Texting and Sexual Health: Experimental Evidence from an Information Intervention in Kenya

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ABSTRACT

While text-messaging is an efficacious method of disseminating health information in developing contexts, we know less about how users adapt their behavior based on that information. Does it matter how the information is conveyed? This paper presents findings from a randomized field experiment that evaluates the impact of a Short Message Service (SMS) sexual health counseling service on individuals' knowledge and behavior in an urban informal settlement of Nairobi, Kenya. Subjects were randomly assigned to one of three treatment conditions which tested different mechanisms through which technology-enabled information provision could work to alter sexual behavior: (1) information gap reduction, (2) personalization and (3) social cues. The evidence suggests that personalizing the information and providing signals about how other people in the community are behaving can dramatically minimize sexual health risk, compared to simply reducing the information gap. Additionally, individuals receiving generic, non-personalized health information were more likely to engage in risky behavior compared to their counterparts.

Categories and Subject Descriptors

[**Law, Social and Behavioral Sciences**]: Psychology, Sociology; [**Life and Medical Sciences**]: Health informatics; [**Human-Centered Computing**]: Ubiquitous and mobile computing, Accessibility

General Terms

Measurement, Experimentation, Human Factors, Theory.

Keywords

Sexual health, HIV/AIDS, behavior, Short Message Service, mHealth, information access, information provision, personalization, field experiment, randomized control trial.

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1. INTRODUCTION

Mathare is one of the largest and oldest urban informal settlements in Nairobi, Kenya. Home to an estimated 500,000-700,000 people living in shanties, Mathare suffers from high rates of poverty and lack of access to basic services. A first visitor to Mathare will be struck, however, by something else: the ubiquity of mobile phone charging stations with colorful hand-painted signs. With over 30 million mobile phone subscribers in Kenya and one billion text messages exchanged every three months [10], texting rates have dropped dramatically in recent years. Sending a text could cost as little as one Kenyan shilling, approximately 1.2 U.S. cents. For a vast majority of men and women in Mathare, using a mobile phone is very much part of daily life.

This is the key insight that some NGO workers are capitalizing on. Since 2011, health counselors in Mathare have been piloting a text-messaging counseling service called Nishauri. When a user texts a question about HIV/AIDS, safe sex, and other matters related to sexual and reproductive health to the advertised number, the message is forwarded to a counselor, who then returns a response to the user's mobile phone.

Innovative applications of new information and communication technologies (ICT) are hardly novel or unique to Kenya. The role of ICTs – in particular mobile technology – in the developing world draws increasing attention from academics and practitioners alike. In the area of health, successful interventions include those that monitor disease outbreaks, streamline diagnoses and support information-sharing among health workers [2, 29]. Some mobile health (or mHealth) projects send out text message reminders for appointments or adherence to treatment regimens; yet others push content *en masse* to encourage HIV screening [43].

Despite the rapidly growing number of mHealth initiatives, we know less about how users adapt their behavior based on information obtained through such interventions. Does it matter *how* the information is delivered? Under what conditions is ICT-enabled information provision effective at improving knowledge about sexual health and promoting less risky behavior?

This paper presents findings from a randomized field experiment that evaluates the impact of a Short Message Service (SMS) sexual health counseling service on individuals' knowledge and behavior in Mathare. Subjects were randomly assigned to one of three treatment conditions which tested different mechanisms through which technology-enabled information provision could work to alter behavior: information gap reduction, personalization, and social cues. The evidence suggests that personalizing the information and providing signals about how other people in the community are behaving can dramatically minimize sexual health risk, compared to access to technical information alone. This finding suggests that facilitating access to information is not, on its own, sufficient to induce changes in behavior. There were no improvements in the level of knowledge about sexual health regardless of the treatment condition. However, those receiving non-personalized health information were not only more likely to engage in risky behavior compared to the pure control and other treatment groups, they also sought out additional sexual partners.

This study joins a rapidly growing literature on the connections between ICT and health by providing new micro-level evidence of how the way in which information is delivered can affect sexual behavior. The rest of the paper is organized as follows. Section 2 highlights relevant findings from an interdisciplinary literature and describes the theoretical motivation for the study. Section 3 describes the research design, followed by a description of the data and results in Sections 4 and 5. I conclude by discussing the findings and potential policy implications in Section 6.

2. THEORETICAL FRAMEWORK

There is broad consensus that new ICTs are dramatically transforming the ways in which individuals access information in developing contexts. Yet empirical findings from studies of mHealth interventions have been mixed. While text-messaging offers an efficacious, cost-effective [7] way of disseminating health information, there are still few stylistic facts about how users respond to — and act on — that information.[1] Drawing on existing interdisciplinary research, I identify three potential mechanisms through which ICT-enabled information provision might influence health-related behavior: (1) information gap reduction, (2) personalization and (3) social cues. In this section, I discuss each of these to theoretically motivate the research design.

