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WP 22-24
October 2022

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Early warning systems, mobile technology, and cholera aversion: Evidence from rural Bangladesh*

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October 14, 2022

Abstract

In Bangladesh, cholera poses a significant health risk. Yet, information about the nature and severity of cholera risk is limited as risk varies over time and by location and changing weather patterns have made historical cholera risk predictions less reliable. In this paper, we examine how households use geographically and temporally personalized cholera risk predictions to inform their water use behaviors. Using data from an eight month field experiment, we estimate how access to a smartphone application containing monthly cholera risk predictions unique to a user's home location affects households' knowledge about their cholera risk as well as their water use practices. We find that households with access to this application feel more equipped to respond to environmental and health risks they may face and reduce their reliance on surface water for bathing and washing—a common cholera transmission pathway. We do not find that households invest additional resources into drinking water treatment, nor do we find reductions in self-reported cholera incidence. Access to dynamic risk information can help households make safer water choices; tailoring information provision to those at highest risk could reduce cholera transmission in endemic areas.

Keywords: Averting behavior; Bangladesh; Cholera; Early Warning; Risk Prediction

JEL codes: I12, I15, O13, Q53

*This research was supported in part through the National Aeronautics and Space Administration cooperative agreement number NNX17AD26A with Resources for the Future to estimate the VOI obtained from satellite-based remote sensing and through the Population Research Institute (PRI) at Pennsylvania State University. The International Centre for Diarrhoeal Disease Research, Bangladesh (icddr,b) research team (particularly Ammatul Fardousi, Srizan Chowdhury, and Mehedi Hasan) and Dr. Md. Al Fazal Khan (Head, Matlab Health Research Centre) provided expert research support and project implementation. Abdullah Islam, Anna Litofsky, Farah Nusrat, and Samiha Taseen provided excellent research assistance. Ana Dammert, Alan Krupnick, Yusuke Kuwayama, Johabed Olvera, Santiago Saavedra, Hilary Wething, and participants at the Association of Environmental and Resource Economists Annual Meeting, European Association of Environmental and Resource Economists Annual Meeting, and Advances with Field Experiments Conference provided valuable comments. Any remaining errors are our own. This project was pre-registered on the AEA RCT Trial Registry at https://doi.org/10.1257/rct.6900-3.0 and approved by Institutional Review Boards at Moravian University and icdddr,b.

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1 Introduction

Cholera remains a pressing public health challenge, imposing significant mortality and morbidity burdens on impacted populations. Recent estimates suggest that over 1.3 billion people are at risk of cholera and that there are at least 2.86 million cholera cases and 95,000 cholera-related deaths annually (Ali et al., 2015). Cholera is transmitted via the bacterium *Vibrio cholerae*, often through contaminated food and water. While cholera can be fatal—especially among young children—it is also highly treatable through oral rehydration solutions (ORS) and preventable through safe water, sanitation, and hygiene practices (Davies et al., 2017; Islam et al., 2018; Mogasale et al., 2020). Indeed, while the disease remains prevalent in low- and middle-income countries (LMICs), municipal water and sewage treatment systems have largely eradicated cholera transmission in high income countries.

Due to its deltaic terrain, monsoon climate, and social factors such as high population density and lack of widespread water and sewer infrastructure, Bangladesh faces public health threats from both endemic and epidemic cholera (Zaman et al., 2020).[1] The seasonal nature of the hydrology—a prolonged dry season in winter and spring followed by an intense monsoon in summer—exposes much of the population to water insecurity and associated cholera outbreaks (Akanda et al., 2009, 2013). During the long dry season, water shortages intensify as sources across the rural landscape become unusable due to worsening quality and insufficient quantity. Frequent and widespread flooding—in part due to elevation and monsoon, but also exacerbated by climate change—elevates the risk of cholera outbreaks across Bangladesh. Indeed, Bangladesh ranks within the top five countries globally in terms of population at risk for cholera, demonstrating the substantial cholera burden in the country (Ali et al., 2015).[2]

Despite improvements in cholera treatment and prevention, there are at least 100,000 cases of cholera and 4500 deaths from the disease in Bangladesh each year (Islam et al., 2018). These estimates are almost certainly an underestimate due to inadequate availability of resources for cholera testing. Further, while much is known about the seasonality and peaks of cholera risk, this information is often inaccessible to the populations most vulnerable to its transmission. Despite

[1]Bangladesh faces a variety of other water-related environmental risks including naturally occurring arsenic contamination of groundwater (Aziz et al., 2015; Nickson et al., 1998) and saltwater intrusion (Khan et al., 2011).

[2]Other high-risk countries include India, Nigeria, China, and Ethiopia (Ali et al., 2015).

some knowledge of cholera's seasonality, as climate change has made weather patterns, especially the timing of the monsoon, more unpredictable, it is increasingly difficult for households to use historical patterns to predict the timing of high disease risk. In this paper, we use a field experiment to examine the effects of providing geographically personalized and temporally dynamic cholera risk predictions directly to households in Matlab, Bangladesh via a smartphone application. These disease risk predictions are generated via a remote sensing model developed for Bangladesh and calibrated to the Matlab sub-district using cholera incidence reports. Thus, in this setting we examine the value of this information in informing household water-use behaviors. In recent years, both mobile phone and smartphone access has expanded across Bangladesh, making these technologies viable platforms for information dissemination. Indeed, systemic reviews of mobile health (mHealth) programs globally demonstrate a rise in the use of mobile phone technology in healthcare provision and services and point to strengths and limitations of these programs (Aamir et al., 2018; Aranda-Jan et al., 2014; Marcolino et al., 2018).

We conducted the field experiment with a sample of 2014 households across 40 villages in Matlab—a rural sub-district of approximately 500,000 households in Bangladesh with a dual-peak seasonality in endemic cholera risk. We disseminated monthly predictions of cholera risk—discretized into low, medium, or high risk messages—to sample households via a simple Android app called CholeraMap. The risk predictions were generated via a remote sensing model that uses rainfall, temperature, elevation, and population density data to predict cholera risk at a one km^2 resolution using a monthly time step. The model was calibrated to this resolution and the Matlab area for the purposes of this information dissemination field experiment. The risk predictions for the entire Matlab area were available to CholeraMap users at the beginning of each month. The risk prediction for the user's home location—set at the point of app installation—were further contextualized for CholeraMap users through a series of interactive app tabs. We also developed a control app, a simple Android app called CholeraApp, that was identical in terms of design and functionality but provided users with only static, publicly available information about averting cholera risk. We use both CholeraApp using households and pure control households (households without CholeraMap or CholeraApp) as comparison groups.

We assess willingness to use and engage with CholeraMap as an early warning system of cholera risk and measure the impact of this information intervention on household cholera-related knowledge, water use and hygiene practices, and cholera incidence. Several results emerge. First, we find that CholeraMap users increased their cholera-related knowledge. Among CholeraMap households, confidence in responding to environmental and health related challenges increased by 9.3 percent and 7.7 percent, respectively, compared to control households over the study period. Further, following the intervention period, CholeraMap users were 21 percent less likely to report diarrhea as a major health concern for household children. Taken together, these results suggest that the information available in CholeraMap increased households' confidence that they could respond to the environmental and health risks they faced—cholera chief among them. Second, we find that CholeraMap households adjusted their water-use behaviors, particularly related to surface water use. Following the study period, adult men and women in CholeraMap households decreased their use of pond water—a commonly contaminated surface water source—for bathing and other washing by 22.9 percent and 25 percent, respectively, compared to control households. We find no evidence that CholeraMap households shifted their drinking water treatment behaviors, perhaps due to high baseline use of groundwater for drinking, which is less likely to contain microbial contamination. Nor do we find changes in handwashing behavior or self-reported cholera incidence. Finally, with regard to app-design, we find higher CholeraMap use compared to CholeraApp use as measured by distinct app visits, pages viewed, and time spent on the app. On the other hand, we find that users were more likely to delete CholeraMap, perhaps due to misconceptions of higher space or data demands due to its dynamic features. Taken together, these results suggest that the additional engagement of CholeraMap, which may have increased the intensive margin of app use among committed users, may have decreased the extensive margin of app use among CholeraMap households. These findings highlight the need to assess app user experience to further refine the platform for information dissemination.

This paper makes at least three contributions to the literature. First, it joins a nascent literature evaluating the impacts of mobile phone-based infectious disease risk messaging on household averting behavior (see Dammert et al. (2014) and Wimberly et al. (2021) for examples related to dengue and malaria, respectively). It demonstrates that modeled cholera risk predictions can be effectively disseminated directly to households using smartphone applications. By examining two different cholera-related applications, the study speaks to how early warning system design—in this case measured by app design—affects information provision and its impacts. Second, building on a literature of environmental health information intervention evaluations (Bennear et al., 2013; Brown et al., 2017; Cutter and Neidell, 2009; Graff Zivin and Neidell, 2009; Guiteras et al., 2015; Haushofer et al., 2019; Jalan and Somanathan, 2008; Janke, 2014; Ward and Beatty, 2016), it provides insight into how a new type of information intervention—a cholera risk prediction early warning system—can shift household perceptions of disease risk and influence averting behavior. Third, it demonstrates how newly widespread technologies, such as smartphones, can be integrated into scalable, effective policy design. This is especially important in contexts—such as the one examined in this study—where environmental risks are dynamic and costly and where populations are vulnerable and difficult to reach.

The rest of the paper is organized as follows. Section 2 provides a background on related literature and water-related health risks in Bangladesh. Section 3 describes the cholera risk prediction model used for the information intervention and the CholeraMap and CholeraApp apps. Section 4 outlines the experimental design and data, and Section 5 specifies our empirical strategy. Section 6 presents our results, and Section 7 provides robustness checks and heterogeneity analysis. Section 8 concludes with a discussion of the policy implications of our findings.

2 Background

2.1 Early warning systems for environmental risk

Environmental risks such as natural disasters, air and water contamination, and vectors and other pests threaten human health and well-being around the world. A recent analysis of the global burden of disease from environmental risks assess that approximately one quarter of global deaths are from modifiable environmental factors (Prüss-Üstün et al., 2016). Early warning systems providing information related to various types environmental risks have been designed and implemented in a number of settings to assess how information provision affects individual and household decisions to avert these environmental risks.

Given the diversity of environmental risk contexts and settings in which they have been tested, existing research on the impacts of such early warning systems provides a range of impact estimates. The environmental engineering, public health, and economics literatures provide background on the design and evaluation of these systems. In two settings most directly related to our own context, Dammert et al. (2014) and Wimberly et al. (2021) assess how disease risk prediction systems affect household behavior and health in the context of vector-borne diseases—dengue and malaria, respectively. Dammert et al. (2014) use a randomized field experiment to examine how various forms of information about dengue risk and prevention affect households' uptake of preventive measures against the disease as well as dengue transmission in Peru. While not explicitly designed as an early warning system, Dammert et al. (2014) sent SMS text messages containing information about dengue prevention, detection, and control and assessed impacts across areas with varying levels of dengue transmission. They find that households that received the informational SMS messages reported increased use of screens and bednets and decreased prevalence of dengue-related symptoms.[3] In the context of malaria, Wimberly et al. (2021) developed a model that uses high resolution satellite observations to assess malaria risk. While the impacts of the model have not yet been assessed, Wimberly et al. (2021) outline efforts to provide user-friendly modeled outputs to researchers and practitioners. Finally, in the context of cholera, previous work shows evidence of demand for cholera early warning systems (Akanda et al., 2018; Aziz et al., 2021)

Early warning systems have also been evaluated in a number of other environmental settings including air pollution alerts (Cutter and Neidell, 2009; Graff Zivin and Neidell, 2009; Janke, 2014; Ward and Beatty, 2016), flood warning systems (Atreya et al., 2017; Ferris and Newburn, 2017; Sufri et al., 2020), and agricultural pests (Gómez et al., 2019). In air pollution-related applications from the United States, Cutter and Neidell (2009) and Graff Zivin and Neidell (2009) show that air quality alerts shift transportation and activity choices. For example, Cutter and Neidell (2009) found that when air quality levels trigger alerts that contain messages about the importance of using public transportation to reduce car emissions, there are small reductions in daily traffic. Similarly, Graff Zivin and Neidell (2009) found reductions in discretionary time spent on outdoor activities on days with smog alerts, suggesting these warnings triggered a short-term averting response. In England, Janke (2014) found that air quality alerts decreased hospital admissions for asthma, suggesting that the alerts provided valuable information to a population vulnerable to poor air quality. The impacts of early warning systems have also been evaluated in the contexts of floods and agricultural pests. For example, Atreya et al. (2017) found that flooding early warning systems

[3] In another dengue-related application, Buczak et al. (2012) use satellite data products to model dengue outbreak predictions in Peru. They do not assess the impacts of providing these predictions to at-risk households.

such as sirens, whistles, and bells in a flood-prone region of Mexico increased household flood preparedness. In the context of agricultural pests, Gómez et al. (2019) developed an early warning system for desert locusts using earth observation datasets. Gómez et al. (2019) demonstrated the validity of their model in Mauritania, however, they have not yet assessed the impact of providing the early warning system to vulnerable households.[4]

Reviewing existing work on early warning systems reveals that there is little existing work evaluating the viability and value of an early warning system for cholera risk. Yet, applications related to other diseases—dengue and malaria—and environmental risks—air pollution—suggest such systems could be used and valuable. Our paper fills this gap, by providing insight into the value of the information provided by an early warning system for cholera risk in a cholera-endemic region, as measured by household early warning system use and behavioral change.

