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Abstract*

Self-led educational technologies have the potential to improve student learning at scale, but sustaining student engagement with these platforms remains a challenge. We present results from an experimental evaluation implemented following the scale-up of a math platform in Peru, where primary school teachers received weekly WhatsApp messages summarizing their students' platform activity and encouraging them to promote their students' engagement. The messages increased the average weekly share of students using the platform by 5 percentage points (a 17% increase) and the average share of math exercises completed by 4 percentage points (a 16% increase). Effects dissipated once the messages stopped, suggesting that salience and simplified monitoring are likely mechanisms. We find little evidence of impact heterogeneity based on teacher characteristics or students' prior platform use and achievement. Non-experimental evidence suggests that increased use of the student math platform improved math learning. Overall, our findings indicate that light-touch communication with teachers can cost-effectively strengthen engagement with EdTech platforms scaled through the education system.

JEL Classifications: I21, I25, D91
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1. Introduction

Educational technologies (EdTech) have generated excitement about their potential to improve student learning, particularly in low- and middle-income countries, where challenges such as low learning levels, diverse student readiness, and high student–teacher ratios are common (Ganimian and Djaker, 2022; World Bank, 2023). EdTech can support self-directed learning, complement classroom instruction, and offer additional practice beyond school hours at low marginal cost. While growing evidence shows that EdTech can boost academic performance when appropriately used (Escueta et al., 2017; Rodriguez-Segura, 2022), sustaining student engagement remains a significant challenge, particularly when use is optional (Banerjee and Duflo, 2014; Kizilcec et al., 2020; Asanov et al., 2023). As digital learning tools become increasingly embedded in national education strategies (Cristia et al., 2022; Rajasekaran et al., 2024), realizing their full potential will require identifying cost-effective, scalable solutions that help students consistently incorporate them into their learning routines.

This paper investigates whether sharing classroom-level engagement information with teachers influences students' sustained use of educational tools. Teachers are central to the learning process and represent a natural leverage point for encouraging students, particularly younger ones who are more difficult to reach directly and often require greater support, to persist in self-directed learning. In practice, however, several barriers may limit the effectiveness of low-touch, teacher-focused approaches. First, teachers may have already optimized their use of supplementary learning tools, leaving limited scope for additional messages to alter their practices. Second, even when behavior can be influenced, teachers may be overburdened, face competing demands, or be unresponsive to simple messages absent stronger incentives. Third, even if teachers do respond, students might not act on the encouragement.

To evaluate whether this type of teacher-facing messaging can improve student engagement with complementary learning tools, we conduct a randomized controlled trial with 853 teachers of grades 4 through 6 in Peru. All participating teachers had at least one student actively enrolled in Conecta Ideas, a digital math platform recently scaled nationally by the Ministry of Education. Teachers were randomly assigned to either a treatment group, which received weekly WhatsApp messages about their students' platform use, or a control group. The messages, sent over eight weeks, encouraged teachers to support student engagement and included personalized information on the share of their students using the platform. The intervention was designed to operate through two main channels: first, by simplifying monitoring, allowing teachers to track student engagement without logging into the platform; and second, by increasing salience and motivation through regular reminders.

The Conecta Ideas platform offered weekly math problems, aligned with the national curriculum, to primary school students. An earlier experimental evaluation in Chile found platform use led to a 0.27 standard deviation (s.d.) increase in test scores (Araya et al., 2019). Motivated by this, Peru's Ministry of Education launched a national rollout in 2022 to strengthen learning and address COVID-related learning losses. However, platform use was optional for schools and teachers, raising concerns about engagement at scale. Indeed, in the study sample prior to the intervention, only 56% of eligible students had connected to the platform at least once, and students engaged during just 22% of the available weeks. These patterns underscore the need for scalable strategies to sustain use that can integrate into existing processes within the education system. Our study evaluates one such strategy.

Using administrative data from Conecta Ideas covering more than 20,000 students linked to the participating teachers, we find that the WhatsApp intervention significantly increased student platform use, both at the intensive and extensive margins. It raised the average weekly share of students logging in by 5 percentage points (a 17% increase) and the share of completed problems by 4 percentage points (a 16% increase). A back-of-the-envelope calculation suggests that these messages are a cost-effective way to boost engagement, particularly if implemented at scale. After the messages ended in week 8, the gap in platform use between treatment and control classrooms gradually narrowed and was no longer statistically significant by the end of the school year. This pattern is consistent with the mechanisms through which we expected the WhatsApp messages to operate: primarily by increasing salience and serving as a monitoring aid for teachers rather than simply raising general knowledge of the platform or changing long-term habits.

The experimental variation was not designed to allow measurement of downstream impacts on test scores.[1] However, we use non-experimental variation to examine learning outcomes. Specifically, we exploit differences in exposure to particular math topics (e.g., geometry, fractions, addition) based on whether students accessed the platform during the weeks those topics were covered. Controlling for overall

[1]The experiment is not sufficiently powered to detect learning effects using exogenous variation from changes in teacher behavior. Identifying such effects would have required a sample size orders of magnitude larger, which would have been difficult to implement. Prior work has documented that computer-assisted learning can improve student outcomes (Banerjee et al., 2007; Bettinger et al., 2022; Büchel et al., 2022; Lai et al., 2013, 2015; Ma et al., 2020; Mo et al., 2014; Muralidharan et al., 2019), including an experimental evaluation of this same platform in Chile (Araya et al., 2019). In contrast, the primary goal of this study is to understand how to sustain student engagement with these learning tools.

platform use and other potential confounders, we estimate how performance varied on those same topics. Drawing on pooled data from all students who used the Conecta Ideas platform in Peru during 2022, which increases statistical power, we find that students scored 0.06 to 0.08 s.d. higher on topics they were exposed to through the platform, as measured by an endline math test. We find no effects on these same topics in a baseline test, mitigating concerns that the estimated improvements simply reflect existing differences in ability or interest.

Our findings contribute to several strands of the literature. First, they speak to the challenges of integrating voluntary curricular tools into school practice, with EdTech as an example. While some of these tools can benefit students, integrating them into day-to-day school routines often depends on teacher initiative, which may be limited by teacher time constraints, competing priorities, or a lack of institutional support. Prior experimental work suggests that teacher motivation and behavioral frictions, such as commitment problems, can limit uptake, and that providing scaffolding or encouragement can improve their use (Jackson and Makarin, 2018; Oreopoulos et al., 2024). We contribute to this literature by showing that even simple, low-cost messages that increase salience and simplify monitoring can facilitate the uptake of such tools, and teachers respond to these messages even in the absence of additional incentives. This is particularly relevant in light of a recent review highlighting the limited evidence on nudging interventions that target teachers (Damgaard and Nielsen, 2018).[2]

Second, our work contributes to a small but growing literature on strategies to sustain engagement with digital technologies. Despite widespread enthusiasm about their potential across various domains, many studies document steep declines in engagement over time when use is voluntary, particularly in education and EdTech, where maintaining student engagement remains a persistent challenge (Banerjee and Duflo, 2014; Kizilcec and Halawa, 2015; Majerowicz and Zárate, 2023).[3] In response, recent studies have tested interventions aimed at promoting sustained use of digital learning tools. Much of this work targets students directly, for instance through nudges or financial incentives, some of which have shown promise (Kizilcec and Cohen, 2017; Kizilcec et al., 2017, 2020; Asanov et al., 2023). However, most of this research has focused on higher education settings, in which students are typically more autonomous.

[2]Following Thaler and Sunstein (2009), we define a nudge as any intervention that ‘‘alters people’s behavior in a predictable way without forbidding any options or significantly changing their economic incentives.’’

[3]Similar patterns of declining use and low retention have been observed in other areas where digital tools also offer potential benefits, such as digital health (Boucher and Raiker, 2024) and digital agriculture (Cole and Fernando, 2021), underscoring the broader need for strategies that sustain meaningful engagement.

Among younger, elementary school students, sustaining engagement may require other external support, and identifying effective channels to reach them can be more challenging.

One promising approach to target younger students is to involve adults. Some efforts have focused on parents. For instance, in the same setting in Peru, albeit during a different period, Aulagnon et al. (2024) find that reminder messages to parents highlighting student engagement streaks increase Conecta Ideas platform use during the summer. Similarly, Goyal et al. (2024) find that messages using self- and peer comparisons improve parental engagement with an early-childhood EdTech platform in India, though in that setting, parents themselves were the primary users, guiding activities with their children.[4] Another approach is to work through teachers: They are embedded in school routines, interact regularly with students, and, as digital tools are increasingly scaled through the formal education system, may be more practical to reach via existing organizational channels. Moreover, evidence suggests that the effectiveness of digital tools in schools depends heavily on how teachers engage with them (Comi et al., 2017; Beg et al., 2022). Yet teachers might not be naturally positioned or incentivized to promote engagement with tools that are voluntary or primarily used outside the classroom. Our work contributes to this discussion by showing that even in the absence of strong incentives, personal benefits, or formal accountability, simple messages directed at teachers can influence how students engage with digital tools.[5]

While teachers can be a promising channel for influencing student outcomes, not all teacher-focused interventions have been effective.[6] In Ecuador, an intervention targeting high school teachers finds that teacher-level nudges, such as encouragement messages, administrative reminders, and comparisons of their students' participation against other classes, do not improve student participation in an online learning platform (Asanov et al., 2023). While it is difficult to isolate the reasons for diverging effects, differences

[4] A broader literature outside EdTech has also documented that low-cost interventions targeting parents in LMICs can improve outcomes such as school attendance and learning (Bettinger et al., 2021; Santana et al., 2019; Angrist et al., 2022).