2.1 Information Gap Reduction

One of the most robust findings in the ICT literature is that ICTs are effective at solving problems of information asymmetry and coordination (e.g. [1, 14, 19, 22]). Mobile phone adoption among fishermen and wholesalers in Kerala, India, for instance, allowed them to access real-time market information about pricing and location of other vendors. This led to an almost complete elimination of waste, increasing welfare for both consumers and producers [22]. Similarly, the introduction of cell phone towers in Niger dramatically reduced price dispersion across grain markets [1]. The underlying mechanism in both cases was the unique role that mobile technology played in reducing traders' search costs, thereby altering their behavior in the market. ICT, here, reduced the information gap by supplying individuals who need time-sensitive information with existing information elsewhere.

Is the problem of risky sexual behavior a problem of an information gap? If individuals are engaging in risky behavior *only* for want of reliable information—about, say, how to use a condom or the consequences of unprotected sex—then disseminating that information should prompt them to alter their behavior. Indeed, recent health studies show that access to information about health risk and specific preventative measures can significantly improve behavioral outcomes [13]. In an HIV/AIDS education intervention in Kenyan schools, providing information (in the traditional way, person-to-person) about the relative risk of HIV infection by partner's age led to a decrease in early pregnancy as well as substitution away from riskier partners [12].

Many mHealth interventions seem to belong to the information gap reduction category: they disseminate crucial health information about the importance of particular treatment regimens, where to receive medical tests, and so on. But their impact on behavior is ambiguous, in part because there are still relatively few empirically rigorous studies conducted in developing contexts. Consider SMS reminders, a common mHealth intervention encouraging patients to keep medical appointments, receive tests, or adhere to a particular treatment regimen. They also typically emphasize the benefits of receiving care or the significant costs to the patient of forgoing such care. SMS reminders had a positive effect on adherence to antimalarial treatment in Ghana [16, 36] and modest positive effects on antiretroviral treatment adherence in rural Kenya [27, 35]. On the other hand, in a randomized control trial of an information intervention in Uganda, passive, "content-push" type counseling on sexual and reproductive health for married couples not only failed to curb risky behavior, it seemed to prompt more risk-taking among males [21]. Implicit in many of these studies is that particular features of the information is doing the work, rather than the substantive content or the access itself. Weekly reminders, for instance, appear to be more effective than frequent ones [35], while adding content to the text message about a treatment had no significant effects on behavior [36].

Taken together, these recent findings may suggest that access to health information alone, while important, may not be sufficient to promote changes in behavior. One possible explanation for this is that individuals discount the future costs of today's risky behavior. A desire to engage in activities which grant immediate benefits but are costly later on might lead you today to indulge in unprotected sex or to avoid long lines at the clinic. When tomorrow comes, the immediate benefits are looking pretty good again (and there will always be tomorrow). In this way, undesirable habits could be maintained even when you are equipped with reliable information about their consequences.[2] Thus, in addition to simply reducing the information gap, other conditions may be required for individuals to alter their behavior based on that information.

2.2 Personalization

A second potential mechanism through which technology-enabled information provision could affect behavior is the personalization of the information that is being disseminated. As Noveck writes of e-Government, if the information is packaged right, it is also more intelligible to individuals and can transform them from passive consumers to active users [34].

Political science scholarship, while not specifically focused on the use of new ICT, offers evidence that personalization matters. Get-out-the-vote experiments conducted in the United States show that personalized messages delivered in ways that approximate person-to-person interaction can be just as effective as traditional canvassing methods [3, 4], while impersonal information campaigns consistently fail to mobilize voters [32, 37, 38]. That the messages are delivered in a personal manner appears to be

[1] Recent reviews of mHealth projects, e.g. [9, 17, 23, 29, 42].

[2] A rich literature in behavioral economics engages with problems of such intertemporal choices related to health, e.g. [13, 28, 41].

more important than the policy content itself [33] or the particular medium through which the information is conveyed (phone calls, e-mail, door-to-door).

In the area of health a recent review of mHealth studies suggests that text-messaging may be most effective when the message is personally tailored to the recipient [42]. One possible reason is that personalization not only makes the information more accessible, but also forges a two-way relationship between receiver and provider. In a study of loan repayment SMS reminders in the Philippines, messages improved repayment only when they were personalized by including the loan officer's name [25]. The authors suggest that personalization may have fostered feelings of personal obligation or reciprocity, thereby improving borrowers' behavior.

2.3 Social Cues

Social cues are a third potential mechanism. Users may be more likely to act on information if it also contains social cues that signal how their peers or others in the immediate community are behaving. Importantly, these "others" need not be known to you or be able to sanction you for non-conforming behavior.