2.2 Water, sanitation, and hygiene behavioral change

Despite the somewhat limited literature on evaluating the impacts of early warning systems for infectious disease, existing research in the economics literature identifies the impacts of information and other environmental health interventions designed to promote improved water, sanitation, and hygiene behaviors in LMICs.[5] Evidence from randomized interventions in Cambodia and India has shown that providing households with results from water quality tests of their drinking water increased demand for water treatment (Barnwal et al., 2017; Brown et al., 2017; Jalan and Somanathan, 2008). These results suggest that personalized risk information can motivate behavioral change. In the sanitation space, Community-Led Total Sanitation (CLTS) campaigns use information—such as messages designed to promote latrine use—as a main triggering tool in community interventions (Kar and Chambers, 2008). Evaluations of CLTS campaigns have shown these information-driven interventions to be effective tools in reducing open defecation despite

[4] A number of early warning system applications discussed in this section used mobile phone platforms and SMS messaging to disseminate warning information. There is a related literature on the use of mHealth platforms to provide or connect users with healthcare services. While these platforms demonstrate how mobile phone technology has been used in healthcare, we do not provide an overview of this literature because these applications are not early warning systems. We refer the interested reader to mHealth systematic reviews (Aamir et al., 2018; Aranda-Jan et al., 2014; Marcolino et al., 2018) and applications (Haenssgen and Ariana, 2017; Haenssgen et al., 2021; Hampshire et al., 2021) for more information.

[5] Pattanayak et al. (2018) provide a review of the literature on environmental health economics in LMICs, specifically detailing work on valuation, adoption, and evaluation of environmental risk reducing technologies related to water, sanitation, and hygiene.

remaining uncertainty regarding the sustainability of improved sanitation behaviors and the cost effectiveness of said interventions (Gertler et al., 2015; Guiteras et al., 2015; Orgill-Meyer et al., 2019; Whittington et al., 2020).

Other types of interventions have also shifted household water, sanitation, and hygiene behaviors. Monetary tools, including subsidization, free provision, and credit, are commonly implemented and evaluated. Using a randomized field experiment in Zambia, for example, Ashraf et al. (2010), found that higher prices for water treatment products decreased demand for these products among households. Interestingly, however, they also resulted in increased use. Evaluating a randomized trial in Kenya that provided drinking water treatment free of charge in exchange for vouchers, Dupas et al. (2016) find similar evidence. Further, recent work by Dupas et al. (Forthcoming) from Malawi showed households were more likely to use freely-available drinking water treatment if they obtained the treatment resources by redeeming coupons rather than automatically from community health workers. In Pakistan, Akram and Mendelsohn (2021) show that among households that track children's diarrhea incidence, drinking water treatment is higher and more consistent, and that the behavioral change persists for a longer period of time. All of these studies suggest that drinking water treatment is more often used when households invest some effort—whether monetary or time—in obtaining treatment materials. In the sanitation space, BenYishay et al. (2017) found that access to microloans increased latrine installation among households in rural Cambodia. Devoto et al. (2012) found similar results for piped water adoption in Morocco, suggesting that credit access helped households pay for private, piped connections—resulting in significant welfare gains. Luoto et al. (2014) combined free provision of point-of-use water treatment products with informational messaging campaigns in Kenya and Bangladesh and found that the combination of pricing and informational tools promoted increased drinking water treatment in both settings.

This evidence from the economics literature demonstrates that informational, monetary, and other tools can effectively promote improved water, sanitation, and hygiene behaviors. These studies also demonstrate that there is important heterogeneity in response to such interventions, identify challenges of evaluating and motivating sustained behavioral change, and draw attention to the cost effectiveness of program implementation. Taken together, the literature suggests that designing scalable and efficient interventions that build on what is known about promoting improved water, sanitation, and hygiene behavior should be prioritized. Further, they suggest that additional evaluations of the mechanisms that underlie successful campaigns to improve water, sanitation, and hygiene behavior can provide valuable inputs for future policy design.

2.3 Water risk communication in Bangladesh

While limited access to safe, improved water sources affect billions globally, Bangladesh is particularly vulnerable as a result of its climate and geography. The combined water quality challenges of both surface and groundwater contamination, by pathogens and naturally occurring arsenic, respectively, have made Bangladesh a common setting for water risk communication efforts. We contribute to this literature by providing insight into the value of dynamic and personalized cholera risk information to Bangladeshi households living in a cholera-endemic region.

Evaluations of efforts to communicate arsenic risk—which varies naturally across Bangladesh—to local populations have generated additional insights into how households respond to environmental risk communication (Aziz et al., 2015). For example, Madajewicz et al. (2007) found that Bangladeshi households responded to messages about groundwater arsenic; when households learned their tubewells were contaminated, the probability of switching to arsenic-safe tubewells increased substantially. Importantly, however, Madajewicz et al. (2007) found that mass communication of arsenic risk was sufficient to motivate behavioral change; a personalized, door-to-door information campaign did not differentially shift behaviors. In a similar context, Bennear et al. (2013) found that more detailed messaging was not more effective in shifting households away from use of arsenic-contaminated tubewells. The authors note, however, that repeated messaging may result in a different outcome compared to the one-time messaging intervention evaluated in their study.

In addition to naturally occurring arsenic, surface water contamination presents the acute risk of cholera and other diarrheal diseases. Evaluations of efforts to promote safe water, sanitation, and hygiene practices to reduce disease risk have shown messaging interventions to be minimally effective in shifting behaviors, while provision of water treatments and handwashing facilities were more effective in increasing use (Guiteras et al., 2016; Luoto et al., 2014). Despite these findings of limited response to messaging campaigns, other work finds evidence of demand for additional information about cholera risk among Bangladeshi households, especially in the form of early warning systems (Aziz et al., 2021).

3 Modeling and communicating cholera risk predictions

To provide temporally and geographically dynamic cholera risk predictions to households in Matlab, we first model predicted cholera risk and then disseminate predictions via a smartphone application.

3.1 Predicting cholera risk

Cholera risk can be predicted based on hydrological and climatic characteristics of a region (Akanda et al., 2011). We developed a model to predict cholera risk based on weather and seasonal characteristics. Informed by remote sensing data including rainfall observations, anomalies, and forecasts, land surface temperature, land surface elevation, and population density, the model generates monthly risk predictions at a one km^2 resolution.[6] The model generates risk predictions scaled from 0 (indicating no cholera risk) to 1 (indicating very high cholera risk). We calibrated the model across Bangladesh using cholera surveillance data.[7] Figure 1 depicts the monthly cholera risk prediction maps generated from this model for March 2021 through November 2021, demonstrating the changing cholera risk predictions in Matlab during this time, and matching with the double peak cholera pattern endemic to the region (Akanda et al., 2011, 2013).

3.2 Early warning systems: CholeraMap and CholeraApp

To disseminate the model-generated cholera risk predictions, we developed a smartphone application called CholeraMap. CholeraMap is a simple Android smartphone application that

[6] Rainfall observations available from the Integrated Multi-satellitE Retrievals for GPM (IMERG) (https://gpm.nasa.gov/data/imerg). Rainfall anomaly data available from the Tropical Rainfall Measuring Mission/Global Precipitation Measurement (TRMM/GPM) (https://gpm.nasa.gov/missions/trmm). Rainfall forecasts available from SERVIR North American Multi-Model Ensemble (SERVIR NMME) (https://iridl.ldeo.columbia.edu/SOURCES/.Models/.NMME/). Land surface temperature data available from the Moderate Resolution Imaging Spectroradiometer (MODIS) (https://modis.gsfc.nasa.gov/data/dataprod/mod11.php). Land surface elevation data available from the Shuttle Radar Topography Mission (SRTM) (https://www.usgs.gov/centers/eros/science/usgs-eros-archive-digital-elevation-shuttle-radar-topography-mission-srtm). Population density data available from the Socioeconomic Data and Applications Center (SEDAC) (https://sedac.ciesin.columbia.edu/data/collection/gpw-v4).

[7] Cholera surveillance data come from the Endemic Cholera Control in Bangladesh Study (ECBS). More information about ECBS is available at https://www.gtfcc.org/research/control-of-endemic-cholera-in-bangladesh-update-the-existing-cholera-investment-case-surveillance-and-developing-the-funding-consortium/.

provides cholera early warning risk maps and associated information about interpreting cholera risk levels and safe water behavior.[8] The cholera early warning risk maps are updated monthly. While the maps depict the entire Matlab region—an area of approximately 484 km^2—app users observe a house marker depicting their location on the map to personalize risk levels. Due to concerns about data service demands and connectivity, the app was designed to minimize location services. Accordingly, the app uses smartphone locations services at the time of registration to set a user's location, which is then held constant anytime the app is used. The only way to change the location from the place where the app was installed is for a user to uninstall and reinstall CholeraMap. All CholeraMap users register with a username and identification number selected by the user.[9]

Following successful use of character association and story telling to promote improved sanitation in Bangladesh (Chesterton, 2004), CholeraMap uses a series of interactive tabs to depict the story of a young woman using a smartphone to learn about cholera risk in her village. Figure 2 depicts the three main tabs of CholeraMap.[10] In the first tab (Figure 2a), the young women views a multi-colored map of Matlab, Bangladesh. A few key landmarks are identified along with a house marker, locating her personalized cholera risk prediction for the month. A legend informs that red coloring on the map indicates high levels of predicted cholera risk; yellow medium risk; and green low risk. In the second tab (Figure 2b), the risk level from the previous tab is further explained. The young women sees her village, with many households colored in red, indicating high risk of cholera transmission. The text on the tab mirrors this message, as does the red color, the number of red colored households, and worried expression on the young women's face. The information provided on this tab varies monthly, along with the risk prediction map, and always matches the risk category of the home location observed on the risk prediction map tab. That is, if the user's location falls in an area with medium (low) risk predictions, the subsequent tabs would display information about medium (low) risk and use yellow (green) coloring. Finally, the third tab (Figure 2c) depicts an animated gif of the young woman boiling her drinking water—a cholera risk averting behavior. This tab also contains additional information about averting cholera

[8] CholeraMap is available on the Google Play store: https://play.google.com/store/apps/details?id=com.cholera_map.

[9] For the purposes of examining CholeraMap use, users that were part of this project used their phone numbers as their identification number to guarantee unique identification numbers among our sample users.

[10] While the app images in Figure 2 show text in English for clarity, all text in CholeraMap is in Bangla.

risk including practicing safe sanitation, frequent handwashing with soap, washing fruits and vegetables before eating, treating drinking water, and using ORS if infected with cholera. As with the previous tab, this the messages and color scheme are updated monthly to match the predicted risk level based on the user's home location.

