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INFORMATION SYSTEMS RESEARCH
Articles in Advance, pp. 1–18
ISSN 1047-7047 (print), ISSN 1526-5536 (online)

From Smartphones to Smart Students: Learning vs. Distraction Using Smartphones in the Classroom

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Received: June 19, 2022
Revised: November 28, 2023; September 3, 2024
Accepted: January 18, 2025
Published Online in Articles in Advance: July 10, 2025

https://doi.org/10.1287/isre.2022.0078

Abstract. We investigate the impact of using smartphones in the classrooms on students' academic performance. We collaborated with a vocational school in China to randomly allocate students taking Chinese verbal lectures into one of four experimental conditions: (i) smartphones banned, (ii) smartphones allowed and used at will by students without guidance, (iii) smartphones allowed and used at will by students with teachers prompting students to use the smartphones to assist instruction, and (iv) smartphones banned with teachers prompting students to use a paper-based aid to assist instruction. We measured the academic performance gains of students by comparing their scores from identical tests taken at the beginning and the end of the lectures. Our findings indicate that allowing students to use smartphones at will in the classroom without guidance reduced their performance gain compared with when smartphones were banned. However, performance gain increased significantly when teachers asked students to use smartphones to assist with instruction. Students using the paper-based aid instruction performed similarly to those with banned smartphones. To delve into the underlying mechanisms that explain these findings, we analyzed video recordings of the classes to track students' time spent learning versus being distracted with or without using smartphones. We found that the increased performance gain when smartphones were used to assist instruction came from the marginal benefit associated with smartphone-assisted learning outweighing the negative effect associated with smartphone-induced distraction. We also found that allowing smartphones into the classroom to aid instruction can help bridge educational gaps between male and female students and between low- and high-performing students. However, smartphones in the classroom may also induce a rich-get-richer dynamic by which students in information technology majors or from urban areas benefit more compared with those in non–information technology majors or born in rural areas. Our work contributes to the literature on technology-assisted learning and offers implications for teachers, school administrators, and policymakers to develop policies for smartphone use in classrooms.

History: Karthik Kannan, Senior Editor; Idris Adjerid, Associate Editor.

Funding: The authors acknowledge funding from Temple University [2016 and 2017 Young Scholar Forum Grants].
Supplemental Material: The online appendix is available at https://doi.org/10.1287/isre.2022.0078.

Keywords: smartphone policy • learning • distraction • academic performance • randomized controlled trial

1. Introduction

Smartphone ownership has grown significantly worldwide over the past decade. In the United States, for example, smartphone ownership rose from 35% in 2011 to 90% in 2023.[1] Ghose (2017) discusses how this increase has stimulated research on the value of smartphones, yet little is known about how their presence in classrooms might affect students' academic performance. Research on the impact of information and communication technologies (ICTs) on productivity has produced mixed results (Acemoglu et al. 2014, Lee et al. 2018), possibly because most studies focus on aggregate economic levels, such as countries, industries, or firms, rather than on individual performance. Only a few studies investigate the role of ICTs at the individual level, and even fewer explore their influence on attention (Alavi and Leidner 2001).

Studies focusing on the impact of ICTs on students' performance also yield mixed findings, likely because they focus on ICT investment and availability in schools rather than on how students use these technologies for learning purposes. Consequently, the current literature provides limited insights into how in-class smartphone use may affect student performance. Instead, it is essential to focus on student-level studies showing how smartphones influence attention, contrasting learning gains against potential distractions to understand the impact of these devices in educational settings.

We contribute to this research gap by conducting two randomized controlled trials (RCTs) to test the effects of smartphone use in classrooms on student performance. Our experiments gather individual-level data on smartphone use during lectures to uncover the causal mechanisms behind the observed effects. Specifically, we address three research questions: (i) How does allowing smartphones in classrooms influence students' time learning versus being distracted? (ii) How do classroom smartphone learning and distraction impact student performance? (iii) How do demographic factors moderate these effects?

In our first experiment, students at a vocational school in China were randomly assigned to one of three conditions during Chinese verbal lectures: (i) smartphones banned from the classroom, (ii) smartphones allowed in the classroom and used by students without restrictions, and (iii) smartphones allowed in the classroom and used by students without restrictions and with the teacher asking students to use the devices to assist instruction. In our second experiment, an additional condition was introduced: (iv) smartphones banned from the classroom with the teacher asking students to use a paper-based aid to assist instruction. In condition (iii), the teacher prompted students to use a custom smartphone dictionary app during lectures to check the words' pronunciation, definitions, and etymology. In condition (iv), students used a paper-based dictionary containing the same content as the smartphone app. All students took identical prelecture and postlecture tests, allowing us to measure performance gain as the difference between prelecture and postlecture scores.

Our analyses reveal significant findings. In our first experiment, allowing smartphones in the classroom without teacher guidance decreased performance gain by an average of 32% of a standard deviation compared with when smartphones were banned. However, when teachers actively encouraged smartphone use for instructional purposes, performance gains increased by an average of 26% of a standard deviation. These statistics were 21% and 41% in the second experiment. These results suggest that smartphone bans may overlook potential learning benefits as positive educational outcomes from guided use may outweigh distraction-related drawbacks. Specifically, a one percentage point (p.p.) increase in time allocated to smartphone-based learning increased performance gain by 2.7 points in our first experiment, whereas a one p.p. increase in distraction time reduced performance gain by only 0.15 points. These effects were 3.2 and 0.11 points in the second experiment, respectively. Additionally, we observed that students were more likely to use smartphones for learning when prompted by teachers. Although this difference was modest in absolute terms, the productivity benefits from teacher-directed smartphone use outweighed the impact of distraction.

To measure the time students allocated to learning and distraction with and without smartphones, video coders analyzed footage from all lectures, noting instances of learning activities (e.g., listening to the teacher, using the dictionary app) and distractions (e.g., dozing, talking, gaming, or social media use). Our analyses confirm that teacher-guided smartphone use led to performance gains even though students spent more time distracted than learning on the smartphone during lectures. We also recorded the teachers' facial expressions and postures, showing that teachers delivered similar classes across all experimental conditions, thus eliminating concerns with potential confounders, such as teacher-side learning. The findings from the second experiment corroborated these results, adding robustness to our conclusions.

Condition (iv) (smartphone banned with paper-based dictionary) in our second experiment allowed us to distinguish the effect of the additional content provided (through dictionary app and paper-based dictionary) from the effect of the channel (smartphone versus paper). When comparing students' performance using a smartphone-based aid to those using paper-based assistance, the effects stem from several factors combined, such as flipping through the pages of the paper-based dictionary versus searching online for words of interest and reading from paper versus a touchscreen. Our results show that the performance gain with the paper-based dictionary is similar to that observed when smartphones were banned from the classroom. Therefore, the paper-based aid did not enhance performance gain as much as the smartphone-based assistance.

Finally, our work highlights a rich set of heterogeneous effects, revealing both the benefits and perils of allowing smartphones in classrooms. Allowing smartphones to aid instruction benefited students in information technology (IT) majors, those born in urban areas, males, and low-performing students. Using smartphones in the classroom may help narrow educational gaps between male and female students and between low- and high-performing students. However, it could also induce a rich-get-richer dynamic whereby students in IT majors and students from urban areas are likely to outpace their peers in other majors or from rural areas. Therefore, teachers, school administrators, and policymakers should consider implementing programs to help students in non-IT majors and from rural areas benefit more from using smartphones in the classroom to facilitate learning.

Our work contributes to the literature in several ways. First, we are among the first to conduct RCTs with smartphones in real-life classroom settings to explore the effect of smartphones on students' performance, overcoming the limitations of observational studies. Second, we decompose the overall effect of smartphones on student performance into the positive effect of smartphone-assisted learning and the negative effect of smartphone-caused distraction. Third, we actively measure the time students spend learning versus being distracted, either using their smartphones or not during lectures in a novel and a way that avoids problems with the self-reported measures used in the prior literature. Finally, our study provides empirical evidence that teachers, school administrators, and policymakers can leverage to develop classroom guidelines and policies for prescribing smartphone use.

2. Research Background and Literature Review

2.1. Impact of ICTs on Student Performance

ICTs are now pervasive in schools. The UNESCO Institute for Statistics reports that, in 2020, more than 87% of secondary schools worldwide had access to computers for pedagogical purposes (UNESCO 2023). Similarly, the U.S. Institute of Education Sciences indicates that 98% of all U.S. schools have computers with 45% of them having one computer per student. Despite widespread accessibility, the literature presents mixed evidence on the impact of ICTs on educational outcomes. For instance, Leuven et al. (2007) find that offering subsidies for ICTs to schools with disadvantaged pupils in the Netherlands hurt learning outcomes. Likewise, Fried (2008) and Carter et al. (2017) also report that introducing computers in U.S. schools can hurt learning outcomes. Studies by Vigdor et al. (2014) and Belo et al. (2014) find that broadband availability and usage in middle schools reduced student grades in the United States and Portugal, respectively.