[5] Related work has also examined how light-touch behavioral messages influence teacher behavior in other domains, such as in their job search. However, in these cases, the behavioral nudges were concerned with directly changing teachers' own actions (Ajzenman et al., 2021, 2024). In contrast, our intervention aims to influence student behavior, with teachers serving as intermediaries.

[6] More broadly, recent studies have documented mixed effects from large-scale light-touch nudge campaigns targeting older students, with evidence of both positive impacts (e.g., Castleman and Page, 2016; Avery et al., 2021) and precise null effects in other contexts (Bettinger et al., 2022; Bird et al., 2021; Gurantz et al., 2021). There are several differences between our study and these interventions. First, much of the existing work has focused on high school or college students in high-income countries, aiming to improve postsecondary outcomes. One possible explanation for the limited success in some cases is that these interventions attempted to alter costly, effort-intensive behaviors, such as by improving study habits (Oreopoulos and Petronijevic, 2023). In contrast, our intervention targets a very different behavior in a middle-income country, indirectly influencing primary school student behavior by reaching teachers. Moreover, the behavior we aimed to support, weekly monitoring of student engagement, while ongoing, may be less effort intensive and more amenable to light-touch support through timely decision tools.

in students' ages or message content may have contributed. A simple tool that helps teachers monitor student use may be important.[7] Consistent with this idea, suggestive evidence from the US shows that personalized student progress reports sent to teachers lead to greater improvements in student outcomes than generic encouragement emails (Duckworth et al., 2025).

Finally, this paper contributes to the literature on the learning impacts of simple EdTech tools that can operate in contexts with weak digital infrastructure, and in particular to the transferability of such programs across settings. Building on prior experimental evidence from Chile (Araya et al., 2019), we provide complementary non-experimental evidence from a new context, showing that increased platform use is associated with student learning gains in this setting. As EdTech initiatives expand across diverse environments, assessing their external validity, understanding whether effects persist at scale, and identifying strategies to address context-specific implementation challenges become increasingly important. Our findings corroborate the positive effects documented in previous experimental work and highlight the value of combining evaluation methodologies to assess program effectiveness across different contexts. Moreover, we show that simple, low-cost adaptations, such as sending WhatsApp messages to teachers, can help address local barriers as programs are adapted to new settings and implemented at scale.

2. Context and intervention

2.1. Education in Peru

Primary education in Peru is free and mandatory, covering grades 1 through 6 for children aged 6 to 11. The national curriculum includes core subjects such as math, language, science, and social studies, along with specialized subjects like art and physical education. The school year runs from March to December.

Peru faces significant challenges in learning outcomes, many of which were exacerbated by the COVID-19 pandemic. Nearly all public schools remained closed throughout 2020 and 2021, with in-person instruction resuming in 2022. According to the Ministry of Education, the share of fourth-grade students reaching math proficiency fell from 34% in 2019 to 23% in 2022, highlighting substantial pandemic-related learning losses (MINEDU, 2023).

[7] While the social-comparison arm in Asanov et al. (2023) could have also served as a form of monitoring tool, they find suggestive evidence that performance comparisons might have had offsetting effects, discouraging teachers whose students were above average while motivating those below.

Household connectivity to digital technologies in Peru is relatively high: 94% of households with children aged 8 to 11 report having internet access and at least one connected device, such as a computer, tablet, or smartphone (OSIPTEL, 2023). Meanwhile, internet availability in public schools is beginning to grow, with 42% of primary schools now connected (MINEDU, 2024).[8]

2.2. Implementation of a math learning platform

Conecta Ideas is a digital math platform that provides primary school students with weekly, curriculum-aligned exercises on rotating topics. Continuous internet access is not required; students needed to connect just once a week to download new exercises and upload completed ones, using minimal data (about 3 MB weekly). The platform is compatible with smartphones (including low-end models), tablets, laptops, and computers, and it can be used both at home and in school.

Originally developed by the Center for Advanced Research on Education at the Universidad de Chile, Conecta Ideas was experimentally evaluated in 2017 in Chile. The study found that twice-weekly use in school computer labs significantly improved math achievement, raising test scores by 0.27 s.d. (Araya et al., 2019).

In 2018–19, the Peruvian research organization Grupo de Analisis para el Desarrollo (GRADE) adapted the platform for deployment in schools in Peru.[9] These efforts were supported by collaborations between the Universidad de Chile, the Ministry of Education of Peru, the International Development Research Center, and the Inter-American Development Bank. In 2021, GRADE and the Peruvian Ministry of Education signed a two-year agreement to promote Conecta Ideas among public primary schools.

To use the platform, teachers had to register themselves and their students via a form on the platform website.[10] While the ministry promoted the platform, participation was voluntary and not centrally monitored. Teachers could support usage by sharing login credentials with parents for home use or by facilitating access at school using classroom or lab devices.

Each Monday, students received a new set of 30 grade-specific math exercises, aligned with the national curriculum. Students had until the subsequent Sunday to complete the exercises. After each exercise,

[8] Another relevant factor is the cost of internet services. Monthly internet costs range from 10 to 120 soles (approximately USD $2.60 to $33), depending on the plan and location (OSIPTEL, 2023). While this represents an additional challenge for low-income families, particularly in rural areas, the widespread adoption of internet access across different platforms suggests that many families find value in making this investment.

[9] GRADE is an NGO and does not profit from the use or promotion of the platform.

[10] See http://www.conectaideasperu.com.

students received immediate feedback on their answers.[11]

2.3. The text-message intervention

This study estimates the impact of sending weekly WhatsApp messages to teachers with information about their students' use of the learning platform. The goal was to increase the intensity of student engagement among those already enrolled. The intervention targeted teachers who had registered both themselves and their students on the platform and who had at least one student who had used it prior to the start of the study. The eight-week intervention began the week of May 30 and concluded in mid-July 2022.

Each WhatsApp message included two components for teachers whose students had logged in the prior week. First, it reported the number of registered students who connected (e.g., ''Last week, 10 of the 30 students you registered logged in''). Second, it delivered a tailored message based on engagement levels: Teachers with fewer than 20% of students connected were encouraged to promote use; those with 20%-–50% received recognition and a prompt to continue; and those above 50% were congratulated and urged to maintain high participation. Teachers with zero active students received a general message emphasizing the platform's low data requirements and inviting questions. The control group received no messages. Full templates appear in Appendix C.

Message delivery was randomly assigned across six subgroups defined by the combination of day (Monday, Tuesday, or Wednesday) and time of day (morning or afternoon).[12] The assignment of treatment teachers to the day/time subgroup was maintained throughout the eight-week intervention period. While not powered to detect small differences by timing, this design helps rule out large timing effects as the main driver of results.

Teachers could respond to the messages, and many did: 35% replied in week 1, falling to 17%-–12% in weeks 2 through 4, and stabilizing at around 6% in the final four weeks (Appendix A1). Pooling the responses across weeks, results indicate generally positive engagement: 64% expressed gratitude (via words or emoticons), 16% included a question, 16% reported a problem (e.g., ''Some students in my

[11] Students also earned virtual flags for each solved exercise: three flags if they solved the exercise correctly on the first attempt, two on the second, and one on the third. Upon completing the full set of 30 exercises, students received a summary of flags earned for the week, month, and year.

[12] Messages were sent at (i) Mondays at 2 p.m.; (ii) Mondays at 5 p.m.; (iii) Tuesdays at 7:30 a.m.; (iv) Tuesdays at 5 p.m.; (v) Wednesdays at 7:30 a.m.; and (vi) Wednesdays at 5 p.m. Ideally, messages on Mondays should have been sent at 7:30 a.m. However, this was logistically complicated because the implementation team needed to process the platform data from the prior week on Monday mornings to generate the personalized messages.

classroom do not have internet access''), and 5% shared other comments. No teacher requested to opt out. While these replies indicate meaningful engagement, they do not capture teachers who read the messages but did not respond. Because of logistical constraints, however, we were unable to collect WhatsApp read receipts (e.g., message views or delivery confirmations), which precludes us from estimating treatment effects for compliers.

