Engagement with Air Quality Information: Stated Versus Revealed Preferences

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Abstract
Air pollution has a significant impact on health but is often invisible to the naked eye. Real-time air quality information can help people take action to protect their health. However, little is known on how to most effectively frame air quality information to promote public health. We conducted a field experiment to study people's engagement with real-time air quality information provided through a smartphone application (app). We tested 12 different messaging strategies on both *intent to engage* with air quality information (through a survey), and *actual engagement* with air quality information tracked through the app in response to the messaging strategies. Our results, based on 835 survey respondents and 2,740 app users, show that intent to engage and actual engagement differ. Overall, users' demographics were the most important predictor of engagement with messages. This research demonstrates the significance of testing messaging strategies through field experiments rather than through surveys, and the importance of targeted messages.

Keywords
air quality, field experiment, survey, behavioral economics, environmental pollution, information strategies

INTRODUCTION

Currently, more than half of all Americans—166 million people—live in areas that do not meet the national ambient air quality standards, exposing them to elevated levels of air pollution (American Lung Association, 2016). The varied and numerous adverse health effects of air pollution, including asthma and cardiovascular disease, are well-documented through hundreds of research studies (Brunekreef & Holgate, 2002; Curtis, Rea, Smith-Willis, Fenyves, & Pan, 2006; Pope & Dockery, 2006). Besides the human suffering, the associated health care costs are exorbitant; in the United States alone billions are spent annually on air pollution-related illnesses (Centers for Disease Control and Prevention [CDC], 2014; Colls, 2002).

Given the large health burden of air quality, it is not surprising that governments worldwide have developed extensive air quality monitoring and information programs. The underlying objective of these programs is to increase the public's awareness of the state of the air, especially

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with regard to health effects, so that individuals can modify their behavior to protect their health (Ruggieri & Plaia, 2012). Real-time information about air quality enables individuals to adjust their daily activities to protect themselves when air pollution is high. For example, individuals can choose to limit time spent outdoors, reschedule outdoor activities and use air conditioning or air filters (U.S. Environmental Protection Agency, 2014).

While real-time air quality information is readily available from these programs through apps and websites, there is still a limited understanding of how people respond to this information (Mansfield, Reed Johnson, & Van Houtven, 2006). Research shows that next-day smog alerts published in the newspaper induce people to reduce outdoor recreational activities to protect their health (Neidell, 2004, 2006), but this effect wanes for alerts issued on consecutive days (Zivin & Neidell, 2009). Beyond these findings, little is known about people's level of interest and engagement with real-time air quality information. It is critical to understand the effectiveness of air quality information on individuals to enhance the effectiveness of these programs. In addition, individual action is required along with public policy to reduce the adverse health effects of air pollution (Laumbach & Kipen, 2012).

To better understand people's engagement with real-time air quality information, we conducted a field experiment. We developed an air quality app, called AirForU, conducted messaging interventions, and tracked app users' engagement with real-time air quality information within the app.

Apps provide an excellent platform for studying user engagement with air quality information. The use of smartphone apps in health care has burgeoned in the past few years because of their potential in improving access to health care information (Ozdalga, Ozdalga, & Ahuja, 2012; Terry, 2010). Apps also provide an innovative platform to conduct research due to their functionality. In addition, they offer unprecedented opportunities to engage a large number of people and collect extensive data; about 77% of adults in the United States use smartphones (Pew Research Center, 2017). While surveys are also an excellent tool for collecting information, apps have some advantages over surveys because they record actual behaviors in real time, while surveys record information about behavioral intention, and with a lower frequency. However, these two different data collection approaches are seldom compared systematically.

After having built a significant app user base (2,740 users) for our air quality app, we conducted a messaging intervention among the app users. We tested the effect of different health messages on engagement with air quality information within the app, measured as how often users checked the app confirms. We compared app users' actual engagement with air quality information to survey responses of hypothetical engagement with air quality information for the same messages collected. We found that survey responses differed significantly from actual engagement. This confirms that researchers need to be careful about the context in which they use survey versus field experiments (Delmas & Arragon-Correa, 2016).

Overall, our results indicate that the content of the message has a smaller effect on influencing engagement compared with the characteristics (such as demographics) of the person receiving the message. We found that people who are highly involved with the issue are more likely to engage initially with the information and to respond to further messaging strategies. Understanding which groups respond (or do not respond) to air quality information via an app, and how to influence their engagement contributes toward improving air quality information programs.

MESSAGE FRAMING HYPOTHESES

Information strategies are based on the principle that more and better information about the environmental or health impact of activities will encourage behavioral change (Delmas, Montes-Sancho & Shimshack, 2010). Messaging interventions (via voice, text, or e-mail) are widely used in public health and environmental programs to change behavior and are a useful tool to protect health (Delmas, Fischlein & Asensio, 2013). Text message interventions for improving health behaviors (e.g., smoking cessation and diabetes management) have been successful in some studies (Fjeldsoe, Marshall, & Miller, 2009; Krishna, Austin Boren, & Balas, 2009), as have Internet-based health interventions (Bennett & Glasgow, 2009). Health message interventions have also been used effectively to promote environmentally friendly behaviors such as energy conservation behavior (Asensio & Delmas, 2015, 2016).

Engagement with information has been shown to be an important first step toward behavioral change. As stated by Stern (1999), "What makes information effective is not so much its accuracy and completeness as the extent to which it captures the attention of the audience, gains their involvement, and overcomes possible skepticism" (p. 467). Several elements can trigger engagement. These include the novelty, actionability, and relevance of the information (Delmas & Colgan, 2018; Loewenstein, 1994; Rosenthal, 2018). We describe these elements in more details below.

Novelty effects amplify an immediate desire to act on alert-based information. A famous example of novelty effects with information campaigns include the announcement through the national media of Betty Ford's and Happy Rockefeller's breast cancer diagnoses, which led to significant increases in breast cancer screenings in treatment centers in the initial year of media coverage (Fink et al., 1978). Technological novelty is the quality of perceiving digital platforms as unfamiliar, interesting, and unlike those presently used or understood (Tokunaga, 2013). The novel stimuli can provide impressions of unfamiliarity and can inspire curiosity in the content, leading individuals to seek further information about it (Loewenstein, 1994; Magni, Taylor, & Venkatesh, 2010). There can be novelty associated with the *content* of information received (e.g., the informational value of learning) and the *mode* of communication in which it is received (e.g., information technologies; Asensio & Delmas, 2016). We postulate that messages that emphasize the novelty of the information provided through the app will increase engagement with the information. We develop below a hypothesis on the effectiveness of novel messages.

Hypothesis 1: Health messages providing novel information about the health effects of air pollution are more effective at engaging people with air quality information, than general messages.

The second important factor that might trigger engagement with air pollution information is the ability of people to take action to protect themselves against air pollution. Information that highlights a sense of control or ability to engage in protective actions might be appealing (Schwartz, 1977; Vining & Ebreo, 2002). On the opposite end, if there are important barriers to action external to the individual, such as significant financial cost or inconvenience, people might disengage with the information (Stern, 1999). Therefore, engagement with information might be increased if a person receives information on how to perform certain activities and the outcomes of these activities. For example, a message that links direct behavior, such as the link between outdoors exercise and air pollution exposure might fall in that category. We therefore develop a second hypothesis on the effectiveness of actionable messages.

Hypothesis 2: Health messages providing actionable information on the health effects of air pollution are more effective at engaging people with air quality information, than general messages.

Third, air quality information needs are personal and varied depending on an individual's health status and location (Bickerstaff & Walker, 2001; Bush, Moffatt, & Dunn, 2001). Therefore, personalized health-based messaging interventions tend to be more effective than general ones (Lustria et al., 2013; Noar, Benac, & Harris, 2007). Similarly, tailored proenvironmental interventions have also been more successful (Abrahamse, Steg, Vlek, & Rothengatter, 2007; Asensio & Delmas, 2015). For example, messages about children's health should be more effective among parents/guardians, and messages about diseases affecting the elderly such as Alzheimer's should be more effective among that group. We therefore develop a third hypothesis on the effectiveness of targeted messages.

Hypothesis 3: Health messages aimed at specific groups are more effective at engaging these groups with air quality information, than general messages.

In addition, information about a health behavior can emphasize the benefits of taking action or the cost of failing to take action. Such negative or positive framing of health-related activities can also influence people's engagement with the information. This has been extensively studied in the "framing" literature, to investigate the effectiveness of different but equivalent descriptions of the same statement. The literature builds on Kahneman and Tversky's (1979) prospect theory, which suggests that potential losses are more motivating than potential gains when risky actions are considered, but gains are more motivating than losses for low-risk behavior.

In the public health domain, studies have assessed the impact of gain/loss or positive/negative language, or commonly called valence framing, for a number of behaviors. Many factors affect the valence framing type that is ultimately more effective. Positive framing has been found to be more effective at encouraging sunscreen use (Detweiler, Bedell, Salovey, Pronin, & Rothman, 1999) and the purchase of lean meat (Levin, 1987), both of which are low-risk behaviors, while negative framing has been more effective at promoting breast self-examinations (Meyerowitz & Chaiken, 1987) and mammography examinations (Banks et al., 1995); the latter themes are highrisk compared with the former. Another factor that further complicates the framing type is the degree of issue involvement. Negatively framed messages have been found to be more effective than positively framed messages for those who have a high degree of involvement with that issue (Greenwald & Leavitt, 1984; Meyerowitz & Chaiken, 1987). Negative messages have also been found to be more effective when detailed processing of the message was required, that is, requiring more attention from the reader such as messages about heart disease (Maheswaran & Meyerslevy, 1990) and skin cancer or sexually transmitted diseases (L. G. Block & Keller, 1995).