Several studies report a null effect of ICTs on student performance. Angrist and Lavy (2002) find that increased computer usage in primary schools in Israel did not change test scores. Goolsbee and Guryan (2006) find that technology use in California's public schools did not influence student performance. Barrera-Osorio and Linden (2009) observe that computer-assisted programs for language learning in Colombia did not affect student learning. Faber et al. (2015) also find no effect of improved broadband speed on educational outcomes in primary and secondary schools in England.

In contrast, other studies highlight the benefits of ICTs for educational purposes. For example, Barrow et al. (2009) demonstrate that computer-aided instruction was more effective than traditional learning methods in several urban U.S. school districts. Kumar and Mehra (2018) and Muralidharan et al. (2019) find positive effects of computer-based learning during after-school programs for middle school students in India. Machin et al. (2007) find that ICT subsidies in several school districts in England improved learning in English and science (though not in mathematics), and Fairlie and London (2012) find that ICT investment in a large community college in California also enhanced student performance.

The studies described above vary significantly in their settings, procedures, and treatments, complicating direct comparisons among them. Nonetheless, the variance in the reported outcomes underscores the complexity of effectively utilizing ICTs to enhance learning. Our study adds to this literature by using RCTs with smartphones in real-life classroom settings, aiming to provide causal evidence on the impact of smartphone use on student learning and academic performance.

2.2. Smartphone Pervasiveness and Bans in Schools

Smartphone and computer ownership statistics continue to exhibit notable differences. According to recent data from Statista, by early 2024 in the United States, 36% of adults aged 30 or older owned a desktop computer, 38% owned a laptop, and 52% owned a tablet. However, smartphone ownership in this group has surged to 90%. For people aged 18 to 29, these statistics are 30%, 40%, 39%, and 89%, respectively, thus showing a similar pattern of high smartphone adoption compared with other devices. Finally, Statista also reports that, in 2023, 35% of eight-year-old children in the United States had a smartphone with this statistic rising to 95% for 18-year-olds.

These statistics, combined with the mixed evidence on the impact of ICTs on student performance, have sparked intense debates over whether schools should allow students to bring smartphones into classrooms (Tamim and Borokhovski 2022). On the one hand, parents and teachers often oppose allowing smartphones in classrooms because of potential adverse effects, such as cyber-bullying (Pieschl et al. 2013), distraction (Kuznekoff et al. 2015, Beland and Murphy 2016), access to unreliable information (Wineburg et al. 2016), cheating (Haller 2017), and physical or mental distress (Ward et al. 2017, Boers et al. 2019). On the other hand, students generally support using smartphones in classrooms, arguing that smartphones can effectively assist learning during classes. The growing number of educational apps for mobile phones that help learning and lecture instruction support these claims by facilitating real-time interaction and collaboration between students and teachers (Faber et al. 2015). Moreover, using smartphones to assist learning in the classroom may alleviate the financial burden on schools to invest in other forms of ICTs, which are useful to enhance students' academic performance, particularly in less privileged schools.

However, the concerns of teachers and parents have prompted several policymakers to ban smartphones from classrooms and, in some cases, from schools altogether. For instance, France passed a bill requiring all students aged 3–15 to leave their smartphones at home or keep them off if taken to school (law no. 2018-698). Likewise, China issued a national notice advising K–12 students to limit smartphone use at school (JJTH no. 3-2021). Similar policies have been proposed or implemented in other countries, such as the United Kingdom, India, and the United States. According to the National Center for Education Statistics (2020), 76% of schools in the United States have already banned cell phones. UNESCO (2023) reports that, by the end of 2022, 13% of countries had introduced laws banning mobile phones from schools and 14% had policies or guidelines to do so. This division (27% versus 73%) calls for a better understanding of whether and how smartphones can be effectively used in the classroom to assist with instruction and facilitate learning.

2.3. Smartphones and the Performance of Students

People asked to multitask (i.e., handling several tasks concurrently) take longer to complete tasks than when tasks are done sequentially. Rubinstein et al. (2001) attribute this slowdown to time lost during task switching, which worsens as tasks become more complex. Foerde et al. (2006) show that, whereas multitaskers can learn factual information, they struggle to apply it to new situations. Chen and Yan (2016), Uncapher and Wagner (2018), and Wilmer et al. (2017) discuss how smartphones may also hinder the reward process, an essential function of learning. Importantly, multitasking requires attentional capacity and reduces cognitive control (Chinchanachokchai et al. 2015, Van Der Schuur et al. 2015), potentially leading to distraction and errors (Courage et al. 2015).

The negative effects of laptop multitasking on student performance have been reported in prior studies (Hembrooke and Gay 2003, Fried 2008, Kraushaar and Novak 2010, Wood et al. 2012, Zhang et al. 2015). Similar to laptops, smartphones incentivize multitasking, increasing the students' cognitive load (Mayer and Moreno 2003) and hindering the cognitive processes used for learning (Judd 2014, Lee et al. 2018). Rosen et al. (2013) show that U.S. students who used Facebook and texting when studying had lower grade point averages (GPAs). Junco and Cotten (2012) find that using Facebook and texting during schoolwork decreased the performance of U.S. college students. Wood et al. (2012) also report lower scores for students who used Facebook during classes than those who did not.

Ramjan et al. (2021) analyze 27 studies in multiple countries, all surveying nursing students. They find that 20 studies report a negative effect of increased smartphone usage on learning in both classroom settings and during clinical practicums. Nursing students report that smartphones distracted them from proper learning processes. In another example, Amez and Baert (2020) review 23 studies and find that 18 report a negative association between smartphones and academic success, whereas the other five studies find no statistically significant associations. However, only four of these studies actively track smartphone usage, and only six use data on grades from teachers or the administration. The rest rely on self-reported smartphone usage data and grades from survey responses, leading to potential inaccuracy and bias as students tend to underreport less desirable experiences (Krumpal 2013).

For this reason, Kates et al. (2018) conduct a meta-analysis of 39 studies involving various constructs of smartphone use, such as the number of text messages or calls sent/received and time spent using the smartphone, as well as objective academic performance measures, such as test scores and GPA. These studies cover about 150,000 students across more than six countries and still find adverse effects of smartphone use in schools on student performance.

All studies analyzed in the reviews described above are correlational and, thus, do not offer empirical evidence of causal effects. An empirical approach to improve simple correlational studies is using longitudinal data. Bjerre-Nielsen et al. (2020) monitor 470 students at the Technical University of Denmark over two years using a mobile app to log their activity unobtrusively. They find a negative association between in-class smartphone usage and grades even after controlling for several observed student characteristics. Specifically, a one-standard-deviation increase in classroom smartphone usage decreases GPA by 18% of a standard deviation. The magnitude of this effect decreases to 6.1% when using fixed effects, suggesting that cross-sectional studies might overestimate the negative effects of smartphones. Nevertheless, this study does not differentiate classroom smartphone usage for learning and distraction.

Amez et al. (2023) collect longitudinal data on smartphone use and students' educational performance at Ghent University and the University of Antwerp over three consecutive years. They survey students and merge their data with exam scores. Using a random effects model, they find that a one-standard-deviation increase in smartphone usage leads to a reduction of 0.349 points (out of 20) in exam scores and a decrease of 2.6 p.p. in the fraction of exams passed. Finally, McDonald (2013) examines the effects of in-class texting policies, including a mild texting policy ("do not use so you can respect others"), a strict cellphone policy ("lose points in final grade if caught texting"), and no policy regarding texting. This study finds a negative relationship between texting and final grades in all conditions even after controlling for student GPA and attendance.

On the other hand, smartphones may also improve student performance. Mobility allows students to use the same information-intensive services (e.g., e-learning websites) available on laptops but with the added convenience of any time, anywhere access (Lepp et al. 2014). Thus, smartphones provide accessibility to study resources that textbooks cannot readily match (Zhang et al. 2014). Smartphones also support individualized learning with predefined teaching materials, such as those found in museums and laboratories (Hall and Bannon 2006). Social networking and messaging apps may also facilitate the rapid sharing of relevant study information among students and between students and teachers, thus leading to more efficient studying and fruitful collaboration (Chen and Ji 2015, Lepp et al. 2015).

The trained attention hypothesis argues that one can train attention as one does with other brain functions (Sohlberg and Mateer 1987). Frequent multitasking may enhance this by promoting mental flexibility (Courage et al. 2015) and improving the ability to filter out irrelevant information (Ophir et al. 2009, Alzahabi and Becker 2013). As such, smartphones could boost the performance of students. However, empirical evidence to support these claims is limited. Still, two large-scale studies provide some insight: Lin et al. (2021) survey more than 10,000 college students in China and find that using mobile learning and news apps increases their academic performance, whereas playing video games and engaging in social media decreases academic performance. Similarly, Rabiu et al. (2016) run a survey on more than 6,000 secondary school students in Nigeria and observe a positive association between smartphone usage and scores in both mathematics and English language achievement tests.

Our study contributes to the literature on smartphones and student performance by providing causal evidence from two RCTs. Unlike previous studies, the rich data on smartphone usage and student learning and distraction captured in our RCTs allows us to offer nuanced insights into the interplay between smartphones in the classroom and students' attention allocation to learning. Analyzing granular data from RCTs helps us provide actionable insights for teachers, school administrators, and policymakers that they can use to integrate smartphones into the classroom effectively.