3. Data and sample

3.1. Data

We use comprehensive administrative data recorded by the math learning platform, spanning March to November 2022. The dataset includes student-exercise-level information, such as completion date and accuracy, as well as registration dates and internal IDs for both students and teachers. The platform also collected teacher-level sociodemographic data, such as gender and age. In addition, we merged school-level characteristics from the (national) School Census, including geographic location and whether a school is classified as multigrade or regular.

Our analysis focuses on the 20,376 students who were registered on the platform by teachers participating in the experiment as of the week prior to the intervention. Using administrative data on class enrollment and platform registration, we estimate that the average teacher in the sample registered all their students on the platform, indicating that incomplete classroom registration was not the primary barrier to student engagement.[13]

We construct three primary outcomes. First, to capture platform use at the extensive margin, we define a dummy variable that equals 1 if a student connected at least once by the end of the reported period. We then multiply this variable by 100 to express it as a percentage. This percentage can only increase throughout the academic year, and we report it at the end of each period of study. We label this variable *Student Connected at Least Once*. This outcome captures the first step in adoption, reflecting whether students overcame basic barriers such as awareness and access.

Second, *Student Average Weekly Connection* captures the frequency of use, defined as the fraction

[13]The mean of the ratio of students registered on the platform to our estimated number of students enrolled in that teacher's class is 1, with a standard deviation of 0.49. Ratios above 1 likely reflect cases in which teachers registered students from other grades or classrooms.

of weeks in which a student connected during the period analyzed. Third, *Student Average Exercises Completed* equals the fraction of exercises assigned to the student that were completed during the analysis period. All three outcomes are expressed as percentages, and treatment effects are reported in percentage points.[14]

3.2. Sample selection and randomization

At the time of sample selection, 3,894 teachers had accessed the platform. Among them, 72% (2,837) had registered at least one student, and 26% (1,028) had at least one student actively using it. After excluding teachers from Callao, Moquegua, and Tacna because of a concurrent intervention, our final baseline sample comprised 853 teachers (see Appendix Table A2 for details on sample construction). Of these, 67% were female, their average age was 51, and 29% taught in rural schools. These characteristics are broadly comparable to national averages reported in the Encuesta Nacional de Docentes, a nationally representative teacher survey, which finds that Peruvian primary teachers are on average 48 years old, 63% are female, and 31% are based in rural areas (MINEDU, 2020). Appendix Table A3 presents a comparison of our sample to average national teacher characteristics for available variables.

Among the 853 teachers in the final sample, 600 were randomly assigned to the treatment group and 253 to the control group. Treatment teachers were further randomized into six equally sized subgroups (100 teachers each), with each subgroup receiving messages on a different day and time (morning or afternoon).

4. Empirical strategy

4.1. Experimental effects of messages

We exploit the random assignment of teachers to receive WhatsApp messages to estimate treatment effects using the following student-level specification:

$$Y_{i,t,post} = \gamma_0 + \gamma_1 Treatment_t + \gamma_2 Y_{i,t,pre} + \epsilon_{i,t} \tag{1}$$

[14] Tracking both the extensive and intensive margins of adoption is important, as these represent distinct stages in engagement and may be influenced by different behavioral or contextual factors (Bensch and Peters, 2015; Lambrecht et al., 2014).

Here, $Y_{i,t,post}$ denotes the outcome of interest for student i registered under teacher t during the post-intervention period. The variable $Treatment_t$ is an indicator for whether the teacher was assigned to the treatment group, and γ_1 captures the estimated average effect of the treatment. We include as a control $Y_{i,t,pre}$, the pre-treatment value of the outcome (e.g., *Student Average Weekly Connection* during the four-week pre-treatment period). $\epsilon_{i,t}$ is the error term. We report heteroskedasticity-robust standard errors clustered at the teacher level, the unit of randomization.

Because we do not observe whether teachers actually read the WhatsApp messages, γ_1 is an intent-to-treat (ITT) estimate, as it measures the effect of being assigned to treatment. A substantial share of teachers responded to the messages, and many others were likely exposed to them even if they did not reply. While we cannot identify treatment effects for compliers, the ITT estimate likely reflects meaningful exposure to the intervention and is particularly relevant from a policy perspective.

Baseline balance. Table 1 presents summary statistics on pre-treatment school and teacher characteristics for both the treatment and control groups, along with balance tests. About 83% of participating students were enrolled in urban schools, and 8% attended multigrade schools. The average student had a teacher who was 50 years old, and about 70% of students had a female teacher. Prior to the intervention, 56% of students had connected to the platform at least once, but the average student connected in only 22% of the four-week pre-treatment period. These figures suggest that while initial uptake was moderate, sustained use remained low, highlighting the potential value of interventions to boost engagement.

We find no statistically significant differences between treatment and control groups across any baseline characteristics, with one exception: A higher share of students in the treatment group lived in Lima. To account for this imbalance, we include a control for Lima residence in equation (1). All results remain robust to its inclusion.

4.2. Platform use and math achievement

We also present complementary, non-experimental evidence on the relationship between platform use and math achievement by exploiting variation in students' exposure to specific math topics.[15] This analysis

[15] The evaluation was not designed or powered to answer this question. For example, the experimental evaluation of the Conecta Ideas platform in Chile found an effect of 0.27 s.d. with approximately 28 hours of use (Araya et al., 2019). Our WhatsApp intervention increased use by an estimated 0.3 hours, implying a likely effect of 0.003 s.d., far too small to detect with our sample size.

provides insights into the impacts of the platform in this specific context and speaks to whether texting teachers to increase platform use was likely beneficial for students.

To maximize statistical power, we include all platform users in 2022, not just those in the experimental sample. In this analysis, we take advantage of the fact that math topics were covered in different weeks throughout the year in a non-systematic order. This allows us to compare students who were exposed to certain topics (e.g., fractions) because they used the platform during the week those topics were covered, with students who were not exposed to the same topics, controlling for the total number of weeks each student connected.[16]

The unit of analysis is the student-topic level. For each student who completed the November 2022 endline math exam, we include one observation per tested topic. Exposure is defined as the fraction of weeks a student connected when a given topic was covered. We estimate

$$Y_{ij} = \alpha_0 + \alpha_1 Exposed_{ij} + \eta_w + \mu_j + \tau_{ij}. \tag{2}$$

Here, Y_{ij} is the standardized score for student i for topic j, and $Exposed_{ij}$ captures their topic-specific exposure. η_w are fixed effects for the interaction of grades with number of weeks that the student connected, μ_j are fixed effects for topics interacted with grades, and τ_{ij} is the error term. As a robustness check, we replace total-week fixed effects with fixed effects for each week of the academic year (e.g., the week of May 30, 2022) interacted with grades and including student fixed effects.[17] We report robust standard errors clustered at the student level.

This analysis exploits variation in students' exposure to math topics across specific weeks. To interpret these estimates causally, we rely on the assumption that the order and timing of topic coverage are exogenous to student characteristics. In particular, this requires that students did not adjust their engagement in anticipation of specific topics. Given the platform's scheduling structure, it is unlikely that students had prior knowledge of which topics would be covered each week. Nonetheless, we acknowledge the limitations of this non-experimental design.

[16] We follow Aulagnon et al. (2024), who exploit variation across students in exposure to topics to assess the relationship between the use of the platform and math academic achievement during the summer vacation.

[17] We interact the dummies for total number of weeks connected, specific weeks connected, and topics with grade fixed effects to flexibly control for grade-specific patterns, while pooling all grades in a parsimonious manner for this analysis.

5. Results

5.1. Experimental effects of messages on platform use

Figure 1 shows the evolution of the main outcomes for the treatment and control groups before, during, and after the intervention. Before the intervention, the percentage of students who connected to the platform at least once was very similar in both groups (Panel A). Following the start of the intervention, the treatment group saw an increase in this outcome, surpassing the control group and maintaining an advantage, though converging as the academic year came to a close. Similar patterns of effects are shown for *Student Average Weekly Connection* (Panel B) and *Student Average Exercises Completed* (Panel C). During the intervention, both outcomes rose in the treatment group and remained elevated for roughly 10 weeks after intervention before declining toward control-group levels.

To formally examine these effects, Table 2 reports estimates from equation 1 across three periods: (i) the treatment period (weeks 1–8); (ii) the immediate post-intervention period (weeks 9–18); and (iii) the delayed post-intervention period (weeks 19–27).[18] During the treatment period (Panel A), we find positive, statistically significant impacts: a 4 percentage point increase in *Student Connected at Least Once* (5% over the control mean), a 5 percentage point rise in *Student Average Weekly Connection* (17%), and a 4 percentage point increase in *Student Average Exercises Completed* (16%). The last of these closely tracks the connection effect, as students who logged in typically completed 85%–90% of assigned exercises, regardless of treatment status. In the immediate post-intervention period (Panel B), the effect on *Connected at Least Once* remains stable but is only significant at the 10% level. The effects on the other two outcomes decline by about half and become statistically nonsignificant. By the delayed post-intervention period (Panel C), all effects fade and are indistinguishable from zero.

