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**Keywords:** distance education and online learning; elementary education; cultural and social implication

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# The Impact of Computer Assisted Learning on Rural Taiwanese Children: Evidence from a Randomized Experiment

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## Abstract

The effectiveness of educational technology (EdTech) in improving the outcomes of poor, marginalized students has primarily been documented by studies conducted in developing countries; however, relevant research involving randomized studies in developed country contexts is relatively scarce. The objective of the current study is to examine whether an in-school computer assisted learning (CAL) intervention can improve the math performance (the primary outcome) and academic attitudes (secondary outcomes) of rural students in Taiwan, including a marginalized subgroup of rural students called Xinzhumin. We also seek to identify which factors are associated with the effectiveness of the intervention. In order to achieve this, we conducted a randomized control trial involving 1,840 sixth-grade students at 95 schools in four relatively poor counties and municipalities of Taiwan during the spring semester of 2019. According to the ITT analysis, the O-CAL intervention had no significant ITT impacts on the primary outcome of student math performance as well as on most secondary outcomes of the overall treatment group (who on average used the software for only about one quarter of the protocol's minimum required time of 30 minutes per week, indicating that compliance was low). However, the LATE analysis revealed significant improvements in the math performance of the 30% most active students in the treatment group (who used the software for about two thirds of the minimum required time). Effect sizes of active users overall (0.16 SD-0.22 SD) increased in accordance with increases in usage and were larger for active Xinzhumin users specifically (0.21 SD-0.35 SD). A wide range of student-level and (in particular) teacher-level characteristics were associated with the low compliance to the intervention, which are findings that may help inform educational policymakers and administrators of the potential challenges of introducing school-based interventions that depend heavily on teacher adoption and integration.



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## 1. Introduction

An increasing body of evidence supports the use of educational technology (EdTech) to help struggling students in low-resource settings of developing countries. Randomized experiments conducted in India (Banerjee et al., 2007; Linden, 2008) and China (Mo et al., 2015; Bai et al., 2018; Mo et al., 2020) indicate that computer-assisted learning (CAL) can significantly improve student academic performance in core subjects such as math and language. These and other studies (Glennerster et al., 2011; Unwin et al., 2017) highlight the ability of CAL specifically and EdTech in general to provide disadvantaged students with tailored remedial tutoring in contexts where shortages of skilled teachers exist.

In more developed nations, in which there are also always vulnerable subgroups of students that live and attend school in low-resource environments and who often struggle academically, there has been less high-quality, evidence-based research on the potential of EdTech to address educational inequalities. Although students in poorly resourced areas of these nations also would almost certainly have a need for the additional learning that could come from EdTech solutions, the existing literature conducted in high-income countries typically has not focused on its application in vulnerable communities (Crump & Twyford, 2010). Moreover, the few existing studies that have explored the potential of EdTech in disadvantaged schools have lacked rigor. One study that included 9,898 secondary school students in the Netherlands found that low-performing schools that used CAL software exhibited significant improvements in standardized math scores, but this study had no control group and the school sample was not randomly selected (De Witte, Haelermans, & Rogge, 2015). A second study conducted in the

U.S. suggested that access to and use of computers and software were positively associated with the academic achievement of African American children. However, in the paper the authors are clear that the study's results were correlational and the authors could not identify which kinds of software were used (Judge, 2005). A third study identified an impact of a three-year teacher professional development program involving technology integration on rural student achievement in Missouri, but it could not isolate to what extent the increased math scores were a result of the technology component of the program (Meyers et al., 2016).

In high-income Taiwan, where there are vulnerable subgroups of children in relatively low-income rural regions, there is also a need to understand whether or not the use of EdTech can effectively help struggling students. As a whole, rural Taiwanese students -- due to a range of factors, including worse socioeconomic conditions, less access to educational resources like private tutoring, and less convenient transportation—have academically lagged behind their urban peers according to performance on standardized academic achievement tests (Chen, 2012) and college admissions rates (Luoh, 2002; Liao et al., 2013). A subgroup of rural children who may be particularly vulnerable is Xinzhumin (新住民). Xinzhumin children—children whose mothers immigrated from surrounding countries in Asia and often do not speak fluent Mandarin—make up approximately 10% of the population in Taiwanese primary schools (and a much higher share in low-income, rural schools—MOE, 2017). In addition, since Xinzhumin often marry into Taiwanese households that are of relatively low socioeconomic status, these children often grow up in poorer environments than their peers (Liao & Wang, 2013). Past research indicates that at school Xinzhumin children may be vulnerable in a number of ways: they may be more likely than local Taiwanese children to face more difficulty in adjusting to school, struggle academically, and encounter mental health issues like depression when struggling academically (Chin & Yu, 2008; Lin & Lu, 2016; Gao et al., 2020).

According to the knowledge of the authors, however, there exists a dearth of evidence as to whether or not EdTech could be a potential avenue for improving the academic outcomes for disadvantaged Taiwanese children at school. Chen et al. (2014) reported significant positive effects of digital game-based learning on math for both urban and rural students compared to corresponding control groups, but this study only included two classes in each experimental group. A larger, randomized study which included a sample of 1,539 rural, predominantly aboriginal students found that CAL improved math scores by 0.08 to 0.20 SD despite relatively low overall compliance (Tang et al., 2018). As students used the CAL software exclusively at home and the sample did not include any Xinzhumin children, however, these results do not necessarily reflect potential outcomes in school settings that include samples of other rural subgroups.

One aspect in which in-school EdTech interventions may differ significantly from those that are home-based is that teachers play a larger role in adoption and compliance, even if the end user is the student (Straub, 2017). A number of studies have explored the complex interplay between teacher characteristics, attitudes towards technology use, and their ultimate decisions on adoption. Teacher-related variables such as age, gender, years of teaching experience, and financial status may be related to their perceptions and ultimate use of technology (Afshari et al., 2009; Bussey, 2000; Hennessy, Harrison, & Wamakote, 2010; Nachmias, Mioduser, & Forkosh-Baruch, 2010; Wong, 2016), though few clear trends have emerged and associations appear to be context-dependent. Teacher computer self-efficacy (i.e., personal competence in computer technology) and the available time teachers have to learn how to use new technologies are cited as factors linked to technology adoption (Scherer et al., 2019; Afshari et al., 2009). Studies have shown many of these teacher-related variables may be relevant to the Taiwan context (Shiue, 2007; Hsu & Kuan, 2013), though not necessarily in rural areas.

In the current study, we seek to examine whether an in-school CAL intervention can improve the educational performance of rural students in Taiwan, including Xinzhumin students, as well as which factors are associated with whether or not the program is effective. In order to answer these questions, we have three specific objectives. First, we utilize an intention-to-treat analysis (using a randomized controlled trial) to calculate the impact of an in-school CAL intervention on student math performance as well as a number of secondary outcomes, such as student attitudes towards math, their teachers, and school. Second, we examine the nature of compliance and whether higher (lower) compliance is associated with a larger (smaller or insignificant) effect size. Finally, we explore which factors are correlated with compliance to the intervention, focusing primarily on student- and teacher-level variables.