This psychological mechanism has been demonstrated in a wide range of public policy areas, from tax compliance [5] to drug use [26], and even the habits of hotel guests of reusing hotel towels [18]. In the same way that tax compliance can be improved by informing citizens that most other people in their neighborhood have already paid their taxes, encouraging hotel guests to reuse their towels was most effective when they shared information that others in the hotel were reusing, rather than messages emphasizing energy conservation and the environment.

The health psychology literature documents how peer group membership can influence sexual behavior, especially among young people [11, 39]. In Uganda and Botswana, safe-sex education programs were more effective when they established a collective narrative, rather than appeals to individual self-interest alone [40]. Simply put, if you're told that other people (especially people you think are like you) are doing something, you're more likely to do it too. It is plausible that group identification along community lines affects the way in which information is perceived and used, even when that information is channeled through a mobile platform.

2.4 Predictions

The field experiment is designed to test the three potential mechanisms of information gap reduction, personalization and social cues. First, easing access to health information is expected to improve individuals' knowledge about sexual and reproductive health, regardless of the way in which the information is delivered. However, given that people may be heavily discounting the future costs of today's risky habits, there is reason to suspect that access to reliable information on its own will not be sufficient to induce changes in day-to-day sexual behavior. Instead, I expect that personalizing the information will be more efficacious than impersonal information in moving individuals away from risky behavior. Finally, I expect that social cues will have an additional positive impact.

3. RESEARCH DESIGN

A field experiment was conducted September 2012-February 2014 in Mathare to identify the impact of a SMS-based sexual health counseling service. Survey data was collected pre- and post-intervention. Subjects were debriefed after completion and participated in open-ended interviews about the perceived usefulness of the counseling service.

3.1 Context

There are high rates of early pregnancy and sexually transmitted diseases (STDs) in Mathare. While the urban prevalence rate for HIV in Kenya was 17-18\% in 2006, the rate in Mathare was estimated to be closer to 25-30% [30].

Aside from the high level of SMS literacy in the community, there are several *a priori* reasons to test a SMS intervention here. First, existing channels of health information can be costly for the average adult in Mathare, who earns approximately $3 a day. While it is possible to obtain confidential sexual health advice for little or no charge at a government-run clinic or voluntary counseling and testing (VCT) site, work hours lost to traveling there and waiting in long lines could amount to significant forgone earnings in the short term—a tradeoff many are unwilling to make. In theory, the same information could be received for a shilling to send an SMS.

Second, some populations do not always enjoy effective access to communication channels for other reasons. Health counselors in Mathare suggest that the potential sources of problems related to STDs in the community are not simply the lack of access to reliable information about sexual behavior and its consequences, but possibly also social stigmas associated with openly seeking information about sex.[3] Entrenched community norms or gender norms associated with decision-making in the household have been found to keep some groups, in particular women, from accessing information about sexual and reproductive health in developing contexts [24, 31]. Users may therefore find the private aspect of SMS appealing. To borrow Burrell's (2010) words, the mobile phone "can keep… secrets" [6, p.240].

Finally, the anonymity of SMS dissolves visible differences. In face-to-face sexual health counseling, older men are typically hesitant to speak to younger female health counselors, and the reverse is also true.[4] SMS ensures that gender and age differences do not hamper the communication of important information. For all of these reasons, an SMS platform was considered eminently appropriate, over alternatives such as voice-messaging.

3.2 Dependent Variables

The two key dependent variables are (1) knowledge about sexual and reproductive health, and (2) behavior associated with varying levels of risk. The measure for knowledge is a composite score constructed from a series of close-ended questions that test the subject's factual knowledge. Questions were adapted from Cleland, et al.'s (2001) survey instrument designed to test sexual health knowledge among young people [8].

Three self-reported measures are used to capture behavior.[5] These include the number of different sexual partners the subject had in

[3] Based on qualitative interviews conducted in Mathare, 2012.

[4] Based on qualitative interviews conducted in Mathare, 2012.

[5] Self-reported measures are not always reliable for sexual behavior [5]. In order to solicit as much honesty as possible, the survey contained questions both about the subject herself and about how the subject perceived "others like her" behaved. Direct

the past month, and the regularity of use of protection and contraceptives, recorded as "never," "sometimes," and "always." A third measure asked the subject to recall the last time she had sexual intercourse and to report what type of protection was used, if any. This measure acts as a consistency check for the regularity measure.

Data was also collected on auxiliary outcomes. This included the number of self-reported visits over the past 12 months to a doctor or local health facility to either screen for sexually transmitted infections and diseases, or to receive additional information and advice related to sexual and reproductive health.