In addition to CholeraMap, which we designed to provide geographically personalized monthly cholera risk predictions to users, we designed and deployed a simpler Android smartphone application called CholeraApp.[11] We designed CholeraApp to contain cholera-related information that would be publicly available to our intended app users—households in rural Matlab. CholeraApp uses the same character, story telling approach, and user navigation as CholeraMap to provide the user with information about reducing their household's cholera risk. These messages include practicing safe sanitation, frequent handwashing with soap, washing fruits and vegetables before eating, treating drinking water, and using ORS if infected with cholera. CholeraApp is a static application; the information in the app is not updated. Accordingly, the value of CholeraApp to a user may be the compilation of cholera-related information into one, easily accessible platform; however, all information provided in CholeraApp is also available on other public health platforms.

4 Experimental design

We implemented a field experiment in the Matlab sub-district of Bangladesh. Matlab is a rural area of 500,000 people located in southeastern Bangladesh, approximately 50 km southeast of Dhaka, the country's capital city (see Figure 3). The region is low in elevation—situated on the banks of the Dhonagoda River and near the confluence of the Padma and Meghna Rivers—putting the area at risk for flooding during the monsoon season. Other water-related challenges, including surface water microbial contamination, saltwater intrusion and groundwater arsenic, limit safe water access in the region (Jabed et al., 2020; Mukherjee and Bhattacharya, 2001).

Due to its proximity to Dhaka and water-related challenges associated with surface water and groundwater contamination, Matlab has been the site of the Heath and Demographic Surveillance System (HDSS) since 1963 (Aziz and Mosley, 1994; Alam et al., 2017). The HDSS monitors demographics, socioeconomic status, water and sanitation conditions, and health of households

[11] CholeraApp is available on the Google Play store: https://play.google.com/store/apps/details?id=com.cholera_app.

in Matlab. In addition, healthcare services are provided in the region by the Government of Bangladesh health service delivery system as well in field hospitals run by the International Centre for Diarrhoeal Disease Research, Bangladesh (icddr,b). These icddr,b field sites have been the location of substantial improvements in cholera treatment since the 1970s, most notably the development of ORS (Lancet, 1978; Zaman et al., 2020). Despite such improvements in cholera treatment and reductions in incidence, cholera remains a public health threat in Matlab. While endemic to the region, cholera risk spikes in two distinct seasons—pre-monsoon (approximately March-May) and post monsoon (approximately September-October) (Akanda et al., 2011). This seasonality in risk notwithstanding, households have minimal access to reliable information about the dynamic nature of cholera risk in their villages. Further, climate change-induced disruptions to the timing of the monsoon and other weather patterns have made it increasingly difficult to predict cholera risk without the use of sophisticated models.

Matlab is divided into seven administrative blocks. Three of these blocks—blocks E, F, and G—are government services areas; the remaining blocks—blocks A, B, C, and D—are icddr,b service areas (icddr,b, 2020). Our study sites fall entirely within the government service area blocks of E, F, and G, which are located in the northern portion of Matlab, primarily north of the Dhonagoda River. To limit informational spillovers across study arms and to reduce implementation burden in a region that experiences intermittent connectivity challenges, study arms (CholeraMap, CholeraApp, and control) were assigned by administrative block, with block E villages assigned to CholeraMap; block G villages to CholeraApp; and block F villages to control. As service access, environmental and geographical conditions, socioeconomic status, and demographic conditions do not vary with block designation within the government service areas, we do not believe this assignment threatens our research design.

From a listing of villages with populations of at least 100 households in each of our study blocks, we randomly selected 40 villages for our study sample. Village selection was stratified by block: 15 villages were randomly selected from blocks E and G and 10 villages were randomly selected from block F. Approximately 50 households in each study village were randomly selected for inclusion using a geographical systematic random sample.[12] To be eligible for the study, a

[12]To generate this sampling frame, a geographically central household was selected for inclusion in the study. Starting with this household, every kth household was selected for the study, where $k = \frac{N}{50}$ and N is the numbed of households in the village.

household had to own at least one, working smart phone. A recent, nationally representative, survey found that 82 percent of Bangladeshi households owned mobile phones and 55 percent of Bangladeshi households owned smartphones (AfAI and A2I, 2018-19). Thus, we note that while a majority of Bangladeshi households have access to smartphone technology, these households are likely more socioeconomically advantaged compared to households without smartphones. Accordingly, we caveat the generalizability of our results on this sampling criterion.

If a selected household was unwilling to participate or did not own a smartphone, a neighboring household that met the sampling criteria was selected in its place. Our final sample contained 2142 households. Of the 2142 households recruited for the study, 2014 households (95 percent) were re-surveyed at the end of the study. The main reasons for attrition included the inability to find the intended respondent after multiple revisit attempts and migration.

4.1 Smartphone application intervention

Households were assigned to one of three study arms—CholeraMap, CholeraApp, or control—based on their locations in blocks E, F, or G. Households assigned to the CholeraMap arm installed the CholeraMap application onto their smartphones with the help of a trained fieldworker. Users installed CholeraMap by either downloading the app from the Google Play store or, if connectivity was limited, via direct transfer of the app Android Package Kit (APK) from a smartphone carried by the enumerator. As the user's location at the time of install was critical to establishing the location of cholera risk prediction information observed by the user, all apps were installed at the user's home. If connectivity was limited, fieldworkers used a data hotspot to facilitate installation. One user per household—generally the primary water procurer and respondent to household survey (see section 4.2)—registered for CholeraMap using their self-selected username and ID number. Fieldworkers answered user questions regarding the app and its functionality at the time of installation. Households assigned to the CholeraApp arm installed the CholeraApp application onto their smartphones with the help of a trained fieldworker. All installation processes used for households in the CholeraMap arm were also implemented for households in the CholeraApp arm. Households in the CholeraApp and CholeraMap arms had access to the apps for the duration of the study, approximately March/April 2021-October/November 2021.[13] Households in the control arm did not receive access to either app.

In addition to installation support, households in the CholeraMap and CholeraApp treatment arms received monthly phone calls, bimonthly text message reminders, and monthly payments for data services. Trained enumerators called app-using households each month to (i) provide technological support; (ii) answer questions about the app; and (iii) ask households about their water use practices and household cholera incidence that month. Each household was contacted up to three times per month; if the intended respondent could not be reached after three calls, enumerators resumed attempts to connect in the following month. App-using households also received bimonthly text messages reminding them about CholeraMap and CholeraApp. Incoming SMS text messages are free in Bangladesh, so households did not incur any costs associated with these messages. CholeraMap households received one text message at the beginning of each month notifying users that the cholera risk prediction maps had been updated and one text message in the middle of each month reminding users that cholera risk information was available on their phones in CholeraMap. CholeraApp users received two text messages—one at the beginning of each month and one in the middle of each month—reminding them that there was information about reducing cholera risk available on their phones in CholeraApp. Finally, to offset any data related costs associated with the use of CholeraMap or CholeraApp, app-using households received monthly payments of 100 taka (approximately US$1.20) through bKash, a common payment service in the area.[14] As one gigabyte of mobile data in Bangladesh costs approximately 60 taka (US$0.70), these payments were significantly higher than the data costs incurred using CholeraMap and CholeraApp.

[13] CholeraMap and CholeraApp are currently updated and maintained by Akanda Labs. If the apps are updated or discontinued, households still using the apps will receive a notification alerting them of the change.

[14] Receiving bKash payments requires a free account tied to a mobile phone number and bKash account. If households did not have bKash accounts and wanted to receive the payments, fieldworkers helped them open bKash accounts. Households could opt out of receiving bKash payments if they did not want to receive them or did not want to create a bKash payment account.

4.2 Data

Household surveys

The baseline household survey was conducted in March–April 2021. The primary adult water procurer was targeted as the survey respondent as this individual would be knowledgeable about household water use behaviors as well as household health. Based on usual household water procuring responsibilities, the targeted respondent was generally a female household head or wife of household head. For CholeraMap and CholeraApp households, the survey respondent was also the intended app user; this was the case in approximately 75 percent of households.[15] The baseline household survey collected household roster information and contained sections on household cholera incidence, treatment costs, and knowledge; sources of public health messaging; household water treatment and storage; sanitation and hygiene; routine water-related behaviors of household members; risk preferences; smartphone and data use; and socioeconomic characteristics. Enumerators also collected household GPS coordinates.

Table 1 reports baseline descriptive statistics for our household sample and comparisons across study arms. Panel A reports household characteristics. The average household in our sample has about five household members, and over a third of households have at least one child under the age of five. Education levels are fairly low, with the 60 percent of household heads' education levels under the secondary level. In line with the rural setting, 70 percent of sample households own land. Nearly 70 percent of households own televisions and approximately 20 percent of the sample owns either a bicycle or motorbike. Across study arms, household characteristics are fairly balanced. We do find that CholeraMap households are more likely to own land and less likely to own a bicycle or motorbike compared to CholeraApp and control households. They are also less likely to own televisions than CholeraApp households, suggesting that CholeraMap households may be slightly more socioeconomically disadvantaged. We also find that CholeraApp households are more likely to own televisions and have slightly lower education compared to control households. As these imbalances do demonstrate some differences in observable characteristics across study arms, we use a difference-in-differences study design and control for household characteristics in

[15] In approximately 25 percent of households the app user and survey respondent were different members of the same household. There were a variety of reasons for this including smartphone sharing within a household and a survey respondent's lack of comfort with app technology.

our empirical analysis.

Panel B reports household knowledge and behaviors related to water use, sanitation and hygiene, and cholera. Approximately 15 percent of our sample households had experienced at least one case of cholera in the previous month. Despite this evidence of cholera transmission, average perceptions of cholera risk throughout the year were low at baseline (1.13 on a 1 (low) to 3 (high) scale). The average sample household spends 15-30 minutes collecting water daily, uses some sort of pumped water as their primary drinking water sources, and does not report high levels of water insecurity or stress. Rates of permanent water storage and drinking water treatment are low, with averages of 19 percent and 16 percent, respectively. In terms of hygiene and sanitation, the average sample household reported handwashing frequency of 4 times per day and latrine ownership is nearly universal. Finally, in terms of non-drinking water use, over a third of adults use pond water (a common surface water source in the area) for bathing and washing.

As with household characteristics, we check for balance on knowledge and behaviors related to water use, sanitation and hygiene, and cholera across study arms. We find that CholeraMap households are slightly less likely to use pumped water, treat drinking water, and rely on pond water for non-drinking water compared to CholeraApp households. They also report lower handwashing and higher permanent water storage. Compared to control households, CholeraMap households report slightly longer water collection times, water refilling frequency, and water stress. Finally, compared to control households, CholeraApp households report slightly longer water collection times and more frequent water refilling, drinking water treatment, and handwashing. As these imbalances do demonstrate some differences in observable characteristics across study arms, we use difference-in-differences for our empirical analysis.

Households were revisited in October–November 2021 for an endline household survey. Whenever possible, the same respondent who answered the baseline survey was re-surveyed. The endline survey was identical to the baseline survey with the exception of an additional module on CholeraMap or CholeraApp use and functionality for CholeraMap and CholeraApp households, respectively.

Cholera risk predictions

Using GPS coordinates collected during the household survey, we obtained monthly predictions of cholera risk for all study households based on the results from our cholera risk model (see Section 3.1). For CholeraMap households, this data allows us to identify the risk level each household observed in the app each month; for all study households, this data allows us to examine the underlying cholera risk environment to contextualize our results.

App analytics

App analytics for CholeraMap and CholeraApp were collected for the duration of the study. Analytics including the data, start time, end time, and tab name were collected for each tab view of CholeraMap and CholeraApp. These analytics data were identified by the identification number entered by a user at installation. Because we ensured these identification numbers were unique within our sample, we were able to match app analytics data to app using households to examine app use and contextualize our findings. We were able to match app analytics and survey data for 96 percent of households. To assess app engagement, we compare app use analytics between CholeraMap and CholeraApp users for the duration of the intervention (approximately April 2021-October 2021). We examine four outcomes: (i) distinct app visits; (ii) time spent on app; (iii) pages viewed; and (iv) time spent per visit. We consider distinct visits our main outcome of interest as CholeraMap has more pages and contains more information than CholeraApp, thus increasing the likelihood of higher pages viewed and longer time spent on CholeraMap. We find these outcomes illuminating, however, as differences would suggest users found the additional information provided by CholeraMap of value.

