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CAN APPS MAKE AIR POLLUTION VISIBLE?

USER ENGAGEMENT WITH AIR QUALITY INFORMATION

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Abstract

Air pollution is one of the largest environmental health risks globally but is often imperceptible by people. Air quality smartphone applications (commonly called apps) provide real-time localized air quality information and have the potential to help people learn about the health effects of air pollution and take action to protect their health. Hundreds of air quality apps are now available, however, there is scant information on how effective these mobile apps are at educating stakeholders about air pollution and at promoting behavioral change to protect their health. In this paper, we test how intrinsic and extrinsic motivations can enhance users' engagement with air quality information and favor changes in protective behavior. We developed an air quality app, AirForU, with a built-in research study that was downloaded by 2,740 users. We found that user engagement, measured as checking the app, and talking to someone about air pollution, was strong in the first few weeks after downloading the app but faded significantly after 12 weeks. Engagement was higher for users with intrinsic motivations, such as those who are health conscious, either because they are suffering from heart disease or other conditions aggravated by air pollution, or because they exercise often and want to maintain a healthy lifestyle. Extrinsic motivations such as notifications were also effective. App users stated that they shared air quality frequently with others while using the app, learned information about the Air Quality Index (AQI), and took measures to protect their health.

Keywords: Air pollution, information strategies, mobile applications, information technologies, sustainability, health protection, behavior change

JEL: Q01, Q28, Q58, D83

Introduction

Mobile devices, and their associated applications, are increasingly prevalent and connected to our daily activities. One example is air quality mobile applications (commonly called apps) that provide information about local air quality to help people take action to protect their health against pollution. While these apps are diffusing rapidly, we do not have a good understanding of their effectiveness at educating stakeholders about air pollution and at promoting behavioral change.

Air pollution affects most people worldwide; poor air quality is ubiquitous and often invisible to the naked eye. The World Health Organization (WHO) announced that air pollution is the single largest environmental health risk globally (UN WHO, 2014); particularly in urban areas (Bickerstaff & Walker, 2001). Currently, more than half of all Americans – 166 million people – live in areas that don't meet national air quality standards (ALA, 2016). The varied and numerous adverse health effects of air pollution to almost every organ and bodily system are well established (Brunekreef and Holgate 2002; Pope and Dockery 2006; Curtis et al. 2006). Besides the human suffering, the associated health care costs run into billions of dollars annually just in the United States (US) (CDC, 2014; Colls, 2002). Furthermore, air quality is expected to worsen with climate change (Bergquist et al., 2012; Jacob & Winner, 2008; Mickley, Jacob, Field, & Rind, 2004).

While people may be generally aware that air pollution in certain cities is high, they are often unaware of the actual air quality levels they are being exposed to. And despite the extensive health burden associated with air pollution, there is a lack of awareness among the public regarding the links between air pollution and health (Bickerstaff & Walker, 2001). One reason for this lack of awareness is that air pollution is often imperceptible and when it is, people's perceptions can often be inaccurate (Semenza et al., 2008).

Real-time and localized information about poor air quality, as well as air quality forecasts, can help individuals take steps to reduce their exposure and protect their health against pollution. Some steps that individuals can take to protect their health are to limit time spend outdoors, reschedule outdoor activities and use air conditioners with air filters or other stand-alone devices that purify air (US EPA, 2014). Governments worldwide have developed extensive air quality monitoring and reporting programs to inform the public. The basis of these programs is to increase the public's awareness of the state of the air, especially with regards to health effects so that individuals can adjust their behavior to protect their health (Ruggieri & Plaia, 2012). As forecasting and modeling technology has progressed, real-time (hourly) air quality updates for most cities are now available and can be disseminated rapidly through websites and apps owing to advances in information technology.

The success of air quality informational programs through mobile apps hinges on their effective communication. While many apps have been developed for weather forecasts (Zabini, 2016), or health management (Free et al., 2013), we know almost nothing about what populations use air quality apps and how they respond to the information provided in the app. Air pollution disproportionately affects a large proportion of the general population; young children, the elderly, pregnant women, asthmatics heart and lung disease patients and those with a compromised immune system (Brook et al., 2004; Mansfield 2006; Pope & Dockery, 2006). It is therefore important to understand how air quality information diffused through apps reaches these populations particularly.