Because the literature found that positive framing for low-risk behaviors tends to be more effective, we hypothesize that positive framing might be more effective for air quality messages because avoiding exposure to outdoor air pollution is a relatively low-risk behavior. We therefore develop the following hypothesis:

Hypothesis 4: Positively framed health messages are more effective at engaging people with air quality information than negative framed messages.

METHOD

To test our hypotheses, we developed air pollution messages for the intervention and conducted two different experiments to test the messages. We first tested the air pollution messages through a survey using Amazon Mechanical Turk (MTurk) to gauge hypothetical engagement with air quality information. We then conducted a field experiment with the same messages among the app users to measure actual engagement within the app. Two facets of the air pollution messages were tested—the content of the message (i.e., the type of health impact) and the framing of the message (i.e., positive or negative wording of the message). While the sample of survey respondents and the sample of app users differ, we think we can learn from the combination of these two approaches.

Messages

We relied on the air pollution health literature to develop the content of the messages. Because the air pollution health literature is extremely vast, focus groups were conducted to identify some of the more relevant health impacts among the public. Initially, we developed 13 messages along the following dimensions: actions that might increase the impact of air pollution (going outdoors and exercising), mix of health issues associated with air pollution (asthma, cognitive impairment, premature deaths, and shortened life span), and messages that pointed out the need to get information on air pollution through the app because of the invisibility of air pollution. Some of the messages were based on common and well-known health conditions of air pollution such as asthma, while others were based on more threatening health conditions such as cancer, Alzheimer's, and shortened life span that had been relatively recently linked to air pollution (Bickerstaff & Walker, 2001). Others were factual messages based on the consequences of exposure to air pollution; these included numbers of school absences due to air pollution, shortened life span due to air pollution, and deaths linked to air pollution in the United States and worldwide. Finally, some of the messages targeted different groups of the population—parents of children, pregnant women, the elderly and those who exercise outdoors frequently. Appendix Table A1, which is available online as supplemental material, lists these initial messages.

We tested these messages with three focus groups of 15 to 20 individuals each. Based on the feedback we received, we selected the following five categories of health effects that people were most interested in and affected by—outdoor exercise, child asthma, child cognition, Alzheimer's, and invisibility of air pollution. Some of these categories emphasize novel information (invisibility of air pollution and Alzheimer's), others link exposure to air pollution with action (outdoor exercise), and some are targeted at specific populations (child asthma and cognition). We describe these five categories in more details below.

Outdoor Exercise. Outdoor exercises such was walking, biking, and running are the most common and accessible forms of exercise and thus affect most people. While exercise has many benefits, exercising outdoors during high air pollution can have a detrimental impact (Giles & Koehle, 2014). Exercise-based messages focused on outdoor exercise and were targeted at a wide range of the population.

Child Asthma. Asthma is the leading chronic condition affecting children (Neidell, 2004) and is the primary reason for school absenteeism and hospital admissions among children (U.S. Department of Health and Human Services, 2012). Child asthma is also on the rise (CDC, 2015). We developed a message geared toward caretakers of asthmatic children.

Child Cognition. High levels of air pollution have been linked to cognitive decline in children (Calderón-Garcidueñas et al., 2008; Freire et al., 2010; Suglia, Gryparis, Wright, Schwartz, & Wright, 2008). We developed two messages focused on child cognition because they tend to illicit a stronger response (Davis, 1995) and the public is highly concerned about the health impact of air pollution on their family (Bickerstaff & Walker, 2001).

Alzheimer's. Early air pollution health studies were primarily focused on respiratory ailments but in recent years, air pollution has been linked to diseases where the connection is less intuitive. Similar to cognitive decline in children, air pollution has been linked to brain damage and neurodegenerative disorders like Alzheimer's disease (M. L. Block & Calderón-Garcidueñas, 2009; Calderón-Garcidueñas et al., 2002; Kampa & Castanas, 2008; Levesque, Surace, McDonald, & Block, 2011; Moulton & Yang, 2012; Weuve et al., 2012). We developed a message geared at the elderly (~55 years and older) who are at higher risk for Alzheimer's disease (Brookmeyer, Gray, & Kawas, 1998).

Air Pollution Invisibility. The last category chosen is a general one not geared at a specific group. This message highlights that even if air pollution is invisible, it can still have adverse health effects. The basis for this message is also to encourage people to check air quality information rather than relying on their perception of air pollution which often tends to be inaccurate (Semenza et al., 2008).

For each category of impact, we developed two messages. One that was framed positively and another one that was framed negatively using language common in the framing literature. For the outdoor exercise category, we developed an additional message that combined positive and negative framing.

Below, we provide an example of positively and negatively framed air pollution messages from the child asthma category, respectively, with the differences in italics.

1. Do you know that high air pollution can cause or worsen childhood asthma? *Avoiding air pollution can reduce this risk*. Check your local air quality on AirForU today before engaging in outdoor activities!
2. Do you know that high air pollution can cause or worsen childhood asthma? *Exposure to air pollution can increase this risk*. Check your local air quality on AirForU today before engaging in outdoor activities!

We randomly assigned one question from each category to each respondent; either positively or negatively framed. Besides these five categories, we developed the following control statement: "Protect your health. Check your local air quality on AirForU today before engaging in outdoor activities." Table 1 lists all 12 messages used in the experiments.

DATA

Stated Preferences

We conducted a survey experiment to identify air pollution messages that most influence (hypothetical) engagement with an air quality app. Engagement in this context refers to checking air quality levels on the app before engaging in outdoor activities. Respondents were asked to rate each of the 12 messages for comprehensibility, realism, relevance, and whether they would check air quality on an app before engaging in outdoor activities after reading the message. Each message was rated on a 7-point scale ranging from *strongly disagree* to *strongly agree* on these four aspects. In addition, demographic information and respondents' knowledge of common air quality terms was also part of the survey. The survey was conducted via MTurk, an online survey service frequently used by researchers (Buhrmester, Kwang, & Gosling, 2011). Respondents received $1 for their participation. We collected 835 responses. The response rate was 100% because respondents received payment only if they completed the survey.

The survey sample consisted of 835 respondents, with an average age of 35 years, an annual income of $54,563, and consisted of 44.7% women. Appendix Tables A2 and A3 provide a complete description of the survey demographics. Each respondent received only one message from each of the six air pollution message categories.

Most air pollution messages received a high comprehensibility score, implying that most people understood the messages clearly. The average comprehension score was 6.22 out of a 7-point scale. Realism of messages also received a high score for the most part with an average 5.64 out of a 7-point scale. The child cognition and Alzheimer's messages received the lowest scores with averages of 5.47 and 4.99 out of a 7-point scale. This is possibly because these effects are not as common or as intuitively linked to air pollution as asthma or outdoor exercise. Messages geared at children (child asthma and child cognition), and the elderly (Alzheimer's) received the lowest score on the relevance scale. This is expected because only about 30% of the respondents had children and only about 7% of the respondents are 55 years or older. Relevance received a score of 4.93 out of a 7-point scale, indicating that air quality health impacts have less significance for some respondents (see more details in the appendix Table A4).

We conducted regressions to identify which air pollution message categories respondents perceived as the most effective at encouraging them to check air quality. The dependent variable was whether respondents would be more likely to check air quality and the message category/type were the treatment variables. We describe our regression model and the results in the Results section.

Table 1. Air Pollution Messages Used in the Survey and App Experiment.

Message category	Message framing	Message
Baseline	N/A	Protect your health. Check your local air quality on AirForU today before engaging in outdoor activities!
Exercise	Positive	Do you know that exercising outdoors when air pollution is low is beneficial to your health? Protect your health. Check your local air quality on AirForU today before engaging in outdoor activities!
	Negative	Do you know that exercising outdoors when air pollution is high can harm your health? Protect your health. Check your local air quality on AirForU today before engaging in outdoor activities!
	Mixed	Do you know that while exercising is beneficial for your health, exercising outdoors when air pollution is high can harm your health? Protect your health. Check your local air quality on AirForU today before engaging in outdoor activities!
Child asthma	Positive	Do you know that high air pollution can cause or worsen childhood asthma? Avoiding air pollution can reduce this risk. Check your local air quality on AirForU today before engaging in outdoor activities with your children!
	Negative	Do you know that high air pollution can cause or worsen childhood asthma? Exposure to air pollution can increase this risk. Check your local air quality on AirForU today before engaging in outdoor activities!
Child Cognition	Positive	Do you know that air pollution slows cognition in children by affecting their brain development? Avoiding air pollution can reduce this risk. Check your local air quality on AirForU today before engaging in outdoor activities!
	Negative	Do you know that air pollution slows cognition in children by affecting their brain development? Exposure to air pollution can increase this risk. Check your local air quality on AirForU today before engaging in outdoor activities with your children!
Alzheimer’s	Positive	Do you know that air pollution is linked to Alzheimer’s disease? Avoiding air pollution can reduce this risk. Check your local air quality on AirForU today before engaging in outdoor activities!
	Negative	Do you know that air pollution is linked to Alzheimer’s disease? Exposure to air pollution can increase this risk. Check your local air quality on AirForU today before engaging in outdoor activities!
Air pollution invisibility	Positive	Do you know that harmful air pollution is often invisible to the naked eye? Avoiding air pollution can reduce your risk of harmful health effects. Check your local air quality on AirForU today before engaging in outdoor activities!
	Negative	Do you know that harmful air pollution is often invisible to the naked eye? Exposure to air pollution can increase your risk of harmful health effects. Check your local air quality on AirForU today before engaging in outdoor activities!