Outcomes of interest

We examine three categories of outcomes in our main analysis: (i) cholera-related knowledge; (ii) water and hygiene behaviors; and (iii) health. In regard to knowledge outcomes, we examine if households report feeling equipped to deal with environmental challenges they face, if households report feeling equipped to deal with health challenges they face, and if households report diarrhea as a top health concern for their children. In regard to water use behaviors, we examine if households report treating drinking water before use—which could include any type of filtration or boiling—and use of pond water (main surface water) for bathing and washing among adult male and female household members. In terms of hygiene behavior, we examine the number of daily scenarios in which households report washing hands with soap. Finally, in terms of health, we examine cholera incidence in the previous month. All outcomes were gathered on baseline and endline household surveys.

To examine whether CholeraMap impacts households in a more dynamic fashion, we rely on data collected via a monthly phone survey of application (CholeraMap or CholeraApp) households. For these analyses, we examine four alternative outcomes. Specifically, we examine impacts on (i) household drinking water treatment; (ii) household cholera incidence; (iii) household water stress; and (iv) household water security.

5 Empirical strategy

We estimate differences in app use between CholeraMap and CholeraApp users as well as the impacts of app access on household cholera-related knowledge and water use behaviors. To examine differences in app use across treatment arms, we use a simple linear regression model. To evaluate the impacts of app access, we use difference-in-differences and modified event study designs to estimate the effects of CholeraMap and CholeraApp on household water use behaviors. We consider these analyses as indicative of estimating the value of the information provided by CholeraMap and CholeraApp to households, as they demonstrate how the information impacted household outcomes. These empirical approaches use the panel structure of our data, with the difference-in-differences analysis using only household survey data from the baseline and endline surveys and the modified event study using data from both the baseline and endline household surveys as well as the monthly phone surveys.

5.1 Estimating difference in CholeraMap and CholeraApp use

To examine differences in app use across CholeraMap and CholeraApp households we provide both graphical and regression results. The graphical results depict the difference in the average number of visits, time spent, and pages viewed between CholeraMap and CholeraApp users. The regression results are estimated using linear regressions of the following specification:

$$Y_i = \alpha + \beta CM_i + X_i \cdot \theta + \varepsilon_i \tag{1}$$

where Y_i represents the outcome of interest (app visits, time spent on the app and per visit, and app pages viewed), CM_i is an indicator for households in the CholeraMap treatment, and X_i is a vector of household controls including respondent age and gender, education and gender of the household head, household size, presence of children under five, land, television, and bike/motorbike ownership, and perceived cholera risk. We cluster standard errors at the village level, which was the level of app assignment. Endline data from CholeraMap and CholeraApp households are used for these analyses. Our coefficient of interest β provides an estimate of the effect of having CholeraMap on app visits, pages viewed, and time spent, relative to CholeraApp.

We also estimate differences in stated app use and self-reported information receipt and behavioral change among app-using households at endline. We use the same specification as Equation 1 but focus on three different outcomes. In particular, we measure if the app is still installed at endline as well as self-reported information gained from the app and self-reported behavioral change as a result of the information from CholeraMap or CholeraApp.

5.2 Difference-in-differences specification

To assess how access to CholeraMap and CholeraApp impacted household knowledge about cholera, water use and hygiene behaviors, and cholera incidence, we use a difference-in-differences study design. We compare differences in outcomes across treatment arms (first difference) and between baseline and endline (second difference). The difference-in-differences design accounts for differences in baseline characteristics between households assigned to the three study arms, making it our preferred empirical approach.

We obtained difference-in-differences estimates using linear regressions of the following specification:

$$Y_{it} = \alpha + \beta_1 CM_i + \beta_2 CA_i + \beta_3 Post_t + \beta_4 (CM \times Post)_{it} + \beta_5 (CA \times Post)_{it} + X_{it} \cdot \theta + \varepsilon_{it} \tag{2}$$

Y_{it} is a household-level outcome for household i in wave t (outcomes of interest detailed in

Section 4.2). CM_i is an indicator for assignment to CholeraMap treatment, CA_i is an indicator for assignment to CholeraApp treatment, and $Post_t$ is an indicator for the post-intervention wave. X_i is a vector of household controls including respondent age and gender, education and gender of the household head, household size, presence of children under five, land, television, and bike/motorbike ownership, and perceived cholera risk. We cluster standard errors at the village level, which was the level of app assignment. The comparison group for all estimates is control households. Our main coefficient of interest is β_4, which provides a causal estimate of CholeraMap access on household cholera knowledge, water use and hygiene behaviors, and cholera incidence, relative to control households. β_5 provides the comparable estimate for CholeraApp. Identification is achieved under the assumptions of parallel trends and no spillover effects. Our study design addresses both of these assumptions. First, random household selection provides support for the existence of parallel trends in our setting, despite our inability to test this assumption directly. Second, as our study design ensured that neighboring villages were not assigned to different study arms, we limited the potential for information spillovers.

5.3 Modified event study specification

To investigate whether households make short-term behavioral adjustments in response to dynamic cholera risk information, we use a modified event study specification. In this analysis, which is estimated using only app-receiving (CholeraMap or CholeraApp) households, we interact CholeraMap receipt with monthly indicators. The monthly indicators measure the time since application installation. We present results of the following specification

$$Y_{it} = \alpha + \sum_{j=1}^{5}[\pi_j \cdot CM_i \cdot 1 \cdot (t = j)] + \beta_1 risk_{it} + \beta_2 visit_{it} + \beta_3 mins_{it} + \delta_t + \rho_i + \varepsilon_{it} \tag{3}$$

Equation 3 relies on data from the baseline and endline surveys as well as the monthly phone surveys conducted with all CholeraMap- and CholeraApp-receiving households. Thus, we focus on four outcomes collected across all surveys including: (i) household drinking water treatment; (ii) household cholera incidence; (iii) household water stress; and (iv) household water security. Given the monthly time step of this analysis, we also control for the risk prediction category of the household ($risk_{it}$) which is known only for CholeraMap households but observable for both

CholeraMap and CholeraApp households; whether the household visited their app in month t ($visit_{it}$); and the amount of time the household spent on the app in moth t ($mins_{it}$). We also include monthly and household fixed effects and cluster standard errors at the village level. Finally, we use the month of app installation (i.e., the baseline survey data) as omitted event study category. Our coefficients of interest, π_j , map the trend in behavioral differences between CholeraMap and CholeraApp households across the project implementation period.

6 Results

We first examine differences in application use between CholeraMap and CholeraApp households. Then, we present results of our difference-in-differences specification. Finally, we present results from our modified event study specification.

6.1 App use

Figures 4 and 5 depict average app use among CholeraMap and CholeraApp households. For each outcome—monthly app visits and time spent on the app—CholeraMap users were more engaged with the app than were CholeraApp users. In the month following app installation, approximately 50 percent of CholeraMap users visited the app, compared to just under 30 percent of CholeraApp users. In subsequent months, the percent of users visiting the apps each month declines, yet users consistently return to CholeraMap more frequently compared to CholeraApp. The same pattern holds for app use. In the month following app installation, CholeraMap users spent an average of around 2 minutes on the app, compared to less than 1 minute among CholeraApp users. In subsequent months, users consistently spent more time visiting CholeraMap compared to CholeraApp. These patterns follow expectations of differences in app use between CholeraMap and CholeraApp households; as CholeraMap is dynamic and contains more information, we would expect users to spend more time on CholeraMap and revist the app more frequently.

Table 2 reports results from the app use regression model, which are consistent with the descriptive trends observed in Figures 4 and 5. The average CholeraMap user made 1.5 more distinct app visits over the study period compared to the average CholeraApp user. Similarly, the average CholeraMap user viewed 266.3 more pages and spent 81.2 more minutes on the app during the intervention period compared to the average CholeraApp user. Users also spent much more time on CholeraMap per visit; the average CholeraMap visit is approximately 20 minutes longer than the average CholeraApp visit. These patterns are consistent with app design. First, CholeraMap was dynamic, with the cholera risk maps and associated messages for users changing monthly. CholeraApp, on the other hand, was static. Second, CholeraMap had three information pages (in addition to the home page), while CholeraApp had only one information page (in addition to the home page). Finally, CholeraMap contained more substantive content than did CholeraApp; engaging with this information took users additional time. We note, however, that while these patterns align with design expectations, they also demonstrate that CholeraMap users found it worthwhile to engage with all the information pages in the app, suggesting that the information provided by CholeraMap was of value to user households. That is, users did not view only first or second page (i.e., mirroring CholeraApp content); rather, they spent time engaging with multiple pages.

Table 3 reports results from the app use regression model, focusing on endline outcomes. We find that CholeraMap households are thirteen percentage points less likely to have the app installed at endline compared to CholeraApp households.[16] This could reflect a perception—although incorrect—among CholeraMap households that the app had substantial storage and data-use requirements. Subsequent app design and communication must take these features into account to meet the technical expectations of potential users. We also find that CholeraMap households are six percentage points more likely to self-report behavioral change based on the information they received in CholeraMap. While these results are descriptive, this correlation does suggest that the information provided by CholeraMap was informative and helpful, perhaps motivating safer water-use behavior. Finally, we find no measurable difference in the stated receipt of new information in the app between CholeraMap and CholeraApp households. We do note, however, that nearly 80 percent of CholeraMap and CholeraApp households reported that the apps provided their households with new information. This suggests a considerable need to provide cholera risk information to vulnerable and at-risk households in cholera-prone regions and a willingness among households to receive health-related information through these app platforms, again suggesting

[16]We took a conservative approach to assessing endline installations. Enumerators requested to see the household smartphone and observe whether the app was still installed. Thus, our metric of households with the app still installed at endline should be considered a lower bound.

the value of the information provided by these apps to households living in a cholera-endemic region.

6.2 Impacts on knowledge, water use, hygiene, and health

Table 4 reports our main difference-in-differences findings which indicate the impacts of CholeraMap and CholeraApp on cholera-related knowledge, water use and hygiene practices, and cholera incidence. Columns (1)-(3) report knowledge-related behaviors. We find CholeraMap households increased their confidence in their abilities to respond to environmental and health risks. After using CholeraMap for 8 months, CholeraMap households were 8 percentage points (a 9.3 percent increase from the baseline mean) more like to report they felt equipped to deal with environmental risks and 7 percentage points (a 7.7 percent increase from the baseline mean) more likely to report they felt equipped to deal with health risks compared to control households. In addition, following the study period, CholeraMap households were 12 percentage points (a 21 percent decrease) less likely to report diarrhea as a major health concern for children in the household relative to control households. We see similar, although slightly less precise, results for CholeraApp households: Following the study period, CholeraApp users reported feeling more equipped to address health challenges and were less likely to report diarrhea as a major health concern for household children compared to control households. While our results form CholeraApp are less precisely estimated, we are unable to reject the null hypothesis of no difference in effect size between CholeraApp and CholeraMap users in the post period.

Columns (4)-(7) report impacts on household water use and hygiene practices. We find no evidence that CholeraMap or CholeraApp shifted drinking water treatment or handwashing frequency. For drinking water this result is, perhaps, unexpected. At baseline, the majority of households reported use of groundwater from tubewells as their primary drinking water source throughout the year. As groundwater is less susceptible to microbial contamination, few households would view groundwater treatment as a cholera-related averting behavior. We do, however, find that CholeraMap users decreased their use of pond water (a common surface water source in Matlab) for non-drinking purposes including bathing and washing clothes. We find this pattern of behavioral change for both adult men (a 22.9 percent reduction) and women (a 25 percent reduction) in CholeraMap households relative to control households. While the estimate of the effect on pond water use for CholeraApp households is similar, it is much less precisely estimated; however, we are unable to reject the null hypothesis of no difference between these two sets of estimates. This shift in non-drinking water use, taken together with descriptive water use statistics from our sample, suggests an interesting trend in water-related behavior among CholeraMap households. Most households in our sample relied on groundwater sources (specifically private or shared tubewells) for drinking water. As households generally view groundwater as safer from a contamination standpoint, the use of water filtration and regular boiling practices is low within our sample. Households do engage with surface water, however, through other activities such a bathing and clothes washing. Further, many men also engage in regular ablution rituals with pond water for prayers multiple times a day, often taking contaminated pond water in the mouths in the process. Our results suggest that CholeraMap using households shifted these interactions in response to up-to-date information about cholera risk.