In this paper, we address the following research question: how effective are sustainability mobile apps at educating stakeholders about air pollution issues and promoting behavioral change? Apps could be useful in educating stakeholders if we can understand the conditions under which stakeholders (the users) engage with this information, and conditions under which they change their behavior. We build on behavior change theories to investigate whether intrinsic and extrinsic motivations can enhance users' engagement with the air quality information provided through apps, and favor changes in protective behavior. Knowledge of these motivations can help design more effective apps.

To answer our research question, we developed an air quality app, AirForU, with a built-in research study. The app relied on data from the Environmental Protection Agency's (EPA) AirNow program. App users could access hourly air quality information and next-day air quality forecasts. Through an intake survey within the app, we collected demographic and medical condition information about app users, and using google analytics, we tracked how users engaged with air quality information through the app. The results of our study show that air quality apps are a promising tool to educate people about air quality. However, it is challenging to keep users engaged over time. Our analysis indicates a set of intrinsic and extrinsic motivations that enhance user engagement. First, we find that user involvement with the issue, such as health consciousness is an important intrinsic motivational factor. Second, we find that reminders built in the app's design, can act as extrinsic motivations to engage with the information. Based on our observations we provide some suggestions to improve the effectiveness of air quality apps.

In addition, because the app was developed in part by graduate students, we share how developing an air quality app can be a useful experience for students interested in advancing corporate sustainability in their career. With the looming threat of climate change, increasing stakeholder, educator and student interest in environmental and social sustainability, among others, have led schools to incorporating these topics in their curriculum (Christensen, Peirce, Hartman, Hoffman, & Carrier, 2007; Starik, Rands, Marcus, & Clark, 2010). There is a strong need to design new tools and resources, increase interdisciplinary collaboration and take advantage of the technology boom to make progress in protecting the Earth's resources and its inhabitants (Starik et al., 2010). The development of an app provides a platform that can bring together people with different skills to work on solutions to complex environmental problems. It helps students experience directly the challenges associated with promoting behavior change in a contested setting.

This paper is organized as follows. First, we review the literature on the effectiveness of mobile apps for behavior change. Second, we develop hypotheses on the role of motivations on users' engagement with the information provided in the app and on behavior change. Third, we test our hypotheses on user engagement with data gathered through our air quality app, AirForU. Fourth, we present some evidence of behavior change related to the use of the app. Finally, we provide recommendations to improve the effectiveness of air quality apps and offer a concluding discussion on using apps for active collaborative learning in academia.

Background

Mobile apps are a type of third-party software designed to run on a mobile device such as a smartphone or tablet. These devices are intended to be always on and carried on the person throughout the day (i.e., during normal daily activities) (Riley et al., 2011). Compared to internet interventions delivered to desktop and laptop computers, mobile interventions have the capacity to interact with the individual with much greater frequency, and in the context of the behavior (Riley et al., 2011).

Mobile technologies offer unprecedented advantages in the public health domain – a variety of audiences can be engaged on a large scale through education, messaging interventions and behavior change strategies (Lefebvre, 2009; Ozdalga, Ozdalga, & Ahuja, 2012; Terry, 2010). There are over 100,000 health apps available currently and millions of people globally are using these apps (Dorsey et al., 2017). Educational information, such as when and what to do to promote health, is a key precursor to behavior change and is, not surprisingly, one of the most common behavior change techniques in health promoting apps such as those for physical activity (Conroy, Yang, & Maher, 2014).

Reviews of existing health apps indicate their potential to influence behavior change and improve health (Payne, Lister, West, & Bernhardt, 2015; Zhao, Freeman, Li, & Building, 2016). Apps aimed at changing behavior are more effective when they incorporate behavior change theory principles (Michie & Johnston, 2012; Riley et al., 2011; West et al., 2012). The behavior change theories that have been used for delivering interventions include the health belief model, social cognitive theory, self-determination theory, theory of planned behavior, and the transtheoretical model (Payne et al., 2015; Riley et al., 2011; Zhao et al., 2016). Certain design and content features make apps successful. Highly-rated health apps are simple and easy-to-use, provide clear instructions on managing health, are not time-consuming, allow data sharing and incorporate well-designed health tracking tools (Mendiola, Kalnicki, & Lindenauer, 2015). Apps that raise awareness of certain behaviors and provide information about action steps are well-received by users (Payne et al., 2015). App users have also indicated that they would like to be reminded to take action, however, users have also indicated that it is sometimes inconvenient to receive these reminders (Dennison, Morrison, Conway, & Yardley, 2013). Gamification is another feature that can be added to apps; a diabetes app with gamification was effective at improving health outcomes (Cafazzo, Casselman, Hamming, Katzman, & Palmert, 2012).