Heterogeneity. Assessing heterogeneity is important to understand whether some types of teachers were more effective at translating the information into student engagement, or whether certain types of students were more responsive to teacher encouragement. Table 3 examines heterogeneous effects on *Student Average Weekly Connection*, but similar patterns are observed for other outcomes (Appendix Table A4).[19]

[18] To explore trends in the post-treatment period, we split the time window into roughly two periods containing about the same number of weeks.

[19] For ease of exposition, we focus on one outcome variable and present results for the others in the Appendix. The conclusions are similar, except for some suggestive evidence of larger effects among teachers whose students had low pre-intervention

Panel A explores heterogeneity by teacher characteristics. While point estimates vary somewhat by teacher age, gender, school location (rural or urban), baseline student connection rates, and student academic performance, none of these differences are statistically significant. We cannot reject the null that the intervention was equally effective across teacher subgroups. Panel B examines heterogeneity by student characteristics—specifically, whether they had connected in the four weeks prior to the intervention and whether their baseline math performance was above the median. Again, we find no evidence of differential effects, consistent with teachers offering general encouragement rather than targeting specific students, and students responding similarly regardless of baseline characteristics.

Although these analyses do not suggest that the WhatsApp intervention amplified disparities in platform use, the analysis is underpowered to detect small effects and should be interpreted with caution. Moreover, broader impacts on preexisting inequalities, particularly those related to home digital access, for which we lack data, remain an open question for future research.

As a sensitivity check, we also compare impacts by message delivery day—Monday, Tuesday, or Wednesday (see balance in Appendix Table A5 and effects in Appendix Table A6). While point estimates are somewhat larger for the Monday group, differences across days are not statistically significant. Similarly, we examine the robustness of the effects by comparing messages sent generally in the morning versus the afternoon, and we again find no evidence of differences in effectiveness along this dimension (see balance in Appendix Table A7 and effects in Appendix Table A8). Given the limited power of these split-sample tests, we cannot rule out modest timing effects, but this evidence suggests that message timing is unlikely to be a primary driver of the overall treatment impact.[20]

5.2. Is increased platform use linked to math achievement?

This section examines the relationship between platform use and math academic achievement. Table 4, Panel A reports estimates from equation 2. Students fully exposed to a topic (i.e., those who connected in all weeks in which a specific topic was covered) scored 0.08 s.d. higher on that topic than students who were not exposed, after controlling (with fixed effects) for the number of weeks students connected and

connection rates, though these differences are not statistically significant at the 5% level.

[20] With six treatment arms (100 teachers each) and a control group of 257 teachers, assuming a 5% significance level, 80% power, an intracluster correlation of 0.44, and 24 students per teacher, the minimum detectable effect is 11 percentage points for treatment-vs.-treatment comparisons and 9 percentage points for treatment-vs.-control comparisons.

the topics covered (column 1).[21]

Column 2 replaces fixed effects for the number of weeks connected with fixed effects for specific weeks. This offers greater flexibility by accounting for variation in the times when students connected. For example, more academically motivated students may have been more active in particular weeks. It exploits the fact that connection in some weeks should produce a larger increase in achievement on the topic covered that week compared to topics covered in other weeks. The estimated impact remains positive and statistically significant: Full exposure is associated with a 0.06 s.d. increase in achievement. Column 3 adds student fixed effects, controlling for each student's overall performance level and comparing scores across topics within student. In this specification, full exposure to a topic is associated with a 0.07 s.d. gain. The results remain virtually unchanged across specifications when clustering standard errors at the teacher level.

The consistency of these coefficients across different specifications strengthens the case for a causal interpretation. However, unobservable factors could still bias the results. To further assess the validity of the estimated effects, we conduct a placebo exercise: We replicate the analysis from Panel A using students' performance on a baseline test administered in April 2022 as the dependent variable. Panel B shows no association between topic exposure and baseline performance across all three specifications. This reduces concerns that the main results are driven by preexisting differences in achievement on exposed topics. Taken together, the findings suggest a positive and likely causal effect of platform use on math academic achievement.

5.3. Cost-effectiveness

We provide back-of-the-envelope estimates of the program's cost-effectiveness in increasing platform use under different assumptions (see Appendix Table B1 for a description of the parameters and assumptions used for these calculations). Using the actual costs incurred during the experiment, the marginal cost of treating a teacher over the eight-week intervention is estimated at \$2.76, or \$0.35 per teacher per week. This translates to a cost of \$0.12 per student for the full intervention, or \$0.015 per student per week. Given that the intervention increased the weekly connection rate by approximately 5 percentage points, we estimate a cost of about \$0.30 to induce one additional student to connect in a given week.

[21] Practicing a specific topic may produce spillovers to related topics, which would attenuate these estimates. If so, our results represent a conservative estimate of the true effect of topic-specific exposure.

Importantly, these costs decline with scale, as the marginal cost of sending messages is very low and fixed costs can be spread across many more students. Under national implementation, the per-student cost would fall from \$0.12 to \$0.05. With partial automation of the service, it could decrease further to \$0.04 per student. At even-larger scales, fixed costs become negligible, and the primary remaining expense is the marginal cost of sending WhatsApp messages, estimated at \$0.56 per teacher and \$0.02 per student. These effects appear cost-effective in increasing platform use. As a comparison, in Ecuador, lottery incentives to boost high school student engagement cost \$0.17 per student, while the teacher-facing interventions were about \$0.30 per additional user (Asanov et al., 2023).

6. Discussion

The intervention had modest but cost-effective impacts during the treatment period, followed by a gradual decline once the messages stopped. One likely explanation is that in busy classroom environments, teachers face competing priorities, and without salient reminders or simplified monitoring tools, it becomes difficult to consistently track and support students' engagement. The messages may have prompted teachers to take low-effort but regular actions, such as reminding students to use the platform. Once the reminders ended, engagement returned to baseline levels, suggesting that the effects operated through salience and ease of monitoring rather than increased awareness of or knowledge about the platform. This aligns with prior work showing that light-touch interventions often require ongoing reinforcement to sustain impact (Goyal et al., 2024; Fabregas et al., 2025; Suffoletto, 2024). Future research could examine whether the effectiveness of such interventions diminishes over time because of message fatigue.

The messages shared class-level summaries, not individual student data. While teachers could access student-level information by logging into the platform, the summary messages likely reduced cognitive load and were more scalable, though potentially less effective for targeting support to students falling behind. The absence of heterogeneous effects across student subgroups aligns with the idea that teachers used the messages to encourage whole-class engagement. Future work could assess whether providing more granular data improves effectiveness or helps narrow digital gaps. In addition, experimental designs aimed at testing the underlying mechanisms, such as varying message content or collecting richer data on teacher and student behavior, could more precisely identify the channels through which the intervention operates—specifically, what prompts teachers to act and how they motivate student engagement. The inability to directly observe these mechanisms is a limitation of the study, but understanding them more clearly could help explain why similar interventions targeting teachers have sometimes produced null results (Asanov et al., 2023) and whether these differences are driven by message content, student age, or other factors.

Although our focus is on behavioral barriers to EdTech use, we recognize these are marginal relative to structural constraints like inadequate digital infrastructure, unreliable connectivity, and gaps in teacher digital literacy. This study does not aim to minimize those challenges but to show that a practical, low-cost behavioral tool can complement broader investments. This type of messaging could be attractive for governments and EdTech providers, especially when embedded in existing workflows or delivery systems.[22]

7. Conclusion

We evaluate a low-cost teacher-facing intervention designed to increase student engagement with a nationally scaled digital math platform in Peru. Over an eight-week period, teachers received personalized WhatsApp messages with updates on the share of their students actively using the platform. The messages led to statistically significant effects: a 4–5 percentage point rise in the likelihood that a student connected in a given week and in the number of exercises completed. These effects gradually faded in the weeks after the intervention ended.

While the effects are modest, the intervention's low cost, approximately \$0.05 per student if implemented at scale, makes it highly cost-effective. Moreover, its ease of delivery through existing communication channels makes it a scalable strategy for boosting EdTech engagement.

We also document a positive association between students' exposure to specific math topics on the platform and their performance on those same topics on an endline math test, with full exposure linked to improvements of 0.06 to 0.08 s.d. While these findings are not based on experimental variation and should be interpreted cautiously, they help to corroborate prior experimental evidence and suggest that increased platform use likely translated into learning gains in this context as well.

