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TRANSLATING INFORMATION INTO ACTION: A PUBLIC HEALTH EXPERIMENT IN BANGLADESH

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Abstract

While models of technology adoption posit learning as the basis of behavior change, information campaigns in public health frequently fail to change behavior. We design an information campaign embedding hand-hygiene edutainment within popular dramas using mobile phones, randomly distributed to households in Bangladesh. We document no change in hygiene knowledge, yet substantial improvements in handwashing and health. Employing machine learning techniques with temporal data on media exposure and handwashing, we find that a combination of cumulative and immediate exposure predicts washing, consistent with cue-based habituation. Results highlight how behavior change may be induced by tacit, rather than explicit, knowledge acquisition.

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1 Introduction

Models of technology adoption frame behavior change as precipitated by information acquisition: agents possess some knowledge, or priors, over the returns to a behavior, receive new information via information provision or experimentation, update their priors, and engage if returns outweigh costs (Arrow (1962); Janvry, Macours, and Sadoulet (2017); Foster and Rosenzweig (1995); Conley and Udry (2010)). A shift in knowledge is a prerequisite to behavior change. It is this theory of change that motivates the profusion of information campaigns in public health.

Against this backdrop, we administer an information campaign that fails to alter explicit knowledge, yet meaningfully improves behavior and health. How does such change transpire? Our high-frequency temporal data on informational inputs and behavioral outcomes points to the role of salience and tacit knowledge, or know-how via accumulated exposure and experience that cannot be measured directly (Hadjimichael and Tsoukas, 2019), in transforming informational content into action.

We explore this process in the context of handwashing with soap in Bangladesh. To focus on the translation of information into action, we choose a setting in which neither the raw materials required for the act nor the social norms surrounding it are a constraint: 100% of our households own soap and 99% rinse their hands with water before eating. Families possess some, but not complete, knowledge of proper hygiene behavior: 83% of mothers believe soap removes germs from hands, but 64% do not think that soap will make hands clean if they already appear clean. 54% of mothers volunteer handwashing as a method of preventing diarrhea, but only 1% believe handwashing can prevent colds. We therefore operate in a space where an information campaign may alter behavior either by shifting the priors about returns that individuals may hold, or through the 'translation function' of priors into action.

Such behavior change is critical to child health across the developing world. Diarrheal and respiratory illnesses from unsafe sanitation and hygiene practices kill nearly one million people each year and stunt the growth of millions more (WWAP, 2019). Relative to expensive infrastructural investments, improvements in individual hygiene involve small changes with potentially substantial returns: handwashing with soap, for example, can drastically reduce diarrhea and respiratory infection by interrupting the transmission of pathogens into the body (Freeman et al., 2014; McGuinness et al., 2018). While successful in intensive and costly programs, practitioners face the challenge of identifying low cost, scalable interventions that yield sustained improvements in behavior and health.[1] This study proposes one such

[1]While there exist a wide array of studies in the space of sanitation and hygiene in the developing world,

program.

We design a scalable edutainment campaign using existing public service announcements on hand hygiene. The intervention is motivated by the documented successes of other edutainment in shifting behavior around fertility (Ferrara, Chong, and Duryea, 2012), migration (Farré and Fasani, 2013), and energy (Jacobsen, 2011), among others. Our medium is the mobile phone, whose penetration in rural Bangladesh has grown rapidly (GSMA, 2014), a trend mirrored across much of the developing world. Network reliability and internet accessibility remain poor, so households forgo streaming and rely on SD cards preloaded with content (see Figure A1) for their entertainment needs.[2] Our intervention embeds edutainment within popular dramas and movies and distributes call-disabled smartphones with preloaded SD cards to randomly selected households in rural Bangladesh. We provide an equal platform for all treated households to view content by issuing them a simple smartphone (valued at 50 USD). We disable network capabilities to focus the intervention on the preloaded edutainment.

To measure changes in hand hygiene due to the intervention, we distribute handsoap dispensers embedded with time-stamped sensors to all households. This technological innovation addresses the serious challenges posed by standard participant observation measures of hand hygiene, making data collection unobtrusive, objective, and precise (Hussam et al., 2021; Ram et al., 2010; Biran et al., 2008) (see Figures A2 and A3 for sensor diagram and installation).

Our analysis proceeds in three steps. We first examine the relationship between edutainment consumption and behavior change. We find that daily handwashing rates, as measured by the sensor technology, increase significantly due to the intervention: treated households wash 20% ($p = 0.000$) more than their control counterparts.

Contrary to the purported intent of such a campaign however, this change in behavior is not driven, insofar as can be measured through detailed survey questions, by a shift in knowledge about the returns to handwashing. Nor is baseline knowledge correlated with the size of the treatment effect. What, then, is the nature of information exposure that

many suffer from methodological limitations (see a survey of the literature in Kremer and Peterson Zwane (2007)). Those that utilize methods such as randomized control trials employ intensive and costly interventions to improve both hygiene practices and health (e.g., Khan (1982); Haggerty et al. (1994); Luby et al. (2005)). Bennett, Naqvi, and Schmidt (2018) designs a particularly effective, but costly, learning-based intervention: they find that individual examination of microbes under a microscope yields meaningful improvements in hand hygiene and health, relative to instruction alone. Efforts to identify scalable interventions are mixed: some community- or school-based interventions, by utilizing local volunteers receiving modest compensation for information dissemination, generate modest behavior and health impacts (Bowen et al., 2012; Huda et al., 2012; Biran et al., 2014), while similar community-based hygiene promotion interventions do not (Biran et al., 2009; Lewis et al., 2018).

[2] Also seen in India (Tenhunen, 2018).

leads to behavior change? We collect data on patterns of exposure and find that, controlling for a rich set of household characteristics, households where children watched any phone entertainment within the last reporting period are significantly more likely to wash, as are households in which the mother volunteers the children's handwashing cartoon as one of her favorite pieces of entertainment. The former suggests that recency of exposure matters (the entertainment may serve as a reminder, or trigger, to wash), while the latter suggests that parental preferences are complements to child exposure in behavior change.

To further probe the role of exposure recency in behavior change, we exploit minute-level time series data from an application within the mobile phones that tracks media consumption. Paired with our minute-level data on handsoap dispenser use, we assemble a unique panel dataset of behavioral inputs (media exposure) and outputs (handwashing behavior) and employ machine learning techniques to uncover which patterns of entertainment exposure best predict future handwashing behavior. The machine learning approach is suited to this objective, as *ex ante* the literature offers no priors around what temporal patterns of exposure generate shifts in behavior. However, the application is nontrivial: existing machine learning work with time series data (for example, stock price predictions, such as that in Gu, Kelly, and Xiu (2019)) employ past features (eg. prices) to predict like future features. In such settings moreover, an interpretable weighting of features is unnecessary as long as the model's predictive capacity is high. In our setting, we employ one set of past features (exposure to campaign) to predict a separate future feature (handwashing), and recovery of relative weights is necessary to the underlying policy goal: how should edutainment campaigns be structured, in frequency and length of stimulation, to maximize behavior change? Improving upon existing work to address these challenges, we find that cumulative exposure to edutainment during the month prior to a washing episode is most predictive of soap use, followed by immediate exposure to entertainment 30 minutes prior to a washing episode. All other temporal features, including exposure to content beyond one month or 31 to 60 minutes prior, have near zero predictive value. This is consistent with handwashing becoming a cue-based habit, in which cumulative exposure to edutainment familiarizes one with the behavior and associates it with phone exposure, and immediate exposure then serves as the necessary trigger to wash.