However, the limitation of many health apps used in research studies is their small sample sizes (Payne et al., 2015; Zhao et al., 2016). This is often due to the fact that the use of apps can be irregular and only over the short-term (Dennison et al., 2013; Hebden, Hons, Cook, Hons, & Ploeg, 2006).

While many studies have been conducted on health apps, there is still very limited research on response to air quality apps. The only research related to response to air pollution information refers to response to smog alerts or search for online information about air pollution. For example, Neidell (2004; 2006) found that people protect their health against next-day smog alerts published in the newspaper by reducing outdoor recreational activities but this effect wanes for alerts issued on consecutive days (Zivin and Neidell 2009). Air quality alerts have also been shown to reduce cycling behavior in Australia (Saberian, Heyes, & Rivers, 2017). In China, elevated air pollution levels are positively associated with higher online searches for anti- $PM_{2.5}$ masks and air filters (Liu, He, & Lau, 2018). Beyond that, there is little information on how people engage with real-time information, what they learn from this information and the steps they take to protect their health in response to this information.

Mechanisms through which apps help users learn about air quality

Advances in mobile communication technologies could, in principle, improve the effectiveness of air quality communication and help users learn about air pollution and encourage them to take action to protect themselves i.e. change their behavior. Behavior change can be preventive, such as avoiding going outdoors during episodes of high pollution, or protective, such as using air filters at home. Behavior change can also be social, such as discussing air pollution with a doctor, or informing others how to reduce their exposure to air pollution.

But what are the mechanisms through which air quality apps help users learn about air quality and change their behavior to protect themselves? The theory of planned behavior is often used to understand these mechanisms. It suggests that if you intend to do something, then you are likely to perform that behavior (Ajzen, 1991). It has been applied in various contexts such as technology, health care, politics, and sustainability, to explain the individual behavior of adoption (Armitage & Conner, 2001; Barnard-Brak, Burley, & Crooks, 2010; Conner & Armitage, 1998; Sunio & Schmöcker, 2017; Taylor & Todd, 1995; Zimmerman & Noar, 2005). Building on the theory of planned behavior, we can identify two main elements in an air quality app that facilitate changes in intentions and behavior.

The first element is to help users learn the importance of the health problems associated with air pollution. This is an important step, because realizing there is a problem helps people develop intentions to change their behavior to solve the problem. The awareness of the impact of air pollution on health can change beliefs and attitudes. According to the theory of planned behavior, changes in beliefs and attitudes affect intentions and inform behavior (Carrington, Neville, & Whitwell, 2010).

All of the studies undertaken in geographical situations associated with urban and industrial air pollution problems stress the role of situational learning, or practical everyday experience in how people come to learn about air pollution (Saksena, 2011). An air quality app provides real-time localized information about air quality, including alerts for high air pollution levels, as well as prediction of future air pollution levels.

Always-on connectivity allows users to receive specific information or notifications and always reach updated information, accessing the data stream with immediacy. Therefore, the frequency of localized information can help users realize the importance of the problem. For instance, this might be particularly salient for people who have asthma because they could visualize the levels of air pollution when they have asthma attacks and then better make the connection between air pollution and their health.

The second element is the ability to learn how to protect our health. An air quality app that provides prediction of future air quality levels and tips to reduce exposure can help users improve their perception of behavioral control. Indeed, when they learn that air pollution will be high they can easily access these tips on the app and try them out. These tips about potential behavior to protect health include - avoiding outdoor exercise, closing windows, using air conditioning/heating systems with properly maintained filters, using stand-alone air purifiers, and wearing protective masks during outdoor activities.

The ability to learn how to protect our health helps people realize how they can affect the problem. Research has shown that apps that “provide instruction on how to perform the behavior” and “model/demonstrate the behavior,” support the formation of the intention to change behavior (Conroy et al., 2014).

Indeed, not all behaviors are easy to perform. Individuals might prefer to engage in certain behaviors, but feel they lack the ability to do so. Individuals are also more likely to engage in certain behaviors when they understand the behavioral procedures. This role is important because individuals can misperceive their behavioral control, and a behavioral intention built on a false sense of control is unlikely to translate into actual behavior (Rosenthal, 2018).