3.3 Experimental Design

Randomization occurs at two levels. Subjects are first randomly assigned to either get the short code for a sexual counseling service, or not. The group that does not get the short code is the *pure control*. Those who receive the short code are invited to use the service by texting a question to the dedicated number. A subject self-selects into using the service by submitting her first question to the number (this counts as compliance). At that time, the complier is randomly assigned to one of three treatment conditions: *generic* counseling, *personalized* counseling, or personalized counseling with an additional *social cue* (Table 1).

Table 1. Treatment conditions.

Code	Intervention	Description
No	Pure control	Surveys only
Yes	Generic	Automated response
Yes	Personalized	Counselor response
Yes	Personalized + social cue	Counselor response + cue

The *generic* group receives a response that contains non-personalized, generic information about sexual health. These responses were generated through an automated system using Google SMS Health Tips. The system flags keywords and phrases to generate responses, even if the text is written in so-called "text-speak."[6] The response is generic in the sense that the same information would be available at any ordinary health facility.

The *personalized* group receives responses from human community health counselors. If a subject submitted a question in text-speak, the counselor also responded in text-speak. In this way, the messages are tailored to the user-submitted questions.

Finally, the *social cue* group receives the personalized response from counselors as in the previous condition, but each response contains the following additional text: "Thank you! You have joined hundreds of other people in the community you are using Nishauri [name of the service] to improve their health!"[7] The additional piece of information is intended as a subtle signal that other people around you — people of *your* community specifically — are actively consuming this information and adapting their behavior accordingly.

3.4 Observable Implications

If the information gap is the principal reason for which people are behaving in risky ways, then we expect to see no significant difference between the mean outcomes of the *generic* and *personalized* groups. However, my prediction is that this would not be the case. The theory predicts better outcomes for subjects in the *personalized* group, compared to those receiving *generic* information. This can be observed with a simple difference-in-differences approach.

The identification strategy requires that the *generic* treatment approximate vacuous information that could be found in normal places if one wanted to obtain that information, for whatever reason. By contrast, the *personalized* condition aims to mimic a face-to-face interaction with a health counselor. Therefore, even if it were the case that individuals who were more forward-looking or simply "on top of things" were self-selecting into using the service, the additional randomization allows causal estimation of the effect of personalized information provision as distinct from effects driven by otherwise unobserved native characteristics about those individuals. In sum, any differences observed between pre-post differences in the *generic* and *personalized* groups can be attributed to personalization.

The additional impact of the social cue may also be observed by comparing the means in pre-post differences subjects in the *social cue* group and the *personalized* group. The theory predicts that cuing subjects on how others in the community are behaving will have an additional positive impact on knowledge and behavior.

4. DATA

4.1 Subject Pool

The subject pool consists of randomly selected individuals aged 18 and up in Mathare, with regular access to mobile phones. 939 potential subjects from the 13 sub-villages in Mathare were recruited for the baseline survey in September 2012, and 884 agreed to participate in the study. Enumerators explained to subjects that they were conducting a health survey in the neighborhood and were gauging interest for participation, but they did not disclose information about the mobile technology treatment.

The information interventions continued until the endline survey in Jan 2014. There were 821 subjects in the endline data (92%), with 166 in the pure control group and 655 treated subjects (175 *generic*, 241 *personalized*, and 185 *social cue* subjects). All but 51 out of the original 684 that were assigned to treatment texted into the service. The attrition rate was exceptionally small (8%) and balanced across groups and covariates.

4.2 Demographics

Table 2 presents summary statistics for standard demographic variables. 49% of the subjects were male, and the mean age in the full sample was 26. Over half of the subjects had completed secondary school. The mean weekly income was 1801 Kenyan shillings, or roughly $20. Finally, 88% in the full sample owned the phone they used regularly. Covariates had good balance across groups.

behavioral or biological measures are ideal for data analysis, but would also have been more invasive.

[6] Based on focus group discussions with peer health counselors in the community, the automated responses were deemed reliable. The system was Swahili and English compatible.

[7] The message was crafted based on focus group discussions with peer health counselors and users who participated in a pilot.

Table 2. Summary statistics on demographic variables.