Taken together, our results show that behaviorally informed low-cost messaging to teachers can en-

[22]Sustaining engagement may align with the interests of nonprofit and private platforms, given that many digital tools face significant drop-off in use over time. Embedding interventions within schools or education systems, where regular monitoring and messaging can be institutionalized, could be a promising approach for increasing platform impact.

hance EdTech uptake by increasing salience and simplifying monitoring. This approach offers a practical tool for education systems, particularly for budget-constrained ministries in low- and middle-income countries, to promote sustained engagement with digital learning platforms at scale.

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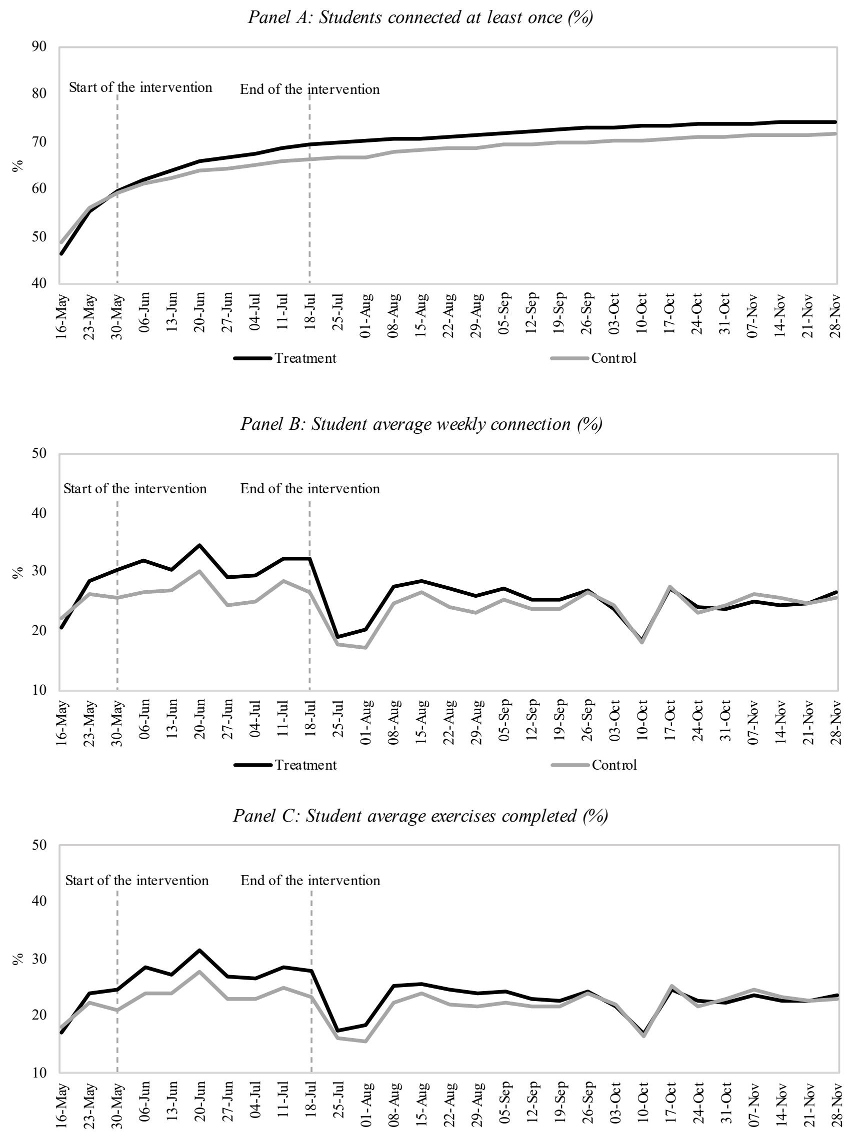
Figures and Tables

Figure 1: Effects on Platform Use per Week



Notes: These figures show the share of students that had connected at least once by week (Panel A), the share of students connected to the platform by week (Panel B), and the average fraction of exercises completed by week (Panel C). All statistics are estimated at the student level.

Table 1: Summary Statistics and Baseline Balance

	Treatment (1)	Control (2)	Difference (3)	*N* (4)
School characteristics				
Urban (%)	83.50	82.96	0.54	20,376
			(2.62)	
Multigrade (%)	8.44	7.72	0.72	20,376
			(1.68)	
Located in Arequipa (%)	29.45	30.81	-1.36	20,376
			(3.83)	
Located in Cajamarca (%)	15.82	19.42	-3.60	20,376
			(3.08)	
Located in Junin (%)	10.32	11.33	-1.01	20,376
			(2.25)	
Located in Lima (%)	26.81	18.57	8.24**	20,376
			(4.04)	
Teacher characteristics				
Age	50.31	50.06	0.24	20,376
			(0.69)	
Female (%)	67.23	72.45	-5.22	20,376
			(4.25)	
Pre-treatment use of the platform				
Students connected at least once (%)	55.32	56.14	-0.82	20,376
			(3.00)	
Student average weekly connection (%)	22.27	22.42	-0.15	20,376
			(1.72)	
Student average exercises completed (%)	18.67	18.52	0.14	20,376
			(1.57)	
Math academic achievement	0.07	-0.00	0.07	9,312
			(0.04)	
Omnibus F-test			F= 0.84	
			p-value: 0.62	

Notes: This table presents summary statistics and mean differences between the students of teachers randomized to the treatment and control groups. *Multigrade* are schools that have classrooms with students from more than one grade. Arequipa, Cajamarca, Junin, and Lima are regions in Peru. All the pre-treatment variables correspond to the average of the four weeks prior to the start of the intervention, except for *Student Connected at Least Once*, which corresponds to the week prior to the intervention. The variable *Math Academic Achievement* has only 9,312 observations since some students did not use the platform during the pre-treatment period and hence their performance cannot be assessed. A joint test for balance across baseline covariates (omnibus F-test) and the corresponding p-value are also shown. Robust standard errors, clustered at the teacher level, are reported in parentheses.*$p < .10$, ** $p < .05$, *** $p < .01$.

Table 2: Effects on Platform Use

	Treatment (1)	Control (2)	Adjusted difference (3)	*N* (4)
Panel A: During the intervention (weeks 1-8)				
Student connected at least once (%)	69.37	66.40	3.55**	*20,376*
			(1.53)	
Student average weekly connection (%)	31.28	26.76	4.63***	*20,376*
			(1.66)	
Student average exercises completed (%)	27.72	23.87	3.75**	*20,376*
			(1.54)	
Panel B: Immediate post-intervention (weeks 9-18)				
Student connected at least once (%)	72.94	69.94	3.52*	*20,376*
			(1.82)	
Student average weekly connection (%)	25.36	23.29	2.15	*20,376*
			(1.69)	
Student average exercises completed (%)	22.98	21.15	1.75	*20,376*
			(1.59)	
Panel C: Delayed post-intervention (weeks 19-27)				
Student connected at least once (%)	74.19	71.72	2.96	*20,376*
			(1.94)	
Student average weekly connection (%)	24.24	24.42	-0.11	*20,376*
			(1.94)	
Student average exercises completed (%)	22.29	22.48	-0.27	*20,376*
			(1.84)	

Notes: This table presents results from the effects of receiving WhatsApp messages on student platform use during the year. Panel A shows effects during weeks 1–8 (week 1 is when the intervention started), Panel B presents effects on platform use during weeks 9 to 18 and Panel C during weeks 19 to 27. The dependent variables are the fraction of students that had connected at least once during the year up to the end of the period analyzed (*Student Connected at Least Once*), the share of weeks that the student connected during the period analyzed (*Student Average Weekly Connection*), and the share of total exercises assigned completed by the student during the period analyzed (*Student Average Exercises Completed*). The unit of observation is at the student level. Robust standard errors, clustered at the teacher level, are reported in parentheses.* $p < .10$, ** $p < .05$, *** $p < .01$.