## 2. Methods

### 2.1. Ethical Approval

Ethical approval for this study was granted by the Stanford University Institutional Review Board (IRB) (Protocol ID 35635). All subjects gave written informed consent in accordance with the Declaration of Helsinki.

### 2.2. Study Location

The data for the present study were collected in the fall of 2018 (baseline) and summer of 2019 (endline) from schools in four different counties/municipalities in central and southern Taiwan. These four regions have two common characteristics relevant to our study. First, they have relatively low levels of economic development compared to other areas of Taiwan in terms of primary income: Miaoli, Jiayi, and Yunlin are ranked in the bottom half of Taiwan's 20 counties and municipalities; Tainan has the lowest level of income of any special municipality in southern Taiwan (Chen & Wang, 2015). Second, these counties have relatively large numbers of Xinzhumin children compared to the national average, either in terms of share of the local population (between 15-19% of children in Miaoli, Jiayi, and Yunlin were Xinzhumin, compared to the national average of 11%), or in terms of the absolute number. Specifically, Tainan had 13,538 Xinzhumin children, making it fifth out of 20 counties and municipalities in terms of the gross number of Xinzhumin children (MOE, 2017).

### 2.3 Sampling and Randomization

The sampling strategy for our survey was as follows. First, we obtained a list of all rural elementary schools from the local bureaus of education of each county or special municipality. The research team used the list to choose the 101 schools that participated in the study. Next, in each sample school, we randomly selected one class in fourth grade and one class in fifth grade. Finally, once the schools and classes had been selected, we enrolled all students in the sample classes into our study. In total, 2,050 fourth-grade and fifth-grade students from 202 classes in 101 schools participated in the baseline survey in November and December of 2018.

Following the baseline survey, we randomly assigned schools in each county to either the treatment group or the control group. Through this randomization procedure, we ultimately assigned 51 schools (comprising 1,021 students) to the treatment group and 50 schools (comprising 1,038 students) to the control group. According to a set of student and teacher characteristics, we were able to successfully create a balanced sample across the treatment and control groups at the school level. The results of our balance tests in Table 1 show that none of the variables are significantly different between the groups except for one variable, teacher gender. By the time of the evaluation survey, we followed up with 1,840 students: 878 students in the treatment group and 962 students in the control group, resulting in a 10% attrition rate (see Appendix 1 for more details about attrition and corresponding balance tests).

### 2.4 Experimental Intervention

Following the baseline survey in November and December of 2018 and the random assignment procedure, we launched the intervention in March of 2019. All students in the treatment group were slated to participate in the same intervention. The intervention involved online computer-assisted remedial tutoring sessions designed to complement the regular in-class math curriculum for the spring 2019 semester. All of the teachers, parents, and students in the treatment and control schools were blind to the fact that they were involved in a randomized controlled trial.

There were two stages to the intervention. First, program teachers in each treatment group school (who were initially trained by the enumerator team during baseline) instructed students on how to use O-CAL for the first time. The program teachers—who were usually either the homeroom teachers of the students (who generally also taught them math) or their computer teachers—held the mandatory instructional sessions in their school's computer room. Referring to the training manual provided by the enumerators, teachers guided their students on how to log in to their private accounts and operate the software.

In the second stage, according to intervention protocol, teachers were supposed to ask students to log onto the O-CAL software in their school computer room and complete at least one 30-minute O-CAL session each week of the spring semester. Besides this, the main responsibility of program teachers was to assist with computer and software operation, but the protocol did not restrict them from providing additional tutoring in the subject area. There were also no restrictions regarding when the O-CAL sessions should take place. Teachers could arrange them anytime during the school day. Teachers received a small amount of remuneration (300 TWD, roughly equivalent to 10 USD) for their participation in the program, as well as two payments of 200 TWD (approximately 7 USD) during the baseline and endline surveys.

In the O-CAL sessions, students answered practice questions tailored to review the material they learned in their school's math textbook. The software provides students with immediate feedback upon answering each round of questions and also includes an adaptive learning component, automatically adjusting the difficulty of practice material based on each individual's student's prior performance. The O-CAL software is also a game-based learning platform, allowing students to explore a virtual world and earn in-game rewards as they complete learning challenges. In short, the platform is remedial in nature, as it is based on the material that is in student textbooks and reviews the material taught in school in that same week.

Students in schools that were assigned to the control group did not participate in the O-CAL intervention. According to the protocol (and since the exact nature of the intervention and the details of the OCAL program were blinded to all participants), they were not allowed to access the O-CAL software and did not receive user accounts and passwords. To our knowledge, no one in the control group used the O-CAL software for any purpose.

### 2.5 Data Collection

The data collection consisted of two rounds, before and after the intervention. As mentioned, the baseline survey took place near the end of the fall semester in 2018. The endline survey took place at the end of the spring semester in June 2019. Each round of surveying was conducted by an enumeration team made up of local university students, who received several days of training from survey leaders at Academia Sinica before visiting the 101 sample schools. At each sample school enumerators followed a strict protocol, including providing the sample classes a detailed explanation of the survey expectations and enforcing strict time limits.

Each round of data collection consisted of a three-block survey. In the first block, students were given a standardized math test which included 29 to 32 questions (tests in different rounds included slightly different numbers of questions). In the second block, the questionnaire asked about student attitudes towards various aspects of school ("secondary outcomes"). In the third block, enumerators collected data on the characteristics of students and teachers. For more information about the survey instruments and contents, please see Appendix 2.

During the course of the semester, the research team monitored the backend of the O-CAL software, which allowed them to track O-CAL usage on the student, class, and school levels. When the research team discovered non-compliance among treatment schools, they called up the school's program teacher and reminded them to follow the protocol. At the end of the semester, the team collected summary data on student usage over the duration of the intervention.

2.6 Statistical Methods

To estimate the change in academic and non-academic outcomes in the treatment group relative to the control group, we ran an Ordinary Least Squares (OLS) model, regressing the outcome variables (i.e. post-program outcome value) on the baseline value of the outcome variable and a dummy variable of the treatment (O-CAL intervention) status, controlling for a set of control variables. As randomization was conducted within schools, we also controlled for school fixed effects to disentangle the systematic within-school differences between the treatment and control classes in $Y_{ijk}$ and to obtain an unbiased estimate of the genuine treatment effect of the O-CAL intervention. We included control variables to improve the efficiency of the estimation. In all regressions, we constructed Huber-White standard errors (relaxing the assumption that disturbance terms were independent and identically distributed within schools) to account for the clustered nature of our sample.

To conduct the Intention-to-Treat (ITT) analysis, we estimate by using the following ordinary least squares (OLS) model:

$$y_{ijk}=\alpha+\beta*treatment+\theta*y_{0ijk}+\gamma*s_{ijk}+\delta*t_{ijk}+c+\varepsilon_{ijk} \quad (1)$$

where $y_{ijk}$ is the outcome variable (math score and other secondary outcomes of student i in school j in county k); treatment is a dummy variable that is equal to one if the student is in a treatment school, and zero otherwise; $y_{0ijk}$ is the baseline value of the dependent variable; $s_{ijk}$ is a vector of student characteristics; $t_{ijk}$ is a vector of teacher characteristics; c is a set of fixed county effects; and $\varepsilon_{ijk}$ is a random disturbance term clustered at the school level. The parameter, $\beta$, gives the ITT estimate of the O-CAL program treatment. We present these results and an expanded vector of baseline characteristics in Tables 2-4.