Column (8) reports impacts on household cholera incidence in the previous month. We find no significant evidence to suggest that cholera incidence in CholeraMap or CholeraApp households decreased over the study period relative to control households. We note that while households can take actions to avert cholera risk, given the infectious nature of the disease, household health outcomes are tied not only to the household's own behavior but also to the behaviors of other households in their village. As app access was limited to study households, there may have been insufficient access to CholeraMap to achieve reductions in cholera incidence as a result of app dissemination.

6.3 Behavior over time

Figure 6 plots the event-time coefficients and associated 95 percent confidence intervals that estimate dynamic changes in water-use practices, concerns, and household health. We find that there are some differences in behavior between CholeraMap and CholeraApp households over time. First, as 6a shows, in the month following app installation, we see a slight, and imprecisely estimated, increase in drinking water treatment among CholeraMap households. This shift is not sustained; however, in the following months we see no measurable difference between drinking water treatment between CholeraMap and CholeraApp households. Second, as shown by 6b, we do not see any dynamic difference in cholera incidence between CholeraMap and CholeraApp households. Third, as shown by 6c and 6d, we find changes related to households' perceptions of their water security. We find that CholeraMap households report higher levels of water stress, perhaps generated by additional information about risks of water-related diseases. This stress, however, does not generate concerns related to water security. CholeraMap households report higher water security than do CholeraApp households, perhaps suggesting that information provided by CholeraMap helps households seek out more secure water sources.

7 Robustness checks and heterogeneity analysis

To assess the robustness of our primary analysis and examine heterogeneity in the impacts of CholeraMap and CholeraApp, we conduct a series of robustness tests and heterogeneity analyses. We consider three alternative empirical specifications, relying on household fixed effects, ANCOVA analysis, and instrumental variables to assess the robustness of our findings. For heterogeneity, we consider differences in impact based on cholera risk levels (i.e., the type of information receive) and by app use.

7.1 Robustness checks

We first assess whether the impacts of CholeraMap estimated in our main difference-in-difference framework are robust to the inclusion of household fixed effects. Supplemental Table A1 reports the results of this analysis, demonstrating consistent, albeit slightly less precise, findings. Importantly, we find that our main behavioral change—reduced reliance on surface water among adult men and women in the household—remains highly significant. Adults in CholeraMap households are approximately 8 percentage points less likely to rely on surface water, representing about a 23 percent reduction from the baseline mean. We do find that our results related to households feeling more equipped to deal with environmental and health concerns remain similar in terms of magnitude, but are less precisely estimated.

While the study design provides evidence regarding the applicability of the standard assumptions necessary to draw causal conclusions from the difference-in-difference specification, we also consider an alternative ANCOVA analysis in which we use only data from the endline survey and control for baseline characteristics (McKenzie, 2012). As the ANCOVA analysis does not rely in the linearity of the difference-in-differences specifications, we use non-linear regression models for these estimates. For regressions with binary outcomes, we use a logit model and for regressions with count outcomes we use a Poisson model. Supplemental Table A2 reports these estimates, displaying odds ratios as the logit results in Columns (1)-(4) and Columns (6)-(8) and incidence rate ratios as the Poisson results in Column (5). We find that CholeraMap and CholeraApp households are more likely to report feeling equipped to deal with environmental and health risks their households are facing, and less concerned about diarrheal disease. These results are consistent with our main findings. Inconsistent with our primary specification, we do not find significant changes in surface water use among adult household members, perhaps due to the reduction in estimate precision as a result of the smaller endline sample on which these specifications are estimated.

Finally, recognizing that our difference-in-difference specifications estimate the effect of access to CholeraMap or CholeraApp on household knowledge, water-use behavior, and health, and not use of CholeraMap or CholeraApp, we use an instrumental variables specification to estimate the effect of app use on our outcomes of interest. Specifically, we instrument frequent app use—defined as at least six distinct app visits during the implementation period—with experimental treatment. As there are two apps, we run separate regressions for CholeraMap and CholeraApp households. Each regression uses data from only the endline survey, and app households and control households for the estimation. Supplemental Table A3 reports the results of this specification, showing results for CholeraMap in Panel A and results for CholeraApp in Panel B. We find that both CholeraMap and CholeraApp using households are more likely to report feeling equipped to deal with environmental and heath risks and less likely to be concerned with diarrhea. These results are consistent with our main analysis. We do not find, however, precise estimates regarding impact on surface water use among household adults. While the magnitude and direction of the estimate for CholeraMap is similar to our primary specification, the estimate lacks statistical precision.

7.2 Heterogeneity by cholera risk levels and app use

In addition to our main results, we assess whether factors such as the content of the information available in CholeraMap (i.e., information associated with varying predictions of cholera risk) and app use mediate the estimates. Turning first to information content, Table 5 reports the effects of receiving information about high cholera risk compared to medium or low cholera risk.[17] We define "high risk" as households that received at least one high risk cholera prediction during the study period (approximately 80 percent of the sample). Households that only received low or medium cholera risk predictions are defined as not high risk. Because risk messages were only available to CholeraMap households, this analysis only includes CholeraMap users. As the risk messages received were entirely dependent on environmental characteristics, we consider this a source of exogenous variation in information content.

We find that CholeraMap households that received high risk messages felt less equipped to respond to environmental and health challenges at the end of the study compared to CholeraMap households that never received high risk messages. This suggests that while some information about averting cholera was available in CholeraMap, it may have been insufficient to address households' heightened concerns about the disease when risk of transmission was especially high. We also find that high risk CholeraMap households decreased pond water use for bathing and other washing. This suggests that behavioral change may be driven by households that received high risk information from CholeraMap. Finally, we find marginally significant evidence of high cholera incidence in high risk CholeraMap households at the end of our study period relative to CholeraMap households who never received high cholera risk predictions. These higher incidence rates suggest both that the cholera risk predictions are consistent with higher cholera prevalence and that responses to these high risk messages were insufficient to overcome the environmental cholera conditions.

Turning next to app use, Table 6 reports the effects of CholeraMap (relative to CholeraApp) among frequent app users.[18] We define frequent app users as households that made at least 6 distinct visits to CholeraMap or CholeraApp during the study period. As app use is an applicable metric only among app study arms, control arm households are omitted from this analysis. Our

[17]We use a difference-in-differences framework to estimate these results:

$$Y_{it} = \alpha + \beta_1 HR_i + \beta_2 Post_t + \beta_3 (HR \times Post)_{it} + X_{it} \cdot \theta + \varepsilon_{it} \tag{4}$$

All variables are defined as in Section 5, and HR_i is an indicator for receiving at least one message of high cholera risk during the study period, zero otherwise.

[18]We use a difference-in-differences framework to estimate these results:

$$Y_{it} = \alpha + \beta_1 CM_i + \beta_2 Post_t + \beta_3 (CM \times Post)_{it} + X_{it} \cdot \theta + \varepsilon_{it} \tag{5}$$

All variables are defined as in Section 5.

results suggest only minor differences in impacts of CholeraMap relative to CholeraApp among frequent app users. First, we find that frequent CholeraMap users increased their handwashing at endline compared to frequent CholeraApp users. Second, we find that self-reported cholera incidence increased among frequent CholeraMap users at endline compared to frequent CholeraApp users. As frequent app users are a selected sampled, the generalizability of these results is limited. They do suggest, however, that households may have turned to CholeraMap as a information source after contracting cholera.

8 Discussion and conclusion

In this paper, we assess the willingness of households to use a smartphone application that conveys dynamic and geographically personalized cholera risk predictions. Further, we estimate the causal effect of access to this information on household cholera-related knowledge, water and hygiene behaviors, and cholera incidence. In so doing, we provide insight into the value that information about cholera risk—generated using a remote sensing model and disseminated using a smartphone app—has for households living in cholera-endemic areas. We examine these relationships in the context of Matlab, a rural sub-district of Bangladesh southeast of Dhaka. Matlab provides a distinctive setting in which to assess household response to cholera risk information due to its geographic, climatic, and socioeconomic demographics. That is, this low-lying region faces regular monsoon flooding, which elevates the risk of cholera outbreaks; climate change impacts have affected the regular seasonality of cholera risk; and a lack of widespread water and sewer infrastructure limits the ability to halt local cholera transmission (Ali et al., 2015; Zaman et al., 2020).

We designed a field experiment in which we disseminated cholera risk predictions through a simple Android smartphone app called CholeraMap. We evaluated knowledge, behavior, and health changes eight months after CholeraMap installation. We used two comparison groups to measure the impacts of CholeraMap—a control app group that received access to an app containing only publicly available cholera risk information called CholeraApp and a pure control group with no access to either app.

We found that households in the CholeraMap study arm were 13 percentage points less likely to have CholeraMap still installed on their smartphones at the time of endline data collection compared to CholeraApp users. Despite this extensive margin of app use, we find that CholeraMap users were more engaged with the app relative to CholeraApp users, consistent with expectations given the dynamic and more comprehensive nature of CholeraMap's design. CholeraMap users made an average of 1.5 more visits to the app during the study period than CholeraApp users. They also viewed an average of 266 more pages and spent approximately 81 more minutes on the app than did CholeraApp users. Although a different context, these results mirror those found by Ashraf et al. (2010), Dupas et al. (2016), and Dupas et al. (Forthcoming), which all find that small financial or time investments required to obtain drinking water treatments decreased the number of households accessing them but increased the intensive margin of use. Our results may reflect a similar pattern: Not all households were willing to keep the app installed on their phones; however, for those that did, CholeraMap proved more engaging.

We also found that feelings towards environmental and health concerns changed for CholeraMap users, relative to control households. Following the intervention period, CholeraMap users reported 9.3 percent and 7.7 percent increases in their confidence to respond to environmental and health concerns, respectively. This could reflect a reduction in stress related to a critical environmental health concern, cholera, as a result of access to CholeraMap. Further, we find that CholeraMap households changed their water use behavior. Adults in CholeraMap households reduced their reliance on pond water (a common surface water source) for non-drinking purposes such as bathing and other washing. We find no evidence of changes in drinking water treatment, handwashing, or cholera incidence among CholeraMap households.

The significant reduction in pond water use for bathing and other washing and lack of behavior change related to drinking water aligns with patterns of water use in Matlab as measured by our baseline survey. Nearly all households in our survey used private or shared tubewells as their primary water source throughout the year. Groundwater is generally safer from bacterial contamination relative to surface water unless contaminated by a nearby latrine or through storage. Accordingly, rates of drinking water treatment among sample households were low. Thus, there was limited space for drinking water behavioral response to CholeraMap. For non-drinking water use, however, sources and interactions were more varied at baseline. Thus, our findings could reflect households shifting away from surface water interactions in general rather than specifically tied to drinking water sources.

We also examine heterogeneity in CholeraMap impact by the type of informational messages received (i.e., the cholera risk predictions) and by app use. We find that, relative to CholeraMap households that never received high risk messages, CholeraMap households that did receive high risk messages felt less equipped to respond to environmental and health challenges at endline. This demonstrates that the message content played a role in users' responses to CholeraMap. Further, it suggests that, while some information about averting cholera was available in CholeraMap, future app design should expand these messages to better address households' heightened concerns about high cholera risk. Finally, we find that among frequent app users, CholeraMap users increased the frequency of handwashing relative to CholeraApp users. We also see higher cholera incidence among frequent CholeraMap users. As there is selection into app use, these estimates are correlational; however, they suggest differential use patterns and behavioral responses between CholeraMap and CholeraApp users. For example, it is possible that CholeraMap household rely on CholeraMap not only as an early warning system, but also as a reference source when households experience cholera or cholera-like illnesses.