Table 3: Heterogeneous Effects on Student Average Weekly Connection (%)

	Treatment	Control	Adjusted difference	*N*
	(1)	(2)	(3)	(4)
Panel A: Effects by Teacher Characteristics				
Age				
Young	29.97	27.05	4.04*	*9,137*
			(2.36)	
Old	32.34	26.52	5.18**	*11,239*
			(2.29)	
P-value (difference)			[0.73]	
Gender				
Female	33.81	28.15	6.14***	*14,013*
			(1.92)	
Male	26.10	23.10	1.67	*6,363*
			(2.82)	
P-value (difference)			[0.19]	
Area				
Rural	29.85	21.93	6.42**	*3,394*
			(2.65)	
Urban	31.56	27.75	4.22**	*16,982*
			(1.92)	
P-value (difference)			[0.50]	
Fraction of students connected in the week prior to the intervention				
Low connection	16.55	11.82	4.65**	*10,170*
			(1.84)	
High connection	46.52	40.39	5.30**	*10,206*
			(2.68)	
P-value (difference)			[0.84]	
Math academic achievement prior to the intervention				
Low performance	26.69	22.23	4.38**	*9,136*
			(2.01)	
High performance	40.81	35.80	5.21*	*9,488*
			(2.78)	
P-value (difference)			[0.81]	
Panel B: Effects by Student Characteristics				
Number of weeks connected in the weeks prior to the intervention				
0 weeks	13.84	10.20	3.64**	*11,064*
			(1.45)	
1 to 4 weeks	52.00	46.46	5.73**	*9,312*
			(2.60)	
P-value (difference)			[0.41]	
Math academic achievement prior to the intervention				
Low performance	45.51	41.68	4.52*	*4,468*
			(2.64)	
High performance	57.81	51.16	6.47**	*4,844*
			(2.95)	
P-value (difference)			[0.39]	

Notes: This table presents heterogeneous effects of receiving WhatsApp messages on student platform use by baseline teachers and student characteristics. The dependent variable is the share of weeks that the student connected during the eight-week intervention period (*Student Average Weekly Connection*). The unit of observation is at the student level in both panels A and B. However, students were divided by their teacher characteristics in Panel A and by their own characteristics in Panel B. For the analysis in Panel A, teachers were divided into two groups based on the median value of the average fraction of students connecting in the week prior to the intervention. Teachers whose connection rates were below the median were classified in the "Low Connection" group, while those above the median were categorized in the "High Connection" group. Similarly, teachers were grouped based on the average fraction of students with low or high performance based on the average performance in the four weeks prior to the intervention. We computed the median of this teacher-level variable and classified teachers into the "Low Performance" group if their students' average performance was below the median, and into the "High Performance" group if it was above the median. In Panel B, students are divided into two groups based on their math academic achievement. "Low Performance" students are those whose average performance is below the median, while "High Performance" students are those above the median. Robust standard errors, clustered at the teacher level, are reported in parentheses. $^{*}p < .10$, $^{**}p < .05$, $^{***}p < .01$.

Table 4: Exposure to a Topic and Math Achievement

	(1)	(2)	(3)
Panel A: Association with endline test			
Connected for the tested topic	0.08***	0.06***	0.07***
	(0.01)	(0.01)	(0.01)
N (observations)	*229,902*	*229,902*	*229,902*
N (students)	*25,209*	*25,209*	*25,209*
Topic fixed effects	Y	Y	Y
Number-of-weeks-connected fixed effects	Y	N	N
Specific-weeks fixed effects	N	Y	N
Student fixed effects	N	N	Y
Panel B: Association with baseline test			
Connected for the tested topic	0.01	0.00	0.00
	(0.02)	(0.02)	(0.02)
N (observations)	*21,935*	*21,935*	*21,935*
N (students)	*3,541*	*3,541*	*3,541*
Topic fixed effects	Y	Y	Y
Number-of-weeks-connected fixed effects	Y	N	N
Specific-weeks fixed effects	N	Y	N
Student fixed effects	N	N	Y

Notes: This table presents regression results showing the association between exposure to a specific topic and math achievement in that topic, as measured in the endline (Panel A) and baseline tests (Panel B). Each column in a panel corresponds to a separate OLS regression, with the unit of observation being the student-topic in all regressions. All regressions include topic fixed effects. Controls also include number-of-weeks-connected fixed effects, specific-week fixed effects, and student fixed effects, depending on the column. Math achievement for each subject has been normalized by subtracting the mean and dividing by the standard deviation of the control group for each grade-test. Robust standard errors, clustered at the student level, are reported in parentheses. $^{*}p < .10$, $^{**}\ p < .05$, $^{***}\ p < .01$.

Appendix

A. Additional Tables

Table A1: Teacher Responses to WhatsApp Messages Over Time

	Answered the message (1)	Expresses gratitude (2)	Asks a question (3)	Reports a problem (4)	Other (5)
Week 1	35%	18%	11%	5%	1%
Week 2	17%	12%	3%	4%	1%
Week 3	13%	11%	0%	3%	0%
Week 4	12%	10%	1%	1%	1%
Week 5	3%	3%	0%	1%	0%
Week 6	8%	6%	1%	1%	2%
Week 7	5%	4%	0%	1%	0%

Notes: Percentages are computed based on the replies received to the messages sent each week. Since a single message could fall into multiple categories, the sum of percentages in each row does not necessarily equal the total response rate. No teacher requested to stop receiving messages. The column ”Answered the message” includes any reply from teachers. ”Expresses gratitude” refers to messages of appreciation, such as “Thank you” or an emoji with a smiley face. ”Asks a question” includes inquiries about the platform or its use. ”Reports a problem” covers difficulties mentioned by teachers, such as lack of internet access. The category ”Other” includes any response that did not fall into the previously described categories.

Table A2: Evolution of the Sample Across Selection Stages

	Teachers with at least one student (1)	Teachers with at least one connected student (2)	Teachers with connected students not from excluded regions (3)
School characteristics			
Urban (%)	62.60	72.57	71.28
Multigrade (%)	25.48	16.34	17.47
Located in Lima (%)	10.65	14.88	17.94
Teacher characteristics			
Age	49.93	50.65	50.62
Female (%)	69.15	67.57	65.98
Observations	*2,837*	*1,028*	*853*

*Notes:*This table reports mean characteristics of teachers and their schools at different stages of the sample construction process. Column 1 includes all teachers who registered at least one student on the platform. Column 2 retains only those whose students actively used the platform. Finally, column 3 further excludes teachers whose connected students were from Moquegua, Tacna, or Callao, regions who are included in other intervention. The final sample consists of 853 teachers.

Table A3: Comparison of the Study Sample to the National Teacher Survey

	National survey (1)	Study participants (2)
School characteristics		
Urban (%)	68.70	71.28
Located in Lima (%)	16.33	17.94
Teacher characteristics		
Age	47.71	50.62
Female (%)	62.62	65.98
Observations	*11,955*	*853*

Notes: This table is constructed at the teacher level. Statistics presented in column 1 are computed based on data from the 2020 National Teacher Survey (ENDO). Statistics presented in column 2 are generated using data collected in the platform matched to administrative data from the Ministry of Education. The column 1 includes the sample of primary school teachers, applying expansion factors to obtain representative estimates. The column 2 corresponds to the 853 teachers included in the study.

Table A4: Heterogeneous Effects on Students Connected at Least Once (%)

	Treatment	Control	Adjusted difference	*N*
	(1)	(2)	(3)	(4)
Age				
Young	64.48	66.70	1.14	*9,137*
			(2.47)	
Old	73.32	66.15	5.71***	*11,239*
			(1.70)	
P-value (difference)			[0.13]	
Gender				
Female	71.64	69.42	4.09**	*14,013*
			(1.59)	
Male	64.71	58.47	2.47	*6,363*
			(3.23)	
P-value (difference)			[0.65]	
Area				
Rural	66.98	55.65	8.26***	*3,394*
			(2.87)	
Urban	69.84	68.61	2.59	*16,982*
			(1.73)	
P-value (difference)			[0.09]	
Fraction of students connected in the week prior to the intervention				
Low connection	49.56	43.16	6.64**	*10,102*
			(2.89)	
High connection	89.42	87.73	0.91	*10,274*
			(0.78)	
P-value (difference)			[0.06]	
Math academic achievement prior to the intervention				
Low performance	69.30	63.98	5.00***	*9,136*
			(1.78)	
High performance	79.97	78.53	2.56*	*9,488*
			(1.54)	
P-value (difference)			[0.30]	

Notes: This table presents heterogeneous effects of receiving WhatsApp messages on student platform use by teachers characteristics. The dependent variable is a dummy that equals one if the student had connected at least once by the end of the intervention period (*Student Connected at Least Once*). The unit of observation is at the student level. For this analysis, students were divided by their teacher characteristics. Teachers were divided into two groups based on the median value of the average fraction of students connecting in the week prior to the intervention. Teachers whose connection rates were below the median were classified in the "Low Connection" group, while those above the median were categorized in the "High Connection" group. Similarly, teachers were grouped based on the average fraction of students with low or high performance based on the average performance in the four weeks prior to the intervention. We computed the median of this teacher-level variable and classified teachers into the "Low Performance" group if their students' average performance was below the median, and into the "High Performance" group if it was above the median. Robust standard errors, clustered at the teacher level, are reported in parentheses. *$p < .10$, ** $p < .05$, *** $p < .01$.