3. Empirical Context and Setup

We conducted two RCTs in a vocational school in China to study how allowing smartphones in the classroom affects student performance. Before our experiments, this school did not implement any smartphone-related regulations or formal policies. The sections below describe the design of our experiments.

3.1. First Experiment

At the time of our first experiment, there were 482 students in the class of 2019, all in their second year of study. These students, aged between 14 and 23, were enrolled in eight majors. Their core classes were held in a large classroom accommodating up to 125 students, whereas elective courses took place in smaller classrooms. Our first experiment was conducted in November 2018 during three Chinese verbal lectures. Figure 1 depicts our experimental protocol. We randomly selected 125 students from the class of 2019 for each of the three experimental conditions without repetition. In condition B, smartphones were banned from the classroom. In condition Ta, students were allowed to use smartphones during lectures as they wished. In condition Ti, students were allowed to use smartphones during lectures as they wished, and the teacher asked them to use smartphones to assist with instruction.

The same teacher delivered three identical lectures to all 375 students in this experiment. During all these lectures, the teacher explained the pronunciation, definition, and etymology of several words and their logical functions in sentences from preidentified pieces of literature, including folktale, drama, and poetry, in both classical and vernacular Chinese. Classical Chinese prose from the usual curriculum of this course, with which students were unlikely to be familiar, was used for these classes. In fact, students across all conditions had little prior knowledge of the new words taught to them (as we see below the relatively low scores in the

Figure 1. Design of Our Experiments

pretests), making the experiment a representative case of imparting new knowledge to students. The teacher was instructed to deliver the same lecture to the three groups of students in our experiment at the same pace. The lectures took place on three consecutive weekdays, all at the same time of the day and always in the same large classroom.

Because of the availability of only one teacher, we could not deliver all three classes simultaneously. Therefore, conditions *B*, *Ta*, and *Ti* were implemented sequentially in this order to minimize potential interference. Suppose students in different conditions chat about the lecture. Still, students in condition *Ta* were unlikely to anticipate that they could use smartphones during the lecture given that the students who took the lecture before were not allowed to do so. Similarly, students in condition Ti could potentially anticipate that they could use smartphones during this lecture but were unlikely to anticipate being provided specific instructions for how to use their smartphones for learning purposes (for example, using the dictionary app).

Each of the three 90-minute lectures began with a pretest (five minutes), during which smartphones were turned off, to assess the student's knowledge of the words that would be taught. These tests included multiple-choice questions similar to other quizzes taken in Chinese verbal lectures, and the test scores were used to compute final grades. After the pretest, the teacher announced the smartphone use policy. In condition *B*, students were requested to place their smartphones in a wall hang-up organizer at the back of the classroom, preventing smartphone use during lectures. In condition *Ta*, students were informed that they could use their smartphones during the lecture at will. In condition *Ti*, students were informed that they could use their smartphone during the lecture at will and access a web-based dictionary app. The teacher demonstrated how to use this study aid after the pretest.

Figure 3 in Online Appendix A shows a snapshot of the app screen. Students could use their smartphones during lectures to scan a QR code in the corner of their desks, access the app, and search for words to learn about their pronunciation, meaning, and etymology. After the announcement of the smartphone policy, the teacher delivered the lecture. The only difference between conditions *Ta* and *Ti* was that, in the latter, the teacher actively instructed students to use the dictionary app whenever a new word was introduced. At the end of the lecture, all students in all conditions took the same test as at the beginning (although they did not know a priori that there would be a postlecture test).

The large classroom used for our experiment was equipped with a video anticheating system with 20 ceiling-mounted cameras as part of a school-wide security system. This system is regularly used during examinations to ensure academic integrity with students and parents consenting to it. Students were aware of the cameras in the classroom in which our experiment took place but did not know they were being used during our experiment until the delayed debriefing at the end of the experiment (details provided in Online Appendix B). Several video coders reviewed the video feeds in this unique setting to measure student attention versus distraction by identifying the time students spent using their smartphones and not using them, either learning or being distracted.

3.2. Second Experiment

In November 2022, we conducted a second experiment during eight additional Chinese verbal lectures. At that time, there were 524 students in the class of 2024, all in their second year of studies, between 14 and 23 years of age, enrolled in eight different majors. The design of this experiment was similar to our first experiment as depicted in Figure 1. We randomly selected 125 students from the class of 2024 for each of the four experimental conditions without repetition. The first three conditions mimicked the three conditions in our first experiment. In the fourth condition, *Tp*, smartphones were banned from the classroom, and the teacher asked students to use a paper-based dictionary for learning purposes.

During this experiment, a new (male) teacher delivered four identical lectures in Chinese verbal to all 500 students. Another new (female) teacher provided another four identical lectures on other topics in Chinese verbal. The structure of all these classes was similar to those in our first experiment. As before, teachers were instructed to deliver the same lecture at the same pace to the four groups of students assigned to each of them in our experiment. The first teacher's four lectures took place on four consecutive weekdays, all at the same time of the day and always in the same classroom. The second teacher followed the same protocol in the following week. Our experimental conditions *B*, *Ta*, and *Ti* were implemented in the same order as in our first experiment. Condition *Tp* was added on the fourth day to mitigate potential interference concerns. Even if students discussed smartphone use in the classroom, those in the *Tp* condition were unlikely to anticipate being asked to use a paper-based dictionary to aid instruction instead of the dictionary app.

Figure 3 in Online Appendix A shows a picture of the paper-based dictionary provided to students in condition *Tp* as part of the announcement regarding smartphone policy. The handouts mimicked the presentation of words offered to students on the smartphone app. Furthermore, the content printed in the handouts was the same as that uploaded to the dictionary app. This design allows us to compare the performance gain of students between conditions *Ti* and *Tp* to isolate the effect of the channel (smartphone versus paper), which is the interest of this study, from the effect of content. When doing so, the observed effect may come from several combined factors that arise from using the smartphone versus the paper-based aid, such as flipping through the pages of the paper-based dictionary versus searching online for words of interest or reading from paper versus a touchscreen. Finally, this experiment occurred in the same large classroom as our first experiment.

4. Data and Empirical Strategy

4.1. Data

We used three anonymized data sets in our research: (i) student demographics provided by the school, (ii) scores from pretests and posttests, and (iii) video feeds of the lectures. Table 1 describes the key variables. We measured each student's performance gain during each lecture by comparing the student's pretest and posttest scores. Again, the pretest and posttest were identical, making their scores directly comparable. A group of experienced Chinese verbal teachers designed this test with the following guidelines: (i) the questions only covered material taught during lecture, (ii) the questions were multiple choice to facilitate objective grading, and (iii) a 100-point scale was used with the distribution of scores approximating a normal distribution (that is, the test was not excessively easy or difficult). The teacher delivering each lecture during our experiment graded all tests anonymously from all students attending that lecture, thus ensuring grading consistency and anonymity.

We analyzed video feeds from the lectures to measure the time that each student spent during lectures on (i) learning using the smartphone (*L.S.*), (ii) learning without using the smartphone (*L.O.*), (iii) distraction using the smartphone (*D.S.*), and (iv) distraction without using the smartphone (*D.O.*). Students in the videos were matched to those in our experiments using the seat number reported at the top of their answer key, a common practice that students at this school were used to.

Estimates for *L.S.*, *L.O.*, *D.S.*, and *D.O.* were obtained by local teams of video coders, including faculty and staff at the school, who reviewed the video feeds. We used 20 coders for the first experiment and 30 for the second. Coders were trained to play the video clips; label events as *L.S.*, *L.O.*, *D.S.*, and *D.O.* for each student; and estimate their duration by taking note of the corresponding start and end time stamps. The cameras in the classroom provided high-definition video streams, allowing coders to check the screens of the students' smartphones to determine if they were learning (e.g., using the dictionary app or other educational apps/websites) or being distracted (e.g., playing games, browsing social media).

We assembled 180 and 480 30-minute video clips during our first and second experiments, respectively. Coders were divided into groups of three or four with each coder in a group independently coding the videos randomly assigned to them. Agreement across coders for the same video was very high. The average intercoder reliability statistics (Cohen's κ) were 0.96 ($p < 0.001$) and 0.92 ($p < 0.01$) for the first and second experiments, respectively, which provides evidence of robustness and consistency in how the behavior (learning versus distraction) of students during our experiments was coded.

In the second experiment, we employed a camera directed at the instructor during lectures to monitor the consistency of the instructor's behaviors across different lecture sessions. Video feeds from this camera were sampled every five seconds, capturing frames of the instructor's face for subsequent analysis. Facial emotion extraction and face matching were conducted using the FER library in conjunction with the HSEmotion package (high-speed face emotion recognition) by Savchenko.[2] Head pose detection was achieved using MediaPipe,[3] whereas eye gaze tracking was implemented via the GazeTracking package by Lame.[4] Lip movement analysis was performed using the Open Computer Vision (OpenCV) library.[5] Table 15 in Online Appendix C describes the covariates used in our analyses.