In order to explore the O-CAL program's impact on students who had higher levels of usage, we added variables to the ITT model to estimate the effects of being in the top percentage of active users (LATE):

$$y_{ijk}=\alpha+\beta*treatment+\theta*y_{0ijk}+\lambda*usage_{ijk}+\gamma*s_{ijk}+\delta*t_{ijk}+c+\varepsilon_{ijk} \quad (2)$$

where treatment is a dummy variable that is equal to one if the student is in a treatment school and zero otherwise; $y_{0ijk}$ is the baseline value of the dependent variable; $usage_{ijk}$ is a dummy variable that is equal to one if the student is in a top usage group and zero otherwise; $s_{ijk}$ is a vector of student characteristics; $t_{ijk}$ is a vector of teacher characteristics; c is a set of fixed county effects; and $\varepsilon_{ijk}$ is a random disturbance term clustered at the school level. As in equation (1) the parameter, $\beta$, gives the estimate (using the adjusted model) of the O-CAL program treatment effect on students who had higher levels of usage. The results of this model are presented in Table 6 and are also discussed in the next section of the paper.

In order to estimate the O-CAL program's impact on students who had higher levels of usage and are Xinzhumin, we use the following model on top of the LATE model:

$$y_{ijk}=\alpha+\beta*treatment+\theta*y_{0ijk}+\lambda*usage_{ijk}+\mu*Xinzhumin+\rho*treatment*Xinzhumin+\tau*usage_{ijk}*Xinzhumin+\gamma*s_{ijk}+\delta*t_{ijk}+c+\varepsilon_{ijk} \quad (3)$$

where treatment is a dummy variable that is equal to one if the student is in a treatment school and zero otherwise; $y_{0ijk}$ is the baseline value of the dependent variable; $Xinzhumin$ is a dummy variable that is equal to one if the student is Xinzhumin and zero otherwise; $usage_{ijk}$ is a dummy variable that is equal to one if the student is in a top OCAL usage group and zero otherwise; $s_{ijk}$ is a vector of student characteristics; $t_{ijk}$ is a vector of teacher characteristics; c is a set of fixed county effects; and $\varepsilon_{ijk}$ is a random disturbance term clustered at the school level. The parameter, $\beta + \lambda + \rho + \tau$, gives the estimate (using the adjusted model) of the O-CAL program treatment effect on students who had higher levels of usage and are Xinzhumin. The results of this model are presented in Table 7 and are also discussed in the next section of the paper.

## 3. Results

### *3.1 Balance test*

Student baseline characteristics displayed in Table 1 demonstrate that the control and treatment groups were statistically balanced across all variables. Teacher characteristics were also statistically balanced with the exception of teacher gender (28.5% of the control group was male, as opposed to 50.7% of the treatment group). Please see Appendix 3 for a more detailed introduction to the descriptive statistics of the sample.

*3.2 Intention to Treat (ITT) Impact*

According to the ITT analysis, there was no significant impact of the intervention on student math scores (Table 2). This is true for both the unadjusted (0.010 SD – Table 2 column 1) and adjusted (0.015 SD – Table 2, column 2) models. There was also no significant impact on the math scores of Xinzhumin or non-Xinzhumin students, with neither subgroup benefiting more than the other (Table 3, rows 3 and 5). These results contrast with the findings of other CAL evaluations in under-resourced contexts, which have observed significant and positive effect sizes on student academic achievement between 0.10 SD and 0.35 SD (Banerjee et al., 2007; Linden, 2008; Mo et al., 2015).

For most secondary student outcomes, as well, there was no evidence of an ITT impact (Table 3). The one exception was for the variable "like math teacher" according to the adjusted model. For this outcome, the Z-score increased by 0.143 SD (significant at the 5 percent level – Table 4 column 6). In other words, to the extent that this result is measuring the underlying "feelings" of the students in the treatment group, the intervention of giving O-CAL to the students ended up making students look favorably upon their math teacher. For "like school" and "like math," however, the ITT impact was non-significant.

*3.3 Analysis of O-CAL Usage and Corresponding Impacts (LATE Analysis)*

Recent research on the effectiveness of CAL has shown that insignificant or small impacts may be linked to a lack of compliance with the intervention (Tang et al., 2018; Mo et al., 2020). Moreover, these studies indicate that, when subsets of the students in the sample adhere to the protocol, they may still benefit from participation—even though this impact can be undetectable using just the ITT analysis (which measures average effects of compliers and non-compliers). The previous literature also suggests that among students who comply, the higher their degree of compliance to the CAL intervention is (i.e., the more they use CAL), the larger the effect size is (thereby producing marginal impacts for those that use the CAL program relatively more – De Witte, Haelermans, & Rogge, 2015).

To investigate whether or not there was low compliance to the experimental protocol, we calculated the mean usage time among all students in the treatment group (Table 5 row 1). Ultimately, we found that on average students had only used the software for about 83 minutes over the ten-week period of the intervention, which is an average of 8 minutes per week (compared to the 30 minutes per week stipulated by the protocol—which was the 40-minute class period, minus 10 minutes for log-in and stand-down time). This low rate of average use (about 30% of full compliance) confirmed that compliance was low and suggested this may have been a potential reason for the lack of ITT impact, thus warranting further investigation.

Next, in order to better understand whether compliers benefited from the intervention as well as whether or not there were marginal impacts among them, we first define *active users* as students in the top 40% of users – who used the software for an average of 160 minutes overall or 16 minutes per week (about 60% of full compliance). Next, we divided active users into six subgroups (referred to throughout the rest of the paper as *active user subgroups* – Table 5, rows

2-7).[1] On average, students in the top 5% (the most active of the six subgroups) used the software for an average of 259 minutes during the ten weeks of the spring semester (about 26 minutes per week—or nearly 90% of full compliance). The top 10% used the software for 230 minutes on average (23 minutes per week). The mean usage of the remaining active user groups was 212 minutes (21 minutes per week) for the top 15%, 199 minutes (20 minutes per week) for the top 20%, 177 minutes (17 minutes per week) for the top 30% and 160 minutes (16 minutes per week) for the top 40%.

We next examined the impact of the intervention on these active user subgroups in terms of math achievement (Table 6). We measured this according to two dimensions. First, we calculated the marginal impact of belonging to an active user subgroup (or, in other words, the additional effect of using O-CAL above a certain threshold relative to the rest of the treatment group). Second, using equation (2), we measured the overall impact of both belonging to the treatment group and using O-CAL for a minimum amount of time.