This paper contributes to a nascent literature evaluating the impacts of early warning systems for infectious disease and to the established literature on the adoption of environmental risk reducing technologies related to water, sanitation, and hygiene. Our results show that risk predictions from complex environmental models can be effectively disseminated to households. Further, they show that while challenges remain related to connectivity, storage, and technology/data access, the use of existing and widespread technologies such as mobile phones and, increasingly, smartphones, provides a user-friendly and accessible platform for information dissemination. From a policy perspective, phone-based dissemination is highly scalable and low-cost, suggesting that additional efforts to improve app design, functionality, and engagement could further promote the effectiveness of CholeraMap or another platform as an early warning system for cholera in other regions facing endemic or epidemic cholera risk.

Our results also show that user-directed information interventions could be effective in promoting safe water, hygiene, and sanitation behaviors. Unlike information interventions implemented by community health workers, trained intervention staff, or media-based communication campaigns, CholeraMap provided dynamic and geographically personalized cholera risk predictions on a user's own smartphone device. Accordingly, users had constant access to this information. Our findings suggest that the combination of personalized and easily accessible information—made possible through a smartphone platform—could be key elements of an effective early warning system for cholera.

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Figures

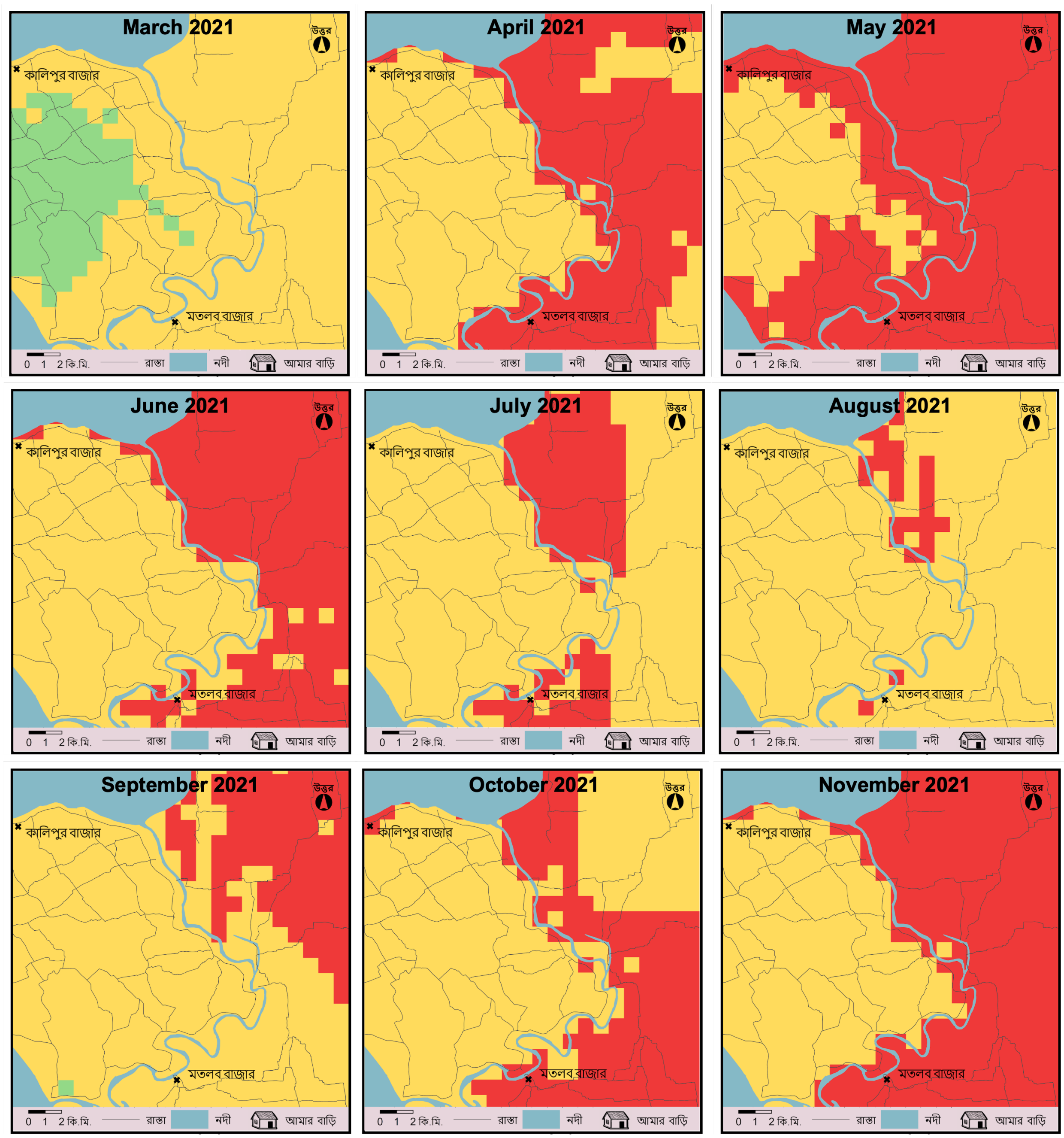
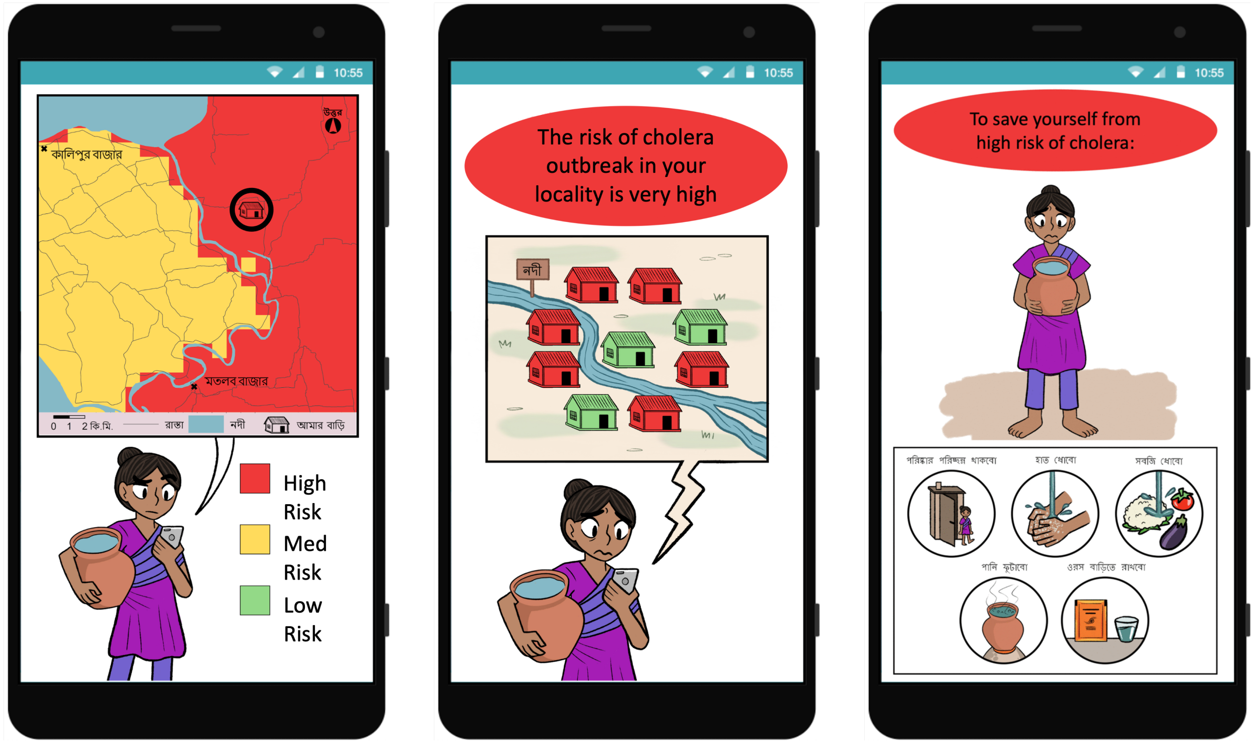


Figure 1: Cholera risk prediction maps for Matlab, Bangladesh, March 2021-November 2021. Cholera risk measured on a scale of 0 (no cholera risk) to 1 (high cholera risk). Colors depict discretized risk levels: green areas have predicted risk levels between 0 and 0.33; yellow between 0.33 and 0.66; and red 0.66 and 1.



(a) Cholera risk map tab with geolocation of CholeraMap

(b) Cholera risk visualization tab of Cholera Map

(c) Risk-reducing behaviors tab of CholeraMap

Figure 2: Screenshots from CholeraMap in a month predicting high cholera risk

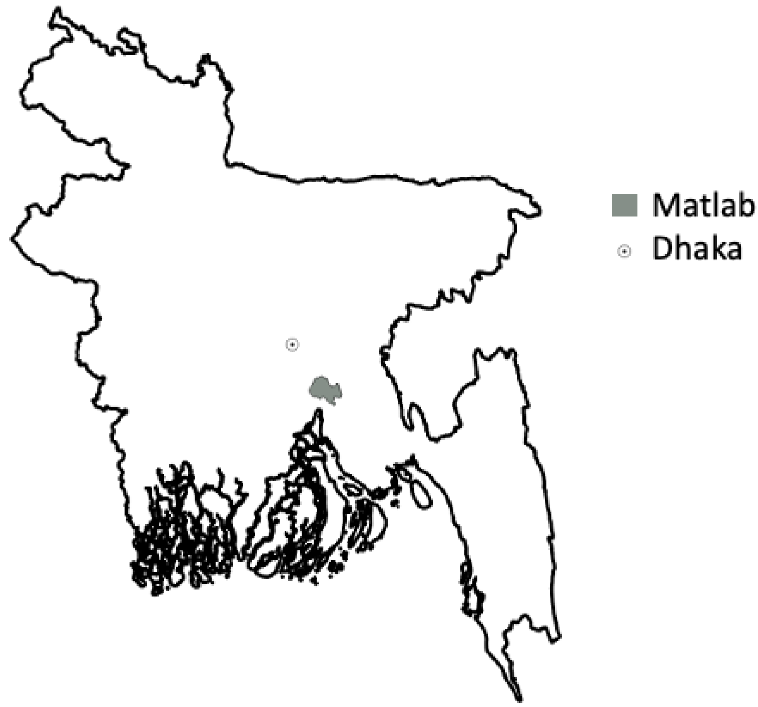


Figure 3: Map of Bangladesh showing Matlab study area

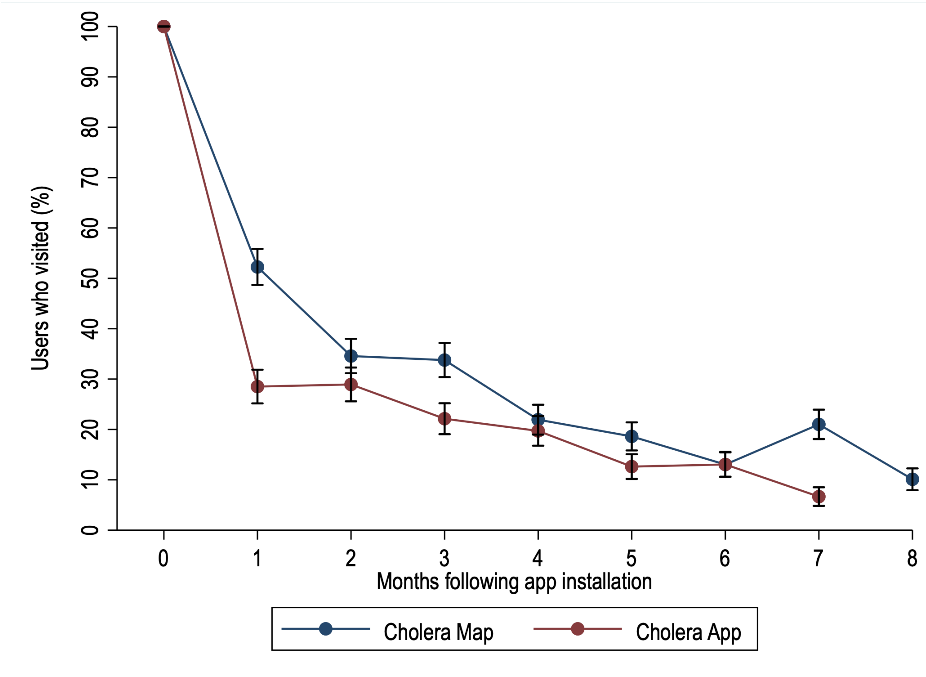


Figure 4: Percent of users who visited CholeraMap and CholeraApp in the months following installation