Table 1. Key Variables Used in Our Empirical Analyses

Variable	Definition
Experimental conditions	Dummy variables
Banned (*B*)	Smartphone banned from the classroom
Allowed (*Ta*)	Smartphone allowed in the classroom and used at will by students
Instruction (*Ti*)	Smartphone allowed in the classroom and used at will by students and for instruction
Paper (*Tp*)	Smartphone banned from the classroom and paper-based aid used to assist instruction
Performance	Scores in 0–100 scale
Pretest	Score in the test at the beginning of the lecture
Posttest	Score in the test at the end of the lecture
Performance gain	Posttest score minus pretest score
Endogenous variables	Measured in seconds
Learning smartphone	Time learning using the smartphone
Distraction smartphone	Time being distracted using the smartphone
Learning other	Time learning without using the smartphone
Distraction other	Time being distracted without using the smartphone
Controls: *gender, age, ethnicity, local graduate, place born, middle school graduate, schooling system, major*	

4.2. Empirical Strategy

We followed three steps to analyze our data. First, we examined the effect of smartphone policy on posttest scores and student performance gain using the following specification:

$$Y_j = \beta_0 + \beta_1 Ta_j + \beta_2 Ti_j + \boldsymbol{X}_j' \beta_3 + u_j,$$

where the unit of analysis is a student, $\boldsymbol{X}_j$ is a vector of student characteristics, and Ta_j and Ti_j are dummy variables indicating whether the student is in condition Ta or Ti. Condition B serves as the baseline. Our dependent variable, Y_j, represents the student's posttest test score or performance gain, and u_j is the idiosyncratic error term. This specification allows us to measure how the dependent variable changes across our three experimental conditions in causal terms given that students were randomly allocated to these conditions. We also used this setup with the pretest score as our dependent variable to test balance across conditions. Given our randomized setup and the inclusion of all student-level covariates we observed in our regressions, we do not cluster the standard errors. We report statistical significance using Bonferroni correction for multiple testing.

Second, we examined the effect of smartphone policy on how students used the device during the lectures using regressions similar to the above, but here, Y_j represents the student's percentage of learning and distraction time allocated to the smartphone, $\%LS = LS/(LS + LO)$ and $\%DS = DS/(DS + DO)$, respectively. Also, in this case, this specification allows us to measure the causal effect of smartphone policy on these percentages across experimental conditions.

Third, we study how $\%LS$ and $\%DS$ affect the performance gain of students using the following specifications:

$$\%DS_j = \alpha_0 + \alpha_1 Ta_j + \alpha_2 Ti_j + \boldsymbol{X}_j' \alpha_3 + \epsilon_j$$
$$\%LS_j = \beta_0 + \beta_1 Ta_j + \beta_2 Ti_j + \boldsymbol{X}_j' \beta_3 + \zeta_j$$
$$Y_j = \gamma_0 + \gamma_1 \widehat{\%DS}_j + \gamma_2 \widehat{\%LS}_j + \boldsymbol{X}_j' \gamma_3 + \eta_j\,.$$

The first two regressions above serve as the first stages of our instrumental variable estimation and are the two regressions in the second step of our empirical strategy. The third regression above is our second stage, allowing us to measure the local average treatment effect (LATE) of $\%L.S.$ and $\%D.S.$ on student performance gain (Angrist and Imbens 1995). Using LATE is customary when analyzing the effects of endogenous mechanisms using the randomly assigned conditions in RCTs as instrumental variables.

This empirical strategy allows us to understand why the effects observed arise. For example, if the effects of Ta and Ti on $\%L.S.$ and $\%D.S.$ are relatively small in magnitude, then students were unlikely to be motivated to use smartphones during the lecture. Specifically, if $\%L.S.$ does not increase from Ta to Ti, teachers could not induce students to use the smartphone to aid instruction. In this case, our first stage regressions would not work as intended, preventing us from concluding how $\%L.S.$ and $\%D.S.$ affected performance gain. However, if the effects of $\%L.S.$ and $\%D.S.$ are relatively large, students were likely motivated to use smartphones during the lecture. In this case, the effects obtained in the second stage identify how productively students use their smartphone devices to learn and be distracted. The potential trade-off between these two effects determines what happens to the overall impact of smartphones on performance gain.

5. Analysis of the First Experiment

5.1. Summary Statistics

Table 2 provides descriptive statistics for the key variables used in our first experiment. Across all three conditions, the average pretest and posttest scores were 28.9 and 80.8 points (out of 100), and this indicates a significant performance gain. Students spent 76% of lecture time engaged in learning (4,090 s/60 = 68 min), most of it not on smartphones. In condition Ti, approximately 50% of the students used smartphones for learning, of which about 10% spent more than 16.6 minutes doing so. However, in this experimental condition, about 80% of the students spent time being distracted on their smartphones with an average of 57% of their distraction time on smartphones.

Notably, students spent a similar amount of time learning across all conditions, suggesting that they devoted as much attention to learning as possible during the lecture regardless of whether smartphones were banned or allowed in the classroom. This consistency may be because of the inherent limitations of attention spans as suggested by prior research Kahneman (1973) and Lachman et al. (2015) as these prevent students from allocating more (maybe 100%) of the lecture time to learning.

Students allocated a similar amount of time, approximately nine minutes, to smartphone use in both conditions Ta and Ti, suggesting a consistent level of (albeit, in our case, relatively low) smartphone engagement during the lecture. Attention is a scarce resource allocated to different behaviors and devices depending on their style or rhetoric (e.g., direct manipulation, multimedia presentation; see Lanham 2006). As observed in prior studies (e.g., Piccoli et al. 2001), the nature of the human–machine interaction also seems to dictate the allocation of human attention to machines rather than the nature of the content per se (learning versus distraction in our case). In our setting, the substitution of non-smartphone time for smartphone use reflects students' choices encompassing both learning and distraction with their smartphones with minimal influence from how they are prompted by the teacher.

Table 2. Experiment 1: Descriptive Statistics for the Key Covariates Used in the Analysis

Variable	*B* (*N* = 125)	*Ta* (*N* = 119)	*Ti* (*N* = 123)	All (*N* = 367)
Pretest score				
Mean (SD)	29.5 (22.0)	27.3 (21.5)	29.8 (21.6)	28.9 (21.7)
Median [min, max]	28.0 [0, 98.0]	21.0 [0, 94.0]	27.0 [0, 88.0]	24.0 [0, 98.0]
Posttest score				
Mean (SD)	82.1 (15.0)	73.1 (24.2)	86.8 (10.5)	80.8 (18.3)
Median [min, max]	87.0 [18.0, 100]	83.2 [4.0, 100]	87.0 [65.0, 100]	86.0 [4.0, 100]
Performance gain				
Mean (SD)	52.6 (21.6)	45.6 (23.8)	57.0 (16.8)	51.8 (21.4)
Median [min, max]	56.0 [−13.0, 91.0]	49.0 [−25.0, 86.8]	60.0 [12.0, 92.0]	55.0 [−25.0, 92.0]
Smartphone learning				
Mean (SD)	0 (0)	35.8 (117)	218 (332)	84.6 (224)
Median [min, max]	0 [0, 0]	0 [0, 520]	0 [0, 1,450]	0 [0, 1,450]
Smartphone distraction				
Mean (SD)	5.84 (30.4)	504 (628)	333 (494)	277 (502)
Median [min, max]	0 [0, 256]	293 [0, 3,330]	125 [0, 3,330]	44.0 [0, 3,330]
Other learning				
Mean (SD)	4,130 (583)	3,990 (719)	3,880 (750)	4,000 (693)
Median [min, max]	4,330 [2,190, 4,800]	4,160 [1,470, 4,800]	4,040 [847, 4,800]	4,160 [847, 4,800]
Other distraction				
Mean (SD)	660 (581)	274 (402)	371 (584)	438 (554)
Median [min, max]	464 [0, 2,610]	117 [0, 2,180]	201 [0, 3,860]	206 [0, 3,860]
Total learning				
Mean (SD)	4,130 (583)	4,020 (691)	4,110 (759)	4,090 (680)
Median [min, max]	4,330 [2,190, 4,800]	4,190 [1,470, 4,800]	4,400 [847, 4,800]	4,280 [847, 4,800]
Total distraction				
Mean (SD)	665 (583)	779 (691)	704 (759)	715 (680)
Median [min, max]	470 [0, 2,610]	608 [0, 3,330]	404 [0, 3,950]	521 [0, 3,950]
Total smartphone				
Mean (SD)	5.84 (30.4)	540 (658)	551 (586)	362 (566)
Median [min, max]	0 [0, 256]	293 [0, 3,330]	405 [0, 3,330]	65.0 [0, 3,330]
Total nonsmartphone				
Mean (SD)	4,790 (583)	4,260 (658)	4,250 (586)	4,440 (566)
Median [min, max]	4,800 [4,540, 4,800]	4,510 [1,470, 4,800]	4,400 [1,470, 4,800]	4,740 [1,470, 4,800]

5.2. Main Results

Table 3 shows the main results from our first experiment. Notably, pretest scores remained consistent across all experimental conditions, providing evidence of balance. On average, allowing smartphones into the classroom without teacher guidance (*Ta*) led to a reduction in a performance gain of 19.4% (−6.729/34.71) (32% of one standard deviation) compared with when smartphones were banned from the classroom (condition *B*). Conversely, allowing smartphones into the classroom with teachers asking students to use them to aid instruction (*Ti*) led to an increase in performance gain of 15.9% (5.528/34.71) (26% of one standard deviation) relative to when smartphones were banned from the classroom.