The time between intention and action can be reduced with air pollution apps because they provide context relevant and timely information to reduce vulnerability to air pollution hazards. This allows users to take immediate steps to protect their health against potential or current air pollution events by engaging in protective behaviors. This is similar to using information from a weather app to decide whether to wear a coat when it is cold or take an umbrella to protect oneself against the rain (Sharma, 2014; Zabini, 2016).

The intention construct is central to the theory of planned behavior. Intentions are assumed to capture the motivational factors that in influence a behavior and to indicate how hard people are willing to engage with the information or how much effort they would exert to perform the behavior. However, the theory falls a little short in describing these motivational factors.

Here we argue that the effectiveness of these two elements, learning about the problem and learning about solutions, should be enhanced with user engagement with the information. Indeed, engagement with information has been shown to be an important first step towards 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” (Stern, 1999). The more engaged are people with the information, the more they learn about the problem and the solutions and the more likely they might adopt a protective behavior. Engagement is defined as looking at the information on the app, and possibly sharing it with others.

The theory of issue involvement is helpful to understand user engagement with the information. The theory shows that the effectiveness of advertising messages is widely believed to be moderated by audience involvement (Zaichkowsky, 1986). It demonstrates that involvement with an issue affects how people process information about it and respond to that information (Greenwald & Leavitt, 1984). The theory was developed in the marketing and consumer psychology literature, and, has also been used in the field of sustainability and consumer behavior (de Velde, Verbeke, Popp, & Huylenbroeck, 2010; Wang & Anderson, 2011)

Hypotheses

Building on this line of thought, we argue that there are two main motivators that influence users' engagement with the information provided in the app. The first motivator, users' health consciousness, relates to the interest that users have in learning about air pollution. Indeed, the learning literature has shown the importance of motivation on cognitive processes (Tobias, 1994). Interest in an issue (Deci & Ryan, 1990) suggest that "intrinsically motivated behaviors are those the person undertakes out of interest" (p. 241); from this perspective, interest and intrinsic motivation are almost synonymous. The second motivator refers to push notifications or messages provided by the app to remind the users of engaging with the information.

We therefore propose two different types of motivations for engagement with air quality information. The first type, health consciousness represents an intrinsic motivation, which is regulated from within the user. The second type, notifications from the app, is extrinsic motivation, and is regulated from an external source. The first motivation is related to the users' characteristics, while the second is a feature of the app.

Health consciousness and engagement

Because an air pollution app aims at helping users to protect themselves against air pollution, those who are health conscious should be more intrinsically motivated in the information provided in the app. Therefore, user engagement should vary depending of the level of health consciousness of people.

Environmental harm and human health are often closely linked. The WHO defines the environment in the context of health as “all the physical, chemical, and biological factors external to a person, and all the related behaviors (UN WHO, 2016).” Not everyone makes the connection between environmental impacts and health, but when they do, it becomes a powerful motivator to change consumption behavior.

People search for solutions when they become aware of health problems associated with their environment. For example, increased awareness leads them to seek out green products to protect their health (Bennett, 1997). Therefore, those with health issues, as well as those who are particularly health conscious, might be more likely to seek information and engage with the information. For example asthmatics and other sensitive groups usually seek more information about the health effects of pollution (Beaumont, Hamilton, Machin, Perks, & Williams, 1999; Bush, Moffatt, & Dunn, 2001). Considerable research has established that involvement with an issue affects how people process information about it and respond to that information (Greenwald & Leavitt, 1984). Those that are more invested in an issue, such as sensitive groups affected by air pollution, should be likely to engage with relevant information by spending more time processing the information presented, air quality information in this case. Thus, they are also more likely to respond to it by changing their behavior to protect their health when they perceive that doing so will benefit them. We therefore develop the following hypothesis:

H1: Health Conscious users are more likely to engage with air quality information provided through a mobile app.

Notifications and engagement

Beside intrinsic motivations, extrinsic motivations, or those that are external to the user might also effectively push users to engage with the information provided through the app. Users might gradually become inattentive to the information provided in the app after the novelty effect of the app has faded. Inattention, or the inability to direct and sustain attention, is a well-known phenomenon in the learning literature, and is particularly prominent in the online environment Some have said we live in a world of constant inattention, a time when we are surrounded by a multitude of information sources (Rose, 2010).