Revealed Preferences

To test actual engagement with air quality information, we developed an air quality app that provides information about the state of the air and associated health risks (Delmas & Kohli, 2019). Global Positioning System (GPS) capability in smartphones allows users to access air quality based on their current location easily. While many other air quality apps exist on the market, AirForU is specifically and uniquely designed as a research tool to characterize engagement with air quality information. We tracked user engagement with air quality information within the app, and used Google Mobile Analytics.[1]

Development for the AirForU app began toward the end of 2014. Testing began a few months later and the final version was launched in October 2015 under the UCLA Health brand in the Google Play (for Android devices) and App Store (for iPhones; together, these devices heavily dominate the smartphone market; Statista, 2017). The app was made available free to the public.

Air quality and health data are obtained from the Environmental Protection Agency's (EPA) AirNow program, which publishes hourly updates of air quality as well as next-day forecasts for the entire nation on their website. Within the app, the air quality is reported based on EPA's guidelines in the form of an Air Quality Index (AQI), which accounts for the ambient concentrations of several pollutants. The AQI communicates how clean or polluted the outdoor air is along with the associated health effects that may be of concern at those levels (U.S. Environmental Protection Agency, 2006). See Figure 1 for a depiction of the app layout.

We used a number of avenues (social media, newsletters, websites, and flyers) to diffuse the app, including posting on the UCLA Health website.

We tested the same 12 messages with the app users as we did for the survey. We randomly assigned users in one control or one of the 12 treatment groups (~200-250 users in each group) and they received one message per week delivered via e-mail for five consecutive weeks starting toward the end of May 2017 and continuing through most of June. The treatment variable was receiving the e-mail rather than opening.[2]

One challenge was to develop a relevant metric for user engagement. Engagement can be generally defined as a user's level of involvement with a product; for technological items, it usually refers to behavioral proxies such as the frequency, intensity, or depth of interaction over some time period (Rodden, Hutchinson, & Fu, 2010). Engagement with technology is multifaceted and highly dependent on the technology (Attfield, Kazai, & Lalmas, 2011; Lehmann, Lalmas, Yom-Tov, & Dupret, 2012); hence, it is important to define engagement based on an application's objectives (Fagan, 2014; Lalmas, O'Brien, & Yom-Tov, 2014). For AirForU, the main objective is to check air quality (either current or forecast) and hence engagement is defined as opening the app. We did not use the duration of the app visit since a visit may last only a few seconds but that is sufficient for the user to access air quality information.

The 2,740 app users differed from the general population regarding their health conditions.[3] Incidence of asthma among app users and among their children/guardians was much higher than United States and CA averages; 15.4% for adults compared with 7.4% for the United States and

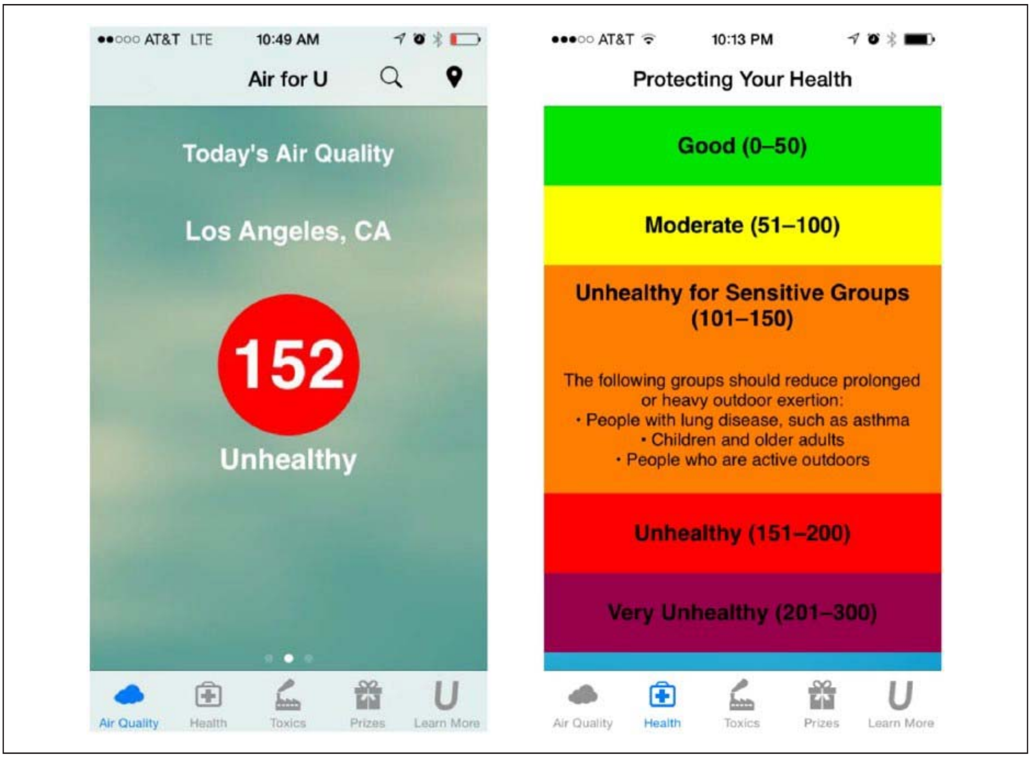

Figure 1. AirForU app displays real-time air quality for Los Angeles and the associated health impact.
Note. Coloring scheme is based on the Environmental Protection Agency's air quality reporting guidelines.

8.7% for CA and for children 18.7% compared with 8.6% for United States averages, more than double the national average. Indeed, 14.1% of the users had heart disease compared with the U.S. average of 10.2% (see the appendix Tables A5 and A6). There was a self-selection bias among the app users with regard to health conditions associated with poor air quality (see the appendix Table A7). This is unsurprising because people are likely to seek information that is relevant and useful for them. App users were predominantly iPhone users (75%). Since its launch, users opened the app a total of 66,000+ times and accessed air quality information 164,000+ times. Health info was also accessed very frequently.

To compare the sample of app users with those of the MTurk survey respondents, we ran *t* tests using Welch's test for unequal variances (see the appendix Table A8). The survey respondents and the app users were similar in their gender and age distribution and in the incidence of child asthma.[4] Apart from that, the populations were different in their incidence of health conditions, presence of children in their home, and their frequency of outdoor exercise. App users had less children, lower rates of asthma, and exercised less often. There were two questions in the survey to gauge people's knowledge of air quality, one testing the typical AQI range in one neighborhood and another question testing the definition of $PM_{2.5}$. MTurk survey respondents were more knowledgeable about the AQI than app users, while both scored similarly in the $PM_{2.5}$ question.

SURVEY REGRESSION ANALYSIS

We used an ordinary least squares regression model, as described in Equation (1), to explore the effectiveness of the different messages in influencing respondents to check air quality.

$$y_i = \alpha + \beta_{ti}x_{ti} + \beta_{c1i}x_{c1i} + \ldots + \beta_{cni}x_{cni} + \varepsilon \qquad (1)$$

The dependent variable y_i is the score that each message received in the survey for the question "After reading this message, I would check air quality." The response was based on a 7-point scale from 1 to 7 ranging from *strongly disagree* to *strongly disagree*. x_{ti} is the treatment variable indicating which message a respondent received in the survey, that is, one of the 12 messages and $\square_{ti}$ is the coefficient of the treatment variable reflecting the size of the treatment in influencing a respondent to check the app. x_{c1i}, x_{c2i},…, x_{cni} are the control variables such as the demographics, frequency of outdoor exercise, health conditions, and other background information collected in the survey and their corresponding coefficients are β_{c1i}, β_{c2i},…. β_{cni}.

While the R^2 values are small (.14 and .05) for relevance and check air quality, the independent variables explain a nontrivial component of the dependent variables based on the *F* values ($p < .000$).

For regressions with the message framing type as the treatment variable (Table 2, column 2), messages from the exercise and air pollution invisibility category were the only significant ones. Besides the exercise category, the framing type did not have a significant impact on effectiveness. For the exercise category, the negative framing and combined positive and negative framing were statistically significant and of the two, the combined exercise message was more effective (Table 2, column 2). In fact, the combined exercise message was the most effective of all messages. Those who received this message were 0.68 times more likely to check the app than other groups or in other words for every 10 people who received this message compared with other messages, one would expect about six to seven more app visits. For the invisibility category, there was no statistically significant difference between the two types of framing. These two categories—air pollution invisibility and exercise—may be more effective compared with the other categories is because they are less threatening, that is, they have a lower fear appeal compared with the Alzheimer's, child brain cognition, and child asthma messages. Results indicate that respondents found these messages to be more relevant (relevance results in the appendix Table A4). A large majority of people exercise outdoors and everyone breathes in air pollution when they are outdoors whether they are exercising, which might explain the relevance of these messages. Thus, Hypothesis 1 did not hold for the air pollution messages in the survey as the more novel health messages were not as effective as the more general messages about air pollution.

We conducted additional regressions for the same dependent variables but this time including controls for frequent outdoor exercise, college education, income, and race for 430 respondents. The results with the added controls are in the appendix Tables A9 and A10. No difference was observed in the message categories or framing except that non-White races/ethnicities are 0.4 times more likely to check air quality compared with Caucasians or Whites. Minorities are often exposed to higher levels of pollution so this information may suggest that they are aware of the discrepancy and take measures to protect against it. The trends in other controls remained the same, while knowledge of AQI was no longer significant.

The next set of regressions included interactions to expand the understanding of which messages were more effective among which groups. The following interaction terms were included— treatment message category (i.e., six categories) with children, treatment message category with asthma, and treatment message category with age (Table 3; complete regression results with all controls presented in the appendix Tables A11, A12, and A13). Including an interaction term for children and treatment category (Table 3) significantly changes the results. People with children are much more likely to respond to messages geared at children irrespective of whether their children have asthma. Someone who has a child is likely to respond to check the app when they read the messages geared at children's health, that is, asthma and cognition. There is no

Table 2. Regressions for Message Categories Relative to the Baseline Message for Survey Respondents (N = 835).