Table 4 presents the first stage results. Students exhibited minimal smartphone use for learning when the smartphones were allowed in the classroom and teachers did not ask them to use the devices to aid instruction. However, this changed when teachers did so. The percentage of smartphone usage for learning increased from Ta to Ti by 3.8 p.p. Smartphone usage

Table 3. Experiment 1: Effect of Smartphone Policy on Test Scores and Performance Gain

Variable	Pretreatment		Posttreatment		Performance gain	
Ta (vs. Ban)	−2.21 (2.78)	−1.82 (2.45)	−9.25*** (2.23)	−8.29*** (1.90)	−7.30** (2.68)	−6.729** (2.48)
Ti (vs. Ban)	0.28 (2.76)	−1.33 (2.43)	4.644 (2.21)	4.195* (1.88)	4.368 (2.66)	5.528* (2.45)
Constant	29.50*** (1.94)	46.97* (24.70)	82.11*** (1.56)	81.67*** (19.17)	52.62*** (1.87)	34.71 (24.93)
Controls	No	Yes	No	Yes	No	Yes
Ti vs. Ta	2.49	0.49	13.89***	12.49***	11.67***	12.26***
Observations	367	367	367	367	367	367
Adjusted R^2	0.64	0.73	0.96	0.97	0.86	0.88

Note. Standard errors with Bonferroni correction in the parentheses.
Statistical significance levels: *$p < 0.1$; **$p < 0.05$; ***$p < 0.01$.

Table 4. Experiment 1: Effect of Smartphone Policy on the Smartphone Use Time Allocation

Variable	First stage %*LS*	First stage %*DS*	First stage %*LS*	First stage %*DS*
Ta (vs. Ban)	0.01 (0.006)	0.59*** (0.040)	0.01 (0.006)	0.59*** (0.039)
Ti (vs. Ban)	0.05*** (0.006)	0.49*** (0.039)	0.05*** (0.005)	0.49*** (0.040)
Constant	−0.02 (0.016)	0.06 (0.103)	−0.04 (0.064)	−0.13 (0.417)
Controls	No	No	Yes	Yes
Ti vs. Ta	0.04***	−0.10**	0.04***	−0.10**
Observations	359	359	359	359
Adjusted R^2	0.16	0.41	0.17	0.45

Note. Standard errors with Bonferroni correction in the parentheses.
Statistical significance levels: *$p < 0.1$; **$p < 0.05$; ***$p < 0.01$.

for distraction was prevalent across both smartphone-permitted conditions: the percentage of distraction time allocated to smartphones during the lecture was 64% and 47% in conditions *Ta* and *Ti*, respectively, and these two averages are statistically different.

Table 5 presents the second stage results. First, the Cragg–Donald statistic indicates that our instruments are not weak (Stock and Yogo 2005). Second, the percentage of learning time allocated to smartphones (%*L.S.*) increased performance gain. At the average of %*L.S.*, a one p.p. increase in *L.S.* increased performance gain by 2.7 points. Conversely, the percentage of distraction time allocated to the smartphone (%*D.S.*) decreased performance gain. At the average of %*D.S.*, a one p.p. increase in *D.S.* reduced performance gain by 0.15 points. Therefore, the percentage of learning time allocated to the smartphone had a significantly larger marginal impact on performance gain than that associated with distraction. Thus, allowing smartphones into the classroom and having teachers ask students to use them for instruction can improve performance gain because the gain that arises from even little usage of the smartphone for learning purposes can significantly counteract (2.7/0.15 = 18×) the loss that arises from more usage of smartphones for distraction. Our findings reveal that how students perform is related to how much learning versus distraction is performed using the smartphone versus not or, in other words, how smartphone-intensive these activities are. Finally, the percentage of time spent learning during lectures did not predict performance gain because it did not change significantly across conditions as shown by the summary statistics in Table 2.

6. Analysis of the Second Experiment

6.1. Summary Statistics

Table 6 provides descriptive statistics for the key variables obtained from our second experiment. Across all conditions, the average pretest and posttest scores were 27.8 and 78.5 points, indicating again a notable performance gain. Students spent again 78% of the lecture time learning (4,170 s/60 = 70 minutes), most of it not on the smartphone. In the Ti condition, about 45% of students used the smartphone for learning, of which about 10% spent more than 13.8 minutes learning, using the smartphone. However, in this condition, all the students experienced smartphone-related distractions with 61% of their distraction time spent on smartphones. Again, students spent a similar amount of time learning across all conditions. The time spent by students on smartphones, an average of 10 minutes, remained identical in both *Ta* and *Ti*.

6.2. Main Results

Table 7 shows the main results from our second experiment. On average, allowing smartphones into the classroom without teacher guidance led to a reduction in performance gain by 12.9% (−4.952/38.463) or 21% of

Table 5. Experiment 1: Effect of the Smartphone Use Time Allocation on Performance Gain

Time use	Performance gain	
Percentage learning smartphone	253.19*** (72.40)	273.38*** (70.20)
Percentage distraction smartphone	−15.76*** (5.77)	−14.95*** (5.60)
Percentage learning	−3.96 (9.02)	−11.01 (9.21)
Constant	56.07*** (8.07)	51.32 (32.00)
Controls	No	Yes
Cragg–Donald statistic	25.53 > 7.03	25.93 > 7.03
Observations	359	359
Adjusted R^2	−0.23	−0.17

Note. Standard errors with Bonferroni correction in the parentheses.
Statistical significance levels: *$p < 0.1$; **$p < 0.05$; ***$p < 0.01$.

Table 6. Experiment 2: Descriptive Statistics for the Key Covariates Used in the Analysis

Variable	*B* (*N* = 250)	*Ta* (*N* = 238)	*Ti* (*N* = 246)	*Tp* (*N* = 244)	All (*N* = 978)
Pretest score					
Mean (SD)	26.8 (21.7)	24.9 (21.6)	27.9 (21.9)	31.0 (23.1)	27.6 (22.1)
Median [min, max]	24.9 [0, 91.3]	16.6 [0, 91.3]	24.9 [0, 83.0]	24.9 [0, 91.3]	24.9 [0, 91.3]
Posttest score					
Mean (SD)	76.2 (15.5)	69.2 (24.4)	84.9 (11.0)	83.2 (15.6)	78.5 (18.3)
Median [min, max]	83.0 [8.3, 91.3]	78.9 [0, 99.6]	83.0 [58.1, 99.6]	91.3 [16.6, 99.6]	83.0 [0, 99.6]
Performance gain					
Mean (SD)	49.4 (21.7)	44.3 (24.5)	57.1 (16.9)	52.3 (21.8)	50.8 (21.8)
Median [min, max]	49.8 [−16.6, 91.3]	49.8 [−24.9, 91.3]	58.1 [16.6, 99.6]	58.1 [0, 99.6]	49.8 [−24.9, 99.6]
Smartphone learning					
Mean (SD)	0 (0)	40.7 (117)	220 (331)	0 (0)	65.3 (198)
Median [min, max]	0 [0, 0]	5.00 [0, 527]	6.00 [0, 1,460]	0 [0, 0]	0 [0, 1,460]
Smartphone distraction					
Mean (SD)	0 (0)	564 (626)	363 (493)	0 (0)	228 (463)
Median [min, max]	0 [0, 0]	355 [41.0, 3,390]	152 [18.0, 3,370]	0 [0, 0]	0 [0, 3,390]
Other learning					
Mean (SD)	4,230 (575)	3,960 (714)	3,870 (748)	4,340 (517)	4,100 (672)
Median [min, max]	4,430 [2,260, 4,800]	4,130 [1,410, 4,760]	4,030 [842, 4,770]	4,560 [2,530, 4,800]	4,290 [842, 4,800]
Other distraction					
Mean (SD)	574 (575)	237 (387)	347 (579)	426 (517)	398 (535)
Median [min, max]	374 [0, 2,540]	55.0 [0, 2,140]	91.5 [0, 3,830]	202 [0, 2,260]	164 [0, 3,830]
Total learning					
Mean (SD)	4,230 (575)	4,000 (685)	4,090 (754)	4,370 (517)	4,170 (654)
Median [min, max]	4,430 [2,260, 4,800]	4,160 [1,410, 4,760]	4,390 [844, 4,780]	4,600 [2,540, 4,800]	4,390 [844, 4,800]
Total distraction					
Mean (SD)	574 (575)	800 (685)	710 (754)	526 (517)	626 (654)
Median [min, max]	374 [0, 2,540]	638 [41.0, 3,390]	415 [22.0, 3,960]	202 [0, 2,260]	407 [0, 3,960]
Total smartphone					
Mean (SD)	0 (0)	604 (656)	583 (585)	0 (0)	294 (528)
Median [min, max]	0 [0, 0]	360 [45.0, 3,390]	435 [20.0, 3,370]	0 [0, 0]	0 [0, 3,390]
Total nonsmartphone					
Mean (SD)	4,800 (0)	4,200 (656)	4,220 (585)	4,800 (0)	4,510 (528)
Median [min, max]	4,800 [4,800, 4,800]	4,440 [1,410, 4,760]	4,370 [1,430, 4,780]	4,800 [4,800, 4,800]	4,800 [1,410, 4,800]

one standard deviation) compared with when smartphones were banned from the classroom (condition *B*). Conversely, allowing smartphones into the classroom with teachers asking students to use them to aid instruction (*Ti*) led to a higher performance gain by 23.2% (8.914/38.463 or 41% of one standard deviation) compared with when smartphones were banned (condition *B*).