	n	mean	med	min	max	se
Gender						
full sample	821	0.49	0	0	1	0.02
control	166	0.49	0	0	1	0.04
generic	175	0.50	1	0	1	0.04
personalized	241	0.49	0	0	1	0.03
social cue	185	0.49	0	0	1	0.04
Age						
full sample	814	26.29	24	18	80	0.27
control	166	27.74	26	18	65	0.66
generic	175	25.11	24	18	47	0.45
personalized	238	26.04	24	18	56	0.52
social cue	181	25.66	24	18	80	0.58
Secondary schooling						
full sample	816	0.58	1	0	1	0.02
control	165	0.54	1	0	1	0.04
generic	175	0.59	1	0	1	0.04
personalized	241	0.62	1	0	1	0.03
social cue	183	0.55	1	0	1	0.04
Weekly income						
full sample	776	1801	1400	0	25000	70
control	158	1756	1500	0	7000	121
generic	165	1823	1200	0	15000	183
personalized	231	1911	1400	0	25000	147
social cue	169	1779	1400	0	10000	109
Married						
full sample	821	0.43	0	0	1	0.02
control	166	0.46	0	0	1	0.04
generic	175	0.38	0	0	1	0.04
personalized	241	0.44	0	0	1	0.03
social cue	185	0.44	0	0	1	0.04
Catholic						
full sample	802	0.43	0	0	1	0.02
control	162	0.41	0	0	1	0.04
generic	174	0.47	0	0	1	0.04
personalized	236	0.42	0	0	1	0.03
social cue	177	0.45	0	0	1	0.04
Phone ownership						
full sample	814	0.88	1	0	1	0.01
control	166	0.93	1	0	1	0.02
generic	173	0.83	1	0	1	0.03
personalized	237	0.84	1	0	1	0.02
social cue	184	0.90	1	0	1	0.02

5. RESULTS

5.1 Knowledge

In the pre-intervention stage, subjects answered on average 66.3% of the knowledge questions correctly. The mode was 73% of questions correctly answered. A separate question asked if subjects knew confidently how to use a condom. 76% of subjects responded they knew with confidence; 24% did not know.

Table 3 presents statistics on changes between baseline and endline in the knowledge composite scores and in knowledge of condom use, by group. The intervention did not produce statistically significant improvements in knowledge, regardless of treatment type. Similar results were obtained when subjects were asked at the endline if they knew how to use a condom properly. There were very slight improvements across the board, and the proportion of subjects in the full sample who didn't know how to use a condom had dropped from 24% to 17% by the endline, but these improvements were not statistically significant. (The one exception is the *social cue* group, which had a 0.1 unit increase on the proportion of those who knew how to use a condom properly. However, within-subject pre-post differences were not significantly different from those of other treated groups.) In sum, there were no substantive differences between the baseline and endline in the knowledge of factual information about sexual health.

Table 3. Changes in knowledge.

	n	mean	sd	med	min	max	Se
Knowledge score (0 – 10 scale)							
control	166	0.06	1.68	0	-6	5	0.13
generic	175	-0.17	2.67	0	-9	8	0.20
personalized	241	0.04	2.48	0	-8	9	0.16
social	185	-0.08	2.60	0	-10	9	0.19
Confident knowledge of condom use (binary)							
control	166	0.06	0.50	0	-1	1	0.04
generic	175	0.03	0.53	0	-1	1	0.04
personalized	241	0.02	0.53	0	-1	1	0.03
social	185	0.10	0.56	0	-1	1	0.04

5.2 Behavior

The results for the behavioral variables provide support for both the personalization and social cue hypotheses. Both personalized counseling and counseling with the added social cue had significant positive effects on measures of protection—both the regularity of use, and whether the subject used protection the last time she had sex. However, *generic* subjects were not only less likely to be using protection than other treated subjects, they were even less likely than the pure control (who did not receive the service number). Additionally, there is suggestive evidence that those assigned to treatment sought out additional sexual partners.

5.2.1 Protection

Figure 1 (left panel) shows within-subject movement on the regularity measure, decomposed by treatment condition and pre-treatment response. Of those *generic* subjects who had responded at the baseline that they "never" used protection, just 30% remained in the "never" category at the endline. For the *personalized* and *social cue* groups, the never-users were down to 20% and under 7% respectively at the endline. 79% and 87% of never-users assigned respectively to *personalized* and *social cue* groups became always-users at the endline. These two treatment types consistently fared better at minimizing never-users. (The frequency of messaging did not seem to matter; the mean number of interactions with the service was 13.96 in the full sample, and group means did not statistically differ from one another.)

An ordered logistic regression model, with regularity as the outcome with three levels ("never," "sometimes", "always"), confirms patterns in the descriptive data. Table 4 summarizes the results, including the proportional odds ratios for each group and 95% confidence intervals. The odds of "always" using versus the odds of "sometimes" or "never" using are 1.33 times greater if a subject becomes assigned to *personalized*; 1.60 times greater if *social cues*. By contrast, moving into the *generic* category diminishes the odds of "always" or "sometimes" using against the odds of "never" using.