	Check AQ	Check AQ
Question treatment		
Exercise	0.38*** (0.05)	
Exercise positive		0.32*** (0.09)
Exercise negative		0.14 (0.09)
Exercise positive and negative		0.66*** (0.08)
Child asthma	−0.03 (0.06)	
Child asthma positive		−0.05 (0.08)
Child asthma negative		0.00 (0.09)
Child cognition	0.01 (0.06)	
Child cognition positive		0.02 (0.09)
Child cognition negative		0.00 (0.09)
Alzheimer	0.00 (0.06)	
Alzheimer's positive		−0.06 (0.09)
Alzheimer's negative		0.06 (0.08)
AP invisibility	0.42*** (0.05)	
AP invisibility positive		0.44*** (0.07)
AP invisibility negative		0.39*** (0.07)
Controls		
Age >55 years	0.28 (0.19)	0.29 (0.19)
Female	0.25*** (0.09)	0.25*** (0.09)
Asthma	0.66*** (0.11)	0.65*** (0.11)
Children	0.34*** (0.11)	0.34*** (0.11)
Children with asthma	0.07 (0.18)	0.06 (0.18)
Knowledge of AQ	0.39*** (0.11)	0.38*** (0.11)
Constant	4.41*** (0.08)	4.41*** (0.08)
Observations	5,010	5,010
Adjusted R^2	.05	.06
F	22.44	16.26

Note. AQ = air quality; AP = air pollution. Robust standard errors are in parentheses.
$^*p < .1$. $^{**}p < .05$. $^{***}p < .01$.

significant difference between the asthma and the cognition messages so they are likely to respond to each equally. Similarly, those with asthma are more likely to check air quality in response to the message about child asthma even if they do not have children (Table 3).

In contrast, people older than 55 years do not show a significant response to the Alzheimer's message (Table 3). They are also unlikely to respond to messages based on child conditions based on the negative coefficients, which is not surprising. They do not find the Alzheimer's message relevant and this may be because they do not believe that this statement is true (based on negative coefficients for realism). There is evidence indicating that people know about the general health impacts of air pollution but do not know as much as the specific impacts (Bickerstaff & Walker, 1999). The Alzheimer's message is not effective for its target audience. Similarly, including a term for exercise frequency interacted with message category does not indicate a strengthened response for the exercise message among those who exercise more frequently. Thus, Hypothesis 2 was true for some of the targeted groups except for the elderly group with regards to the Alzheimer's message. The coefficients for the targeted messages (0.9-1) were a lot higher than

Table 3. Regression Coefficients for Treatment Categories Interacted With Population Characteristics for Survey Respondents (N = 835).

	Interaction terms		
	Have children	Have asthma	Age >55 years
Treatment	Check AQ	Check AQ	Check AQ
Exercise	−0.14 (0.10)	0.16 (0.17)	−0.13 (0.16)
Child asthma	0.98*** (0.13)	0.93*** (0.19)	−0.46* (0.24)
Child	1.00*** (0.13)	0.33 (0.20)	−0.64*** (0.23)
cognition	−0.04 (0.13)	0.41** (0.17)	−0.04 (0.23)
Alzheimer's	0.02 (0.10)	0.19 (0.16)	0.10 (0.18)
AP invisibility			

Note. AQ = air quality; AP = air pollution. Robust standard errors are in parentheses. Relevance indicates the relevance of messages and check AQ indicates the effectiveness of each message at encouraging people to check AQ.
*p < .1. **p < .05. ***p < .01.

those for the general messages (0.4-0.7) indicating that targeted messages might be more useful in improving health protection against air pollution.

In summary, we found that the exercise and air pollution invisibility message categories were the most effective among all users. The valence framing had little effect for most message categories except for the exercise category where the combined positive and negative framing was more effective not only in its own category but also among all categories. Children-based messages were more effective among parents/guardians even if the children did not have asthma and the child asthma-based message was effective even among adults with asthma irrespective of whether they had children. In contrast, the Alzheimer's message was not effective among the elderly and the exercise message was not more effective among those who exercise outdoors frequently.

APP REGRESSION ANALYSIS

To test the effectiveness of the messages on the likelihood of users to check air quality on the app, we used a difference-in-differences model to measure engagement before and after the e-mail experiment. Differences-in-differences is a common method in social sciences research for measuring the effects of an experiment or quasi-experiment. In addition to the difference-in-difference, the data were set for a panel analysis. Each user was tracked on a weekly basis from the time they downloaded the app until the e-mail experiment was completed. Equation (2) below describes our model:

$$y_{it} = \beta_0 + \beta_1 dB_{it} + \delta_0 d2_{it} + \delta_1 d2_{it} \cdot dB_{it} + \beta_1 x_{1it} + \beta_2 x_{2it} + \ldots\ldots\ldots + \beta_n x_{nit} + \varepsilon_{it} \quad (2)$$

Where y_{it} is the dependent variable and is measured as the number of app visits per week for user i and week t. $d2_{it}$ is a dummy variable for the second time period and captures any changes that would have occurred over time even in the absence of a treatment, dB_{it} captures differences between the control and treatment groups prior to the treatment, and the coefficient of interest δ_1 is a measure of the change in y_{it} (i.e., outcome of interest) due to the treatment dB_{it}. The control variables included week dummies to control for seasonality or other time-related factors potentially affecting engagement, demographic controls from the intake survey, and a control to account for the user's activity with the app prior to the experiment. The activity control accounted for whether a user had been active (or inactive) with the app for a number of weeks (5 weeks, 10 weeks, 15 weeks, and 20 weeks) since they downloaded it. New users were more engaged in general and this factor accounted for that as well.

We ran regressions to identify the effect of the air pollution message categories, message framing, and other control factors affecting engagement with the app (refer to the appendix Table A14 for complete list of variables).[5]

Table 4 presents the regression results based on the difference-in-differences model presented in Equation (2). Weekly app visits (open_app) is the dependent variable in the regressions. Column 1 presents the results for all app users; column 2 for users inactive during 5 weeks, column 3 for users inactive for 10 weeks, and column 4 for users inactive for 15 weeks.6 These different samples allow us to evaluate how much inactivity impacts reengagement after the e-mail messages. The control group for these regressions is the group that received no e-mail messages. Engagement after and before the messages were sent out is split by the six treatment message categories (including the baseline message). Health and demographic controls as well as controls for prior engagement were included but are not presented in Table 4 (refer to the appendix Table A15 for complete regression results). Week dummies were included in the model. When considering the results for all users (column 1), it appears that all the e-mail messages had about the same positive and significant impact on user engagement with the app. The coefficients for the message categories range between 0.18 and 0.28, and are not statistically different from one another except for the child cognition category. Users who received any message were about 0.2 to 0.3 times more likely to check the app than those who did not receive a message or in other words for every 10 people who received a message, there were an additional two app visits per week. For the groups of app users who have been inactive for periods of 5, 10, or 15 weeks (i.e., not checked the app even once for those durations), we see a similar effect. Apart from the child cognition category, it appears that all message categories were effective at increasing engagement with the app. Based on the coefficients, it can be concluded that for every 10 people who received a message compared with those that did not receive any message, there was about one additional app visit per week. These results suggest that users might be responding to the e-mails as a reminder to check the app rather than responding to the content of the e-mail. For the group that had been inactive with the app for 20 weeks or more (column 5), there was limited reengagement after the e-mails were sent out, that is, three to six additional app visits per week for every 100 users.

When looking at the impact of engagement on the different groups, we observe that users who have been inactive between 5 and 15 weeks (columns 2-4) reengaged with the app to some degree after we sent the e-mails. This engagement began to wane with users who have been inactive longer than that as shown in column 5. We did not include the group that were active with the app because there is not much change in their engagement (period of inactivity <5 weeks, *n* = 119 out of 2,740). These users were consistently active with the app and continued to remain active with/without the e-mail reminders. The e-mail messages were mostly effective at increasing engagement for those who had been inactive for intermediate periods, that is, between 5 and 15 weeks. While the e-mail messages were effective at increasing engagement among participants who had been inactive between 5 and 15 weeks (*n* = 300 out of 2,740), there was no significant difference among users who had been inactive for 15 weeks or longer (*n* =2,321 out of 2,740 users).[7] One of the limitations of our study was that the e-mails were sent out after a large majority of the users (>2,000) had disengaged with the app. While the e-mails had some impact in reviving engagement, it was not a very large effect relative to the disengagement. This can be observed by comparing the coefficients of the predummy/postdummy (this is d2 dummy described in Equation 2 and it captures the decline in engagement occurring over time even in the absence of the treatment) to the coefficients of the posttreatment message categories. For the regression with all users (column 1, Table 4), the coefficient of the predummy/postdummy is −5.21, while the dummy for the message categories ranges between 0.18 and 0.28. This means

Table 4. App Engagement Before and After the E-mail Experiment Split by Levels of User Activity (Control Group Received No E-Mail).