Because only treated households can produce data on watching patterns, we venture no causal claims in these latter two exercises. However, the random placement of ads within a larger entertainment package reduces the role of choice in exposure, and the inclusion of day and household-level fixed effects in the machine learning exercise ease concerns of parallel time trends, reverse causality and selection on household-type. We uncover a sensible set of patterns around recent exposure, cumulative exposure, and familial complementarities that can inform the design of future mechanism experiments and the administration of public health information campaigns.

Having documented impacts of the intervention on hand-hygiene behavior, we next estimate the effect of the edutainment package on the health of treated children. We find substantial reductions among children in treated households relative to their control counterparts on the incidence of loose stool (-54%, $p = 0.011$) and symptoms of acute respiratory infection (ARI) (-29%, $p = 0.005$). We find no effect of the campaign on other sanitation or hygiene behaviors, suggesting that the estimated health impacts are indeed driven by changes in hand hygiene. These health improvements persist over the course of the twelve months of data collection despite an edutainment intervention which lasts only eight months.

To benchmark our health results against the status quo (households with soap but no edutainment campaigns *and* no dispensers), we supplement our randomized sample with a sample of households drawn from our initial census. While this "pure control" group is not randomized, their only observable divergence from our experimental sample is that mobile phones were already employed as a primary source of entertainment in these homes, making them ineligible for our experimental sample. We collect child health data from this sample for the final six months of the experiment. We find that, relative to this "pure control" sample, children who received the dispenser (but no edutainment treatment) exhibit 68% lower incidence of loose stool ($p = 0.015$) and 52% lower incidence of symptoms of ARI ($p = 0.029$). This suggests that the dispenser alone had substantial effects on hand hygiene behavior and subsequent health, echoing a finding of Hussam et al. (2021) in West Bengal. Reframing the results of the edutainment campaign in light of the effect of the dispenser alone, we interpret the dispenser as a potentially critical complement to edutainment: households require not only the material resources of soap and water (which all households in our setting possess), but also a convenient and user-friendly medium of use, in order to act upon the content delivered in a public health campaign.

We view the contributions of this study as threefold. First, our results on exposure recency build upon literature around the value of reminders, often delivered via text messages, for building healthy behaviors (e.g. Patrick et al. (2009); Koshy, Car, and Majeed (2008); Karlan et al. (2016).[3][4] Beyond the binary presence or absence of a reminder, our mobile phone and dispenser technology allow us to examine precise temporal relationships

[3]Related is recent work by Bettinger et al. (2021), which finds that 'content-less' text message reminders are as effective as texts bearing informative content about a child's inputs to education. The primary channel in this context, however, remains information: content-less messages encourage parents to secure the relevant information to encourage their childrens' educational performance.

[4]While the underlying mechanism of increasing salience may be the same, text message interventions require the decision of timing to be made by the experimenter, precluding an exploration of which temporal patterns of exposure are most predictive of behavior change.

between inputs (edutainment exposure) and outputs (handwashing behavior). We identify the features of edutainment exposure that are most predictive of handwashing, clarifying the windows of time during which exposure may be most impactful. This high-frequency time-series data on both information stimuli and subsequent behavior has not been utilized, to our knowledge, in existing studies of behavior change or technology adoption, and offers a path forward to empirically constructing the translation function of information exposure into action even in the absence of explicit changes in knowledge.

Second, we document that prolonged information campaigns can generate meaningful changes in behavior despite no measurable change in knowledge. This suggests that designers of information campaigns may be well served to consider the tacit means by which their campaigns can engender behavior change, rather than focusing on the dispensation of facts *per se*. While consumers may be unable to consciously recognize factual information about the returns to a technology or behavior, the act of repeatedly conveying informative content to a captive audience of families can serve to familiarize, and associate a cue, with the promoted behavior (cumulative exposure), make the behavior salient by triggering the cue (immediate exposure), and facilitate complementary behavior change between parent and child, resulting in increased adoption with no commensurate change in explicit knowledge. We denote this combination of effects under the umbrella of 'tacit knowledge,' distinct from explicit knowledge in a manner similar to Romer (2000)'s theoretical distinction between 'feeling' and 'thinking.' Our findings are consistent with psychological and economic models of cue-based habit formation (Wood and Neal, 2007; Laibson, 2001) as well as recent work in neuroscience that identifies the brain's 'default mode network' to serve the role of autopilot: through repeated exposure and contextual triggers, we engage in behavior with no conscious awareness of why or that we are doing so (Vatansever, Menon, and Stamatakis, 2017; Raichle, 2015). Our results, however, also offer insight into why impacts of information campaigns may be short-lived: in the absence of the intervention, cues to trigger behavior disappear. As underlying priors about the returns have not shifted, neither will subsequent behavior.

Third, we devise a simple and scalable intervention that manages to not only shift hygiene behavior but also generate meaningful and sustained improvements in child health. The greater part of information campaigns in the hygiene and sanitation space have been unable to produce health improvements (see, for example, Biran et al. (2009); Chase and Do (2012); Galiani et al. (2016); Null et al. (2018); Lewis et al. (2018); Bennett, Naqvi, and Schmidt (2018), with its innovative use of microscopes, is a notable exception in health outcomes and affordability), and the few that record changes in behavior without subsequent health effects employ self-reports or observational data (such as Tidwell et al. (2019), which also documents improvements in handwashing from a media campaign) with their concomitant challenges (Ram et al., 2010; Biran et al., 2008). Health effects of the magnitudes we document are uncommon in the literature: a lower bound of $6.50 USD per household for the cost of the SD card ($2 USD), dispenser ($3.50 USD), and ten months of soap ($1 USD), and an upper bound of $65 USD for the cost of the SD card, dispenser, soap, card delivery, and phone - both estimates that are likely to drop as phone and internet penetration grow, and dispensers are produced domestically at scale, across the developing world.

Beyond hand hygiene, a behavior of increasing importance in the wake of the global COVID-19 pandemic, this work may speak to the design and dissemination of public health information campaigns for other low cost, high return, and repetitive behaviors, with particular relevance to behaviors such as water treatment and mask-wearing.

The remainder of the paper proceeds as follows. Section 2 describes the design and implementation of the experiment, Section 3 presents the analysis and results, and Section 4 concludes.

2 Experimental Design

Our study was conducted in Gaibandha District, Bangladesh, among 333 households across 34 villages. All households had at least one child of primary school age, access to a latrine, and a female head of household who did not own a mobile phone. All households received a handsoap dispenser with a sensor embedded inside. Randomization was executed via computer, with 50% of households allocated to treatment.