Upon examining the impact of the intervention on active user subgroups, we made two discoveries. First, the longer these students used O-CAL, the more they benefited from it academically relative to less active users in the treatment group (i.e. there was a significant marginal impact). Moreover, the marginal impacts for students in the most active subgroups were the largest. Specifically, the marginal impact was 0.212 SD (significant at the 1% level – row 2 column 1) for the top 5% of users and 0.225 SD (significant at the 5% level – row 3 column 2) for the top 10% of users. There were also significant marginal impacts for students in the top 15% (0.198 SD, significant at the 10% level – row 4 column 3), top 20% (0.181 SD,

[1] Less active subgroups also include students in the more active subgroups. For instance, the top 10% active user subgroup also includes those in the top 5% subgroup.

significant at the 5% level – row 5 column 4), and top 30% (0.152 SD, significant at the 10% level – row 6 column 5) of users.

The second finding was that the math scores of the active user subgroups not only improved significantly when compared to other students in the treatment group but also when compared to students in the control group (i.e. there was a significant overall impact). Similar to marginal impacts, the longer the students used O-CAL the larger the overall impact was, with the top 5% of users (0.217 SD, significant at the 5% level – row 9 column 1) and top 10% of users (0.219 SD, significant at the 10% level – row 9 column 2) benefiting the most. There were also significant overall impacts for students in the top 15% (0.185 SD, significant at the 10% level – row 9 column 3) and top 20% (0.161 SD, significant at the 10% level – row 9 column 4) of users, though there were none for those in the top 30% and top 40% subgroups (row 9 columns 5-6).

Moving beyond examining effects on the overall student population, the research team also narrowed the scope of the analysis to measure impacts on active Xinzhumin users. To do this, using equation (3), we calculated the overall impact on the Xinzhumin students in each active user subgroup compared to the control group. As a part of this overall impact, we also measured whether or not there were marginal impacts for Xinzhumin relative to the non-Xinzhumin students in these subgroups.

According to the findings, the math achievement of active Xinzhumin users significantly improved, particularly in terms of overall impact compared to the control group but also – in some cases – in terms of marginal impact compared to non-Xinzhumin in the same active user subgroups (Table 7). The math scores of Xinzhumin in five of the six active user subgroups increased significantly relative to the control group (row 9), including Xinzhumin in the top 5%

(0.345 SD, significant at the 5% level), top 10% (0.312 SD, significant at the 10% level), top 15% (0.291 SD, significant at the 5% level), top 30% of (0.191 SD, significant at the 10% level), and top 40% (0.211 SD, significant at the 10% level) of users. In two of the active user subgroups, the marginal impact of the intervention on math scores was significantly larger for Xinzhumin when compared to non-Xinzhumin students. This was the case for the top 30% of users (a difference of 0.191 SD, significant at the 10% level – row 13 column 5) and the top 40% of users (a difference of 0.234 SD, significant at the 5% level – row 15 column 6).

These results indicate that in Taiwan, O-CAL has the potential to improve the academic performance of not only poor rural students in general but also the marginalized rural subgroup of Xinzhumin in particular. In the current study, a precondition was that students needed to use O-CAL for a certain amount of time (15-16 minutes per week over the course of ten weeks) to reap any significant benefits. If this precondition was met, however, the benefits they accrued fall in the range of effect sizes seen in previous studies of CAL interventions (0.10 SD to 0.35 SD – Banerjee et al., 2007; Linden, 2008; Mo et al., 2015). For the sample as a whole (including both Xinzhumin and non-Xinzhumin students), the effect size of using O-CAL for between 16 and 26 minutes per week for ten weeks (0.11 SD to 0.22 SD) fall in the lower part of this range. For active Xinzhumin users specifically, the overall effect sizes corresponding to the same amounts of usage time (0.21 SD to 0.35 SD) were even larger than for the overall sample, falling in the upper part of this range. Moreover, the marginal impacts in Table 7 confirm that in some cases Xinzhumin benefited significantly more from the intervention than their non-Xinzhumin peers despite similar levels of compliance.

*3.4 Association of Student and Teacher Characteristics with O-CAL usage*

The results so far highlight that compliance to an in-school O-CAL intervention conducted in rural Taiwan over a ten-week period was low and that such compliance – in terms of using the software for a minimum amount of time – was necessary in order for students to have any additional improvement in math performance. It is yet unclear, however, what factors were linked to such low treatment fidelity. To answer this question, we explored the correlation of student and teacher characteristics with student O-CAL usage. For this sub-section, we measured usage both in terms of overall usage (in minutes - Table 7 column 1) as well as the likelihood of belonging to the top 40% of users (i.e. being an active user – Table 7 column 2).

*3.4.1 Student Characteristics*

When implementing the correlational analysis, the findings demonstrate that there were five subgroups of students who used O-CAL significantly less than others. The first of these subgroups was students with lower baseline math scores. Compared to their higher-scoring peers, they used the software for an average of 8 minutes less overall (significant at the 1% level) and were 4.2% less likely to be in the top 40% of users (significant at the 5% level). Male students also used the software less than female students, both in terms of overall usage (26 minutes less, significant at the 1% level) and a lower likelihood to be in the top 40% of users (16% less likely, also significant at the 1% level). In Tang et al. (2018), the study in rural Taiwan previously mentioned in which overall compliance was also low, both of these two subgroups were also less likely to use the software. It is possible that lower compliance among these two subgroups may at least partially be due to their lower engagement and participation in school, as the literature has shown that student engagement tends to be lower among both poor-performing students (Wang & Holcombe, 2010) and boys (Lam et al., 2012) when compared to their peers.

In contrast with male gender and low baseline score, the other three student characteristics associated with lower usage – having a college-educated father, having a private tutor, and having a computer at home – tend to be associated with better academic performance in the literature (Olanike, 2010; Bray, 2006; Casey et al., 2012). Students with college-educated fathers used the software for 11 minutes less (significant at the 5% level), while those with private tutors used the software for 12 minutes less (significant at the 5% level) and were 10% less likely to be an active user (significant at the 1% level). Students who used a computer at home also used the software for 12 minutes less on average (significant at the 5% level). As all three of these household characteristics are also sources of remedial education, it is possible that these additional resources may have in effect "crowded out" the O-CAL intervention. While it unclear to what extent parents intervened in their children's participation in the experiment, it is possible that some may have seen the supplementary remedial tutoring provided by O-CAL as unnecessary or even a distraction. This may have particularly been the case when teachers chose to organize O-CAL sessions after school, which would have led to scheduling conflicts with other forms of remedial tutoring arranged by parents. Indeed, the highly competitive education system in Taiwan incentivizes families to focus their child's out-of-class time on the most efficient methods of boosting test scores, which many still perceive to be private tutoring (often in the form of cram schools – Liu, 2012; Chang, 2013).

From this analysis, it appears that there may have been two major reasons on the individual student level for why certain students were less likely to comply. For poor-performing and male students, their relative lack of academic participation and discipline in general likely carried over to the O-CAL sessions. On the other hand, those students who already enjoy a number of remedial resources at home (such as a college-educated father, a private tutor, and a computer) may have been less likely to comply for a completely different reason – they (or their parents) simply did not see the need for additional tutoring. While these two reasons may have played a certain role in understanding the low compliance in the current study, we will next explore factors that may have been even more important: those related to teachers.