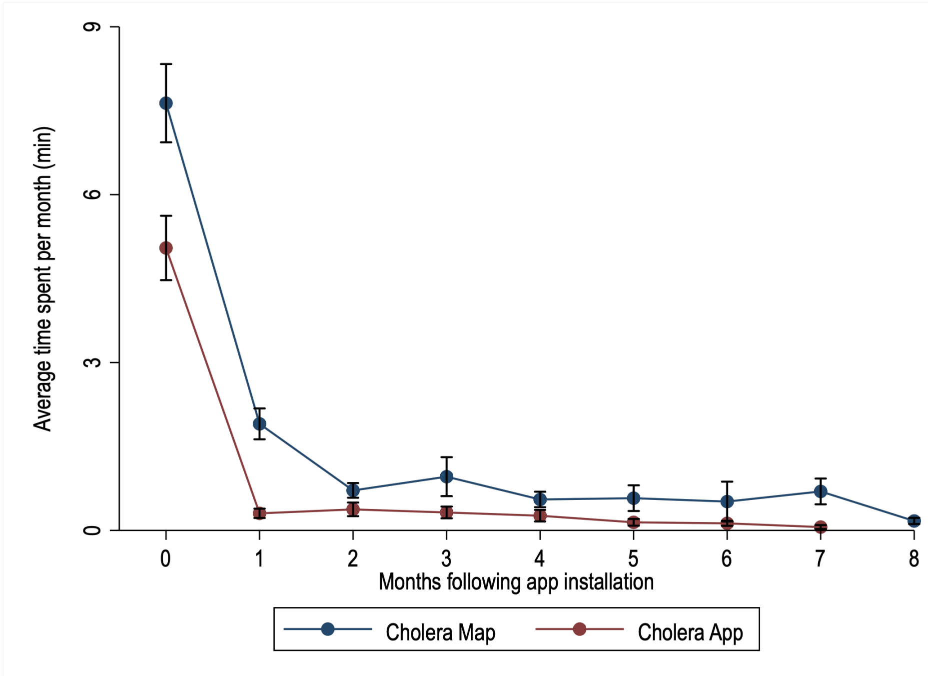
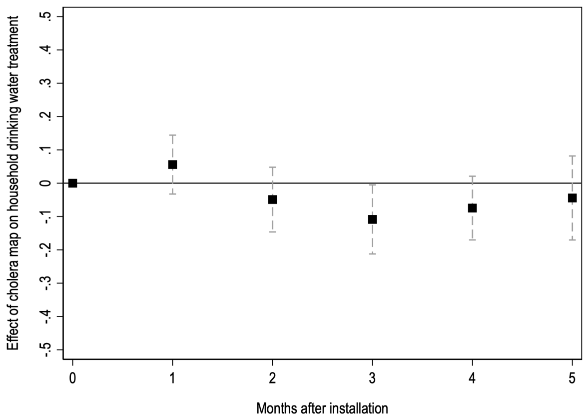
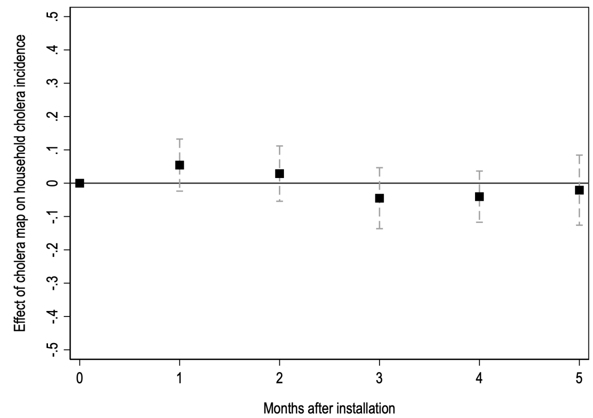


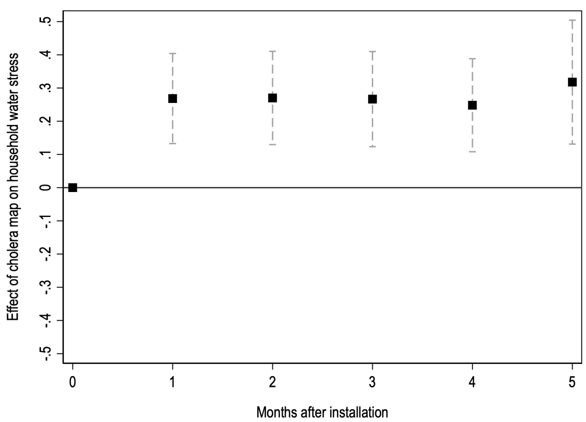
Figure 5: Average time spent monthly on CholeraMap and CholeraApp in the months following installation



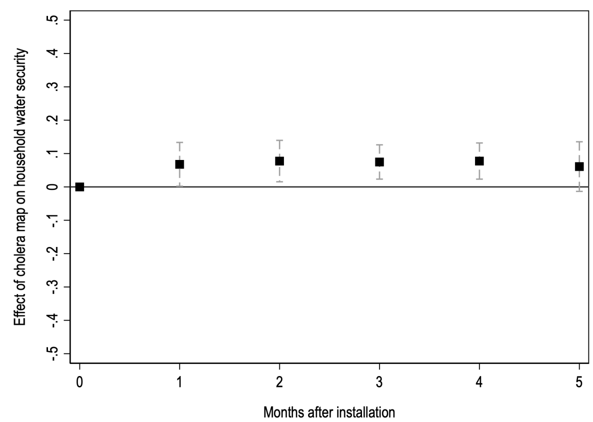
(a) Treat drinking water



(b) Cholera incidence



(c) Water stress



(d) Sufficient water

Figure 6: Modified event study estimates

Notes: The panels in this figure present the modified event study results comparing outcomes for CholeraMap and CholeraApp households. Each panel depicts a different outcome: drinking water treatment (Panel (a)), cholera incidence (Panel (b)), water stress (Panel (c)), and sufficient water (Panel (d)). Each plot shows the coefficient estimate from Equation 3 and its 95 percent confidence interval. All specifications are run using linear regression and control for app visits, cholera risk, and time spent on app; they also include month and household fixed effects. Baseline data (i.e., zero months after installation) is used as the omitted event-time category.

Tables

Table 1: Sample descriptive statistics

	(1) Full Sample	(2) CholeraMap	(3) CholeraApp	(4) Control	(5) Map-App	(6) Map-Control	(7) App-Control
Panel A. Household Characteristics							
Female respondent	0.94	0.93	0.97	0.94	-0.04***	-0.01	0.03**
	(0.23)	(0.26)	(0.18)	(0.25)	(0.01)	(0.01)	(0.01)
Respondent age	38.23	38.63	36.45	40.14	2.18***	-1.51**	-3.69***
	(12.30)	(12.73)	(11.65)	(12.22)	(0.63)	(0.71)	(0.69)
Male household head	0.57	0.58	0.56	0.58	0.02	-0.00	-0.02
	(0.50)	(0.49)	(0.50)	(0.49)	(0.03)	(0.03)	(0.03)
Household size	4.68	4.62	4.71	4.73	-0.09	-0.11	-0.03
	(1.74)	(1.75)	(1.77)	(1.68)	(0.09)	(0.10)	(0.10)
Household head education below secondary	0.60	0.59	0.58	0.63	0.00	-0.04	-0.05*
	(0.49)	(0.49)	(0.49)	(0.48)	(0.03)	(0.03)	(0.03)
Children under 5	0.38	0.36	0.39	0.39	-0.04	-0.03	0.01
	(0.49)	(0.48)	(0.49)	(0.49)	(0.03)	(0.03)	(0.03)
Land ownership	0.70	0.74	0.66	0.68	0.08***	0.06**	-0.02
	(0.46)	(0.44)	(0.47)	(0.47)	(0.02)	(0.03)	(0.03)
Television ownership	0.68	0.66	0.74	0.62	-0.07***	0.04	0.12***
	(0.47)	(0.47)	(0.44)	(0.48)	(0.02)	(0.03)	(0.03)
Bike/motorbike ownership	0.20	0.16	0.23	0.22	-0.07***	-0.06***	0.01
	(0.40)	(0.36)	(0.42)	(0.41)	(0.02)	(0.02)	(0.02)
Panel B. Water and sanitation							
Cholera incidence	0.15	0.14	0.16	0.15	-0.01	-0.01	0.01
	(0.36)	(0.35)	(0.36)	(0.36)	(0.02)	(0.02)	(0.02)
Perceived cholera risk	1.13	1.13	1.13	1.12	0.01	0.01	0.00
	(0.36)	(0.37)	(0.35)	(0.35)	(0.02)	(0.02)	(0.02)
Pumped water source	1.00	0.99	1.00	1.00	-0.01*	-0.01	0.00
	(0.06)	(0.09)	(0.04)	(0.04)	(0.00)	(0.00)	(0.00)
Water collection time	1.93	1.98	1.95	1.83	0.03	0.14***	0.11**
	(0.82)	(0.85)	(0.80)	(0.82)	(0.04)	(0.05)	(0.05)
Permanent water storage	0.19	0.21	0.17	0.20	0.03*	0.00	-0.03
	(0.40)	(0.41)	(0.38)	(0.40)	(0.02)	(0.02)	(0.02)
Daily water refilling	0.85	0.86	0.86	0.81	-0.00	0.04*	0.05**
	(0.36)	(0.35)	(0.35)	(0.39)	(0.02)	(0.02)	(0.02)
Treat drinking water	0.16	0.13	0.21	0.13	-0.08***	-0.00	0.07***
	(0.36)	(0.34)	(0.40)	(0.34)	(0.02)	(0.02)	(0.02)
Water stress	0.07	0.09	0.06	0.06	0.03**	0.03**	0.00
	(0.25)	(0.28)	(0.23)	(0.23)	(0.01)	(0.01)	(0.01)
Handwashing (soap)	4.05	3.99	4.29	3.79	-0.30**	0.20	0.50***
	(2.37)	(2.40)	(2.51)	(2.05)	(0.13)	(0.13)	(0.13)
Latrine ownership	0.94	0.94	0.94	0.93	-0.00	0.01	0.01
	(0.24)	(0.23)	(0.23)	(0.25)	(0.01)	(0.01)	(0.01)
Pond water use (men)	0.37	0.35	0.39	0.37	-0.05*	-0.02	0.03
	(0.48)	(0.48)	(0.49)	(0.48)	(0.03)	(0.03)	(0.03)
Pond water use (women)	0.35	0.33	0.38	0.33	-0.06**	-0.01	0.05*
	(0.48)	(0.47)	(0.49)	(0.47)	(0.02)	(0.03)	(0.03)
Observations	2014	769	732	513			

Notes: Statistics reported as mean (standard deviation). P-value of difference between study arms indicated by stars: *** p<.01, ** p<.05, * p<.10. Perceived cholera risk measured on a scale ranging from 1 (low perceived risk) to 3 (high perceived risk). Water collection time measured on a scale from 1 (less than 15 minutes) to 4 (greater than 60 minutes). Handwashing (soap) measured as a count of reported daily handwashing scenarios.