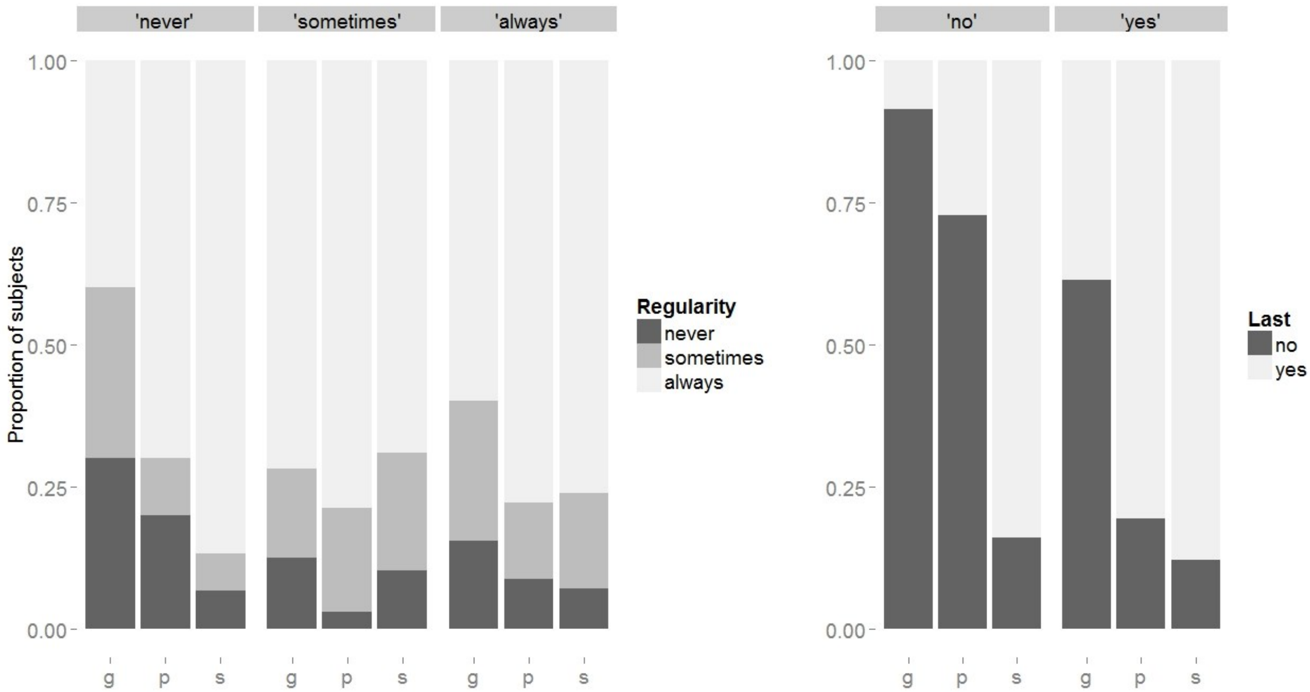

Figure 1. Mapping within-subject movement on regularity (left panel) and protection use the last time (right panel). Post-treatment outcome is expressed as proportions, decomposed by treatment group (bottom labels) and pre-treatment responses (top labels).

Table 4. Ordered logit with regularity as outcome.

	value	se	p-value	OR	2.5%	97.5%
generic	-0.33	0.23	0.0143	0.72	0.46	1.12
personalized	0.29	0.23	0.0207	1.33	0.85	2.09
social	0.47	0.25	0.0062	1.60	0.98	2.66

Figure 1 (right panel) shows that similar patterns hold for the alternative measure of protection, which asked a subject whether or not she had used protection the last time she engaged in sex. While almost 80% of *generic* subjects at the baseline had reported using protection in the previous sexual encounter, the percentage was down to 33% at the endline. Of the *generic* subjects who had not used protection at the baseline, 91% remained in the no protection category at the endline. This was 72% for *personalized* subjects. In stark contrast, 84% of *social cue* subjects whose pre-treatment response was no protection moved into the protection use category by the baseline. Troublingly, 61% of *generic* subjects who had reported using protection at the time of the baseline had moved into the no protection category after the intervention.

Table 5 shows results from difference-in-differences estimation (estimated difference in pre-post differences in protection use during the last sexual encounter between groups B and A). *Generic* subjects were consistently much less likely to have used protection than subjects who received personalized information and social cues. The difference in pre-post differences between the *personalized* and *generic* groups was almost 0.37. The *social cue* group not only had a 0.95 unit advantage over the *generic* group, it also fared much better than the *personalized* group.

Note that the difference-in-difference estimate for the *generic* and *control* groups is -0.47, suggesting that the generic group was faring even worse than the pure control, whose pre-post differences were statistically zero. While personalized information did not seem have a statistically significant advantage over no information, social cues had a positive difference of 0.49.

Table 5. Difference-in-differences of protection use last time.

B / *A*	Generic	Personalized	Social Cue
Control	-0.469* [-.590, -.347]	-0.095 [-.194, .003]	0.492* [.367, .617]
Generic		0.369* [.280, .459]	0.951* [.835, 1]
Personalized			0.568* [.474, .662]

**Statistically significant at p-value <0.05. 95% confidence intervals in brackets. Measure is binary, 1 if subject used protection, 0 if not.*

5.2.2 Sexual Partners

There is suggestive evidence that treated subjects, in particular the generic group, sought out additional sexual partners. Table 6 shows estimates of difference-in-differences for the reported number of sexual partners in the previous month.