*3.4.2 Teacher characteristics*

As the current experiment was an in-school intervention that depended on teachers to arrange O-CAL sessions according to the protocol, the degree of student compliance to a large extent likely reflects teacher compliance. We found that to varying degrees, many of the teacher characteristics that we gathered at baseline appeared to be related to student usage. These included variables related to teacher demographic characteristics, educational background, attitudes towards their job, workload, and prior experience with technology.

In terms of demographic characteristics, both teacher gender and age were correlated with student compliance. Students with male teachers used the software for significantly less than those with female teachers, both in terms of overall usage (43 minutes less, significant at the 1% level) and likelihood of belonging to the top 40% of users (30% less likely, significant at the 1% level). Past research has indicated that male teachers in Taiwan tend to have a weaker interest in their profession than female teachers (Huang & Fraser, 2009). As intrinsic motivation is an important aspect of teacher technology adoption (Ketelhut & Shifter, 2011; Lai & Chen, 2010), it is possible that this may explain their lower levels of compliance. Age was also a factor linked to usage in our study: students of younger teachers also used the software less (2 minutes less, significant at the 1% level) and were less likely to belong to the active user group (0.8% less likely, significant at the 10% level). Younger teachers who are newer to the teaching profession may be more likely to experience occupational stress and burnout (Antoniou et al., 2006), and thus those in the present study may have been more inclined to shirk the additional responsibility of arranging O-CAL sessions.

Just like students whose teachers were young or male, those whose teachers had received higher levels of education (in terms of college attainment) also used O-CAL less (22 minutes fewer, significant at the 1% level) and were less likely to be active users (15.2% less likely, significant at the 1% level). Previous studies conducted in low-resource schools have indicated that – similar to younger and male teachers – teachers with higher levels of educational attainment tend to have lower levels of job satisfaction, as their higher qualifications may lead them to compare their current jobs with alternative opportunities perceived as more desirable (Sargent & Hannum, 2005; Michaelowa, 2002). Thus, our finding is consistent with the existing literature if we again assume that teachers who are less satisfied or motivated in general would be less likely to adopt new innovations.

Supporting the above reasoning, in the current study the attitudes of teachers towards their jobs were also related to the O-CAL usage of their students. Not surprisingly, the students of teachers who liked their work less also used the software less (19 minutes fewer, significant at the 1% level) and were less likely to be active users (12.0% less likely, significant at the 1% level). Satisfaction with income, however, had the opposite association with student O-CAL usage: the students of teachers who expressed that they were more satisfied with their income used the software for 12 minutes less overall (significant at the 1% level) and were 5% less likely to be an active user (significant at the 1% level). In other words, teachers who liked their work were more likely to comply but those who were satisfied with their income were less likely. One previous study that distinguished between these two facets of teacher job satisfaction – satisfaction with the work itself and satisfaction with pay – found that the prior was correlated with teacher motivation but the latter was not (Oades, 1983). A number of other studies likewise suggest that intrinsic work elements – such as the gratification received from teaching – are significantly related to teacher motivation, whereas extrinsic elements – like teacher pay – are unrelated (Sylvia & Hutchinson, 1985; Abd-El-Fattah, 2010; Sargent & Hannum, 2005). It is still unclear why teachers who were more satisfied with their salaries would be less (as opposed to equally) likely to comply, though it is possible that such teachers were less motivated than their less-satisfied peers by the conditional stipend offer to program teachers.

Our analysis also revealed that several aspects of the teacher's workload were linked to student usage, though some were positively correlated and others were negatively correlated. While weekend workload and homeroom workload were both negatively correlated to student usage (all significant at the 1% level), students of teachers who organized more tutoring classes per week used the software for a longer duration (6 minutes longer, significant at the 1% level) and were more likely to be active users (4.6% more likely, significant at the 1% level). This contrast may be due to O-CAL's nature as a remedial educational platform, as it is possible that teachers may have used it to replace a number of their tutoring sessions. Provided this were true, teachers who normally engaged in more tutoring would have been more likely to comply. For other types of work in which teachers engage on the weekend (e.g. grading and class preparation) and during homeroom (e.g. taking attendance and other administrative duties), however, teachers could not have used O-CAL as a form of replacement. Teachers with heavier loads of these latter work categories – and particularly those who did not normally engage as much in tutoring – might have (similar to younger teachers) instead viewed O-CAL as imposing an even greater burden. This is in line with the results of Wong (2016), who showed that teachers who have heavier workloads are less likely to adopt new technologies, especially when the use of the technology does not fit within their existing workflow.

A final set of variables that we included in this analysis was related to other conditions that are also demonstrated by the literature to predict a teacher's adoption of technology: computer self-efficacy and previous experience using educational technology (Wong, 2016; Scherer et al., 2019). Consistent with the findings of these previous studies, the results demonstrate worse computer skills and a lack of prior experience in using technology in class both led to lower compliance among teachers (reflected by less usage by students). Students whose teachers indicated that they had worse computer skills were 2.7% less likely to be active users, while students whose teachers had previously used technology more often in class used O-CAL for an average of 10 minutes more (significant at the 1% level) and were 6% more likely to be active users (significant at the 1% level). Similar to those who teach more tutoring classes, teachers who have more experience with using technology in class may have seen the O-CAL intervention as being compatible with their existing workflow. The literature has identified compatibility – the degree to which an innovation is perceived as consistent with the existing values, needs, and past experiences – to be one of the most important factors determining the decisions of potential adopters (Lai & Chen, 2011).

What can the above analysis, which involves a relatively large number of teacher characteristics and correlations, tell us about why certain teachers were less likely to comply? Although we cannot draw direct lines of causality, we can attempt to identify broad reasons for why certain teacher characteristics were associated (either positively or negatively) with compliance. First, the literature suggests that teachers with certain traits – such as those who are male, those who have a college education, and those who are less interested in their profession –

may have less intrinsic motivation in teaching than their peers, a trait which could also decrease their engagement in the O-CAL intervention. Second, a lack of compatibility with existing work schedules and routines of teachers may explain why the younger teachers, the teachers who had heavier workloads, the teachers who taught fewer tutoring sessions, and the teachers who had less previous experience using technology in the classroom were less likely to comply. A lack of confidence in using technology, which does not quite fit into either of these first two explanations, was perhaps a third factor that hindered some teachers from complying.

## 4. Discussion

Through a randomized experiment involving 1,840 students at 95 schools in rural parts of eastern and southern Taiwan, the current study has demonstrated that the effectiveness of a ten-week in-school CAL intervention at improving the academic performance of poor, disadvantaged students depended on student and teacher compliance to intervention protocol. O-CAL had no significant ITT impacts on the primary outcome of student math performance as well as on most secondary outcomes of the overall treatment group (which on average used the software for 8 minutes each week – approximately one quarter of the protocol's minimum required time of 30 minutes). The LATE analysis, however, revealed significant improvements in the math performance of the 30% most active students in the treatment group, who used the software for at least 20 minutes per week (two thirds of the minimum time required by the protocol). These active users not only improved relative to students in the control group (in terms of overall impacts) but also relative to each other (in terms of marginal impacts), with effect sizes increasing in accordance with increases in usage. Moreover, among active users, the impacts appeared to be just as large for the marginalized rural subgroup of Xinzhumin children as for their non-Xinzhumin peers (and in some cases even larger). The range of effect sizes in this study (0.11 SD-0.35 SD) are comparable to those documented by studies in low-resource contexts of developing countries (Banerjee et al., 2007; Linden, 2008; Mo et al., 2015), thereby demonstrating the potential of CAL interventions to address educational inequalities in high-income countries like Taiwan.