One way to fight this inattention is to provide notifications or reminders to app users about air pollution. Notifications are a core feature of mobile phones. They inform users about a variety of events. Users may take immediate action or ignore them depending on the importance of a notification as well as their current context. A large-scale assessment of the effectiveness of notifications showed that they can be effective if their content is important and relevant for the user (Shirazi et al., 2014). Indeed, not all notifications are appreciated, and thus they can have an inverse effect. In the case of air pollution, we argue that such notifications can effectively direct the attention of the user to the information presented in the app, if the frequency of these notifications is low. Notifications can act as light nudges to engage users with the information. We therefore develop the following hypothesis:

H2: Users who receive notifications are more likely to engage with air quality information provided through a mobile app.

Our framework for engagement is summarized in Figure 1 below. Engagement with an air quality app that provides frequent and localized air pollution information enhances learning about the problem and the solution and can lead to behavior change, but this engagement might be more likely for health-conscious users, and those who receive notifications. In other words, engagement is enhanced with these intrinsic and extrinsic motivations. While intrinsic and extrinsic motivations could act independently, they might also interact and enhance each other. It is also possible that engagement with the app enhances health consciousness, and that those who change their behavior decide to engage further with the app. In other words, these different elements could build on each other over time.

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[Insert Figure 1 About Here]

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In this paper, we first test these hypotheses by observing users' engagement with a mobile app. Then, we provide some evidence of behavior change associated with engagement with the mobile app. In doing so, we provide a comprehensive picture of response to air quality information that includes the conditions under which users engage with the information and those that drive behavior change.

AirForU Development and Features

To test our hypotheses, we developed an air quality app that was available free to the public.[1] Development for the AirForU app began towards the end of 2014. Testing began a few months later and the final version was launched in October 2015 under the XXXX Health brand in Google Play

[1] We developed two versions of the AirForU app – one for iPhones and one for Android devices; both versions were identical apart from cosmetic differences due to their native development platforms.

(for Android devices) and the App Store (for iPhones) (together these devices heavily dominate the smartphone market (Statista, 2017)).

Air quality data obtained from US EPA AirNow website includes real-time hourly updates of air quality as well as next-day AQI forecasts. The air quality information is gathered from monitoring stations throughout the nation and supplemented with modeled predictions. The air quality is reported to the public based on EPA's guidelines in the form of an AQI, which accounts for ambient concentrations of criteria 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. It is reported on a scale of 0-500 with 100 corresponding to the National Ambient Air Quality Standards (NAAQS). The scale is divided into 5 levels, each of which is color coded and associated with different health effects and sensitive populations that may be at risk (Figures 2 and 3). This information is available on the app via an application program interface (API) that connects the AirNow website to the server site where the app is hosted.

AQI within the app

AQI data has to first be downloaded onto an internal server from the AirNow website before it can be accessed in the app. The AirNow program has a Rich Site Summary (RSS) feed that allows users to access AQIs easily and regularly. The server uses an API to access AirNow's RSS feed and stores the data on the server. This data is updated hourly.

AQIs are provided by zip code from AirNow. Each time the user searches by city, the data is first converted to a zip code and then the zip code is checked against the AirNow AQI data. When the user searches by current location, the latitude/longitude is converted to a zip code within the server and checked against the AirNow AQI data. When users access the AirForU app, a default AQI is presented based on the zip code provided by the user in the intake survey. This is also the home screen i.e. the default screen displayed when the app is opened (see middle screenshot in Figure 2 - "Today's Air Quality Screen" displaying the real-time AQI). In addition to the default setting, users can search for the AQI in a number of ways: by zip code, by city name or based on their current location.

Three types of air quality information are available through the app - hourly air quality updates, next-day air quality forecasts and 7-day historical daily averages (screenshot on the left in Figure 2). AQI is reported using EPA guidelines on colors and modifiers. The background color in the app changes based on the level of pollution in the air: the higher the AQI the "dirtier" the depiction of air.

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[Insert Figure 2 About Here]

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Health

Health information for each range of AQI is based on EPA guidelines for AQI levels and colors (US EPA, 2006). Health information can be accessed through the health tab or by clicking on the colored circle on the air quality home screen (Figure 3).

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[Insert Figure 3 About Here]

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Other tabs include a toxic tab, with information about large industrial facilities that release toxic chemicals into the environment, a prize tab that provides incentives to encourage people to respond to the daily survey questions, and a tab with more information about the project and frequently asked questions about air quality and tips for health protection. More information on each of these tabs is provided in Appendix 1.