Table 6. Difference-in-differences of sexual partners.

B / *A*	Generic	Personalized	Social Cue
Control	0.619* [.331, .907]	0.196 [-.056, .447]	0.350* [0.093, 0.607]
Generic		-0.574* [-.817, -.332]	-0.553* [-.822, -.284]
Personalized			0.044 [-.151, .239]

**Statistically significant at p-value <0.05. 95% confidence intervals in brackets. Measure is reported number of sexual partners in the previous month.*

As a group, *generic* subjects had a 0.89 unit increase in partners from the baseline. Since subjects reported the number of partners from a short period of time (one month), this jump is nontrivial. The pre-post differences for the *personalized* and *social cue* groups were respectively 0.57 and 0.55 units higher than pre-post differences in the *generic* group. The mean of the differences among *generic* subjects was almost 0.62 units higher than that of control subjects, whose movement on the measure was statistically zero.

The *personalized* and *social cue* groups also saw a modest increase in the number of partners since the baseline but the pre-post differences on their own were statistically insignificant. It is only the *generic* category that had a decidedly positive jump compared to the other treated groups. Moreover, it was not the case that subjects in the *generic* category were having more sex. There was no statistically significant change in the number of sexual encounters between baseline and endline, and this was true for all of the groups. Nor were there significant shifts in marital status for any of the groups.

5.2.3 Auxiliary outcomes

The interventions did not have statistically significant effects on the number of visits to a doctor or local clinic to receive screenings, advice or treatment.

6. DISCUSSION

6.1 Changes in Knowledge and Behavior

The intervention did not produce any statistically significant improvements in knowledge of factual information about sexual health, regardless of the treatment condition. It may be the case that subjects learned something new occasionally or sporadically, but there was no evidence of retaining new knowledge in the long term. This result may be a consequence of the fact that subjects already had an adequate baseline understanding of sexual health.

While there were no significant improvements in knowledge, the results indicate positive behavioral changes for the personalization and social cue groups. Relative to providing generic information, personalizing the messages and providing social cues had significant effects on easily actionable forms of risk minimization: greater regularity of protection use and protection use in the previous sexual encounter. These interventions, however, did not affect behavior on more costly actions, such as visiting a doctor or a clinic to screen for STDs or receive advice.

A crucial point is that the way in which the information is delivered can make a significant difference. A social cue—even a very subtle one—could wield a substantial impact on behavior. In this case, the observed behavioral changes did not require great tradeoffs in time. Further research would be required to understand how social cues work to nudge people on some forms of behavior and not others. Whether changing the content or strength of the social cue variably alters sexual behavior is another interesting open question.

The results also indicate unintended, and arguably quite worrisome, effects of simply reducing the information gap. Not only were subjects in the *generic* information group using less protection than other treated subjects, they used less protection that the pure control after the intervention. There was also suggestive evidence that the intervention either directly or indirectly led individuals to seek more sexual partners.

What should we make of this "more partners effect"? The results hold for an alternative post-hoc intent-to-treat analysis (not reported here), suggesting that it was not the case that only individuals who were contemplating adding sexual partners self-selected into receiving treatment. There may be something distinctive about being given the short code on its own that makes people behave differently. This view is consistent with the observation that all treatment groups, when compared to the pure control, exhibit a positive "more partners effect." Difference-in-differences estimation among the three treatment conditions suggests that there is, additionally, something distinctive about given non-personalized information about sexual health that is driving people to add sexual partners.

With the given data it is difficult to establish definitively why we observe the "more partners effect," but it is worth discussing possible explanations. The first is that the factual information confers a (false) sense of security, leading individuals to adopt more risk-taking behavior. (False, since the *generic* subjects were also those using less protection compared with all other groups.) A second possible explanation is what Jamison, et al. (2013) call "sexual sorting" [21]. In qualitative interviews they conducted in Uganda, the authors find that married women who learned more about the relative risks associated with having multiple sexual partners insisted that their husbands be faithful and that they go get tested together. When the husbands did not comply, the wives would deny them sex, and the husbands would go and seek sex with other partners. Nonetheless, it is not obvious why the generic information in particular would lead to sexual sorting.

Yet another explanation is that the increased number of sexual partners has less to do with individuals behaving differently in their sex lives, than with individuals answering the question differently in the endline survey. For instance, their self-reporting may be more accurate or exaggerated. While the data presented here cannot distinguish whether the *generic* group is answering or behaving differently, the puzzle remains: it is not clear what it is specifically about the generic information that affects individuals in either of these ways.