Table 8 presents the first stage results. Once again, students exhibited minimal smartphone use for learning when the devices were allowed into the classroom and teachers did not ask students to use them to aid instruction. Again, this changed when teachers did so. The percentage of learning time allocated to the smartphone increased from *Ta* to *Ti* by 3.9 p.p. Smartphone use for distraction remained prevalent across both conditions with smartphones taking 71% and 51% of distraction time in *Ta* and *Ti*, respectively, and these averages are statistically different.

Table 9 presents the second stage results. Our instruments are not weak (Stock and Yogo 2005) as shown by the Cragg–Donald statistic. The percentage of learning

Table 7. Experiment 2: Effect of Smartphone Policy on Test Scores and Performance Gain

Variable	Pretreatment		Posttreatment		Performance gain	
Ta (vs. Ban)	−1.96 (1.97)	−1.249 (1.73)	−7.037*** (1.61)	−5.841*** (1.38)	−5.08** (1.92)	−4.592** (1.80)
Ti (vs. Ban)	1.044 (1.95)	−0.933 (1.68)	8.696*** (1.59)	7.981*** (1.34)	7.652*** (1.91)	8.914*** (1.75)
Constant	26.83*** (1.37)	26.38 (16.55)	76.23*** (1.12)	64.84*** (13.20)	49.40*** (1.34)	38.46** (17.23)
Controls	No	Yes	No	Yes	No	Yes
Ti vs. Ta	3.004	0.317	15.73***	13.82***	3.004	13.51***
Observations	734	734	734	734	734	734
Adjusted R^2	0.60	0.71	0.95	0.97	0.85	0.88

Note. Standard errors with Bonferroni correction in the parentheses.
Statistical significance levels: $^*p < 0.1$; $^{**}p < 0.05$; $^{***}p < 0.01$.

Table 8. Experiment 2: Effect of Smartphone Policy on the Smartphone Use Time Allocation

Variable	First stage %*LS*	First stage %*DS*	First stage %*LS*	First stage %*DS*
Ta (vs. Ban)	0.01** (0.005)	0.73*** (0.026)	0.01*** (0.005)	0.73*** (0.026)
Ti (vs. Ban)	0.05*** (0.004)	0.62*** (0.025)	0.05*** (0.004)	0.61*** (0.025)
Constant	−0.02 (0.012)	−0.27*** (0.065)	0.06 (0.044)	0.04 (0.252)
Controls	No	No	Yes	Yes
Ti vs. Ta	0.04***	−0.11***	0.04***	−0.12***
Observations	712	712	712	712
Adjusted R^2	0.17	0.57	0.22	0.59

Note. Standard errors with Bonferroni correction in the parentheses.
Statistical significance levels: **p* < 0.1; ***p* < 0.05; ****p* < 0.01.

time allocated to the smartphone (%*L.S.*) increased performance gain. At the average of %*L.S.*, a one p.p. increase in *L.S.* increased the performance gain by 3.2 points. The percentage of distraction time allocated to the smartphone (%*D.S.*) decreased performance gain. At the average of %*D.S.*, a one p.p. increase in *D.S.* reduced performance gain by 0.11 points.

As in our first experiment, we conclude that allowing smartphones into the classroom and having teachers ask students to use them for instruction (*Ti*) can improve performance gain because the gain that arises from even little usage of the smartphone for learning can compensate (3.2/0.11 = 29×) the loss that arises from more smartphone use for distraction even when the total learning and distraction times remain the same. Again, the percentage of time learning during lectures did not predict performance gain because it did not change significantly across our conditions as indicated by the summary statistics in Table 6. In sum, we observe remarkably consistent results across both experiments, providing evidence of empirical replication and credence to our conclusions.

6.3. The Effect of Channel vs. Content

The second experiment introduced a fourth condition in which smartphones were not allowed in the classroom and teachers asked students to use a paper-based dictionary to aid instruction (*Tp*). This condition allows us to disentangle the effect of the channel—smartphone versus paper—from the effect of the content given to students to aid instruction. The handouts given to students under condition *Tp* included the same content uploaded to the smartphone app used in condition *Ti*. Furthermore, in condition *Tp*, teachers were required to use the same prompts to ask students to use the paper-based dictionary as they did in condition *Ti* when asking them to use smartphones to aid instruction.

Table 10 shows the results obtained, including condition *Tp* in the analysis. The student performance gain was similar in conditions *B* (smartphones banned from the classroom) and *Tp*. Whereas the coefficients for *Tp* in the regressions of performance gain are marginally positive, suggesting that the paper-based dictionary was not completely useless, they lack statistical significance, contrasting sharply with the robust effects found under condition *Ti* (the coefficients in *Tp* are roughly three times lower in magnitude than those observed in *Ti*). This finding clarifies that the positive effects observed in condition *Ti* are indeed associated with smartphone use.

Further insights from Table 10 reveal that the results above arise because of the differential engagement with the paper-based dictionary compared with the smartphone-based aid. Students demonstrated limited inclination toward using the paper-based dictionary, likely because of its relatively lesser allure, resulting in challenges for teachers to promote its usage effectively.

Table 9. Experiment 2: Effect of the Smartphone Use Time Allocation on Performance Gain

Time use	Performance Gain	
Percentage learning smartphone	292.37*** (51.72)	315.30*** (52.06)
Percentage distraction smartphone	−10.47*** (3.63)	−11.25*** (3.73)
Percentage learning	−5.07 (6.75)	−10.01 (6.91)
Constant	52.78*** (5.91)	25.91 (23.59)
Controls	No	Yes
Cragg–Donald statistic	54.71 > 7.03	54.24 > 7.03
Observations	712	712
Adjusted R^2	−0.34	−0.28

Note. Standard errors with Bonferroni correction in the parentheses.
Statistical significance levels: **p* < 0.1; ***p* < 0.05; ****p* < 0.01.

Table 10. Experiment 2: Effect of Smartphone Policy on Test Scores and Performance Gain

Variable	Pretreatment		Posttreatment		Performance gain	
Ta (vs. Ban)	−1.96 (2.000)	−1.71 (1.90)	−7.04*** (1.56)	−6.49*** (1.43)	−5.08* (1.93)	−4.79* (1.88)
Ti (vs. Ban)	1.04 (1.98)	−0.24 (1.86)	8.70*** (1.55)	8.27*** (1.40)	7.65*** (1.92)	8.51*** (1.84)
Tp (vs. Ban)	4.13 (1.99)	3.47 (1.91)	7.01** (1.55)	6.22*** (1.44)	2.88 (1.92)	2.75 (1.89)
Constant	26.83*** (1.40)	37.87* (15.24)	76.23*** (1.09)	66.54*** (11.48)	49.40*** (1.35)	28.67 (15.05)
Controls	No	Yes	No	Yes	No	Yes
Ti vs. Tp	−3.09	−3.70	1.69	2.05	4.77*	5.76**
Observations	978	978	978	978	978	978
Adjusted R^2	0.61	0.66	0.95	0.96	0.85	0.87

Note. Standard errors with Bonferroni correction in the parentheses.
Statistical significance levels: *$p < 0.1$; **$p < 0.05$; ***$p < 0.01$.

The regressions in Table 11 include all four conditions, allowing us to incorporate the time spent using the paper-based dictionary in condition *Tp* as a dependent variable we termed “time on the tool” instead of the time spent on smartphones under *Ti*. The tool refers to the smartphone-based dictionary under *Ti* and the paper-based aid under *Tp*. We find a decrease in distraction time, which suggests that students spent negligible time being distracted by the paper-based dictionary, which is reasonable, considering its inherent limitations to offer opportunities for distraction compared with what smartphones are capable of.

6.4. Teacher Learning Across Experimental Conditions

In our experiments, condition *Ti* took place after condition *Ta*, and thus, teachers may have behaved differently in these two conditions because of, for example, potential learning during condition *Ta*. The possible positive effects of teacher-side learning could, thus, confound our results. Despite our instructions for teachers to deliver identical classes at the same pace across all experimental conditions, ensuring perfect consistency remains challenging. To address this concern, we scrutinized the two teachers’ facial emotions and facial posture during their lectures in our second experiment.