The app also included three questions that were posed daily to the users towards the end of the day (after 4 pm). Users could only access these questions if they checked the app after 4 pm. The questions were: Have you or will you engage in outdoor activity today? Did you or a household member have an asthma attack today? Did you talk to someone about air quality today? These questions were aimed at obtaining information about user behavior related to air quality for that day.

Recruitment strategy

A number of avenues (social media, newsletters, websites, and flyers) were used to diffuse the app. The XXXX Health Media and Marketing team provided support in marketing the app and recruiting users through their health network. Collaborating with XXXX Health facilitated contact with a larger number of sensitive groups. Their health newsletters have over 650,000 subscribers consisting of healthcare professionals. In addition, we promoted the app through interviews on local public radio shows. Flyers were distributed at several conferences on sustainability and related topics.

Development team

An interdisciplinary team consisting of business students, social scientists and engineers in partnership with the XXXX Health marketing department developed the app. It was also one of the projects of the Leaders in Sustainability graduate program at XXXX. It included five students, a postdoctoral researcher and a faculty, all interested in exploring the use of information technologies to solve environmental problems. The team met weekly to discuss the design of the app and team members worked independently on different elements of the app. These meetings included discussions on how to design the app to make it easy to access and attractive to users, how to integrate academic research into the design of the app, ethical issues related to the use of information, and how to communicate the app to the public to recruit users. It also involved education on the technological complexities involved in bringing together many different sources of data. It is important to note that communication between team members of different fields was central to the development of the app. These discussions allowed the combination of different skills. Social scientists alone or engineers alone would not have been able to develop the app. In addition, the team partnered with the marketing team of XXXX health to promote the app.

AirForU Users

App users encountered an intake survey when they first downloaded the app before they were able to access the app (See Appendix 2).[2] While the app was downloaded over 3,000 times, users outside the US were dropped from the study. Researchers and beta testers were also dropped from the study. The resulting population studied is 2,740 users. AirForU users were predominantly iPhone users (75%). A majority of the users were from California (63%), and a large number from Los Angeles (41%). This is not surprising since the recruitment effort was focused in Los Angeles.

[2] While they were not required to fill out the survey, they received repeated prompts requesting them to fill out the survey. As a result, the response rate was close to a 100%.

Results from the intake survey are provided in Table A3 in Appendix 3 Overall 55% of the users were male and 45% female. The percentage of female is therefore slightly below the US average, which is 50.8%.[3] Among users, 35% had children, higher than the average of 25% in the US population. Not surprisingly, AirForU users differed from the general population concerning their health conditions. For example, incidence of asthma among app users and among their children was much higher than US and California averages; 15.4 % for adults compared to 7.4% for the US and 8.7 % for California and for children 18.7 % compared to 8.6 % for US averages, more than double the national average. 14.1 % of the users had heart disease compared to the US average of 10.2 %. Among our app users, 49% had no health condition, 55% had a least one health condition, 13% more than one health condition.

Dependent Variable: User Engagement with Air Quality information

Engagement can be generally defined as a user's level of involvement with a product; for technological tools 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 multi-faceted 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 the application's objectives (Fagan, 2014; Lalmas, O'Brien, & Yom-Tov, 2014).

To test our hypotheses, we used two measures of user engagement with the app. The primary measure is how many times users checked the app, and the second measure of engagement is when

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[3] https://www.census.gov/quickfacts/fact/table/US/LFE046217

users reported sharing air quality information about air quality with others through the short daily survey questions.

Users checking the app

We generated a variable *check air pollution app* that represents the number of times a user checked air quality on AirForU each week. This is because for AirForU, the only “critical” objective is to check air quality (either current or forecast) and hence engagement is defined as opening the app.

The first screen the user is led to it the current air quality for that purpose. We did not use the duration of the app visit since a visit may last only a few seconds yet the user might have accessed already “critical” content and be “satisfied” with the information. Table 1 provides a summary of all the views of the pages since its launch in October 2015 and until the end of the study period in June 2017. The app was opened 66,000+ times and air quality information was accessed 164,000+ times. However, about 75% of the visits occurred within the first 12 weeks of downloading the app. On average, since its launch, the app was accessed 107 times per day and 753 times per week. The majority of the views were for the hourly air quality information screen. The second screen was the health information corresponding to the AQI levels. The other tabs were accessed less frequently.