Besides highlighting the importance of compliance in determining the success of in-school CAL interventions, the present study also indicates that certain subgroups (of both students as well as the teachers responsible for implementation) may comply (with this intervention as well as possibly with other schooling initiatives) significantly less than others. Although we cannot determine the actual underlying reasons for low compliance based on our results, we can make inferences based on previous literature that identifies relevant traits associated with these subgroups. While the low compliance of poor-performing students and male students might be explained by their tendency to be less engaged in school (Wang & Holcombe, 2010; Lam et al., 2012), parental opposition due to scheduling conflicts with after-school cram sessions might explain the low compliance of other student subgroups (such as those whose fathers attended college, those who had a private tutor, and those who used a computer at home – Olanike, 2010; Bray, 2006; Casey et al., 2012; Liu, 2012). Likewise, the low compliance of different subgroups of program teachers may also have different interpretations. For example, the literature suggests that male teachers, teachers with a college education, and teachers who are less interested in their profession tend to have lower intrinsic motivation at work, which could have lowered their compliance in this study (Sargent & Hannum, 2005; Michaelowa, 2002; Scherer et al., 2019). However, for other teacher subgroups that did not comply – including those who were younger, those with heavier workloads, those who tutor less, and those with less

EdTech experience – O-CAL's lack of compatibility with existing work schedules and routines might explain their low compliance (Wong, 2016; Antoniou et al., 2006).

## 5. Conclusions

The findings of this experiment – particularly those regarding the lower compliance among certain teacher subgroups – may help inform school administrators on how to successfully implement EdTech (and other types of new) interventions that depend on teacher adoption and integration. One potential takeaway from this study is that administrators need to work with teachers to ensure that new interventions are compatible with their existing workflows. This may involve providing additional guidance to teachers on how to make adjustments to their schedules or accommodating teachers by reducing their burdens in other areas (such as their homeroom duties). Second, professional development involving technology-related (or other types of) training may also increase uptake, as low confidence in computer skills was associated with lower compliance in the current experiment (as well as in many past studies – Scherer et al., 2019; Sang et al., 2010; Park, 2004) and technology training has been shown to increase both computer self-efficacy and technology adoption (Zhao & Bryant, 2006; Dawson & Rakes, 2003). Although the O-CAL experiment included intervention-specific training, it is unlikely that this would have increased teachers' computer self-efficacy in general. Finally, incorporating the adoption of technology into teachers' mandatory duties and factoring compliance into teacher evaluations may incentivize those with lower intrinsic motivation, as ongoing performance evaluations can be an effective way of changing teacher behavior (Taylor & Tyler, 2012).

In regard to this study's limitations, it is important to note that although we were able to measure associations between low compliance and study participant characteristics, these results are only correlational and may have causes beyond those stated above. For example, it is possible that the teachers did not perceive the O-CAL software as being useful or easy to use, which are two factors that may also be correlated with teachers' intention to adopt (Joo et al., 2018; Teo et al., 2011; Chen & Tseng, 2011). Future research could utilize a combination of quantitative and qualitative approaches to understand the role that such attitudes play in the technology adoption of rural Taiwanese teachers and how such attitudes may vary by subgroup.

**Table 1. Baseline characteristics after attrition (N = 1,840)**

| | VARs | Control group | Treatment group | Difference |
|---|---|---|---|---|
| | | (1) | (2) | (3)=(1)-(2) |
| ***Student characteristics*** | | | | |
| [1] | Standardized baseline math score | -0.027 | 0.030 | 0.049 |
| | | (0.996) | (1.005) | (0.071) |
| [2] | One child (1 = yes) | 0.127 | 0.121 | -0.009 |
| | | (0.333) | (0.326) | (0.016) |
| [3] | Male (1 = yes) | 0.534 | 0.525 | -0.009 |
| | | (0.499) | (0.500) | (0.024) |
| [4] | Student age (years) | 10.356 | 10.413 | 0.064 |
| | | (0.744) | (0.739) | (0.049) |
| [5] | Mother education level (1 = college or above) | 0.525 | 0.492 | -0.036 |
| | | (0.500) | (0.500) | (0.030) |
| [6] | Mother lives at home (1 = yes) | 0.873 | 0.892 | 0.018 |
| | | (0.333) | (0.311) | (0.014) |
| [7] | Mother is Taiwanese (1 = yes) | 0.771 | 0.784 | 0.008 |
| | | (0.420) | (0.412) | (0.024) |
| [8] | Father education level (1 = college or above) | 0.489 | 0.479 | -0.016 |
| | | (0.500) | (0.500) | (0.031) |
| [9] | Father lives at home (1 = yes) | 0.865 | 0.863 | -0.003 |
| | | (0.342) | (0.344) | (0.017) |
| [10] | Private tutor (1 = yes) | 0.529 | 0.517 | -0.015 |
| | | (0.499) | (0.500) | (0.042) |
| [11] | Parent helps on homework (1 = yes) | 0.649 | 0.642 | -0.011 |
| | | (0.478) | (0.480) | (0.029) |
| [12] | Asset index | 0.002 | -0.057 | -0.064 |
| | | (1.263) | (1.288) | (0.078) |
| [13] | Uses computer at home (1 = yes) | 0.662 | 0.639 | -0.027 |
| | | (0.473) | (0.481) | (0.027) |
| ***Teacher characteristics*** | | | | |
| [14] | Teacher gender (1 = male) | 0.285 | 0.507 | 0.222** |
| | | (0.452) | (0.500) | (0.085) |
| [15] | Teacher age (year) | 41.300 | 42.494 | 1.201 |
| | | (7.720) | (8.204) | (1.437) |
| [16] | College education (1 = yes) | 0.698 | 0.618 | -0.083 |
| | | (0.460) | (0.486) | (0.073) |
| [17] | Tenure (year) | 14.954 | 16.541 | 1.654 |
| | | (7.857) | (8.189) | (1.469) |
| [18] | Like work Z score | -0.009 | 0.165 | 0.173 |
| | | (1.018) | (0.898) | (0.152) |
| [19] | Satisfaction with pay Z score | -0.017 | 0.141 | 0.170 |
| | | (1.043) | (0.857) | (0.166) |
| [20] | Number of classes per week (classes) | 15.544 | 15.928 | 0.358 |
| | | (1.664) | (1.996) | (0.273) |
| [21] | Number of tutoring classes for students per week (classes) | 1.532 | 1.688 | 0.167 |
| | | (1.294) | (1.438) | (0.252) |
| [22] | Weekend workload per week (hours) | 5.293 | 5.011 | -0.306 |
| | | (4.298) | (4.721) | (0.694) |
| [23] | Homeroom teacher workload per week (hours) | 15.504 | 11.790 | -3.893 |
| | | (16.909) | (15.248) | (2.665) |