Once per month, all households were visited, and their dispensers were refilled. Given our limited supply of sensors, a randomly selected third of dispensers included sensors in any given month; in the subsequent month, these sensors were extracted, data downloaded, and sensors then inserted into the next third of households, and so on over the course of eight months. As such, we have approximately two months of sensor data per household, but representative data of a balanced sample of control and treatment households.

The intervention lasted from April 2017 to November 2017. During this period, enumerators collected sensor data as well as data on child health and [for treatment households] self-reported entertainment exposure during their monthly visits. Using an application preloaded onto the smartphones, enumerators also extracted data for treated households on mobile phone watching patterns. An endline survey was conducted in April 2018. Follow-up rates vary by data type: the endline survey was completed for 86% of the sample, interim health surveys for 97% of the sample, the sensor data for 85% of the sample, and the mobile phone data for 54% of the [treated] sample. Lower followup rates for sensor and mobile phone data come not from household attrition but rather technical failures. Enumerators faced difficulties transferring data to laptops in the field, and many files were corrupted during extraction.

Table A1 demonstrates balance across treatment and control households at baseline along a host of sociodemographic, hygiene behavior, and hygiene knowledge characteristics. Table A2 presents balance along these features for the subsample of households in each data source. We see no evidence of differential attrition: baseline characteristics are balanced between treated and control households for whom we were able to secure followup data in each source, and the subsample of households for whom we have mobile phone data are comparable to the full sample of households.

2.1 Edutainment campaign

The edutainment campaign was delivered via a smartphone for which the phone technology had been disabled, leaving only a screen. The device was provided to treatment households after the baseline with an SD card preloaded with three hours of dramas and cartoons.

Between each preloaded [non-informative] drama or cartoon, we embedded an ad campaign around proper hand hygiene. These ads ranged from thirty seconds to seven minutes and were drawn from a set of publicly available material (for example, see links to the following: Meena Cartoon, Bangladesh campaign, and Sesame Street). Enumerators delivered SD cards with new dramas and cartoons to all treatment households monthly.

3 Analysis and Results

We present the results in three stages. First, we examine whether the intervention reached its intended audience. We then estimate its impact on hand hygiene behavior and explore the underlying mechanisms. Third, we consider whether these behavioral changes were consequential in terms of child health.

3.1 Impact of edutainment campaign on media consumption

To document that our intervention reached its intended audience, we run the following regression:

$$Media_h = \alpha + \beta Treated_h + M_h^0 + \epsilon_h \tag{1}$$

Where $Media_h$ represents a series of outcomes around media engagement for household h drawn from the endline data, namely: whether the phone is used for entertainment by the mother, how many minutes per day is spent watching entertainment on the phone, whether the child edutainment content ('cartoons') are watched on the phone, whether the children use the phone as entertainment, how many minutes per day the child watches, whether the child watches daily, what time of day the phone is engaged with, and whether the child watches cartoons on the phone. M_h^0 represents the baseline value of the outcome.

Results are presented in Table 1. Treated mothers report using a mobile device for entertainment 73 pp (340%, Column 1) more than control households. Treated children are 38 pp (132%, Column 4) more likely to employ their phone as a source of entertainment than control children, and more than three times more likely to watch the device daily (Column 6). All other measures exhibit similar magnitude effects, are significant at the one percent level, and are robust to the inclusion of a rich set of sociodemographic controls (not shown).

3.2 Impact of edutainment campaign on handwashing behavior

We now examine whether edutainment exposure resulted in behavior change, as documented from the dispenser sensor data. To do so, we run the following regression:

$$Handwashing_{ht} = \alpha + \beta Treated_{ht} + \gamma_t + \delta_v + \epsilon_{ht} \tag{2}$$

Where $Handwashing_{ht}$ represents daily dispenser use as measured either in binary form (one if the dispenser was pressed at all in the day and zero otherwise) or continuously (the total number of presses that day), γ_t is day level fixed effects, and δ_v is village level fixed effects. Standard errors are clustered at the household level.

Results are presented in Table 2. Treated households use the soap dispenser 20% more on a given day than their control counterparts. Figure A4 depicts the evolution of handwashing behavior over the course of the eight months during which we collected sensor data. Both treated and control households exhibit enthusiasm with the dispenser in the initial weeks, with treated households particularly engaged, and engagement declining over time.

Is this behavioral change consequential? Section 3.3 explores whether this increase in hand soap use yields health improvements. The short answer is yes: this impact, though temporary, has significant and lasting consequences for child health. Columns 5 and 6 of Table 2 suggest why: treated households are not only more likely to wash more per day, but are also 3.4 percentage points, or 19%, more likely to wash during dinnertime, a critical time of day in which exposure to germs can directly affect health through food consumption.

We spend the remainder of this section exploring the mechanisms of information internalization: what dimensions of exposure to the edutainment campaign generated the behavioral - and consequently health - improvements we observe?

We first estimate whether the edutainment program shifted the knowledge of treated households, ostensibly the central channel through which the intervention should alter behavior. We asked respondents a series of questions regarding their knowledge of hand hygiene: if and why soap is useful, how it differs from washing only with water, whether colds are contagious, and what actions can prevent colds and diarrhea.

Results are presented in Table 3. Across all measures, controlling for baseline knowledge, we see no discernible improvement among treated households; results remain unchanged with the inclusion of sociodemographic controls (not shown). Columns 8 and 9 examine the impact of the intervention on handwashing behavior separately for those above and below the median baseline score on the hygiene knowledge index: households who have more to learn according to self-reported knowledge of handwashing returns do not exhibit larger treatment effects than their more knowledgeable counterparts. This set of results suggests that (1) the content delivered through the information campaigns shifted knowledge in tacit, rather than explicit, ways, and/or (2) the campaign was effective not as an educational tool but rather as a visual reminder to engage in a behavior.

3.2.1 Temporal dynamics of information acquisition and behavior change

To probe these alternative channels, we employ a rich set of data collected over the course of the experiment on how households engaged with the edutainment campaign. We first examine our time-series data on media consumption and handwashing to consider how the temporality of information exposure translates to behavior change. Does exposure over the course of weeks matter? Does immediate exposure matter while earlier exposure is forgotten? Our high-frequency data on the input of edutainment exposure and the output of handwashing, paired with machine learning techniques, presents a unique opportunity to shed light on the temporal nature of information-driven behavior change.

Given that we only observe media exposure data for treated households, and watching the media is a potentially endogenous choice, this exercise is by nature exploratory. However, three features of the setting and the analysis reduce the primary channels of endogeneity: edutainment videos are interspersed unexpectedly within the entertainment, and all models include fixed effects for households - reducing concerns of selection into washing - and days - reducing concerns of parallel time trends or reverse causality from washing to watching.

Our dataset for this exercise is composed of the handwashing outcome, which takes the form of a binary variable in which a one indicates that the dispenser was pressed at least once during the breakfast (dinner)-time range on a given day and zero otherwise, and a series of temporal feature variables around exposure to the hygiene information campaign:

namely, binary and continuous measures of exposure to edutainment and entertainment in the previous thirty minutes, hour, week, twelve weeks, and interims periods. All observations are collapsed to the household-day-mealtime level. Details on all temporal features and data construction decisions are described in Appendix A.2 (Chawla et al. (2002), Norberg (2016), Bergstra and Bengio (2012)).