	Check app				
	All users (N = 2,740)	Inactive 5 weeks (n = 2,621)	Inactive 10 weeks (n = 2,456)	Inactive 15 weeks (n = 2,321)	Inactive 20 weeks (n = 2,171)
Posttreatment					
Baseline	0.27*** (0.09)	0.10*** (0.03)	0.12*** (0.03)	0.12*** (0.03)	0.06*** (0.02)
Exercise	0.24*** (0.08)	0.06*** (0.02)	0.06*** (0.02)	0.09*** (0.02)	0.03* (0.02)
Child asthma	0.25*** (0.08)	0.03 (0.03)	0.04** (0.02)	0.05*** (0.02)	0.01 (0.02)
Child cognition	0.18** (0.08)	−0.04* (0.02)	−0.02 (0.02)	−0.02 (0.02)	−0.07*** (0.02)
Alzheimer's	0.22*** (0.08)	0.05** (0.02)	0.08*** (0.02)	0.09*** (0.02)	0.04* (0.02)
AP invisibility	0.28*** (0.08)	0.10*** (0.03)	0.09*** (0.03)	0.11*** (0.03)	0.03** (0.02)
Pretreatment					
Baseline	−0.01 (0.02)	−0.03* (0.02)	−0.05*** (0.02)	−0.06*** (0.02)	−0.03** (0.02)
Exercise	0.03 (0.02)	−0.04** (0.02)	−0.04** (0.02)	−0.06*** (0.02)	−0.01 (0.01)
Child asthma	0.04 (0.02)	0.05*** (0.02)	−0.03 (0.02)	−0.05*** (0.02)	−0.00 (0.01)
Child cognition	0.04** (0.02)	0.07*** (0.02)	0.05*** (0.02)	0.04** (0.02)	0.09*** (0.02)
Alzheimer's	0.04* (0.02)	−0.00 (0.02)	−0.03* (0.02)	−0.04** (0.02)	0.02 (0.01)
AP invisibility	−0.05** (0.02)	−0.06*** (0.02)	−0.05*** (0.02)	−0.08*** (0.02)	−0.02* (0.01)
Predummy/ postdummy	−5.21*** (0.21)	−4.82*** (0.20)	−4.75*** (0.19)	−4.67*** (0.19)	−4.59*** (0.19)
Constant	4.81*** (0.20)	4.65*** (0.20)	4.61*** (0.19)	4.57*** (0.19)	4.49*** (0.19)
Observations	168,726	165,792	161,719	156,916	150,681
Adjusted R^2	.14	.07	.07	.08	.08
F	37.83	36.56	40.59	39.53	39

Note. AP = air pollution. Robust standard errors are in parentheses.
*p < .1. **p < .05. ***p < .01.

that there were about five fewer apps per week, while the e-mails resulted in an additional 0.28 app visits per week. The e-mails gave a small boost to the engagement but not a whole lot relative to the decline in engagement occurring over time.

Therefore, engagement for app users differed from the survey results that showed the exercise and air pollution invisibility categories to be the most effective. However, this is not an equivalent comparison since the control groups are different. Indeed, the control group in the survey is the baseline message respondents, whereas in the app it is the group that received no message.

To better compare the results of the survey and app, we ran another set of regressions with the baseline message as the control group (Table 5). We find that none of the message categories were more effective among app users than the baseline message. We observe that the child cognition had the reverse effect and actually decreased engagement relative to the baseline. This lends further support to the observation that app users might simply be responding to the e-mail as a reminder to check the app, rather than responding to the content of the message.

The results presented in column 1, Table 4, indicate that app users responded almost evenly to the different e-mail categories but it was not obvious which groups of users were contributing most to the increase in engagement. Therefore, we ran the same regressions as those presented in Table 4; however, we now split the sample into specific groups of app users to identify the most engaged groups (Table 6). We split users into groups based on whether they have children or children with asthma, whether they themselves have asthma and based on their gender. We split the groups by the message categories before and after the e-mail treatment to fairly assess the impact of each message category for each specific group. Prior to the e-mail messages, all users

Table 5. Comparing the Effectiveness of Message Categories in the Survey and App E-Mail Experiment.

Treatment groups	Survey	App experiment
Baseline	(Control)	(Control)
Exercise	0.40***	*ns*
Child asthma	*ns*	*ns*
Child cognition	*ns*	−0.09*
Alzheimer's	*ns*	*ns*
AP invisibility	0.34***	*ns*
Total *N*	835	2,376

Note. AP = air pollution; *ns* = nonsignificant.

Table 6. App Engagement Before and After the E-Mail Experiment Split Into Various Groups of App Users (The Control Group Received No E-Mail).

	Check app				
	Children (n = 959)	Child asthma (n = 2,179)	User asthma (n = 421)	Females (n = 1,226)	Males (n = 1,514)
Posttreatment					
Baseline	0.23 (0.20)	−0.00 (0.30)	0.59*** (0.18)	0.60*** (0.11)	−0.01 (0.13)
Exercise	0.13 (0.20)	0.16 (0.38)	0.70*** (0.11)	0.52*** (0.09)	−0.02 (0.13)
Child asthma	0.13 (0.20)	0.04 (0.27)	0.73*** (0.17)	0.56*** (0.10)	−0.03 (0.12)
Child cognition	0.20 (0.19)	0.16 (0.24)	0.17 (0.13)	0.35*** (0.09)	0.00 (0.12)
Alzheimer's	0.13 (0.19)	0.39 (0.35)	0.55*** (0.15)	0.46*** (0.09)	−0.01 (0.12)
AP invisibility	0.31 (0.20)	0.52 (0.37)	0.45** (0.21)	0.56*** (0.11)	0.00 (0.12)
Pretreatment					
Baseline	0.09*** (0.03)	0.62*** (0.10)	−0.17** (0.07)	−0.24*** (0.05)	0.16*** (0.02)
Exercise	0.24*** (0.03)	0.96*** (0.12)	−0.21*** (0.06)	−0.27*** (0.04)	0.22*** (0.03)
Child asthma	0.18*** (0.03)	0.81*** (0.11)	−0.10 (0.07)	−0.12*** (0.05)	0.14*** (0.02)
Child cognition	0.11*** (0.03)	0.55*** (0.09)	0.21*** (0.07)	−0.06 (0.05)	0.09*** (0.02)
Alzheimer's	0.14*** (0.03)	−0.43*** (0.17)	−0.09 (0.08)	−0.19*** (0.04)	0.17*** (0.02)
AP invisibility	−0.09*** (0.03)	0.25** (0.10)	0.27*** (0.09)	−0.13*** (0.05)	−0.01 (0.02)
Predummy/postdummy	−5.67*** (0.41)	−5.93*** (1.10)	−6.61*** (0.80)	−5.58*** (0.38)	−4.88*** (0.26)
Constant	5.53*** (0.37)	7.38*** (1.08)	5.50*** (0.80)	4.91*** (0.37)	4.88*** (0.24)
Observations	57,310	10,348	24,466	71,748	96,978
Adjusted R^2	.19	.40	.15	.11	.18
F	15.79	6.447	10.28	19.42	22.94

Note. AP = air pollution. Robust standard errors are in parentheses.
$^*p < .1$. $^{**}p < .05$. $^{***}p < .01$.

in each specific group had about the same level of activity as indicated by the similarly sized coefficients for each column in the pretreatment section. After the e-mails were sent out, none of the coefficients in the posttreatment groups are significant except for users with asthma group and the women group (columns 3 and 4 in Table 6). We can now confirm that users with asthma and women are responsible for most of the engagement. Based on the coefficients (0.35-0.73), we can see that, on receiving these messages, for every 10 people in these groups, there were an additional three to seven app visits per week compared with their counterparts (i.e., those who do not have asthma and men).

Overall, the trends for most of the health and demographic control variables were similar to the survey and as expected. Those with health conditions aggravated by air pollution, or with children with those health conditions, were much more likely to check the app compared with those without those health conditions. Women were also 6% more likely to check the app per week compared with men.

We conducted similar regressions with the negative and positive message framing as the for each message category. The results are presented in Table 6. There was no significant difference among the framing types, as we also found with the survey results.[8] Although in the survey, the combined exercise message was more effective than either the positive or the negative version along, no such difference was observed in the app e-mail experiment. Similarly, Hypothesis 1 did not hold for the app experiment either; neither positively or negatively framed were more effective than the other at influencing engagement.

DISCUSSION

Our analysis shows that survey respondents and app users responded differently to the same messages. Clearly, the two experimental settings were different, as were the two samples but by replicating (as much as possible) the experiment among app users and by delivering the same air pollution messages via e-mail and measuring engagement with the app, we were able to compare the results of a survey and field experiment. We can glean some interesting findings from this comparison. In the survey, people stated they would be more likely to respond to messages that emphasize the impact of air quality on exercise and the invisibility of air quality rather than messages about diseases associated with poor air quality. However, through the app, there was no significant difference in messages framing to predict actual engagement. Instead, users' demographics were the most important predictor of engagement with messages. Furthermore, over time, users disengaged with the information.

Message Content and Framing

Through the survey, we learned that people are more likely to check air quality in response to two air pollution messages that are actionable or are linked to the novel element of the app that makes air quality visible by providing real-time infromation. When considering all groups, messages based on exercise and general invisibility of air pollution were the most effective. Thus, our Hypotheses 1 and 2 were partially confirmed. In addition, these were also the least threatening messages. This might indicate that in the case of air pollution, resorting to fear appeal messages might not be effective.

However, positively framed messages were not more effective than negatively framed messages in this study. A combined positive and negative mixed message presenting a problem and then providing a resolution to that message (exercise-combined message) was the most effective message framing among all messages. Studies testing the effect of combined message framing are not as common as valence framing studies but combined framing has been more successful in some instances (Treiber, 1986; Wilson et al., 1990). Thus, our fourth hypothesis on the effectiveness of positive framing was not confirmed.

In the field experiment, there was little difference in engagement based on the content of the e-mail—the message category or the framing type. In other words, our hypotheses 1, 2 and 4, regarding the content and the framing of the message were not confirmed.

Targeted Messages

More promising were the results testing hypothesis 3 regarding targeted messages. The results of the survey were in alignment with previous literature on targeted messages and our second hypothesis. Women, parents/guardians, those with asthma, those with a better knowledge of air quality were more likely to check air quality and thus potentially engage in protecting behaviors. Messages targeted at certain groups were more effective among those groups for the most part and had a higher potential for increasing effectiveness with air quality information. Thus, confirming hypothesis 3.

Similarly, engagement for app users depended on their personal involvement with the issue. Users with health conditions or with children with health conditions were more engaged with the app in general, as were women compared with men. These results indicate that groups that are most affected by air pollution are those who engage with this information.