**Table 2. The ITT impact of O-CAL on student math score (N = 1,840)**

| | VARs | Endline math score | Endline math score |
|---|---|---|---|
| | | (1) | (2) |
| [1] | Treatment (1 = OCAL) | 0.010 | 0.015 |
| | | (0.067) | (0.060) |
| [2] | Standardized baseline math score | 0.706*** | 0.682*** |
| | | (0.018) | (0.019) |
| [3] | Controls | No | Yes |
| [4] | County fixed effect | Yes | Yes |
| [5] | Observations | 1,840 | 1,840 |
| [6] | R-squared | 0.510 | 0.530 |

Robust standard errors in parentheses

*** p<0.01, ** p<0.05, * p<0.1

**Table 3. The ITT impact of O-CAL on Xinzhumin student math score (N = 1,792)**

| | VARs | Endline math score | Endline math score |
|---|---|---|---|
| | | (1) | (2) |
| [1] | Treatment (1 = O-CAL) | 0.007 | 0.015 |
| | | (0.070) | (0.060) |
| [2] | Xinzhumin (1=yes) | -0.047 | -0.013 |
| | | (0.061) | (0.190) |
| [3] | Treatment * Xinzhumin | 0.007 | 0.009 |
| | | (0.093) | (0.087) |
| [4] | Standardized baseline math score | 0.709*** | 0.686*** |
| | | (0.019) | (0.019) |
| [5] | Xinzhumin=[1]+[3] | 0.014 | 0.024 |
| | | (0.096) | (0.095) |
| [6] | P-value | 0.884 | 0.805 |
| | | | |
| [7] | Controls | No | Yes |
| [8] | County fixed effect | Yes | Yes |
| [9] | Observations | 1,792 | 1,792 |
| [10] | R-squared | 0.512 | 0.532 |

Robust standard errors in parentheses

*** p<0.01, ** p<0.05, * p<0.1

**Table 4. The ITT impact of O-CAL on student secondary outcomes**

| | VARs | Like school z-score | Like school z-score | Like math z-score | Like math z-score | Like math teacher z-score | Like math teacher z-score |
|---|---|---|---|---|---|---|---|
| | | (1) | (2) | (3) | (4) | (5) | (6) |
| [1] | Treatment (1 = O-CAL) | 0.033 | 0.032 | -0.047 | -0.044 | 0.099 | 0.143** |
| | | (0.049) | (0.046) | (0.045) | (0.041) | (0.070) | (0.060) |
| [3] | Controls | No | Yes | No | Yes | No | Yes |
| [4] | County fixed effect | Yes | Yes | Yes | Yes | Yes | Yes |
| [5] | Observations | 1,840 | 1,840 | 1,840 | 1,840 | 1,840 | 1,840 |
| [6] | R-squared | 0.218 | 0.247 | 0.007 | 0.016 | 0.065 | 0.120 |

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

**Table 5. Usage of O-CAL of students in the treatment group (minutes)**

| | | Obs | Mean | SD |
|---|---|---|---|---|
| [1] | Usage of all students in Treatment Group | 878 | 83.49 | 73.83 |
| [2] | Top 5 percent | 43 | 259.16 | 36.51 |
| [3] | Top 10 percent | 87 | 229.71 | 39.39 |
| [4] | Top 15 percent | 131 | 212.28 | 40.51 |
| [5] | Top 20 percent | 175 | 199.00 | 41.96 |
| [6] | Top 30 percent | 263 | 177.04 | 46.44 |
| [7] | Top 40 percent | 351 | 159.64 | 50.33 |

Note: Our intervention duration was 10 weeks in the spring semester of 2019-2020. According to the protocol, students were supposed to use the software for at least one 40-minute session each week. On average, the top 5% used O-CAL for 26 minutes per week; the top 10% used O-CAL for 23 minutes per week; the top 15% used O-CAL for 21 minutes per week; the top 20% used O-CAL for 20 minutes per week; the top 30% used O-CAL for 18 minutes per week; and the top 40% used O-CAL for 16 minutes per week.

**Table 6. The impact of O-CAL on school performance of active users**

| | VARs | Endline math score | | | | | |
|---|---|---|---|---|---|---|---|
| | | (1) | (2) | (3) | (4) | (5) | (6) |
| [1] | Treatment (1 = O-CAL) | 0.005 | -0.007 | -0.013 | -0.020 | -0.029 | -0.046 |
| | | (0.060) | (0.060) | (0.061) | (0.063) | (0.064) | (0.071) |
| [2] | Students used O-CAL more than 259 min (1 = top 5%, 0 = otherwise) | 0.212*** | | | | | |
| | | (0.079) | | | | | |
| [3] | Students used O-CAL more than 230 min (1 = top 10%, 0 = otherwise) | | 0.225** | | | | |
| | | | (0.109) | | | | |
| [4] | Students used O-CAL more than 212 min (1 = top 15%, 0 = otherwise) | | | 0.198* | | | |
| | | | | (0.100) | | | |
| [5] | Students used O-CAL more than 199 min (1 = top 20%, 0 = otherwise) | | | | 0.181** | | |
| | | | | | (0.086) | | |
| [6] | Students used O-CAL more than 177 min (1 = top 30%, 0 = otherwise) | | | | | 0.152* | |
| | | | | | | (0.083) | |
| [7] | Students used O-CAL more than 160 min (1 = top 40%, 0 = otherwise) | | | | | | 0.156 |
| | | | | | | | (0.101) |
| [8] | Standardized baseline math score | 0.680*** | 0.680*** | 0.679*** | 0.678*** | 0.679*** | 0.679*** |
| | | (0.019) | (0.019) | (0.019) | (0.019) | (0.019) | (0.019) |
| [9] | Top XX% impact coefficients = Treatment + Students used O-CAL more than XX min | 0.217** | 0.219* | 0.185* | 0.161* | 0.123 | 0.110 |
| | | (0.095) | (0.117) | (0.106) | (0.091) | (0.085) | (0.087) |
| [10] | P-Value | 0.025 | 0.065 | 0.084 | 0.080 | 0.150 | 0.212 |
| [11] | Controls | YES | YES | YES | YES | YES | YES |
| [12] | Observations | 1,840 | 1,840 | 1,840 | 1,840 | 1,840 | 1,840 |
| [13] | R-squared | 0.529 | 0.529 | 0.530 | 0.530 | 0.530 | 0.530 |