A comparison of the predictive performance in training and test sets across the lasso, elastic net, and random forest algorithms is presented in Table A4. The elastic net exhibits the highest testing accuracy at 62%. We then employ this algorithm to rate features by 'importance,' a means of classifying the contribution of each variable to the model which, in the case of the elastic net, is the absolute value of the coefficient for each variable in the tuned model (Kuhn, 2020). Figure A5 presents the top four features selected by the elastic net algorithm. The algorithm identifies the total number of minutes of exposure to the edutainment campaign over the previous three and four weeks as most important (with importance of 0.12 and 0.09 respectively), followed by whether the entertainment portions were watched in the past half hour (importance of 0.06). All other features, including binary or cumulative exposure of edutainment or entertainment at, for example, five or more weeks, two weeks, and two hours, exhibit importance scores of 0.001 or below.

These selected temporal features suggest that both long term, cumulative exposure and immediate exposure to the programs determine whether a household will wash in a given mealtime. Interestingly, while the long term features [of three to four weeks prior] rely on exposure to the edutainment campaign, the immediate feature [of half an hour prior] relies on exposure to the non-informative entertainment components. This suggests that the latter may act as a trigger: having associated the entertainment with the edutainment campaigns from accumulated exposure, watching the entertainment alone may catalyze a handwashing episode. This exercise also implies that the influence of the campaigns, or edutainment 'memory,' does not exceed one month: despite including all temporal features up to twelve weeks prior to each observation in the selection process, no features beyond four weeks prior have predictive power on the likelihood of handwashing in a given mealtime-day.

3.2.2 Environmental and preference correlates of handwashing

While the sensor data provides a sense of the temporal nature of information absorption, we exploit our survey data on media engagement to understand the relational contexts within which content absorption occurs. Because this data only exists for treated households, this exercise makes no causal claim, but reveals a set of sensible patterns. We regress dispenser use on a series of media engagement features: the number of days and times per two weeks that a mother watched, her children watched, and what content they watched. Two features of engagement are significantly and positively correlated with dispenser use (Table A3, Column 1): the number of days the child watched any phone content and whether the mother chose the child's edutainment (the "hygiene cartoon") as one of her favorite items in that month's SD card menu.

Do the mother's preferences bear a causal relationship to hand hygiene, or is the relationship driven by selection on unobservables?[5] We run the same regression only among the sample of households in which the mother did *not* select the child's edutainment as a favorite piece (Column 2). The correlation between child phone exposure and handwashing behavior remains robust, and newly emergent is a negative relationship between handwashing and whether the mother watched any media content with her child. These patterns suggest that parental preferences matter: parents who enjoy the child's campaign can reinforce the behavior in their children, and parents who watch the entertainment with their children but place little value on the edutainment may signal that hand hygiene is not important.

Along the intensive margin of handwashing (Column 3-4), a child's preferences are highly correlated with behavior: a household in which the child volunteers the hygiene cartoon as a favorite will exhibit four additional dispenser presses per day, a 50% increase from the control mean.[6]

3.3 Impact of edutainment campaign on child health

We document statistically significant changes in handwashing behavior and sensible patterns of edutainment exposure that translate to behavior change. Is this change in hand hygiene meaningful enough to impact health? We run the following regression using the health data obtained from our monthly surveys:

$$Health_{ht} = \alpha + \beta * Treated_{ht} + \gamma_t + \delta_v + \epsilon_{ht} \tag{3}$$

Where $Health_{ht}$ represents child health as measured by (1) the presence of any symptoms of acute respiratory infection (ARI) such as coughs, colds, or runny noses in the previous two weeks and (2) the presence of loose stool, a proxy for diarrhea.[7] γ_t is survey round fixed effects and δ_v is village level fixed effects. Standard errors are clustered at the household

[5] All regressions control for a rich set of observable sociodemographic features.

[6] We also run linear lasso models to identify which controls are most predictive of handwashing, yielding results consistent with the above, not shown.

[7] Diarrhea is defined as three or more loose motions in a day. Because mothers often do not observe every child-motion episode, we elicit any observations of loose stool. The presence of loose stool does not necessitate diarrhea, but it is the key symptom.

level.

Results are presented in Panel A of Table 4. The sample is composed of children ages twelve years and below at baseline, though results are robust to expanding and reducing the age cutoff. The edutainment campaign leads to a 54.4% reduction in incidence of loose stool and a 28.8% reduction in symptoms of ARI over the course of the campaign.

Notably, the average incidence of reported illness is low, at 1.5 percent of households reporting loose stool in any given two-week period and 6.6 percent of households reporting any symptoms of ARI. This masks heterogeneity over the course of the year: diarrhea and ARI are seasonal, with diarrhea most likely during summer monsoon months and ARI during the transition into winter month.

Panel A of Figure 1 plots the temporal evolution of illness. Consistent with the seasonality of water-borne diseases, rates of loose stool peak during monsoon season (June to October), during which the impact of the edutainment campaign is most apparent; rates fall rapidly thereafter, with nearly zero loose stool incidence reported for both groups in the winter. This seasonality in treatment effect is not apparent for ARI: both treated and control households exhibit a decline in symptoms over the first two months, a low incidence thereafter (with treated households, notably, hovering near zero during the winter months), and a stable gap between treatment and control.

Our results point to the direct impact of an edutainment program on child health. Can these health improvements be attributed to better hand hygiene alone, or might the intervention have precipitated other hygiene and sanitation improvements among exposed households? Table A.1.1 estimates the impact of the campaign on water treatment practices, open defecation, and construction of a sanitary latrine by endline, and finds no effect on any other margin.

3.4 Impact of hand soap dispensers on child health

Panel A of Figure 1 exhibits a steep decline in ARI and diarrhea incidence in the early months of the intervention *regardless* of treatment assignment. As all households received dispensers at the outset of the experiment, we suspected this decline was due to the dispenser alone and subsequently added a group of "pure control" households to the sample to measure illness incidence among households who received no dispenser. Having been added *ex-post*, these households were not randomly selected; they were rather the subset of households who had been excluded from the experiment because the female head of household owned a mobile phone. We returned to these households and collected an abridged baseline survey and monthly surveys of child health six months after the experiment launched.

Table A.1.1 presents balance between these "pure control" households and the dispenser control households. There exist no significant differences between the two groups along any surveyed margins except phone use. While phone use may be correlated with unobservables such as wealth, these are likely associated with better health status among the "pure control," making estimates of the health impacts of the dispensers lower bounds.

We run the identical regression to Equation (3), with our treated sample now defined as the dispenser control group (who received a dispenser but no edutainment), and the control defined as the pure control. Results are presented in Panel B of Table 4. The impact of the handsoap dispenser alone is substantial. Reported incidence of loose stool is 67.6% lower and symptoms of acute respiratory infection 51.8% lower among households who received a dispenser. These effects appear on a larger base: 3.8% of pure control households report that their children experienced loose stool in each two week period, and 9.2% of households report symptoms of ARI.