The boxplots in Online Appendix C demonstrate the statistical similarity of these covariates across corresponding classes. Yet, even if two teachers register similar average facial emotions and similar average facial posture across lectures, they might still deliver very different lectures. For example, one teacher could appear very happy at the beginning of a lecture and not so pleased toward the end, whereas the other teacher could appear very happy toward the end but less so at the beginning. We address this concern by comparing concurrent lecture segments across conditions. To do so, we randomly chose two moments in time during a lecture. We compare the average of the facial emotions and the average of the facial posture covariates for each teacher between conditions *Ta* and *Ti* only between these two moments. This analysis yields a *p*-value for each covariate, indicating whether a difference existed between conditions *Ta* and *Ti* within the specified lecture segment. We then bootstrapped this exercise and iterated this process 10,000 times. We collected 10,000 *p*-values for each facial emotion and facial posture covariate. We then checked how many times this *p*-value is above 0.05.

Table 12 presents the results for both teachers in our second experiment. All percentages are high, indicating that these teachers delivered statistically similar lectures under condition *Ta* and condition *Ti*, which reassures us against the possibility that teacher learning from *Ta* affected lecture quality in condition *Ti*, thus bolstering the reliability of our findings.

Table 11. Experiment 2: Effect of Smartphone or Paper-Based Dictionary Policy on the Smartphone or Paper-Based Dictionary Use Time Allocation

Variable	First stage %*LSP*	First stage %*DSP*	First stage %*LSP*	First stage %*DSP*
Ta (vs. Ban)	0.01*** (0.004)	0.73*** (0.02)	0.01*** (0.004)	0.73*** (0.02)
Ti (vs. Ban)	0.05*** (0.004)	0.62*** (0.02)	0.05*** (0.004)	0.61*** (0.02)
Tp (vs. Ban)	0.01 (0.004)	−0.01 (0.02)	0.004 (0.004)	−0.02 (0.02)
Constant	−0.01 (0.01)	−0.22*** (0.05)	0.04 (0.03)	−0.04 (0.18)
Controls	No	No	Yes	Yes
Tp (vs. Ti)	−0.046***	−0.628***	−0.049***	−0.628***
Observations	951	951	951	951
Adjusted R^2	0.19	0.66	0.21	0.68

Notes. LSP refers to the learning time using a smartphone or a paper-based dictionary. Similarly, DSP refers to the distraction time using a smartphone or a paper-based dictionary. Standard errors with Bonferroni correction in the parentheses.
Statistical significance levels: *$p < 0.1$; **$p < 0.05$; ***$p < 0.01$.

Table 12. Percentage of p-values >0.05 When Comparing a Teacher Across Conditions Ta and Ti

Covariate	Percentage of p-values >0.05 for teacher 1	Percentage of p-values >0.05 for teacher 2
Angry	99	100
Disgust	100	100
Fear	99	100
Happy	87	84
Sad	98	87
Surprise	61	60
Neutral	86	87
Head pose x	100	100
Head pose y	100	100
Dist lips	96	98
Eye gaze x	100	100
Eye gaze y	99	98

Notes. We detected all seven universal core facial expressions (anger, disgust, fear, happy, sad, surprise, and neutral), head pose position coordinates (the pixel at coordinates (x, y) is found x pixels to the right and y pixels down from the top-left corner). Distances between two lips and eye gaze coordinates are the same as head pose.

7. Analyses of Heterogeneous Effects

We extended our analysis to explore and understand the heterogeneity in the observed effects among student groups. In doing so, we examined five relevant student characteristics, namely, (i) familiarity with technology, (ii) rurality, (iii) gender, (iv) familiarity with the content, and (v) prior academic performance. Figure 2 presents the moderators analyzed for these student characteristics. Specifically, an IT major indicates students enrolled in an IT major, which, in our setting, includes computerized accounting, e-commerce, computer animation, and computer graphic design (in the first experiment) as well as accounting and information systems, accounting, and graphic design, digital design, and computer science (in the second experiment). Being born in rural areas indicates that students are born with a rural Hukou. Hukou is a system of household registration used in mainland China. The classification of Hukous into rural and urban is explained on the government website.[6]

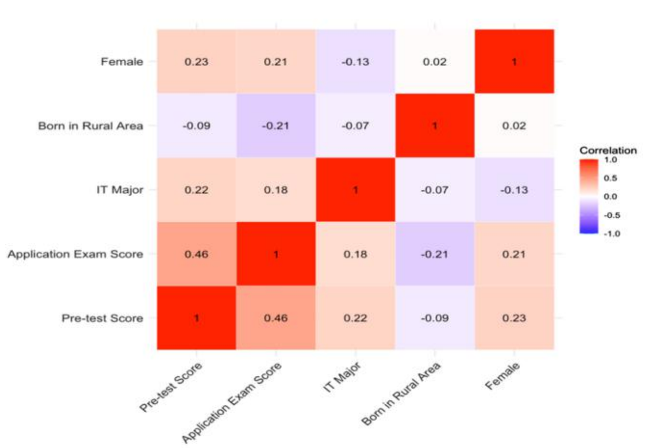
We have the application exam scores (AES) for students in our first experiment. AES is the score obtained in the entrance exam students took to apply for schools. This exam covers many topics, including math, Chinese verbal and writing, English, and science. We used AES to proxy the students' prior academic performance, a strategy commonly used in education research (e.g., Belo et al. 2014). As shown in Figure 2, these moderators are highly independent of each other, capturing different student subpopulations except for the (expected) correlation between AES and pretest scores.

Table 13 presents the simultaneous estimation of several heterogeneous effects on performance gain for both experiments using interactions with our treatment conditions *Ta* and *Ti*. Therefore, in this analysis, we compare these conditions to the baseline condition in which smartphones were banned from the classroom (condition *B*). Columns (1) and (2) show the first and second experiment results, respectively. The consistency of results across these columns enhances our confidence in our findings. The coefficients for the interaction terms reveal the heterogeneous effects that arise in our setting as we discuss below.

7.1. Heterogeneous Effects by Familiarity with Technology (IT Major)

We proxy the students' familiarity with smartphones using their major and assume that students in IT-related majors are more familiar with these devices, potentially leading them to disproportionately benefit from using smartphones for learning. Table 13 indicates a similar performance gain for students in IT and non-IT majors

Figure 2. (Color online) Correlations Across the Moderators Used to Compute Heterogeneous Effects



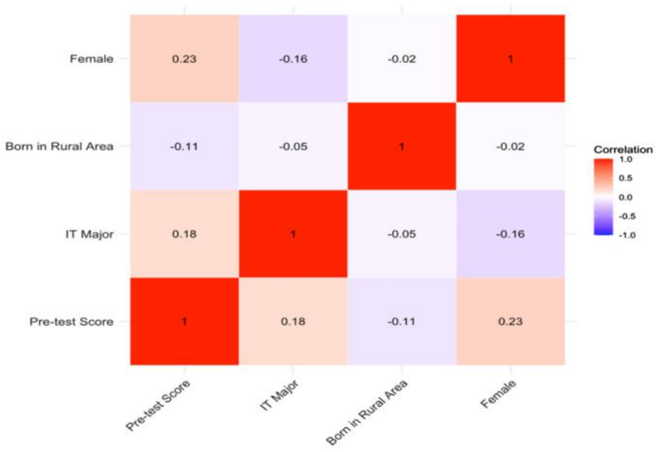


Table 13. Heterogeneous Effects by Gender, Rurality, Major, and Familiarity with Class Content

	Performance gain	
Covariate	Experiment 1	Experiment 2
Ta	−0.94 (5.71)	−4.07 (4.00)
Ti	8.08* (4.83)	8.16** (3.36)
Ta × *non-IT major*	−3.73 (5.42)	2.56 (3.67)
Ti × *non-IT major*	−16.04*** (4.67)	−9.40*** (3.30)
Ta × *Born urban*	8.94* (4.57)	7.94** (3.19)
Ti × *Born urban*	9.19** (4.49)	9.37*** (3.07)
Ta × *Male*	−9.22* (4.79)	−12.49*** (3.33)
Ti × *Male*	9.34** (4.66)	6.77** (3.15)
Ta × *Less familiar*	−2.93 (4.49)	−1.06 (3.43)
Ti × *Less familiar*	5.99 (4.66)	2.33 (3.21)
Non-IT major	−49.84 (48.87)	27.92 (30.16)
Born urban	152.64*** (52.67)	33.36 (33.16)
Male	−35.46 (47.18)	−9.53 (30.15)
Less familiar	51.33 (46.73)	21.56 (31.37)
Constant	19.05 (46.60)	−7.47 (32.48)
Controls	Yes	Yes
Observations	367	734
Adjusted R^2	0.47	0.51

Note. Standard errors with Bonferroni correction in the parentheses. Statistical significance levels: $^*p < 0.1$; $^{**}p < 0.05$; $^{***}p < 0.01$.

in condition *Ta*. However, students in IT majors benefited more from using smartphones than students in non-IT majors when teachers asked students to use their smartphones to aid instruction (condition *Ti*). The average AES for students in IT and non-IT majors are 410 and 376 points, respectively. Therefore, our results support the idea of a rich-get-richer dynamic whereby students in IT majors may benefit more from smartphones, potentially leading to greater performance gaps for non-IT majors.