Novelty and Persistence

One important finding was that even though a majority of the app users was disproportionately affected by air pollution, they tended to lose interest in air quality information over time. Despite the fact that the group of app users had a high proportion of sensitive groups, engagement tended to be short-lived for most users. Within 10 to 15 weeks, most users (>2,000 users) had disengaged from the app. There was a small group of highly motived individuals (~100 users) who remained actively engaged with the app from the time they first downloaded it. This group also reported the adoption of health protective behaviors because of the information provided in the app. Less engaged individuals might have adopted these behaviors as well but because they did not partake in the additional surveys this is mere speculation.

One of the reasons could be that air quality information did not change much for long periods and that the novelty effect faded away. Therefore, while the air quality information might have appeared novel the first few timest, the repetition of the same information over time led to disengagement. The downside of novelty effects is that they fade away over time. Therefore, the challenge is to continue providing novel information over time.

While notifications (sent through the app at weekly intervals) and e-mails from the experiment were effective at reengaging app some of the app users, they were not effective for those who had been inactive for long periods. Timely interventions might be necessary to keep users engaged over time. Different modes of reminders (e-mails and notifications) may be effective for different groups. Survey results indicate that targeted messages have potential but more research would have to be done to understand their effects.

One limitation of this study was the timing of the field experiment. We conducted the experiment over a year and half after the app's launch. Much of the recruiting effort and a large portion of the total downloads occurred when the app was launched and by the time the experiment was conducted, many users had disengaged from the app and perhaps even deleted it from their phones (something we were unable to measure because of smartphone configurations). In addition, while we were able to observe the actual engagement of app users with air quality information in response to repeated messages, we were not able to test the impact of repeated surveys on the intend to engage with air quality information. It is therefore possible that repeated surveys would have also fatigued the respondents.

Another limitation of this study is its external validity to the general population; it is not necessarily a disadvantage. There was a self-selection bias among app users; those whose health was affected by poor air quality were more likely to download and use the app. These individuals are also more likely to contribute to the health burden and thus it is more important that they engage with air pollution information and adopt health-protecting behaviors compared with the general population. Besides, vulnerable groups constitute a large part of the population and engaging these groups is critical to the success of air quality programs.

CONCLUSION

In conclusion, some of the results from the field experiment were different from the survey because of the different setups. In the app, engagement after receiving the e-mails was highly dependent on levels of engagement prior to receiving the e-mails, a factor that was missing from the survey. There was also little effectiveness of messaging for users with high engagement, while those who were less engaged became more engaged over time with messaging. Comparing the survey and field experiment allows us to see the limits of surveys to understand long-term engagement with environmental and health information. It is very difficult for most people to imagine how they would respond to messaging over time, or to imagine their behavior in the marketplace. This is what has been coined as the attitude–behavior gap, or the gap between what people say they will do about the environment or their health, and what they do in the marketplace or in their home (Eckhardt et al., 2010). Because of this gap, it is problematic to rely on surveys to predict behavior. Field experiments are more valuable. They should be used more often in sustainability research (Delmas & Arragon-Correa, 2016).

Environmental information programs have great potential at increasing awareness of environmental pollution and encouraging the adoption of health protective behaviors especially among those that are most affected. Ultimately, this could lead to a lower health burden. One big challenge is to keep people motivated in engaging with the information over time. Personalized information and timely reminders may play an important role in influencing engagement and improving public health protection and the success of environmental information programs.

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Notes

1. Users also had the option to allow notifications from the app; if they signed up for notifications, they received weekly alerts encouraging them to check the air quality.
2. With most smartphones, it is possible to read part of the content of the e-mail without actually opening the e-mail. This is a confounding factor, but it is difficult to disentangle the effect of receiving an e-mail and reading it.
3. While the app was downloaded over 3,000 times, users outside the United States were dropped from the study. Researchers and beta testers were also dropped from the study.
4. We used slightly different bins to categorize age in the two surveys so we were unable to run a *t* test to compare if they were statistically different but the means of the age groups were similar (35 and 43 years for MTurk respondents and app users, respectively).
5. Heteroscedasticity checks were added but standard errors were not clustered.
6. These time periods were determined by analyzing Google Analytics data for overall app activity which indicated that by about 12 to 15 weeks most users had disengaged from the app.

7. It can also be assumed that these users have deleted the app. With the current level of technology, we are unable to record which users have deleted the app so users who have been inactive for a long time appear to be the same as those who have deleted the app.
8. Results available on request from the corresponding author.

Supplemental Material

Supplemental material for this article is available online.

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APPENDIX

Table A1: List of initial tested messages

EXERCISE
Do you know that exercising outdoors when **air pollution is high** can harm your health? Protect your health. Check your local air quality on AirForU before exercising outdoors!
Do you know that exercising outdoors when **air pollution levels are high** can harm your health? Protect your health. Check your local air quality on AirForU before exercising outdoors!
Do you know that if you exercise outdoors when **air pollution is high you are breathing in more pollutants**? Protect your health. Check your local air quality on AirForU before exercising outdoors!
CHILDREN
Do you know that children **are more susceptible to high levels of air pollution**? Protect your children's health. Check your local air quality on AirForU before taking your children out to play!
Do you know that children **are more impacted by high levels of air pollution**? Protect your children's health. Check your local air quality on AirForU before taking your children out to play!
Do you know that **air pollution causes over one million school absences every year in California alone**? Protect your children's health. Check your local air quality on AirForU before taking your children out to play!
Do you know that high **air pollution can cause or worsen childhood asthma**? Protect your children's health. Check your local air quality on AirForU before taking your children out to play!
Do you know that **air pollution slows cognition in children by affecting their brain development**? Protect your children's health. Check your local air quality on AirForU before taking your children out to play!
FUTURE IMPACT
Do you know that **breathing air pollution over many years can shorten your lifespan by up to 10 years**? Protect your health. Check your local air quality on AirForU before going outdoors!
Do you know that high levels of air pollution **have been linked to long-term health conditions such as Alzheimer's disease and lung cancer**? Protect your health. Check your local air quality on AirForU before going outdoors!
GENERAL
Do you know that air pollution poses the largest health risk in the world? Protect your health. Check your local air quality on AirForU before going outdoors!
Do you that **over 200,000 people in the US die early every year due to air pollution**? Protect your health. Check your local air quality on AirForU before going outdoors!
CONTROL
Check your local air quality on AirForU!"

Table A2: Survey Summary Statistics for Demographics (N=835 or N=430)[1]

	Survey Respondents				
	N	M[1]	SD	Min	Max
Female	835	0.430	0.495	0	1
Age (years)	835	35.3	11.1	18-24	≥ 65
Income[a]	430	54563[b]	37518[b]	≤ 24999	≥150000
Frequency of outdoor exercise[a]	430	3.68[c]	1.46[c]	1	6
Education[a]	430	4.05[d]	1.31[d]	1	6
Race (White or Caucasian)	430	0.726	-	-	-
Have Asthma	835	0.115	0.319	0	1
Children (<18 yrs.) living in HH	835	0.295	0.456	0	1
Children (<18 yrs.) with asthma	835	0.236	0.425	0	1
Have Knowledge of AQI	835	0.181	0.385	0	1
Have Knowledge of $PM_{2.5}$	835	0.403	0.491	0	1

[a] N for these demographics is 430 because these questions were only asked in the second set of survey responses
[b] Responses ranged less than $24,999 to $150,000 or more coded as values 1 to 6
[c] Responses ranged from once a year or less to 5 or more times a week coded as values 1 to 6
[d] Responses ranged from less than high school to graduate degree coded as values 1 to 6

[1] The mean and standard deviation for age, income, education and frequency of outdoor exercise (Table 2) were estimated by using the midpoint of each category.

Table A3: MTurk Survey Detailed Summary Statistics for Demographics

	N	%	M	SD	Min	Max
Duration of survey (minutes)	835	-	7.43	7.53	1.08	73.7
Gender	835		0.430	0.495	0	1
Male (value=0)	476	57.0				
Female (value =1)	359	43.0				
Age	835					
18-24 years	103	12.3				
25-34 years	384	46.0				
35-44 years	195	23.3				
45-54 years	98	11.7				
55-64 years	40	4.80				
65 years or older	15	1.80				
Have Asthma	96	11.5	0.115	0.319	0	1
Children (<18 years) living in household	246	29.5	0.295	0.456	0	1
Children (<18 years) with asthma	58	23.6	0.236	0.425	0	1
Have Knowledge of AQI	151	18.1	0.181	0.385	0	1
Have Knowledge of PM2.5	336	40.3	0.403	0.491		
Air quality after 2 pm (Incorrect)	13	1.56				
Particulate matter with diameter less than 2.5 **µm** (Correct)	336	40.3				
Performance measurement standards for air quality equipment (Incorrect)	43	5.16				
Powdered metallics with diameter less than 2.5 **µm** (Incorrect)	10	1.20				
I don't know	432	51.8				
Frequency of outdoor exercise[1]	430					
Once a year or less	46	10.7				
Several times a year	44	10.2				
A few times a month	91	21.2				
1-2 times a week	114	26.5				
3-4 times a week	89	20.7				
5 or more times a week	46	10.7				
Annual household income[1]	430					
Less than $24,999	99	23.0				
$25,000 to $49,999	134	31.2				
$50,000 to $74,999	106	25.6				
$75,000 to $99,999	28	6.51				
$100,000 to $149,999	53	12.3				
More than $150,000	10	2.33				
Highest level of education[1]	430					
Less than high school	5	1.2				
High school degree of equivalent	61	14.2				
Some college but no degree	99	23.0				
Associate or technical degree	53	12.3				
Bachelor's degree	165	38.4				
Graduate degree/professional	47	10.9				
Race/Ethnicity[1]	430					
American Indian or Alaska Native	2	0.47				
Asian	33	7.67				
Black or African American	33	7.67				
Native Hawaiian or Pacific Islander	0	0.00				