Panel B of Figure 1 plots the evolution of illness incidence for the pure control, the control (with dispenser), and the treated (with dispenser and edutainment) groups during the last six months of the experiment, the period during which pure control health data was collected. The seasonality of ARI emerges: incidence is highest among pure control households during winter and steadily decline thereafter. Loose stool rates are relatively stable over winter months and rise as summer approaches. The dispenser alone entirely eliminates loose stool incidence and drastically reduces ARI incidence over the time period observed.

4 Conclusion

The substantial effect of the dispenser equipment alone is striking. It begs the question: is the behavioral change generated by the edutainment campaign meaningful? We posit that the impact of the edutainment campaign must be understood within the context of households who have access to appropriate infrastructure. The results suggest that human-centered design plays an important role in the provision of resources: the dispenser was enjoyable to use and situated near relevant sites of use. We stress the relevance of the product itself beyond simple resource provision: the edutainment may have had little effect on household behavior and health absent the dispensers, despite the ready availability of soap and water in all households. As such, the edutainment campaign may best be seen as a valuable complement to a necessary infrastructural investment. The impacts of this complementary campaign are alone substantial: the campaign is able to halve loose stool incidence during peak monsoon months and effectively eliminate symptoms of ARI during the peak early winter months relative to those households who received a dispenser but no edutainment campaign. As mobile smartphone penetration continues to grow, a program such as this becomes rapidly scalable at low marginal cost.

Our results also problematize the standard understanding of knowledge acquisition. In classical models of technology and behavior adoption, consumers are Bayesian updaters who learn about the returns to a behavior, update beliefs, and alter their behavior accordingly. Related policy recommendations of subsidizing experimentation or information provision assume a conscious acquisition of knowledge. However, knowledge change does not guarantee behavior change, a fact that comes to bear in study after study of information campaigns which document improvements in self-reported hygiene awareness with no corresponding change in behavior or health. The results of this study suggest that the reverse may also be true: behavior change does not require a change in explicit knowledge. The value of an edutainment campaign, when embedded into an everyday activity such as watching television, may be not to educate, but rather to familiarize one with, then serve as a visual reminder of, an activity. In other words, campaigns may be more impactful as tools to subconsciously habituate individuals - rather than consciously shift priors around returns - to an activity. As such, behavioral change programs must consider not simply the provision of information, but importantly the timing, frequency, and context in which such information is delivered, in order to generate behavior change.

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Tables

Table 1: Mobile phone and edutainment use

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
	Is phone used for entertainment	How many minutes is phone watched	Are cartoons watched on the phone	Does the child use the phone as entertainment	How many minutes does child watch phone	Does the child watch the phone daily	Child watches cartoons on phone
Treated	0.734	33.58	0.270	0.378	17.36	0.640	0.223
	(0.0404)	(4.440)	(0.0423)	(0.0439)	(1.957)	(0.0442)	(0.0558)
Control mean	0.216	6.924	0.208	0.285	10.453	0.200	0.256
	(0.412)	(13.515)	(0.406)	(0.452)	(18.613)	(0.401)	(0.437)
Observations	287	287	287	287	287	287	287

Notes: Outcomes come from the endline survey with a two-week lookback period. Standard errors in parentheses. All regressions include the baseline value of the outcome as a control.

Table 2: Handsoap dispenser use

	(1)	(2)	(3)	(4)	(5)	(6)
	Whether dispenser was pressed		Total daily presses		Likelihood of using dispenser during dinnertime	
Edutainment treatment	0.0212	0.0238	1.824	1.877	0.0302	0.0344
	(0.0247)	(0.0234)	(0.730)	(0.712)	(0.0186)	(0.0175)
Control mean	0.59		9.273		0.178	
	(0.492)		(16.526)		(0.0261)	
With controls		X		X		X
Observations	12,846	12,846	12,846	12,846	12,846	12,846

Notes: Outcomes come from dispenser sensor data. All regressions include village and day level fixed effects. Controls are mother's age, age at marriage, literacy level, whether she completed primary education, whether she owns the home, the number of rooms in the home, whether the house has electricity, and respondent religion. Standard errors in parentheses are clustered at the household level. Sensors observed from April 19, 2017 to November 9, 2017.

Table 3: Hand hygiene knowledge

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
	Colds come from germs	Can get a cold from other people	Handwashing can prevent colds	Handwashing can prevent diarrhea	Soap makes hands cleaner than water	Soap is used to remove germs	Knowledge Index	Daily presses (below median knowledge)	Daily presses (above median knowledge)
Treated	-0.0614	-0.00989	-0.0309	0.0253	-0.00401	0.0231	-0.00494	1.849	1.989
	(0.0581)	(0.0298)	(0.0415)	(0.0593)	(0.0589)	(0.0340)	(0.0145)	(0.935)	(1.226)
Control mean	0.438	0.938	0.158	0.507	0.445	0.897	0.678	9.151	9.418
	(0.498)	(0.243)	(0.366)	(0.502)	(0.499)	(0.305)	(0.126)	(16.130)	(16.984)
Observations	287	282	287	287	287	286	287	7,407	5,439

Notes: Outcomes come from the endline survey. Standard errors clustered at household level. Regressions in Columns 1-7 include the baseline value of the outcome as a control. 'Can get a cold from other people' is one if an individual says that colds are contagious and volunteers this as an answer to the question 'How?' Similarly, 'Soap is used to remove germs' is one if an individual says that one should wash their hands with soap even if they look clean and volunteers this as an answer to the question 'Why?' 'Knowledge Index' is an inverse covariance weighted index of the outcomes in Columns 1-6. 'Daily presses' is the total number of times the handsoap dispenser is used per day; Columns 8-9 include day and household level fixed effects.

Table 4: Child health

Panel A: Effect of edutainment campaign

	(1)	(2)	(3)	(4)
	Whether child experienced loose stool in last two weeks		Whether child experienced any ARI symptoms in last two weeks	
Edutainment treatment	-0.00778	-0.00798	-0.0237	-0.0190
	(0.00361)	(0.00314)	(0.00993)	(0.00683)
Control mean	0.0147	0.0147	0.0658	0.0658
	(0.120)	(0.120)	(0.248)	(0.248)
Survey round FE		X		X
Village FE		X		X
Observations	3,292	3,292	3,292	3,292