7.2. Heterogeneous Effects by Rurality

Research on the digital divide indicates that students from rural and urban areas have different levels of IT access and benefit differently from IT (Forman et al. 2005, Lythreatis et al. 2022). Therefore, rurality may also play a heterogeneous role in our findings. Table 13 shows that students born in urban areas benefited more than students born in rural areas from allowing smartphones in the classroom when teachers asked and did not ask them to use smartphones to aid instruction (conditions *Ta* and *Ti*). The average AES score for students born in urban areas and rural areas is 410 and 372, respectively. Therefore, allowing smartphones in the classroom may disadvantage students born in rural areas and exacerbate the digital divide's harmful consequences on educational outcomes.

7.3. Heterogeneous Effects by Gender

Research shows that females and males use IT differently, and thus, gender may also moderate our results (Venkatesh and Morris 2000, Venkatesh et al. 2003, Acilar and Sæbø 2021). Table 13 shows that females benefited more (than males) from allowing smartphones into the classroom when teachers did not ask students to use their smartphones to aid instruction (*Ta*) and males benefited more (than females) from allowing smartphones into the classroom when teachers asked students to use their smartphones to aid instruction (*Ti*). The average AES for females and males are 401 and 363 points, respectively. Therefore, the heterogeneous effect above suggests that using smartphones in the classroom to aid instruction may help close the performance gap between male and female students. However, this gap may widen when smartphones are allowed in the classroom without teacher guidance.

7.4. Heterogeneous Effects by Familiarity with the Content

In our experiments, the pretest and posttest questions were identical, so the pretest score measures the students' prior knowledge of the topics covered in the lectures of our experiments. The results in Table 13 show no heterogeneity in this respect. It is still noteworthy that the coefficient on the heterogeneous effect of *Ta* is negative and that the coefficient on the heterogeneous effect of *Ti* is positive in both experiments, suggesting that allowing smartphones into the classroom may put students less familiar with the content at a disadvantage when teachers do not ask them to use their smartphones to aid instruction and benefit them when teachers do. Nonetheless, an experiment with a larger sample size is needed to confirm this contrast (in case it exists) unequivocally.

7.5. Heterogeneous Effects by Prior Student Performance

According to Cohen and Levinthal (1990), absorptive capacity correlates to accumulated knowledge. If using smartphones to aid instruction enhances performance gain, this effect may be more pronounced for better performing students. To test this heterogeneity, we used the AES data collected during our first experiment (these data are not available for the students in the second experiment) to classify students as low performing and high performing based on whether they fell within the first quartile of the AES distribution. However, AES scores were unavailable for 43 out of the 367 students in this experiment, so the analysis of heterogeneous effects on low-performing versus high-performing students is only based on the subpopulation of 324 students with available AES data. Table 14 presents the results obtained, in which we use the residuals of the regression in column (1) of Table 13 as the dependent variable to ensure that we estimate this heterogeneous effect conditional on the other four heterogeneous effects described earlier. Our findings indicate that low-performing students benefited more from using smartphones in the

Table 14. Heterogeneous Effect by Student Prior Performance

Covariate	Performance gain
Ta	−1.23 (2.47)
Ti	−2.64 (2.38)
Ta × *Low performing*	9.34** (4.69)
Ti × *Low performing*	12.63*** (4.59)
Low performing	−13.36 (45.41)
Constant	−23.14 (22.77)
Controls	Yes
Observations	324
Adjusted R^2	0.01

Note. Standard errors with Bonferroni correction in the parentheses. Statistical significance levels: $^{*}p < 0.1$; $^{**}p < 0.05$; $^{***}p < 0.01$.

classroom when teachers asked them to use their smartphones to aid instruction (*Ti*). Therefore, allowing smartphones in the classroom may help close this performance gap.

8. Discussion and Conclusions

Smartphones have now become ubiquitous, and students frequently bring them into classrooms. However, the impact of smartphones on educational outcomes remains a subject of debate among researchers and practitioners (e.g., students, parents, teachers, educators, school administrators, and policymakers). This uncertainty leads to a lack of consensus on how to manage smartphones in educational settings.

We conducted two RCTs with different classroom smartphone policies. In our baseline condition, smartphones were banned from the classroom. In our second condition, smartphones were allowed into the classroom and used at will by students without guidance. In our third condition, smartphones were allowed into the classroom and teachers asked students to use them to assist with instruction. In the fourth condition of our second experiment, smartphones were banned from the classroom and teachers asked students to use a paper-based aid instead to assist with instruction. Our findings reveal that smartphones in the classroom influence students' behavior and, consequently, their academic performance. On average, banning smartphones from the classroom improved performance compared with allowing use without guidance. However, performance increased even further when teachers guided students to use smartphones to aid instruction. Using a paper-based aid did not affect student performance compared with the baseline smartphone-banned condition. In our case, performance was measured by the difference in test scores taken by students at the beginning and end of each Chinese verbal lecture included in our experiments. Assisted instruction was achieved by having the teacher ask students to use a smartphone dictionary app (developed for our experiment) in one condition and a paper-based dictionary in another condition during lecture to check the pronunciation, definition, and etymology of several words.

Existing research in educational settings has not effectively tracked organic distraction and learning at the student level. In contrast, our study used video feeds of lectures during our experiments to measure the time students spent learning and distracted both on and off the smartphone. Using these measurements, we found that the time students spent distracted versus learning was roughly the same across all experimental conditions, which does not help predict performance. Instead, student performance depends on whether distraction and learning involved the use of smartphones. When the teacher asked students to use the smartphone during the lecture to aid instruction, the time spent learning on the smartphone increased significantly, boosting performance. Although the time students spent being distracted by smartphones also increased, the positive impact of smartphone-assisted learning outweighed the negative effect of smartphone-induced distraction.

Our study also identified several heterogeneous effects. Namely, allowing smartphones to aid instruction benefited students in IT majors, born in urban areas, males, and low-performing students. Using smartphones in the classroom may help narrow educational gaps between male and female students and between low- and high-performing students. However, it could also induce a rich-get-richer dynamic whereby students in IT majors and students from urban areas are likely to outpace their peers in other majors or from rural areas.

Our findings offer several insights for policymakers. Namely, allowing smartphones into classrooms may be productive as long as (i) teachers guide students to use them for learning even if distraction naturally increases and (ii) school administrators and education policymakers implement programs to help students in non-IT majors and from rural areas benefit more from smartphone use in the classroom. Our findings may also encourage educators to focus on developing smartphone apps with teachers to improve technology-assisted learning, ensuring that teachers can effectively manage the balance between learning and distraction associated with using these devices in the classroom. Our study demonstrates that technology, smartphones in our case, can be integrated into classroom settings in ways that improve student performance. Additionally, the rich heterogeneous effects that we report suggest that schools should tailor classroom smartphone usage guidelines based on their specific student demographics.

Our work has several limitations, which can be addressed in future research. First, the effectiveness of smartphones for instruction depends on the subject studied and the context. Our results are specific to Chinese verbal and a particular dictionary app. Outcomes may vary with different subjects and smartphone apps.

Additionally, all lectures in our experiments were 90 minutes long, so we cannot assess the impact of smartphones during shorter or longer lectures. However, contextualization and generalization are not mutually exclusive (Cheng et al. 2016). For example, our study features a dictionary app we developed for these experiments, and thus, professionally developed apps may further enhance learning outcomes. Moreover, whereas our research focused on smartphones, students increasingly use other devices such as tablets. Understanding their impact on educational outcomes is also essential. Although generalizing across devices is challenging, our findings are likely to apply to tablets without much change given that they offer applications similar to smartphones and, thus, have identical potential for both learning and distraction. Lastly, we cannot provide evidence on the long-term effects of smartphones in classrooms on student performance. Measuring long-term effects is difficult in our setting because of potential interference across experimental conditions as well as the inability to track smartphone usage outside the classroom. It would be interesting to explore whether and how using smartphones in the classroom exhibits cumulative learning effects over time and whether such effects could carry over to adjacent learning settings (e.g., at home). We encourage future research to develop appropriate experimental designs and measurement tools to validate our findings more broadly and provide long-term insights on enhancing student learning with technology.

Endnotes

[1] See Statista at https://www.statista.com/statistics/219865/percentage-of-us-adults-who-own-a-smartphone.

[2] HSEmotion is available at https://github.com/av-savchenko/face-emotion-recognition?tab=readme-ov-file.

[3] MediaPipe is available at https://developers.google.com/mediapipe.

[4] GazeTracking is available at https://github.com/antoinelame/GazeTracking.

[5] OpenCV is available at http://opencv.org.

[6] See https://www.stats.gov.cn/sj/pcsj/rkpc/5rp/html/append7.htm.

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