Table A5: Baseline Balance by Day of the Week the Message Was Sent

	Control	Difference			p-value			N
	Control	Monday	Tuesday	Wednesday	M = T	M = W	T = W	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
School characteristics								
Urban (%)	82.96	0.97	-4.12	4.40	0.17	0.30	0.02	20,376
		(3.24)	(3.59)	(3.15)				
Multigrade (%)	7.72	0.35	4.23*	-2.14	0.13	0.23	0.01	20,376
		(2.08)	(2.46)	(1.95)				
Located in Arequipa (%)	30.81	5.51	-4.16	-5.03	0.06	0.04	0.87	20,376
		(4.82)	(4.84)	(4.88)				
Located in Cajamarca (%)	19.42	-6.08*	-2.93	-1.95	0.38	0.28	0.81	20,376
		(3.58)	(3.78)	(4.00)				
Located in Junin (%)	11.33	-2.17	0.71	-1.53	0.34	0.82	0.47	20,376
		(2.71)	(2.97)	(2.81)				
Located in Lima (%)	18.57	4.91	9.48	10.15	0.46	0.45	0.93	20,376
		(4.31)	(5.91)	(6.71)				
Teacher characteristics								
Age	50.06	0.04	0.76	-0.04	0.39	0.94	0.42	20,376
		(0.82)	(0.81)	(0.97)				
Female (%)	72.45	-4.47	-8.74	-2.69	0.49	0.80	0.44	20,376
		(4.75)	(5.88)	(6.79)				
Pre-treatment use of the platform								
Student connected at least once (%)	56.14	-1.68	4.27	-4.67	0.08	0.54	0.08	20,376
		(3.10)	(3.48)	(4.92)				
Student average weekly connection (%)	22.42	0.19	1.69	-2.13	0.48	0.37	0.14	20,376
		(2.03)	(2.04)	(2.49)				
Student average exercises completed (%)	18.52	0.53	1.53	-1.46	0.62	0.40	0.20	20,376
		(1.91)	(1.89)	(2.24)				
Student exercises solved correctly (%)	-0.00	0.05	0.12**	0.03	0.32	0.75	0.19	9,312
		(0.06)	(0.06)	(0.06)				

Notes: This table presents summary statistics and differences in means in variables at baseline between students of teachers randomized to receive the WhatsApp messages on different days of the week (Mondays, Tuesdays or Wednesdays). The unit of observation is at the student level. Robust standard errors, clustered at the teacher level, are reported in parentheses.*$p < .10$, ** $p < .05$, *** $p < .01$.

Table A6: Effects on Platform Use by Day of the Week the Message Was Sent

	Control	Adjusted difference			p-value			N
		Monday	Tuesday	Wednes-day	M = T	M = W	T = W	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Panel A: During the intervention (weeks 1-8)								
Student connected at least once (%)	66.40	5.32***	3.06**	2.39	0.18	0.29	0.80	20,376
		(1.70)	(1.55)	(2.68)				
Student average weekly connection (%)	26.76	7.05***	3.50	3.46	0.16	0.12	0.99	20,376
		(1.93)	(2.42)	(2.23)				
Student average exercises completed (%)	23.87	5.91***	3.13	2.37	0.22	0.10	0.76	20,376
		(1.80)	(2.20)	(2.05)				
Panel B: Immediate post-intervention (weeks 9-18)								
Students connected at least once (%)	69.94	5.37***	2.28	2.97	0.11	0.48	0.83	20,376
		(1.91)	(1.82)	(3.33)				
Student average weekly connection (%)	23.29	4.72**	0.41	1.39	0.09	0.16	0.70	20,376
		(2.09)	(2.35)	(2.17)				
Student average exercises completed (%)	21.15	4.27**	0.33	0.76	0.09	0.11	0.85	20,376
		(1.98)	(2.16)	(2.03)				
Panel C: Delayed post-intervention (weeks 19-27)								
Students connected at least once (%)	71.72	4.95**	1.91	2.12	0.12	0.43	0.95	20,376
		(2.00)	(1.94)	(3.55)				
Student average weekly connection (%)	24.42	1.75	-1.39	-0.62	0.27	0.36	0.79	20,376
		(2.37)	(2.71)	(2.43)				
Student average exercises completed (%)	22.49	1.51	-1.37	-0.88	0.27	0.33	0.86	20,376
		(2.25)	(2.51)	(2.30)				

Notes: This table presents results from the effects of receiving WhatsApp messages on student platform use, by whether the messages were received on Mondays, Tuesdays or Wednesdays. See text for details. The unit of observation is at the student level. Robust standard errors, clustered at the teacher level, are reported in parentheses.*$p < .10$, ** $p < .05$, *** $p < .01$.

Table A7: Baseline Balance by Time the Message Was Sent

	Control	Difference		p-value	N
		AM	PM	AM = PM	
	(1)	(2)	(3)	(4)	(5)
School characteristics					
Urban (%)	82.96	0.63	0.45	0.95	20,376
		(3.05)	(2.93)		
Multigrade (%)	7.72	0.68	0.77	0.96	20,376
		(1.95)	(1.92)		
Located in Arequipa (%)	30.81	-1.63	-1.07	0.90	20,376
		(4.52)	(4.26)		
Located in Cajamarca (%)	19.42	-5.56*	-1.50	0.19	20,376
		(3.35)	(3.53)		
Located in Junin (%)	11.33	-1.86	-0.10	0.47	20,376
		(2.55)	(2.55)		
Located in Lima (%)	18.57	13.21**	2.94	0.07	20,376
		(5.68)	(3.77)		
Teacher characteristics					
Age	50.06	0.45	0.02	0.59	20,376
		(0.84)	(0.74)		
Female (%)	72.45	-8.50	-1.71	0.22	20,376
		(5.71)	(4.22)		
Pre-treatment use of the platform					
Student connected at least once (%)	56.14	-3.57	2.12	0.14	20,376
		(4.05)	(2.90)		
Student average weekly connection (%)	22.42	-2.27	2.11	0.03	20,376
		(2.04)	(1.90)		
Student average exercises completed (%)	18.52	-1.80	2.22	0.03	20,376
		(1.83)	(1.78)		
Student exercises solved correctly (%)	-0.00	0.05	0.08	0.59	9,312
		(0.05)	(0.05)		

Notes: This table presents summary statistics and differences in means in variables at baseline between students of teachers randomized to receive WhatsApp messages at different times of day (morning or afternoon). See text for details. The unit of observation is at the student level. Robust standard errors, clustered at the teacher level, are reported in parentheses.*$p < .10$, ** $p < .05$, *** $p < .01$.

Table A8: Effects on Platform Use by Time the Message Was Sent

		Adjusted difference		p-value	
	Control	AM	PM	AM = PM	*N*
	(1)	(2)	(3)	(4)	(5)
Panel A: During the intervention					
Student connected at least once (%)	66.40	2.54	4.62***	0.30	20,376
		(2.07)	(1.51)		
Student average weekly connection (%)	26.76	3.49*	5.84***	0.26	20,376
		(2.11)	(1.75)		
Student average exercises completed (%)	23.87	2.93	4.63***	0.37	20,376
		(1.92)	(1.64)		
Panel B: 10 weeks post-intervention					
Student connected at least once (%)	69.94	1.99	5.15***	0.19	20,376
		(2.47)	(1.77)		
Student average weekly connection (%)	23.29	0.60	3.80**	0.11	20,376
		(2.06)	(1.84)		
Student average exercises completed (%)	21.15	0.56	3.02*	0.19	20,376
		(1.92)	(1.74)		
Panel C: 19 weeks post-intervention					
Student connected at least once (%)	71.72	1.41	4.62**	0.21	20,376
		(2.65)	(1.86)		
Student average weekly connection (%)	24.42	-2.22	2.15	0.05	20,376
		(2.28)	(2.15)		
Student average exercises completed (%)	22.49	-2.07	1.66	0.07	20,376
		(2.15)	(2.04)		

Notes: This table presents results from the effects of receiving WhatsApp messages on student platform use, by whether the messages were received at different times of the day (morning or afternoon). See text for details. The unit of observation is at the student level. Robust standard errors, clustered at the teacher level, are reported in parentheses.*$p < .10$, ** $p < .05$, *** $p < .01$.

B. Additional details for cost estimations

This appendix outlines the parameters and assumptions used to estimate the costs of the intervention under various scenarios (see Appendix Table B1 below). The intervention lasted 8 weeks, with an additional 2 weeks allocated for staff training and administrative procedures. It targeted 600 teachers, each responsible for an average of 24 students. Regarding personnel costs, three people were involved in the implementation of this intervention:

1. Program coordinator: Responsible for overseeing the promotional effort, allocating 5% of her time to this task. The coordinator's monthly salary was $3,100.

2. Data analyst: Tasked with managing the data related to the messaging intervention, contributing 15% of her time. The data analyst's monthly salary was $1,100.

3. Customer service representative: This role involved responding to messages from teachers, dedicating 25% of their time to this task. The customer service representative's monthly salary was $334.

Based on these assumptions, the total cost for staff is calculated to be $938. In terms of messaging costs, we consider that sending each WhatsApp message had a cost of $0.07 (WhatsApp, 2024). With 600 teachers involved in the intervention and a duration of the intervention of 8 weeks, the total cost of messaging amounted to $337.