Panel B: Effect of dispenser alone

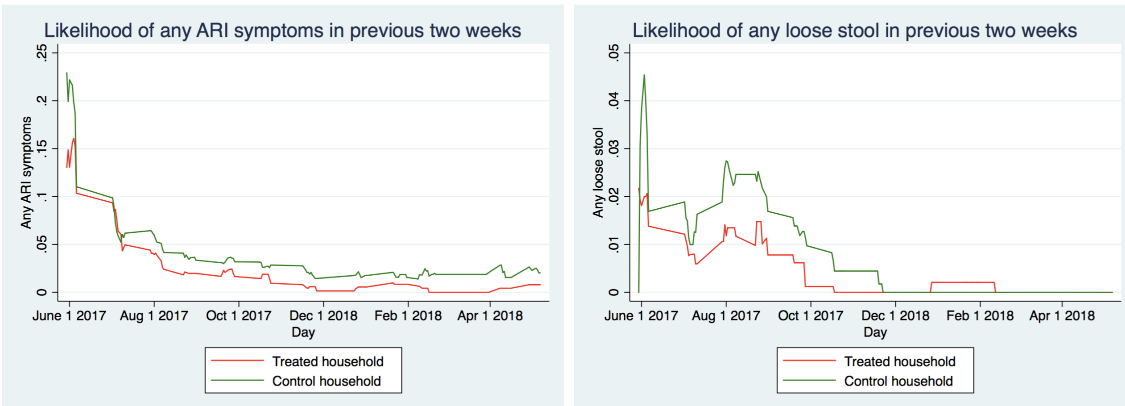
	(1)	(2)	(3)	(4)
	Whether child experienced loose stool in last two weeks		Whether child experienced any ARI symptoms in last two weeks	
Dispenser treatment	-0.0265	-0.0255	-0.0445	-0.0477
	(0.0108)	(0.00907)	(0.0146)	(0.0227)
Pure control mean	0.0377	0.0377	0.0921	0.0921
	(.19056)	(.19056)	(.35452)	(.35452)
Survey round FE		X		X
Village FE		X		X
Observations	4,054	4,054	4,053	4,053

Notes: Health outcomes obtained from monthly health surveys. "Edutainment treatment" are households who received the dispenser and the mobile phone edutainment campaign. "Dispenser treatment" are households who received the dispenser (but no edutainment campaign). "Pure control" are households who did not receive a dispenser (or edutainment campaign). Note that pure control households were not chosen randomly; these households were recruited in the initial sample (prior to randomization) but excluded because they owned a mobile phone which was already utilized for video entertainment by the female household head. Standard errors in parentheses.

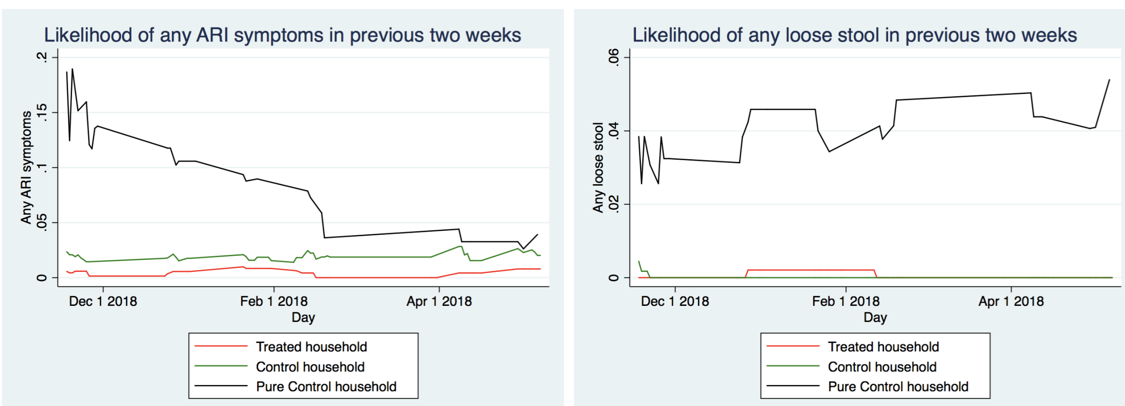
Figures

Figure 1: Child health over time

Panel A: Effect of edutainment campaign



Panel B: Effect of dispenser alone



Notes: Figures show the two-week moving average of reported incidence of loose stool and symptoms of ARI over the course of the experiment in Panel A, and during the last six months of the experiment (during which pure control data was collected) in Panel B. Green line represents dispenser control households, red line represents households who received the edutainment intervention in addition to the dispenser, and black line represents 'pure' control households, who received neither an edutainment program nor a dispenser.

A Appendix [online only]

A.1 Results

A.1.1 Tables

Table A1: Descriptives and balance

		Dispenser control mean	Edutainment treatment mean	p-value	N
Household and mother	Number of rooms	1.699	1.74	0.579	330
	Age at marriage	16.11	16.13	0.928	330
	Education	9.765	8.63	0.576	330
	Eat fish or meat every day	0.578	0.62	0.488	330
Hygiene practice	Drinking water is filtered	0.0241	0.01	0.419	330
	Open defecates	0.0120	0.02	0.404	330
	Owns a latrine	0.970	0.98	0.750	330
	Own soap	0.991	1.00	0.180	330
	Number of times washes hands with soap	4.494	4.40	0.749	330
	Whether hands washed with soap before eating	0.515	0.52	0.893	330
	Whether hands washed with soap before cooking	0.455	0.46	0.937	330
	Whether child washes hands with soap before eating	0.467	0.45	0.676	330
	Whether hands washed with soap after defecation	0.157	0.16	0.950	330
	Whether hands washed with soap after urination	0.506	0.52	0.715	330
Hygiene knowledge	Can get cold from germs	0.0904	0.10	0.823	330
	Handwashing with soap can prevent cold	0.0120	0.01	0.570	330
	Handwashing with soap can prevent diarrhea	0.542	0.53	0.832	330
	Soap makes hands clean even when they look clean	0.361	0.37	0.934	330
	Soap removes germs	0.542	0.52	0.665	206
Entertainment practice	Watches mobile phone for entertainment	0.217	0.16	0.176	330
	Minutes mobile phone watched for entertainment	6.988	5.73	0.413	330
	Child watches mobile phone for entertainment	0.289	0.34	0.308	330
	Minutes child watched mobile phone for entertainment	10.66	13.50	0.211	330
Child (60 months and below)	Any loose stool in last two weeks	0.00268	0.01	0.495	165
	Any ARI symptoms in last two weeks	0.0509	0.05	0.917	165
	Child height (cm)	80.97	79.01	0.613	165
	Weight (kg)	12.52	13.07	0.446	165
	Age (months)	37.09	38.07	0.728	165
	Male	0.550	0.56	0.853	165

Notes: Table reports the p-value and number of observations in a comparison of means between treated and control groups using data from the baseline survey.