There are at least two separate issues here. The first is that the generic information is non-personalized, which is the distinction the research methodology aims to make. On the other hand, the *generic* subjects may have perceived their messages to contain extraneous information, undermining the subjective quality of the information. Subjective evaluation of the information as low-quality may lead individuals to deliberately ignore the information, and even act counter to it. To be sure, these are preliminary speculations. Understanding how the “more partners effect” operates requires more careful research.

6.2 Validity

One concern is that health counselors differ in the quality of the responses they craft. This did not appear to be a problem, since the implementing NGO spot-checked counselor text messages to ensure quality control. Even if we suppose that one counselor consistently produced low-quality responses, no one counselor was systematically responding to a particular group of subjects; randomization thus mitigates the possibility of bias.

The more serious threat to internal validity is the possibility of spillover effects that violate a key assumption of SUTVA, non-interference. Residents of Mathare live in extremely close quarters with little privacy and interact with their neighbors or neighboring businesses on a daily basis. As a practical matter, it is difficult to monitor whether individuals are sharing stories about their participation in the study. The potential concern is twofold. First, subjects assigned to a particular treatment condition may disclose information about that condition to subjects in another group. Second, subjects who initially received the short code may share it with pure control subjects.[8]

First, it is unlikely that participants willingly shared the detailed content of their interaction with the service, given that the content is of a particularly sensitive and private nature.[9] With regard to the second concern, cross-referencing the mobile phone numbers of the pure control subjects with those logged in the SMS counseling system did not show any pure control subjects having used the service. Even if pure control subjects obtained access to the short code and used the service from different mobile phones than the ones they registered with the enumerators, this should not affect the comparisons among the treatment groups. The observed differences between a particular treatment group and the pure control may be affected, but would be downward-biased.

The experiment was designed to preserve as much mundane realism as possible. It allowed for self-selection and leveraged an existing system of community health counselors. Mathare residents were also highly familiar with SMS, removing the need to introduce subjects to an unfamiliar technology. To buttress confidence in the findings reported here, experiments should be replicated in other urban informal settlements with similar features, within and beyond the Kenyan context.

6.3 Policy Implications

The high prevalence of STDs and other problems related to sexual health are not unique to Mathare. I highlight a few implications for future technology-enabled information interventions in the area of health:

(1) In contexts where there exist substantive barriers to face-to-face interaction with information experts, delivering personalized information through mobile platforms can be an effective alternative. This requires, however, that information experts already exist and that the target population have some level of mobile phone literacy.

(2) When nudging individuals to adopt less risk-taking behavior, personalizing information provision is more efficacious than non-personalized methods.

(3) Social cues that provide information about how most other people in the immediate community are behaving can have an additional impact, possibly by increasing incentives to conform. In this light, it is plausible that the perverse side effects of non-personalized “content push” could be countered if the message is coupled with a strong social component, but further research is required to fully evaluate the workings of social cues.

(4) Thorough manipulation checks are encouraged for both researchers and designers. In the study, various iterations of the social cue message underwent focus group discussions with peer counselors and pilot users. This was to ensure that the message was not only culturally appropriate but also cuing what it was supposed to cue. Despite the cue’s subtlety, its performance was surprisingly good.

(5) Finally, depending on the design of the information intervention, we may unwittingly nudge people in the wrong direction. In order to avoid any potential perverse effects of information provision, careful field-testing is essential. Sharing the results of impact evaluations can also promote meaningful knowledge-building among practitioners and designers.

7. CONCLUSION

This paper presented new experimental evidence from Kenya that the way in which information is delivered through SMS can make a crucial difference when the goal is to elicit changes in health-related behavior. Personalized information and social cues had large and significant advantages over non-personalized information in encouraging less risky sexual behavior.

This study also contributes to the growing literature on mHealth by offering an analytical framework of the specific pathways through which information provision could work to influence (health-related) behavior. The three mechanisms examined in the paper are not necessarily exhaustive, but they do offer new questions for a broader research agenda on technology-enabled information provision, more generally. One extension, for instance, would be to examine whether the same mechanisms of personalization and social cues work to benefit the uptake of other kinds of information, such as educational material targeted at improving literacy.

For the time being, personalization and social cues look promising. A social cue — even a very subtle one — can send a real message, so to speak. Yet perhaps the clearest lesson that emerges is this: the way in which information is conveyed can lead to divergent outcomes, some of which are difficult to foresee or observe. It is imperative that ICT information interventions be evaluated carefully if we are to avoid the potentially harmful effects of an otherwise well-intentioned project.

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[8] A cluster-randomized design at the level of sub-villages may seem the obvious solution, but this too fails to overcome the problem. Aside from there only being 13 sub-villages in Mathare Valley, the sub-villages are typically separated by a single innocuous landmark, such as a narrow dirt path. Most residents do not stay in a single sub-village for both work and residence.

[9] Based on open-ended interviews with participants after the interventions and endline surveys were completed.

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