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[Insert Table 1 About Here]

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Overall engagement (measured as total app visits) drops by 90% after 12 weeks. This indicates that either they learn enough during that time, or that we need other strategies to engage users beyond this period. The majority of app visits (~75%) occurred within this period. See Appendix 4 for a graph of user engagement over time. See Appendix 5 for real-time Google Analytics data for active app users.

Users sharing air quality information with others

The second type of engagement we measured is when users shared air quality information with others. Information about users sharing information with others was gathered through a short survey questions within the app ("Did you talk to someone about air quality today?"). Users could only respond to the question once daily. We generated a variable *talk to someone about air pollution*, which is the number of times the user answered "yes" to the daily survey question during the week.

Sharing information with others corresponds to a higher level of involvement with the information, where users start to "elaborate" on the knowledge (Greenwald & Leavitt, 1984). This is a social component of interacting with the information. Users can talk about air pollution with family, friends, their doctor, non-profit organizations that fight air pollution, companies that pollute or policy makers that regulate air pollution. This behavior raises awareness of air pollution and its health impacts. It can also help mitigate some of the impacts of air pollution, for example, by talking to a doctor and getting some medication for asthma or other health problems related to air pollution.

Although we do not have a reference point to compare this to their discussions about air quality in the absence of the app, one of the positive effects of the app might be that people are more likely to discuss air quality with other people, thus further increasing awareness. Of the 2,740 users, 963 (~35%) reported sharing information at least once. For 65% of users, engagement was limited to checking the app while for the other 35% checking the app resulted in this specific behavior change. Information about air quality was shared at least 5,575 times for all users combined over 83 weeks.

Independent and Control Variables

Health consciousness is assessed through several variables representing health problems identified by the users. These include *heart disease, lung disease, asthma, allergies* and *other health conditions* (eczema, bronchitis, migraine headaches, autoimmune disorders, COPD, sinus and rhinitis to name a few). They also include reported health conditions for the children of the users including *children asthma*, *children allergies* and *children other conditions* (heart disease, lung disease or any other health conditions reported by users). These variables are dummy variables and users could report several of these conditions. In addition, we include a variable representing the *frequency of outdoor exercise*, as reported by users, coded from one (once a year or less) to six (5 or more times a week).

The variable *notifications* is a dummy variable; coded one for users who opted to receive weekly notifications, and zero for the others.

We control for users' *knowledge of air quality* by using a dummy variable based on users' response to whether they knew the typical daily AQI in their location.[4] We control for users' *gender, age,* and whether they have *children*. In addition, we control for the *number of weeks* since the app was first downloaded by the user.

Descriptive statistics are provided in Table 2 below and the variables are described in more detail in Table A3 in Appendix 3.

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[Insert Table 2 About Here]

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[4] We asked additional questions about knowledge of air quality that are reported in appendix 3.

Model

To test our hypotheses, we performed a regression analysis on a panel of observations with variables that affected the number of times users accessed the app, or talked to someone about the app, within the first 12 weeks of downloading the app and throughout the study period of 83 weeks. We therefore examine the effectiveness of extrinsic and intrinsic motivations on both the short term and the long term.

In the data we collected, we tracked activity for a number of individuals (i.e. app users) over a certain period of time i.e. the time they downloaded the app until the time end of the study period (in this case a total of 83 weeks). Since the dependent variable, the number of weekly app visits, or the number of times a user talked to someone about air pollution, is a count variable, we use a Poisson panel model. All standard errors were robust and clustered by user.

The basic model for our panel data analysis is as follows:

$$Engagementy_{it} = f(x_{1it},\ x_{2it}, \ldots\ldots\ x_{nit}) \quad (1)$$

Where $Engagementy_{it}$ is measured as number of app visits, or number of times a user reported talking to someone about air quality, for each user i, during time t (week). The independent and control variables are represented by $x_{1it}, x_{2it} \ldots . x_{nit}$. The independent variables include *heart disease*, *lung disease*, *asthma*, *allergies* and *other health conditions*, *children asthma*, *children allergies* and *children other conditions*, and *notifications* (see Table 2). The control variables include *gender*, *age*, *children living in household*, *frequency of outdoor exercise and the number of weeks since the app was downloaded*. We conducted multicollinearity tests for all the variables included in the regression; the variance inflation factors were well below the cutoff value of 5 (Stine, 1995). A correlation table can be found in Appendix 7.