Table A2: Test for differential attrition in followup data

		Interim survey		Endline survey		Sensor data	
		t-stat	N	t-stat	N	t-stat	N
Household and mother	Number of rooms	0.396	6,729	0.771	287	0.956	282
	Age at marriage	-0.750	6,729	0.301	287	-0.389	282
	Education	0.516	6,729	-0.466	287	-0.0208	282
	Eat fish or meat every day	0.116	6,729	0.730	287	0.671	282
Hygiene practice	Drinking water is filtered	-0.396	6,729	-0.785	287	-0.695	282
	Open defecates	0.890	6,729	1.378	287	0.570	282
	Owns a latrine	0.348	6,729	-0.0498	287	0.560	282
	Own soap	1.312	6,729	1.345	287	1.345	282
	Number of times washes hands with soap	-0.518	6,729	0.0450	287	-0.430	282
	Whether hands washed with soap before eating	0.0167	6,729	0.420	287	-0.627	282
	Whether hands washed with soap before cooking	-0.193	6,729	0.363	287	-0.584	282
	Whether child washes hands with soap before eating	-0.196	6,729	-0.276	287	-0.462	282
	Whether hands washed with soap after defecation	-0.620	6,729	0.273	287	0.00539	282
	Whether hands washed with soap after urination	0.640	6,729	-0	287	0.212	282
Hygiene knowledge	Can get cold from germs	1.116	6,729	-0.300	287	-0.108	282
	Handwashing with soap can prevent cold	-0.113	6,729	-0.552	287	0.0801	282
	Handwashing with soap can prevent diarrhea	-0.640	6,729	-0.151	287	-0.680	282
	Soap makes hands clean even when they look clean	-0.470	6,729	0.474	287	0.181	282
	Soap removes germs	-0.301	4,114	0.707	183	-0.680	282
Entertainment	Watches mobile phone for entertainment	-1.807	6,729	-0.605	287	-0.983	282
	Minutes mobile phone watched for entertainment	-1.529	6,729	-0.204	287	-0.630	282
	Child watches mobile phone for entertainment	0.558	6,729	1.089	287	0.996	282
	Minutes child watched mobile phone for entertainment	0.883	6,729	1.175	287	1.215	282
Child (60 months and below)	Any loose stool in last two weeks	0.599	6,788	na	287	na	282
	Any ARI symptoms in last two weeks	0.0977	6,788	0.0350	287	0.570	282
	Child height (cm)	-0.807	1,597	0.749	21	1.216	20
	Weight (kg)	0.641	1,597	0.275	21	0.340	20
	Age (months)	-0.0621	1,597	1.177	21	0.990	20
	Male	-0.331	1,597	-1.768	21	-1.502	20

Notes: Table reports the t-statistic and number of observations in a comparison of means between treated and control groups for the subsamples followed up in each specified data source, using data from the baseline survey.

Table A3: Mobile phone watching patterns

	(1)	(2)	(3)	(4)
	Likelihood of using dispenser (average over two weeks)		Number of daily presses (average over two weeks)	
Number of days mother watched phone	0.0186	0.0211	1.173	0.987
	(0.0181)	(0.0198)	(0.737)	(0.874)
Number of days child watched phone	0.0239	0.0229	0.0271	-0.0842
	(0.00649)	(0.00722)	(0.237)	(0.252)
Number of times child watched phone per day	-0.0217	-0.0204	-0.631	-0.429
	(0.0152)	(0.0154)	(0.530)	(0.575)
Whether mother watched with child	0.109	-0.479	-2.627	-16.75
	(0.260)	(0.103)	(5.984)	(2.114)
Whether mother watched with other adults	0.0879	0.0941	1.503	1.759
	(0.0649)	(0.0661)	(1.817)	(1.860)
Whether the hygiene cartoons were mother's favorite	0.147	na	-0.0105	na
	(0.0785)	na	(2.400)	na
Whether the hygiene cartoons were child's favorite	0.0430	0.0510	3.990	4.199
	(0.0582)	(0.0632)	(2.377)	(2.473)
Control mean of outcome	0.59	0.59	8.195	8.222
	(0.380)	(0.377)	(11.207)	(11.268)
Observations	264	164	264	164

Notes: Sample is of treated households over multiple rounds, observed between April 19, 2017 and November 9, 2017. Columns 2 and 4 restricts sample to those treated households in which the respondent (mother) did not report the hygiene cartoon as one of her favorite pieces. Controls not shown include respondent's literacy, years of education, religion, age at marriage, age at survey, whether she washes with soap at baseline, the number of rooms in the home, and whether the home has a latrine on the premises. All regressions include fixed effects for the survey round and standard errors are clustered at the household level. *** p<0.01, ** p<0.05, * p<0.1

Table A4: Machine learning algorithms comparison

Algorithm and Sampling		Hyperparameters		Training Accuracy	Testing Accuracy
Regression		α	λ		
	Lasso	1.00	0.00	71.61%	59.00%
	Elastic Net	0.85	0.01	74.01%	61.90%
Random Forest		Mtry			
		7.68		72.76%	53.40%

Notes: The λ is the penalty coefficient, or the degree of bias introduced into the ordinary least square regression to counter overfitting; α=1 signifies a LASSO regression. M is number of variables randomly sampled at each split. Both training and testing accuracy are highest for the elastic net algorithm.

Table A5: Descriptives and balance for pure control group

		Pure control mean	Dispenser treatment mean	t-statistic	N
Household	Education of household head	4.500	4.643	0.266	186
	Electricity	0.688	0.6369	-0.548	186
	Sanitary latrine	0.250	0.136	-1.615	186
Hygiene practice	Wash only with water	0.688	0.799	1.380	186
	Wash with ash	0.303	0.186	-1.511	194
	Wash with soap	0	0.00621	0.452	194
Entertainment	Videos on mobile primary source of entertainment	0.970	0.224	-10.06	194

Notes: Table reports the t-statistic and number of observations in a comparison of means between treated and control groups for the subsamples followed up in each specified data source, using data from the baseline survey. Selection of variables is smaller than previous balance tables as we conducted a significantly shorter survey among 'pure control' groups, who were more vulnerable to survey fatigue given that they did not receive any intervention from the research team.

Table A6: Other sanitation and hygiene actions

	(1)	(2)	(3)	(4)	(5)	(6)
	Filters water		Open defecates		Has latrine	
Treated	0	0.000436	0	0	-0.00710	-0.00809
	(0.00811)	(0.00911)	(0)	(0)	(0.00711)	(0.00820)
Control mean	0.024		0.012		0.970	
	(0.154)		(0.109)		(0.171)	
With controls		X		X		X
Observations	287	287	286	286	287	287

Notes: Standard errors are in parentheses. All regressions include the baseline value of the outcome as a control. Additional controls are mother's age, age at marriage, literacy level, whether she completed primary education, whether she owns the home, the number of rooms in the home, whether the house has electricity, and respondent religion. Corrected q-values using Anderson (2008). *** p<0.01, ** p<0.05, * p<0.1

A.1.2 Figures

Figure A1: SD card and mobile phone entertainment

Notes: Top two figures depict a typical street stall from which SD cards with preloaded entertainment are rented or purchased. Bottom figure depicts a family watching the entertainment through the SD card on the distributed mobile phone together.