Robust standard errors in parentheses, *** p<0.01, ** p<0.05, * p<0.1

**Table 7. The impact of O-CAL on school performance of active Xinzhumin users**

| | VARs | Endline math score | | | | | |
|---|---|---|---|---|---|---|---|
| | | (1) | (2) | (3) | (4) | (5) | (6) |
| [1] | Treatment (1 = O-CAL) | 0.008 | -0.000 | -0.005 | -0.013 | -0.009 | -0.022 |
| | | (0.060) | (0.062) | (0.063) | (0.065) | (0.067) | (0.076) |
| [2] | Xinzhumin (1 = YES) | 0.000 | 0.020 | 0.026 | 0.022 | 0.051 | 0.084 |
| | | (0.190) | (0.185) | (0.185) | (0.184) | (0.184) | (0.181) |
| [3] | Treatment * Xinzhumin | -0.004 | -0.018 | -0.026 | -0.019 | -0.061 | -0.097 |
| | | (0.091) | (0.093) | (0.097) | (0.097) | (0.103) | (0.107) |
| [4] | Students used O-CAL more than 259 min (1 = top 5%, 0 = otherwise) | 0.157* | | | | | |
| | | (0.092) | | | | | |
| [5] | Usage_Top5 * Xinzhumin | 0.184 | | | | | |
| | | (0.177) | | | | | |
| [6] | Students used O-CAL more than 230 min (1 = top 10%, 0 = otherwise) | | 0.174 | | | | |
| | | | (0.131) | | | | |
| [7] | Usage_Top10 * Xinzhumin | | 0.157 | | | | |
| | | | (0.150) | | | | |
| [8] | Students used O-CAL more than 212 min (1 = top 15%, 0 = otherwise) | | | 0.149 | | | |
| | | | | (0.117) | | | |
| [9] | Usage_Top15 * Xinzhumin | | | 0.173 | | | |
| | | | | (0.131) | | | |
| [10] | Students used O-CAL more than 199 min (1 = top 20%, 0 = otherwise) | | | | 0.150 | | |
| | | | | | (0.092) | | |
| [11] | Usage_Top20 * Xinzhumin | | | | 0.095 | | |
| | | | | | (0.111) | | |
| [12] | Students used O-CAL more than 177 min (1 = top 30%, 0 = otherwise) | | | | | 0.088 | |
| | | | | | | (0.087) | |
| [13] | Usage_Top30 * Xinzhumin | | | | | 0.191* | |
| | | | | | | (0.108) | |
| [14] | Students used O-CAL more than 160 min (1 = top 40%, 0 = otherwise) | | | | | | 0.096 |
| | | | | | | | (0.110) |
| [15] | Usage_Top40 * Xinzhumin | | | | | | 0.234** |
| | | | | | | | (0.099) |
| [16] | Baseline_MathZscore | 0.684*** | 0.684*** | 0.684*** | 0.683*** | 0.684*** | 0.684*** |
| | | (0.020) | (0.020) | (0.020) | (0.020) | (0.020) | (0.020) |
| [17] | Impact coefficients of treatment on Top XX% who is Xinzhumin=[1]+[3]+ Students used O-CAL more than XX min + Students used O-CAL more than XX min * Xinzhumin | 0.345** | 0.312** | 0.291** | 0.213 | 0.209* | 0.211* |
| | | (0.147) | (0.136) | (0.125) | (0.131) | (0.114) | (0.109) |
| [18] | P-Value | 0.0211 | 0.0236 | 0.0218 | 0.107 | 0.0710 | 0.0550 |
| [19] | Controls | YES | YES | YES | YES | YES | YES |
| [20] | Observations | 1,792 | 1,792 | 1,792 | 1,792 | 1,792 | 1,792 |
| [21] | R-squared | 0.533 | 0.534 | 0.534 | 0.534 | 0.534 | 0.535 |

Robust standard errors in parentheses, *** p<0.01, ** p<0.05, * p<0.1

**Table 8. Association of student and teacher characteristics with O-CAL usage of students in treatment group**

| | VARs | Usage in minutes | Students within top 40 of usage (1 = yes) |
|---|---|---|---|
| | | (1) | (2) |
| ***Student characteristics*** | | | |
| [1] | Standardized baseline math score | 8.173*** | 0.042** |
| | | (2.416) | (0.016) |
| [2] | Only child (1 = yes) | -8.486 | -0.009 |
| | | (7.118) | (0.048) |
| [3] | Male (1 = yes) | -26.229*** | -0.157*** |
| | | (4.601) | (0.031) |
| [4] | Student age (years) | 4.992 | 0.029 |
| | | (3.066) | (0.021) |
| [5] | Mother education level (1 = college or above) | 4.122 | -0.009 |
| | | (5.190) | (0.035) |
| [6] | Mother lives at home (1 = yes) | 1.638 | -0.029 |
| | | (7.757) | (0.053) |
| [7] | Mother is Taiwanese (1 = yes) | -8.273 | -0.049 |
| | | (5.692) | (0.039) |
| [8] | Father education level (1 = college or above) | -11.188** | -0.057 |
| | | (5.181) | (0.035) |
| [9] | Father lives at home (1 = yes) | 2.154 | 0.017 |
| | | (7.009) | (0.048) |
| [10] | Private tutor (1 = yes) | -11.502** | -0.095*** |
| | | (4.778) | (0.032) |
| [11] | Parent helps on homework (1 = yes) | -4.489 | -0.011 |
| | | (4.876) | (0.033) |
| [12] | Asset | 0.696 | -0.001 |
| | | (1.988) | (0.013) |
| [13] | Uses computer at home (1 = yes) | -12.230** | -0.047 |
| | | (5.173) | (0.035) |
| [14] | Like school z-score | -3.866 | -0.012 |
| | | (2.690) | (0.018) |
| [15] | Like math z-score | 0.881 | 0.029 |
| | | (2.604) | (0.018) |
| [16] | Like math teacher z-score | 2.510 | -0.001 |
| | | (2.725) | (0.018) |
| ***Teacher characteristics*** | | | |
| [17] | Teacher gender (1 = male) | -42.687*** | -0.304*** |
| | | (5.492) | (0.037) |
| [18] | Teacher age (year) | 2.125*** | 0.008* |
| | | (0.667) | (0.005) |
| [19] | College education (1 = yes) | -21.972*** | -0.152*** |
| | | (5.132) | (0.035) |
| [20] | Tenure (year) | -0.461 | 0.003 |
| | | (0.706) | (0.005) |
| [21] | Like work Z score | 19.002*** | 0.116*** |
| | | (3.180) | (0.022) |

| | | | |
|---|---|---|---|
| [22] | Satisfied with income Z score | -11.827*** | -0.050** |
| | | (3.130) | (0.021) |
| [23] | Number of classes per week (classes) | 1.835 | -0.006 |
| | | (2.064) | (0.014) |
| [24] | Number of tutoring classes for students per week (classes) | 5.672*** | 0.046*** |
| | | (1.648) | (0.011) |
| [25] | Weekend workload per week (hours) | -2.924*** | -0.017*** |
| | | (0.505) | (0.003) |
| [26] | Homeroom teacher workload per week (hours) | -0.455*** | -0.003** |
| | | (0.152) | (0.001) |
| [27] | Computer skill | 1.561 | 0.027** |
| | | (1.802) | (0.012) |
| [28] | Electronic usage in class | 9.743*** | 0.062*** |
| | | (1.987) | (0.013) |
| [29] | Observations | 827 | 827 |
| [30] | R-squared | 0.267 | 0.238 |

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

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