Table 2: Comparison of CholeraMap and CholeraApp visits and time use

	(1)	(2)	(3)	(4)
	Distinct visits	Pages viewed	Time (minutes)	Time per visit (minutes)
CholeraMap	1.49***	266.30***	81.15***	20.47***
	(0.22)	(20.03)	(7.78)	(3.39)
Mean	4.31	286.32	94.87	31.89
Observations	1488	1414	1416	1416
R^2	0.05	0.16	0.13	0.05

Notes: Standard errors, clustered at the village level, in parentheses. All regressions control for respondent gender and age, household size, household head education, children under five, land ownership, television ownership, bike or motorbike ownership, and perceived cholera risk. Specifications run using analytics data collected over the duration of project implementation (approximately seven months) using data from CholeraMap and CholeraApp households only. Asterisks denote statistical significance: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table 3: Comparison of endline app-use characteristics between CholeraMap and CholeraApp

	(1) App installed	(2) New information	(3) Behavior change
CholeraMap	-0.13***	0.00	0.06*
	(0.03)	(0.02)	(0.03)
Mean (CholeraMap)	0.40	0.78	0.54
Observations	2702	1484	1283
R^2	0.02	0.04	0.02

Notes: Standard errors, clustered at the village level, in parentheses. All regressions control for respondent gender and age, household size, household head gender and education, children under five, land ownership, television ownership, bike or motorbike ownership, and perceived cholera risk. Asterisks denote statistical significance: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table 4: Difference-in-differences estimates of the effects of CholeraMap and CholeraApp on knowledge, water-use behavior, and health

	(1) Equipped environment	(2) Equipped health	(3) Diarrhea concern	(4) Treat drinking water	(5) Handwash with soap frequency	(6) Pond use adult men	(7) Pond use adult women	(8) Cholera incidence
CholeraMap	-0.04	-0.04	0.01	-0.00	0.13	-0.02	-0.01	-0.01
	(0.04)	(0.02)	(0.04)	(0.02)	(0.18)	(0.07)	(0.07)	(0.02)
CholeraApp	0.02	-0.02	-0.04	0.07***	0.41**	0.04	0.06	0.00
	(0.04)	(0.02)	(0.04)	(0.02)	(0.18)	(0.09)	(0.08)	(0.02)
Post	0.03	0.01	-0.05	-0.04*	0.04	0.09***	0.11***	-0.04***
	(0.02)	(0.02)	(0.04)	(0.02)	(0.22)	(0.02)	(0.02)	(0.01)
CholeraMap × Post	0.08**	0.07**	-0.12**	0.01	0.01	-0.07***	-0.08***	0.01
	(0.04)	(0.03)	(0.06)	(0.02)	(0.27)	(0.03)	(0.03)	(0.02)
CholeraApp × Post	0.03	0.06**	-0.10*	0.00	-0.14	-0.04	-0.05	-0.03
	(0.03)	(0.03)	(0.05)	(0.03)	(0.26)	(0.03)	(0.03)	(0.02)
Baseline mean (CholeraMap)	0.86	0.91	0.57	0.13	4.04	0.35	0.32	0.15
Baseline mean (CholeraApp)	0.91	0.93	0.53	0.21	4.26	0.39	0.38	0.16
p-value: CholeraMap vs. CholeraApp	0.23	0.71	0.63	0.90	0.47	0.27	0.28	0.10
Observations	3906	3980	3983	3908	3983	3202	3977	3983
R^2	0.03	0.03	0.03	0.02	0.06	0.03	0.03	0.02

Notes: Standard errors, clustered at the village level, in parentheses. All regressions control for respondent gender and age, household size, household head gender and education, children under five, land ownership, television ownership, bike or motorbike ownership, and perceived cholera risk. Specifications run using data from household surveys collected at baseline and endline among control, CholeraMap, and CholeraApp households. Asterisks denote statistical significance: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table 5: Difference-in-differences estimates of the effects of high cholera risk on knowledge, water-use behavior, and health among CholeraMap households

	(1) Equipped environment	(2) Equipped health	(3) Diarrhea concern	(4) Treat drinking water	(5) Handwash with soap frequency	(6) Pond use adult men	(7) Pond use adult women	(8) Cholera incidence
High risk	0.16**	0.10**	0.02	-0.04**	0.26	-0.21**	-0.21**	-0.06
	(0.06)	(0.03)	(0.06)	(0.02)	(0.18)	(0.07)	(0.07)	(0.05)
Post	0.25***	0.16***	-0.11	-0.03**	0.44	0.06***	0.08**	-0.08**
	(0.07)	(0.04)	(0.09)	(0.01)	(0.33)	(0.02)	(0.03)	(0.03)
High risk × Post	-0.18**	-0.11**	-0.08	-0.00	-0.51	-0.05	-0.06	0.06
	(0.07)	(0.04)	(0.10)	(0.02)	(0.38)	(0.03)	(0.04)	(0.04)
Baseline mean (High risk)	0.89	0.94	0.57	0.12	4.11	0.32	0.29	0.14
Observations	1485	1514	1517	1487	1517	1227	1514	1517
R^2	0.08	0.06	0.04	0.02	0.06	0.06	0.06	0.02

Notes: Standard errors, clustered at the village level, in parentheses. All regressions control for respondent gender and age, household size, household head gender and education, children under five, land ownership, television ownership, bike or motorbike ownership, and perceived cholera risk. Specifications run using data from household surveys collected at baseline and endine among CholeraMap households only. Asterisks denote statistical significance: * p <0.10, ** $p < 0.05$, ***$p < 0.01$.

Table 6: Difference-in-differences estimates of the effects of CholeraMap on knowledge, water-use behaviors, and health among frequent CholeraMap and CholeraApp using households

	(1) Equipped environment	(2) Equipped health	(3) Diarrhea concern	(4) Treat drinking water	(5) Handwash with soap frequency	(6) Pond use adult men	(7) Pond use adult women	(8) Cholera incidence
CholeraMap	-0.06	-0.02	0.03	-0.02	-0.84***	-0.03	-0.06	-0.06*
	(0.04)	(0.03)	(0.05)	(0.04)	(0.23)	(0.10)	(0.09)	(0.03)
Post	0.05	0.04**	-0.18***	-0.01	-0.42***	-0.00	0.02	-0.08***
	(0.03)	(0.02)	(0.04)	(0.03)	(0.15)	(0.04)	(0.04)	(0.03)
CholeraMap $\times$ Post	0.05	0.02	-0.01	-0.04	0.77***	0.02	-0.00	0.08*
	(0.04)	(0.04)	(0.07)	(0.04)	(0.24)	(0.05)	(0.05)	(0.04)
Baseline mean (CholeraMap)	0.85	0.93	0.60	0.15	3.96	0.33	0.29	0.14
Observations	854	871	872	853	872	662	870	872
R^2	0.06	0.05	0.04	0.04	0.09	0.04	0.04	0.03

Notes: Standard errors, clustered at the village level, in parentheses. All regressions control for respondent gender and age, household size, household head gender and education, children under five, land ownership, television ownership, bike or motorbike ownership, and perceived cholera risk. Specifications run using household survey data collected at baseline and endline from CholeraMap and CholeraApp households who visited their apps approximately once per month during the implementation period. Asterisks denote statistical significance: * p <0.10, ** $p < 0.05$, ***$p < 0.01$.

Appendix A Supplemental Results

Table A1: Difference-in-differences estimates of the effects of CholeraMap and CholeraApp on knowledge, water-use behavior, and health with household fixed effects

	(1) Equipped environment	(2) Equipped health	(3) Diarrhea concern	(4) Treat drinking water	(5) Handwash with soap frequency	(6) Pond use adult men	(7) Pond use adult women	(8) Cholera incidence
Post	0.03	0.01	-0.06	-0.05	0.06	0.10***	0.11***	-0.04*
	(0.03)	(0.03)	(0.06)	(0.03)	(0.30)	(0.03)	(0.03)	(0.02)
CholeraMap × Post	0.07	0.07	-0.12	0.01	0.00	-0.08**	-0.08**	0.01
	(0.05)	(0.04)	(0.08)	(0.04)	(0.38)	(0.04)	(0.04)	(0.03)
CholeraApp × Post	0.03	0.06	-0.10	0.01	-0.14	-0.03	-0.05	-0.03
	(0.05)	(0.04)	(0.07)	(0.04)	(0.36)	(0.04)	(0.05)	(0.03)
Baseline mean (CholeraMap)	0.86	0.91	0.57	0.13	4.04	0.35	0.32	0.15
Baseline mean (CholeraApp)	0.91	0.93	0.53	0.21	4.26	0.39	0.38	0.16
p-value: CholeraMap vs. CholeraApp	0.42	0.82	0.72	0.99	0.61	0.25	0.42	0.24
Observations	3906	3980	3983	3908	3983	3202	3977	3983
Household FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
R^2	0.56	0.53	0.56	0.69	0.61	0.83	0.82	0.56

Notes: Standard errors, clustered at the village level, in parentheses. All regressions control for respondent gender and age, household size, household head gender and education, children under five, land ownership, television ownership, bike or motorbike ownership, and perceived cholera risk. Asterisks denote statistical significance: * $p < 0.10$, ** $p < 0.05$, ***$p < 0.01$.

Table A2: ANCOVA estimates of the effects of CholeraMap and CholeraApp on knowledge, water-use behavior, and health

	(1) Equipped environment	(2) Equipped health	(3) Diarrhea concern	(4) Treat drinking water	(5) Handwash with soap frequency	(6) Pond use adult men	(7) Pond use adult women	(8) Cholera incidence
CholeraMap	2.22***	3.27**	0.63**	1.06	1.03	0.67	0.68	1.03
	(0.57)	(1.64)	(0.12)	(0.25)	(0.06)	(0.21)	(0.21)	(0.21)
CholeraApp	2.92***	7.93***	0.57***	2.00***	1.06	1.05	1.10	0.74
	(0.83)	(4.20)	(0.11)	(0.50)	(0.05)	(0.41)	(0.42)	(0.15)
Baseline mean (CholeraMap)	0.86	0.91	0.57	0.13	4.04	0.35	0.32	0.15
Baseline mean (CholeraApp)	0.91	0.93	0.53	0.21	4.26	0.39	0.38	0.16
p-value: CholeraMap vs. CholeraApp	0.34	0.12	0.52	0.00	0.52	0.29	0.23	0.03
Observations	1971	1987	1989	1986	1989	1607	1986	1989

Notes: Standard errors, clustered at the village level, in parentheses. Logit models used to estimate Columns (1)-(4) and Columns (6)-(8); results are reported as odds ratios. A Poisson model was used to estimate Column 5; results are reported as incidence rate ratios. All regressions control for respondent gender and age, household size, household head gender and education, children under five, land ownership, television ownership, bike or motorbike ownership, and perceived cholera risk at baseline and endline. Results estimated using only endline data. Asterisks denote statistical significance: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table A3: Instrumental variables estimates of the effects of CholeraMap and CholeraApp use on knowledge, water-use behavior, and health

	(1) Equipped environment	(2) Equipped health	(3) Diarrhea concern	(4) Treat drinking water	(5) Handwash with soap frequency	(6) Pond use adult men	(7) Pond use adult women	(8) Cholera incidence
Panel A: CholeraMap								
Frequent app use	0.10***	0.08**	-0.30**	0.01	0.36	-0.25	-0.25	0.01
	(0.10)	(0.08)	(-0.30)	(0.01)	(0.36)	(-0.25)	(-0.25)	(0.01)
Baseline mean	0.86	0.91	0.57	0.13	4.04	0.35	0.32	0.15
First stage F-stat	493.92	482.24	475.96	472.97	475.96	413.37	468.56	475.96
Observations	1,255	1,267	1,269	1,267	1,269	1,038	1,267	1,269
Panel B: CholeraApp								
Frequent app use	0.22***	0.17***	-0.69***	0.34***	1.14	0.04	0.09	-0.13
	(0.22)	(0.17)	(-0.69)	(0.34)	(1.14)	(0.04)	(0.09)	(-0.13)
Baseline mean	0.91	0.93	0.53	0.21	4.26	0.39	0.38	0.16
First stage F-stat	120.02	115.11	115.11	113.30	115.11	109.50	114.63	115.11
Observations	1,227	1,235	1,235	1,234	1,235	993	1,234	1,235

Notes: Standard errors, clustered at the village level, in parentheses. All regressions control for respondent gender and age, household size, household head gender and education, children under five, land ownership, television ownership, bike or motorbike ownership, and perceived cholera risk. Results estimated using only endline data. Asterisks denote statistical significance: * $p < 0.10$, ** $p < 0.05$, ***$p < 0.01$.