	N	%	M	SD	Min	Max
Hispanic/Latino	26	6.05				
White/Caucasian	312	72.6				
Other or Mixed	24	5.58				

Table A4: Survey Summary Statistics for Air Pollution Messages (N=835)

		N	M	SD	Min	Max
Baseline Statement	Comprehensibility	835	6.2	0.97	1	7
	Realism	835	5.5	1.3	1	7
	Relevance	835	5.4	1.4	1	7
Exercise Negative	Comprehensibility	277	6.2	1.0	1	7
	Realism	277	5.5	1.3	1	7
	Relevance	277	5.4	1.4	1	7
Exercise Positive	Comprehensibility	278	6.3	0.9	1	7
	Realism	278	5.8	1.2	1	7
	Relevance	278	5.3	1.6	1	7
Exercise Mixed	Comprehensibility	280	6.2	1.0	1	7
	Realism	280	5.9	1.2	1	7
	Relevance	280	5.5	1.4	1	7
Child Asthma Negative	Comprehensibility	421	6.3	0.9	1	7
	Realism	421	5.9	1.1	1	7
	Relevance	421	5.6	1.3	1	7
Child Asthma Positive	Comprehensibility	414	6.3	0.9	2	7
	Realism	414	6.1	1.0	2	7
	Relevance	414	4.3	2.0	1	7
Child Cognition Negative	Comprehensibility	418	6.4	0.8	2	7
	Realism	418	6.1	1.0	1	7
	Relevance	418	4.2	2.1	1	7
Child Cognition Positive	Comprehensibility	417	6.1	1.0	1	7
	Realism	417	5.4	1.4	1	7
	Relevance	417	4.4	1.9	1	7
Alzheimer’s Negative	Comprehensibility	416	6.2	0.9	1	7
	Realism	416	5.5	1.3	1	7
	Relevance	416	4.2	2.1	1	7
Alzheimer’s Positive	Comprehensibility	419	6.1	1.0	2	7
	Realism	419	4.9	1.6	1	7
	Relevance	419	4.6	1.7	1	7
Invisibility Negative	Comprehensibility	434	6.1	1.0	2	7
	Realism	434	5.1	1.5	2	7
	Relevance	434	4.8	1.7	1	7
Invisibility Positive	Comprehensibility	401	6.2	0.9	1	7
	Realism	401	5.9	1.0	1	7
	Relevance	401	5.5	1.2	1	7

Table A5: Correlation Matrix for Survey Questions (N=5010)

		1	**2**	**3**	**4**	**5**	**6**	**7**	**8**	**9**	**10**	**11**	**12**	**13**
1	Message Category	1												
2	Message Framing	0.989	1											
3	Check AQ	0.017	0.021	1										
4	Gender	0.000	0.000	0.120	1									
5	Age	0.000	0.000	0.032	0.090	1								
6	Asthma	0.000	0.002	0.151	0.089	-0.062	1							
7	Children	0.000	0.001	0.088	0.167	0.030	0.059	1						
8	Knowledge of AQ	0.000	-0.002	0.061	0.040	0.107	0.045	-0.032	1					
9	Knowledge of PM	0.000	0.001	0.057	-0.097	0.001	-0.111	-0.029	0.327	1				
10	Non-white ethnicity/race	0.000	0.000	-0.094	-0.041	0.171	0.075	-0.040	0.061	0.033	1			
11	Education	0.000	0.002	0.004	0.031	-0.015	-0.037	0.068	0.044	0.080	0.184	1		
12	Income	0.000	-0.001	0.077	0.064	-0.004	0.068	0.239	0.017	0.033	0.002	0.311	1	
13	Exercise Frequency	0.000	0.006	0.061	-0.083	0.103	-0.021	-0.022	0.101	0.150	0.096	0.089	0.182	1

Table A6: Summary Statistics for App Intake Survey (N=2,741)

	N	%
Gender		
Female	1226	44.7
Male	1514	55.3
Age		
18-24 years	357	13.02
25-30 years	387	14.12
31-50 years	1144	41.77
51-64 years	531	19.37
65 years or older	321	11.71
Health Conditions		
Heart Disease	385	14.1
Lung Disease	102	3.72
Asthma	421	15.4
Allergies	909	33.2
Other Health Conditions	121	4.41
Children (<18 yrs.) living in Home	959	35.0
Children		
Heart Disease	113	11.8
Lung Disease	18	1.88
Asthma	179	18.7
Allergies	337	35.1
Other Health Conditions	32	3.34
Frequency of Outdoor exercise		
Once a year or less	163	5.95
Several times a year	269	9.82
A few times a month	491	17.93
1-2 times a week	656	23.95
3-4 times a week	686	25.05
5 or more times a week	474	17.31
Knowledge of $PM_{2.5}$		
Air quality after 2 pm	24	1.15
Particulate matter with a diameter less than 2.5 □m	810	38.68
Performance measurements standards for air quality	45	2.15
Powdered metallics with a diameter less than 2.5 □m	33	1.58
I don't know	1182	56.45
Knowledge of AQI		
Yes	266	9.70
No	2474	90.30
Knowledge of AQI Range		
Yes	258	9.40
No	2482	90.60

Table A7: Prevalence of health conditions* aggravated by air pollution among app users and their children

	App Users (%)	Children (%)
At least 1 health condition	55.1	55.5
More than 1 health condition	13.3	13.8
No health condition	44.9	44.5

*Health conditions – asthma, outdoor allergies, lung disease, heart disease and other

Table A8: Comparison of Survey and App Users Samples

		MTurk Survey		App Survey		MTurk and App Survey		t-test (Statistically different samples)
		Mean	S.D.	Mean	S.D.	Min	Max	
Female	What is your gender?	0.430	0.495	0.447	0.497	0	1	No (t=0.893; p=0.372)
Asthma	Do you have asthma?	0.115	0.319	0.154	0.361	0	1	Yes*** (t=2.97; p=0.003)
Children (<18 yrs.)	Are any members of your household under the age of 18?	0.295	0.456	0.350	0.477	0	1	Yes*** (t=3.046; p=0.002)
Children (<18 yrs.) with asthma	If Children = yes; Do they have asthma?	0.236	0.425	0.065	0.247	0	1	No (t=-0.414; p=0.679)
Frequency of outdoor exercise[a]	Approximately, how often do you exercise outdoors?	3.68 [c]	1.46[c]	4.04	1.43	1	6	Yes (t=4.756; p=0.000)
Knowledge of AQI	Do you know the typical daily Air Quality Index (AQI) in the area where you live?	0.181	0.385	0.097	0.296	0	1	Yes*** (t=-5.812; p=0.000)
Knowledge of $PM_{2.5}$	What is $PM_{2.5}$?	0.403	0.491	0.387	0.487	0	1	No (t=-0.808; p=4234)

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

Table A9: Survey regression results for message categories relative to the baseline message with added controls (N=430)

Study Characteristic	**Check AQ**
Category Treatment	
Exercise	0.40***
	(0.06)
Child asthma	-0.03
	(0.08)
Child Cognition	-0.04
	(0.09)
Alzheimer's	0.03
	(0.09)
AP Invisibility	0.34***
	(0.06)
Controls	
Age > 55 years	0.41
	(0.26)
Frequent Outdoor Exercise	0.13
	(0.13)
College education	0.05
	(0.13)
Above median income	0.03
	(0.13)
Non-white	0.41***
	(0.14)
Female	0.30**
	(0.13)
Asthma	0.77***
	(0.16)
Children	0.28*
	(0.15)
Children with asthma	-0.04
	(0.28)
Knowledge of AQ	0.20
	(0.17)
Constant	4.23***
	(0.15)
Observations	2,580
Adjusted R-squared	0.06
F	9.430

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

Table A10: Survey Regression results for message framing relative to the baseline message with added controls (N=430)

	Study Characteristic	Check AQ
Question Treatment	Exercise negative	0.29**
		(0.13)
	Exercise positive	0.29**
		(0.12)
	Exercise mixed	0.61***
		(0.12)
	Child asthma positive	-0.16
		(0.11)
	Child asthma negative	0.09
		(0.12)
	Child cognition positive	-0.08
		(0.13)
	Child cognition negative	0.01
		(0.12)
	Alzheimer's positive	-0.12
		(0.12)
	Alzheimer's negative	0.18
		(0.11)
	AP Invisibility positive	0.37***
		(0.10)
	AP Invisibility negative	0.30***
		(0.10)
Controls	Age > 55 years	0.41
		(0.26)
	Frequent Outdoor Exercise	0.12
		(0.13)
	College education	0.05
		(0.13)
	Above median income	0.04
		(0.13)
	Non-white	0.40***
		(0.14)
	Female	0.30**
		(0.13)
	Asthma	0.76***
		(0.16)
	Children	0.27*
		(0.15)
	Children with asthma	-0.05
		(0.28)
	Knowledge of AQ	0.20
		(0.17)
	Constant	4.23***
		(0.15)
	Observations	2,580
	Adjusted R-squared	0.06
	F	7.587

Table A11: Regression with interactions for children and message category for survey respondents (N=835)

Study Characteristic	**Check AQ**
Category Treatment	
Exercise	0.42***
	(0.06)
Child asthma	-0.31***
	(0.07)
Child Cognition	-0.28***
	(0.08)
Alzheimer's	0.01
	(0.07)
AP Invisibility	0.41***
	(0.06)
Interactions with Message Category	
Exercise*Have children	-0.14
	(0.10)
Child asthma*Have children	0.98***
	(0.13)
Child Cognition*Have children	1.00***
	(0.13)
Alzheimer's*Have children	-0.04
	(0.13)
AP Invisibility*Have children	0.02
	(0.10)
Controls	
Age > 55 years	0.28
	(0.19)
Gender	0.25***
	(0.09)
Asthma	0.66***
	(0.11)
Children	0.03
	(0.13)
Child Asthma	0.07
	(0.18)
Knowledge of AQ	0.38***
	(0.06)
Constant	4.50***
	(0.08)
Observations	5,010
Adjusted R-squared	0.07
F	22.67