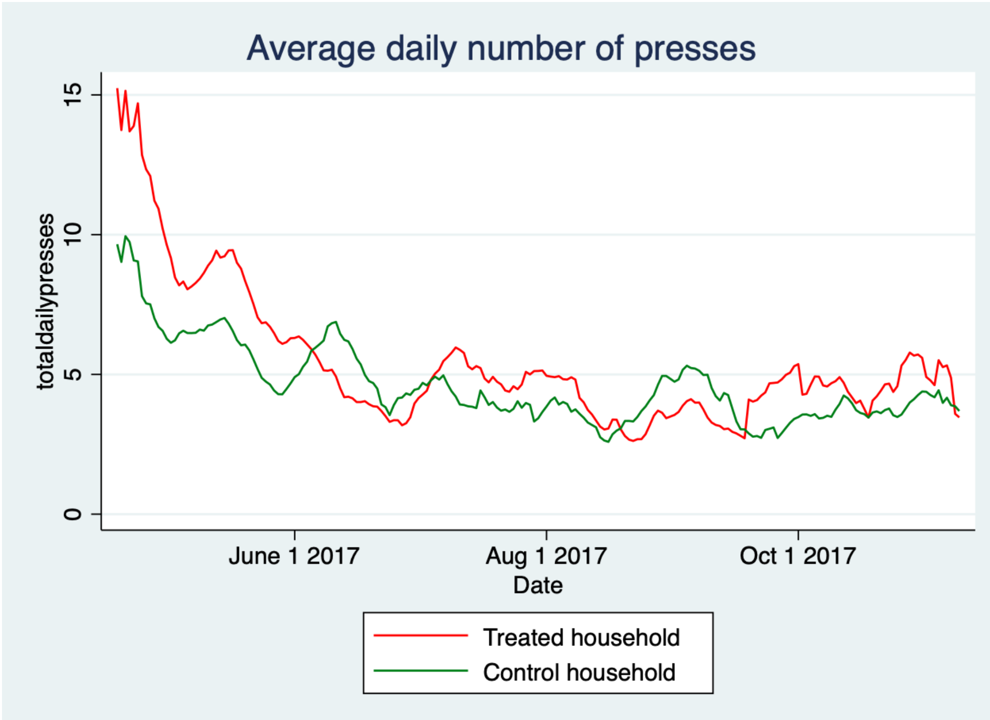
Figure A2: Soap dispenser anatomy

Notes: The dispenser is a standard wall mounted handsoap dispenser with a foaming pump. It is opened with a special key available only to the surveyors. The sensor module is secured inside between the pump and the liter container.

Figure A3: Child using dispenser

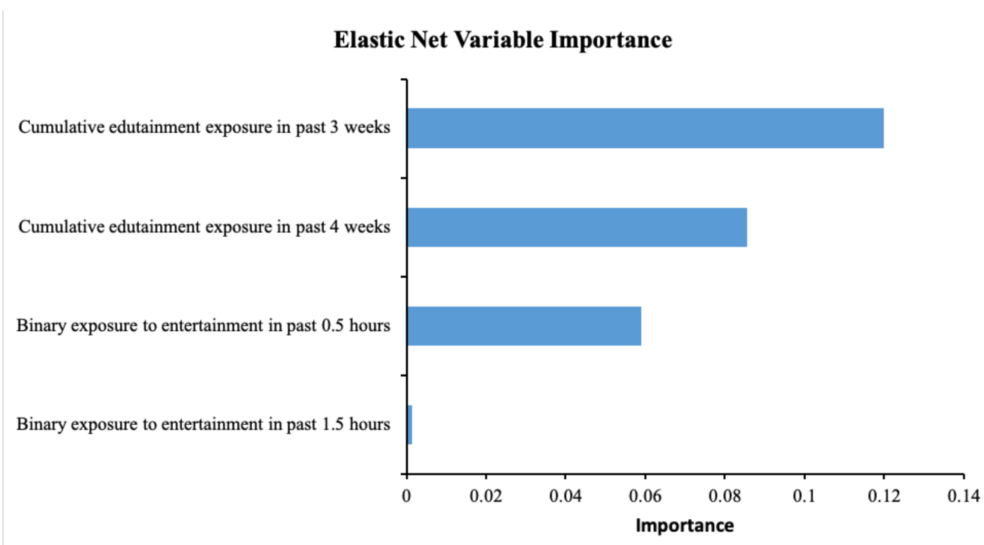
Notes: A child uses the dispenser by pushing the black button once or twice. The foaming soap can be rubbed on the hands without water. He then goes to the nearby water pail or tubewell in the courtyard and rinses the soap off with the help of the mother, who pours the water.

Figure A4: Dispenser use



Notes: Figure shows the average number of individual presses per day over the course of the eight months that sensor data was collected. Green line represents control households and red line represents households who received the edutainment intervention.

Figure A5: Elastic Net Feature Selection



Notes: Figure shows the top four temporal features in order of importance selected by the elastic net algorithm. All 46 remaining features exhibited importance levels below that of 'binary exposure to entertainment in past 1.5 hours.'

A.2 Variable Construction for Machine Learning Exercise

We employ a binary rather than continuous measure of dispenser presses to define handwashing behavior. Our exercise is therefore transformed into one of classification of household-mealtimes into 'washing' or 'non-washing.'

We then collapse our data into two mealtime ranges, which generates a relatively balanced panel. We choose to collapse rather than preserve the original minute-level data as the latter would yield an unbalanced panel in which the vast majority of observations (household-minutes) are 'non-washing' observations, making any machine learning algorithm we employ appear highly predictive yet uninformative by classifying all observations as 'non-washing'. [8]

While handwashing during mealtimes was not the only focus of the edutainment intervention, our sensor data demonstrate that households are most likely to use the handsoap dispenser during the morning breakfast hours (6-11 am) and the evening dinner hours (5-11 pm). As such, we identify the peak handwashing time within each range for each household per day and define the household-day-specific mealtime range as the peak half hour plus and minus an hour (eg. an 8 pm peak implies a dinnertime range of 7 pm to 9 pm). For household-days with no presses (and therefore no peak times), we assign default mealtimes of 7 am and 8 pm, the peak washing times across all households and all days.

Finally, we define a broad set of temporal variables related to information campaign exposure that we generate from second-level data around when and for how long households were exposed to both the edutainment and the entertainment programs on their phones each day. The complete list of temporal features can be provided upon request: fifty features were included. These temporal features range from the cumulative number of minutes the household was exposed to the media in the twelve, eleven, ten, etc. weeks prior to the given mealtime observation, to a binary measure of whether the household was exposed in the half hour prior to the mealtime observation, and defines these measures of exposure separately for the edutainment campaign and the entertainment shows and dramas.

Feature selection proceeds as follows. We randomly subset 80% of treated households into a training dataset and the remaining 20% into the test dataset. A cross-validation exercise then reduces the likelihood of over- or under-fitting the data during the learning process; for this, we choose to employ a holdout cross-validation technique with time slices rather than the more common K-fold cross-validation technique because of the time-series nature of our data: a random splitting of data into K-folds would lead to situations in which future data was used to predict the past (Norberg (2016)). The holdout method instead allows us to divide the training dataset into several month-long folds; we then iteratively train the data on month N-3, N-2, and N-1 and test the resulting model on month N (results are robust to a two month training window as well). We follow this feature selection process using three algorithms: LASSO, elastic net, and random forest.[9]

[8] Because the sample is still not perfectly balanced, we also do a robustness check using the Synthetic Minority Oversampling technique (SMOTE) (Chawla et al. (2002)); we find that this technique produces no change in model accuracy nor the resulting selected features, suggesting that our model is not biased towards the majority class (of 'non-washers').

[9] While the hyperparameters are [by definition] fixed in the LASSO model, we identify the hyperparameters with a random search for the optimal model for the elastic net and random forest algorithms (Bergstra and Bengio (2012)).