We also assume an overhead cost that accounts for 30% of the total costs associated with staff and messaging. This includes ancillary costs related to the implementation of the intervention. The total overhead cost is calculated to be $383.

Summing staff, messaging, and overhead costs, the total intervention cost is estimated at $1,659. This results in a cost of $2.76 per teacher for the entire intervention, or $0.35 per teacher per week. The cost per student for the full intervention period is $0.12, with a weekly cost per student of $0.015.

These costs would decrease with scale, as fixed costs are spread across more users. To illustrate this, we consider a scenario in which the intervention is expanded to all teachers with at least one student connected by the first week of August 2024, a point by which the program had been in place for some time and that aligns with the latest round of enrollment data available to us. The number of teachers would increase from 600 to 5,008, with an average class size of 25 students. We assume the customer service workload scales proportionally, requiring two full-time representatives. Under this scenario, the total cost per teacher falls to $1.32 for the full intervention period, or $5.30 per 100 students.

Additionally, we explore the role of automation in response handling for the scaling scenario. In this hypothetical case, the customer service representatives are replaced by WhatsApp's built-in autoreply feature, which redirects teachers to relevant resources. With this change, the total cost per teacher decreases to $0.92 for the full intervention period, representing a cost of $3.68 per 100 students.

Table B1: Estimated Costs

	Pilot (1)	Scaled-up (2)	Scale + Autoreply (3)
Panel A: Cost per Teacher			
Staff	1.56	0.46	0.15
Program coordinator	0.60	0.07	0.07
Data analyst	0.64	0.08	0.08
Customer service representative	0.32	0.31	0.00
Whatsapp message	0.56	0.56	0.56
Overhead	0.64	0.31	0.21
Total cost per teacher	2.76	1.32	0.92
Panel B: Cost per Student			
Staff	0.07	0.02	0.01
Program coordinator	0.03	0.00	0.00
Data analyst	0.03	0.00	0.00
Customer service representative	0.01	0.01	0.00
Whatsapp message	0.02	0.02	0.02
Overhead	0.03	0.01	0.01
Total cost per student	0.12	0.05	0.04
Panel C: Scale of Implementation			
N (teachers)	600	5,008	5,008
N (students)	14,400	125,200	125,200

Notes: Costs are calculated based on the assumptions outlined in Appendix B. Panel A summarizes costs per teacher. Panel B summarizes costs per student. Panel C presents the number of teachers and students targeted. Column 1 presents cost estimates for the experimentally evaluated pilot implemented in 2022. Column 2 presents results for a scenario in which the program is scaled up based on recent platform usage (teachers with at least one student who connected to the platform during the first semester of 2024). Column 3 shows results for the scaled-up version, but assuming that replies to messages from teachers are automated using a built-in WhatsApp functionality.

C. Messages sent via WhatsApp

This appendix presents the messages used during the eight-week treatment period. Two versions of each message were sent during the treatment period, alternating between even and odd weeks. Both types will be presented here, annotated by (O) for odd and (E) for even. The original messages, sent in Spanish, are presented below alongside their English translations.

- **No connection the previous week**

  If the teacher had no students connected during the previous week, they received a message highlighting the program's benefits.

  Hello, Anawaving-hand-light-skin-tone. Did you know that Conecta Ideas is adapted for students with low connectivity and can be used in the classroom, at home, or both? Downloading and submitting activities consumes very little internet. On average, only 2 to 3MB per week would be required (equivalent to 10 - 12 seconds of a WhatsApp video call). Also, you don't need internet at the moment of doing the activity; the app only needs a bit of internet beforehand to download the task sun-with-face. We remain attentive to any questions or doubts you have about our program! We look forward eagerly to your students' participation.

  The original message in Spanish is presented next:

  Hola, Anawaving-hand-light-skin-tone. ¿Sabías que Conecta Ideas está adaptado para estudiantes con baja conectividad y puede ser usado en el aula, en el hogar o en ambos? La descarga y envío de actividades consume muy poco internet. En promedio solo se requeririan 2 o 3MB por semana (equivalente a 10 - 12 segundos de una video llamada via WhatsApp). Ademas, no necesita tener internet al momento de hacer la actividad, el app solo necesita un poco de internet antes para descargar la tareasun-with-face. ¡Quedamos atentos a cualquier consulta o duda que tengas sobre nuestro programa! Esperamos con muchas ansias a tus estudiantes.

- **Less than 20% of the class connected the previous week**

  If the teacher had at least one connected student but less than 20% of their class in the previous week, they received a message that had two parts: a report on the number of connected students and a call to action. During odd weeks (1, 3, 5, and 7), they received the following message:

Hello, Ana. We're writing to you from Conecta Ideasbrain! Last week, 3 out of the 30 students you registered connected. Encourage your class to practice with us week after week! We're looking forward to seeing yousmiling-face-with-smiling-eyes.

During even weeks (2, 4, 6, and 8), they received the following message:

Hello, Ana. We're writing to you from Conecta Ideasbrain! Last week, you had 3 connected students out of the 30 you've registered. Motivate your students to connect week after week! We're looking forward to seeing yousmiling-face-with-smiling-eyes.

Original messages in Spanish for the odd and even weeks are the following:

(O) *Hola, Ana. ¡Te escribimos desde Conecta Ideasbrain! La semana pasada, 3 de los 30 estudiantes que registraste se conectaron. ¡Anima a tu aula a practicar semana a semana con nosotros! Los esperamossmiling-face-with-smiling-eyes*.

(E) *Hola, Ana. ¡Te escribimos desde Conecta Ideasbrain! La semana pasada tuviste 3 estudiantes conectados de los 30 que ya has registrado. ¡Motiva a tus estudiantes a que semana a semana se conecten! Los esperamossmiling-face-with-smiling-eyes*.

- **Between 21% and 50% of the class connected the previous week**

  If the teacher had a connection rate between 21% and 50% of their registered students during the previous week, they received a message with the report and a call to action motivating them to improve. During odd weeks (1, 3, 5, and 7), they received the following message:

  Hello, Ana. We're writing to you from Conecta Ideasbrain! Last week, 10 out of the 30 students you registered connected. You're very close to a high weekly connection! Encourage your students to practice with us week after week. We're looking forward to seeing you!party-popper

  During even weeks (2, 4, 6, and 8), they received the following message:

  Hello, Ana. We're writing to you from Conecta Ideasbrain! Last week, you had 10 connected students out of the 30 you've registered. You're very close to an impressive weekly connection! Encourage all your students week after week to practice with us. We're looking forward to seeing you!party-popper

  Original messages in Spanish for the odd and even weeks are presented next:

(O) *Hola, Ana. ¡Te escribimos desde Conecta Ideasbrain! La semana pasada, 10 de los 30 estudiantes que registraste se conectaron. ¡Ya estas muy cerca de una alta conexión semanal! Anima a tus estudiantes a practicar con nosotros semana a semana. ¡Los esperamos!party-popper*

(E) *Hola, Ana. ¡Te escribimos desde Conecta Ideasbrain! La semana pasada tuviste 10 estudiantes conectados de los 30 que ya has registrado. ¡Ya estas muy cerca de una impresionante conexión semanal! Anima a todos tus estudiantes semana a semana a practicar con nosotros. ¡Los esperamos!party-popper*

- **More than 50% of the class connected the previous week**

  If the teacher had a connection rate of more than 50% of students, they were considered to have high connectivity, so they received the connected report and congratulations. During odd weeks (1, 3, 5, and 7), they received the following message:

  Hello, Ana. We're writing to you from Conecta Ideasbrain! Last week, 20 out of the 30 students you registered connected. Impressive high connectivity in your class! We send our congratulations and look forward to seeing you every week to practice mathtrophy.

  During even weeks (2, 4, 6, and 8), they received the following message:

  Hello, Ana. We're writing to you from Conecta Ideasbrain! Last week, you had 20 connected students out of the 30 you've registered. Incredible high participation from your students! We send our congratulations and look forward to seeing you every week to practice math with much enthusiasm and many flagstriangular-flag.

  Original messages in Spanish for the odd and even weeks are presented next:

  (O) *Hola, Ana. ¡Te escribimos desde Conecta Ideasbrain! La semana pasada, 20 de los 30 estudiantes que registraste se conectaron. ¡Impresionante la alta conectividad de tu clase! Les mandamos nuestras felicitaciones y los esperamos semana a semana con mucho entusiasmo para practicar matemáticatrophy*.

  (E) *Hola, Ana. ¡Te escribimos desde Conecta Ideasbrain! La semana pasada tuviste 20 estudiantes conectados de los 30 que ya has registrado. ¡increíble la alta participación de tus estudiantes! Les mandamos nuestras más sinceras felicitaciones y los esperamos semana a semana con mucho* *entusiasmo y muchas banderitastriangular-flag*.