicate the potential feasibility for scale in similar rural contexts, where connectivity is intermittent but mobile phone access is growing. Effective implementation, however, will require collaboration with local stakeholders, contextual adaptation of the content, and continued investment in inclusive designs to ensure accessibility for learners with diverse needs. These considerations can support humanitarian and development actors in determining where and how mobile-based EdTech can complement existing EiE interventions to sustain learning continuity during crises.

## RESEARCH ETHICS APPROVAL

The study was submitted to Save the Children's Ethics Review Committee and granted ethics approval (SCUS-ERC-FY2021-100) in October 2021, prior to data collection.

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