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

Table A12: Regressions with interactions for asthma for survey respondents (N=835)

Study Characteristic	**Check AQ**
Category Treatment	
Exercise	0.36***
	(0.05)
Child asthma	-0.13**
	(0.07)
Child Cognition	-0.03
	(0.07)
Alzheimer's	-0.05
	(0.07)
AP Invisibility	0.39***
	(0.05)
Interactions with Message Category	
Exercise*Have asthma	0.16
	(0.17)
Child Asthma*Have asthma	0.93***
	(0.19)
Child Cognition*Have asthma	0.33
	(0.20)
Alzheimer's*Have asthma	0.41**
	(0.17)
AP Invisibility*Have asthma	0.19
	(0.16)
Controls	
Age > 55 years	0.28
	(0.19)
Female	0.25***
	(0.09)
Asthma	0.32*
	(0.16)
Children	0.34***
	(0.11)
Child Asthma	0.07
	(0.18)
Knowledge of AQ	0.39***
	(0.11)
Constant	4.45***
	(0.08)
Observations	5,010
Adjusted R-squared	0.06
F	19.47

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

Table A13: Regressions with interactions for age > 55 years for survey respondents (N=835)

Study Characteristic	**Check AQ**
Category Treatment	
Exercise	0.38***
	(0.05)
Child Asthma	0.01
	(0.06)
Child Cognition	0.05
	(0.07)
Alzheimer's	0.00
	(0.06)
AP Invisibility	0.41***
	(0.05)
Interactions with Message Category	
Exercise* Age > 55 years	-0.13
	(0.16)
Child Asthma* Age > 55 years	-0.46*
	(0.24)
Child Cognition* Age > 55 years	-0.64***
	(0.23)
Alzheimer's* Age > 55 years	-0.04
	(0.23)
AP Invisibility* Age > 55 years	0.10
	(0.18)
Controls	
Age > 55 years	0.47**
	(0.21)
Female	0.25***
	(0.09)
Asthma	0.66***
	(0.11)
Children	0.34***
	(0.11)
Child Asthma	0.07
	(0.18)
Knowledge of AQ	0.39***
	(0.11)
Constant	4.40***
	(0.08)
Observations	5,010
Adjusted R-squared	0.06
F	17.09

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

Table A14: Variables used in the regressions for exploring app engagement

Category	Name and Type	Description
Dependent Variable	open_app	Number of app visits per person per week
Treatment Variable	email_group (dummy)	12 dummies corresponding to the 12 message groups and 1 control group that received no email
	email_cat (dummy)	6 dummies corresponding to the 6 message categories and 1 control group that received no emails
	prepost (dummy)	Time dummy accounting for period before and after the email experiment
	openemail (dummy)	Dummy indicating whether an app user opened the email
Prior engagement controls	notif (dummy)	Dummy to control for the effect of weekly notifications. 0 for disabled always, 1 for enabled always, 2 for switching between enabled/disabled and 3 for android/no data for iPhone.
	wks_inactive5 (10,15 or 20) (dummy)	Dummies to control for user's engagement with the app prior to the experiment. Dummies for this variable represent whether the user has been inactive for periods longer than 5 (10, 15 or 20 weeks) since downloading the app
Demographic and health controls	age (continuous)	Age of the app user (values range from 1 to 6; see **Error! Reference source not found.** in the appendix for categories)
	gender (dummy)	Gender of the app user
	exercise (continuous)	Exercise frequency of the app user (values range from 1 to 6; see **Error! Reference source not found.** in the appendix for categories)
	aqi (dummy)	Knowledge of aqi; also correlated with knowledge of $PM_{2.5}$
	Children (dummy)	Accounting for whether the app user has children (<18 yrs and living in household)
	user_asthma (and other health conditions) (dummy)	Accounting for the user's health conditions aggravated by air pollution
	child_asthma (and other health conditions) (dummy)	Accounting for the health conditions of the user's children (<18 years and living in household) aggravated by air pollution
Time controls	week (dummy)	Week dummies to control for seasonality. Number of dummies correspond to the number of weeks since the user first downloaded the app

Table A15: App engagement before and after the email experiment split by levels of user activity. (control group received no email).

Study Characteristic	(1) Check App All users (N=2,740)	(2) Check App Inactive 5 weeks (N=2,621)	(3) Check App Inactive 10 weeks (N=2,456)	(4) Check App Inactive 15 weeks (N=2,321)	(5) Check App Inactive 15 weeks (N=2,171)
Engagement by group after receiving the email					
Baseline	0.27***	0.10***	0.12***	0.12***	0.06***
	(0.09)	(0.03)	(0.03)	(0.03)	(0.02)
Exercise	0.24***	0.06***	0.06***	0.09***	0.03*
	(0.08)	(0.02)	(0.02)	(0.02)	(0.02)
Child Asthma	0.25***	0.03	0.04**	0.05***	0.01
	(0.08)	(0.03)	(0.02)	(0.02)	(0.02)
Child Cognition	0.18**	-0.04*	-0.02	-0.02	-0.07***
	(0.08)	(0.02)	(0.02)	(0.02)	(0.02)
Alzheimer's	0.22***	0.05**	0.08***	0.09***	0.04*
	(0.08)	(0.02)	(0.02)	(0.02)	(0.02)
AP Invisibility	0.28***	0.10***	0.09***	0.11***	0.03**
	(0.08)	(0.03)	(0.03)	(0.03)	(0.02)
Engagement by group prior to receiving the email					
Baseline	-0.01	-0.03*	-0.05***	-0.06***	-0.03**
	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)
Exercise	0.03	-0.04**	-0.04**	-0.06***	-0.01
	(0.02)	(0.02)	(0.02)	(0.02)	(0.01)
Child Asthma	0.04	0.05***	-0.03	-0.05***	-0.00
	(0.02)	(0.02)	(0.02)	(0.02)	(0.01)
Child Cognition	0.04**	0.07***	0.05***	0.04**	0.09***
	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)
Alzheimer's	0.04*	-0.00	-0.03*	-0.04**	0.02
	(0.02)	(0.02)	(0.02)	(0.02)	(0.01)
AP Invisibility	-0.05**	-0.06***	-0.05***	-0.08***	-0.02*
	(0.02)	(0.02)	(0.02)	(0.02)	(0.01)
Before/After Dummy	-5.21***	-4.82***	-4.75***	-4.67***	-4.59***
	(0.21)	(0.20)	(0.19)	(0.19)	(0.19)
Prior Engagement Controls					
Weeks of Inactivity (5 weeks)	5.01***	-	-	-	
	(0.17)	-	-	-	
Notification (Enabled Always)	0.04***	0.04***	0.01	0.02*	0.06***
	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)
Notification (Alternating between Disabled/Enabled)	0.50***	0.49***	0.31***	0.20***	0.19***
	(0.04)	(0.03)	(0.03)	(0.02)	(0.02)
Notification (Status unknown for some devices)	-0.17***	-0.13***	-0.13***	-0.12***	-0.05***
	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)
Health and Demographic Controls					
Age	0.01***	0.02***	0.01**	0.00	-0.00
	(0.01)	(0.00)	(0.00)	(0.00)	(0.00)
Female	0.07***	0.12***	0.10***	0.09***	0.07***

	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)
Exercise	-0.02***	0.00	0.01***	0.01**	0.01***
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
Heart Disease	0.18***	0.17***	0.17***	0.17***	0.09***
	(0.02)	(0.02)	(0.02)	(0.02)	(0.01)
Lung Disease	0.08**	0.09***	-0.05**	-0.02	0.01
	(0.03)	(0.03)	(0.02)	(0.02)	(0.02)
Asthma	0.05**	0.09***	0.11***	0.09***	0.07***
	(0.02)	(0.02)	(0.02)	(0.01)	(0.01)
Allergies	0.02*	0.05***	0.06***	0.05***	0.02**
	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)
Other health conditions	0.69***	0.37***	0.35***	0.36***	0.21***
	(0.06)	(0.04)	(0.04)	(0.04)	(0.03)
Children	0.12***	0.11***	0.07***	0.06**	0.07***
	(0.03)	(0.03)	(0.02)	(0.02)	(0.02)
Children Heart Disease	-0.44***	-0.29***	-0.15***	-0.15***	-0.12***
	(0.04)	(0.03)	(0.03)	(0.03)	(0.03)
Children Lung Disease	0.31***	0.03	-0.04**	-0.02	-0.02
	(0.04)	(0.02)	(0.02)	(0.02)	(0.02)
Children Asthma	0.06***	-0.02*	-0.05***	-0.03**	-0.02
	(0.02)	(0.01)	(0.01)	(0.01)	(0.01)
Children Allergies	-0.11**	0.01	-0.02	-0.02	0.04
	(0.05)	(0.04)	(0.04)	(0.04)	(0.04)
Children Other health conditions	0.12***	0.11***	0.07***	0.06**	0.07***
	(0.05)	(0.04)	(0.04)	(0.04)	
Knowledge of AQ	0.04**	0.05***	0.07***	0.01	0.02**
	(0.02)	(0.02)	(0.02)	(0.01)	(0.01)
Constant	4.81***	4.65***	4.61***	4.57***	4.49***
	(0.20)	(0.20)	(0.19)	(0.19)	(0.19)
Observations	168,726	165,792	161,719	156,916	150,681
Adjusted R-squared	0.14	0.07	0.07	0.08	0.08
F	37.83	36.56	40.59	39.53	39

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