

Scaling Personalized Adaptive Learning (PAL) for Math and Language in India

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Sector(s): Education

Location: Rajasthan, India (Churu, Jhunjhunun, Udaipur, and Dungarpur districts)

Sample: 80 schools

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Partner organization(s): Government of Rajasthan, Educational Initiatives (EI), Global Innovation Fund, United Kingdom Foreign, Commonwealth & Development Office, Australian Department of Foreign Affairs and Trade (DFAT), Gates Foundation

Many education interventions that prove effective in small-scale randomized evaluations often fail when scaled up. Researchers conducted a randomized evaluation to test the impact of a personalized adaptive learning software integrated into public school schedules on student learning outcomes in Rajasthan, India. After 18 months, students in schools that received the intervention scored higher in math and Hindi relative to students in comparison schools.

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Driven by a goal of improving people's lives by identifying promising interventions and scaling them up, the number of randomized evaluations in economics has increased rapidly in recent decades. However, many programs that “work” in small studies are not effective when implemented at scale, even in the same place or within similar institutions.

Effectively scaling promising interventions requires addressing issues that emerge when programs are implemented at larger levels. Personalized adaptive learning software, which uses data to tailor content to each student and adapt as they progress, is one such intervention. Can a computer-based personalized adaptive learning software that was effective in a small evaluation be successfully adapted and integrated into public schools to improve learning outcomes at scale?

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This study took place in four districts of Rajasthan, India across rural and urban areas. In Rajasthan, educators face significant challenges teaching students with widely varying learning levels within the same classroom. At the time of the study, the average grade 8 student was performing at about a grade 4 level in math, with students in the same grade ranging from grades 2–8 skill levels. This variation makes it difficult for teachers to cater to all students using a common approach based on grade-level textbooks.

The intervention being evaluated was an adaptation of Mindspark, a computer-based personalized adaptive learning software that had previously increased student test scores in a small-scale randomized evaluation. However, the previous implementation was conducted in out-of-school centers, after school hours, and with a group of students who expressed interest in the program, making it difficult to scale.

The current study aimed to adapt this promising technology for implementation within the regular school day in public schools. The researchers partnered with Adarsh schools, which tend to have better infrastructure than stand-alone public primary schools in India and are therefore well positioned to implement educational technology interventions.

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Researchers partnered with Educational Initiatives and the Government of Rajasthan to conduct a randomized evaluation to test the impact of integrating personalized adaptive learning software into public school schedules on student learning outcomes. The researchers randomly assigned 80 Adarsh schools (about 6,500 students) to either an intervention or comparison group:

1. Intervention group (40 schools): Each school had a Mindspark computer lab and a locally-based laboratory in-charge (LIC) to maintain the hardware and help students log in. Schools modified their timetables to replace around 25 percent of weekly math and Hindi instructional time in primary schools and around 40–50 percent of regular classroom time in middle schools with "computer lab" periods where students studied math and Hindi on the Mindspark platform. Teachers accompanied students to the lab to answer questions and manage the class. When the number of students exceeded available computers, two students of the same gender and similar test scores shared a computer.
2. Comparison group (40 schools): These schools continued with their regular instruction without being offered the Mindspark software or computer labs.

The researchers collected data on student learning using independently designed and administered tests in math and Hindi at the start of the evaluation and around the end of each school year. They also collected data on software use in intervention schools, observed classroom practices, and conducted interviews of students and teachers.

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The integration of personalized adaptive learning software into public school schedules improved student learning outcomes in both math and Hindi. The intervention also demonstrated that technology-enabled personalized instruction can be effectively implemented within the school day and at scale in public schools.

Learning outcomes: After 18 months, students in intervention schools scored 0.22 standard deviations higher in math and 0.20 standard deviations higher in Hindi compared to students in comparison schools. These additional gains represented approximately half of the comparison group's total learning gains in math and two-thirds in Hindi over the same period, suggesting a 50–66 percent improvement in the productivity of schooling time. The program produced similar effects across primary and middle school grades, and the results did not vary by gender, socioeconomic status, or initial test scores.

Personalized learning: The intervention helped address the wide variation in student learning levels within the same classroom. Students with higher initial scores made larger gains on challenging questions, whereas students with lower initial scores did better on easier questions, in line with the personalized nature of the software. In addition, the gap between students' assessed learning levels and grade-level standards decreased over time in intervention schools.

School examinations: Despite learning gains on independently administered tests, the intervention had no effects on school exam scores in math or Hindi. This is likely because Mindspark was geared toward students' true learning levels rather than their grade level. Additionally, less class time for grade-level teaching may also explain the lack of improvement in school exams.

Classroom practices: Time devoted to Mindspark did not disrupt standard classroom practices. After two years, teachers in intervention schools had adjusted to having less instructional time: they went through material faster and spent less time on revision. Both teachers and students found Mindspark helpful, with little resistance to continue using it.

Cost-effectiveness: The in-school program was twice as cost-effective as the program studied in the earlier randomized evaluation, which was conducted after school. The program achieved higher cost-effectiveness by using computers more efficiently, avoiding rental costs for outside locations, and operating during school hours with regular teachers.

Implementation quality: As students spent more time on the Mindspark platform, their learning outcomes improved accordingly, offering a simple, low-cost way to track implementation quality as the program scales up. When LIC staffing was reduced in the third year of the program, Mindspark use initially declined but recovered after implementers received this early warning and worked with schools to address challenges.

Use of Results: The implementation procedures evaluated in this study have contributed to scaling up of personalized adaptive learning in public schools across India, with Mindspark operating in over 2,200 government schools, serving more than 266,000 students across thirteen Indian states, as of 2024-25.

Muralidharan, Karthik and Abhijeet Singh. "Adapting for Scale: Experimental Evidence on Technology-Aided Instruction in India." NBER Working Paper #34205, November 2025.