Results

Table 3 presents the regression results. Column 1 & 2 use *check air pollution app* as the dependent variables and column 3 & 4 use *talk to someone* as the dependent variable. Column 1 & 3 provide the results for the first 12 weeks since the user downloaded the app, and column 2 & 4 provide the results for the entire 83 weeks of the experiment.

The factors influencing app visits are the same in the short-term i.e. 12 weeks and in the long-term i.e. 83 weeks, although the effects are slightly different over time.

For the most part, users with health conditions were more engaged with the app than those that did not have pre-existing health conditions. This is an important finding because these are the groups that are more adversely impacted by air pollution. Users with heart disease and other non-specific conditions were most engaged with the app i.e. 1-2 additional app visits per week per user with those conditions. Users who frequently exercised outdoors were also more likely to visit the app. A coefficient of 0.04 in the short-term results in exp^0.04 ≅1 i.e. one additional app visit per week for users who exercise outdoors frequently compared to those that do not exercise frequently. Thus, we confirm hypothesis 1, that health conscious users are more likely to engage with the information provided through the app.

Furthermore, users who were signed up to receive push notifications were much more engaged with the app relative to those who were not, confirming hypothesis 2. Notifications turned on resulted in about two more app visits per week relative to those who did not receive notifications. This supports the finding that alerts are an effective tool at re-engaging app users.

Looking at the control variables, women were more likely to check the app than men were, although the effect disappeared in the 83-week models as compared to the 12-week model. Older users were also more likely to engage with the app compared to younger users and this effect too decreased over time. This is a promising finding because, while the elderly are more vulnerable to air pollution, they are also less likely to engage with new technologies. Finally, knowledge of air quality is not a significant predictor of engagement.

As expected, engagement falls over time (Figure A4 in Appendix 4). Engagement drops sharply in the first 12 weeks compared to engagement over the long-term. This is not surprising because when users download a new app, they are most engaged with it and that engagement drops off over time but the sharpest drop is typically observed a few weeks after the app is downloaded as the novelty wears off.

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[Insert Table 3 About Here]

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To results of the factors that were more likely to encourage users to talk to someone about air pollution are provided in Table 3 (columns 3 & 4). They are similar to the results of the regression where the dependent variable is checking the app. Notifications and the presence of pre-existing health conditions are significant variables that explain users' discussion of air quality with others. However, only heart disease and other health conditions are significant.

In all our models, of all the independent and control variables, receiving notifications increased engagement the most. In addition to the above regression, we tested the interaction effects of notifications with health conditions and exercise to identify the groups that respond most to the notifications by checking the app (Table A6 in Appendix 6). The results indicate that users with heart disease, lung diseases and asthma respond even more to the notifications compared to other groups. For example, those with lung disease who receive notifications check the app two times more per week than those who receive notifications but do not have lung disease. Asthmatics who receive notifications check the app about 1.5 times more per week. The weakest effect is observed from the group with heart disease for whom there are 0.4 additional app visits per week or four additional app visits per week for every 10 users with heart disease because of receiving notifications.

Users Behavioral Responses

To get a comprehensive picture of the impact of user engagement on behavior, we investigated users' behavioral responses to the information provided in the app through a feedback survey towards the end of our study period.[5] We asked users about their learning through the app, their experience with the app and the actions they took in response to the information provided in the app. We also gathered some anecdotal evidence about behavior change.

[5] This survey was conducted towards the end of August 2017, almost two years after the app was launched. Two emails were sent to app users a few days soliciting feedback.

Learning

We highlighted the importance of learning associated with the app as one of the elements that helps develop intention towards protective behavior. To gain more insight about the learning process, we asked the users about their experience with the app in terms of their comprehensibility, relevance and learning associated with the information presented in the app. Most of these users had a positive experience with AirForU. More than 80% agreed that that the air quality information on AirForU was easy to understand, and was relevant to them. The majority stated that the app helped them protect their health against air pollution (69%) and that it helped them learn more about the health impact of air pollution (59%).

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[Insert Table 4 About Here]

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To assess users' learning about air quality we compared the results from the intake survey to those of the exit survey (Table 5). While in the intake survey only 10% stated they know about AQI, the response rose to 70% in the exit survey. Because we did not collect information to identify app users in this feedback survey, it is possible that those who didn't know much about air quality disengaged with the app and were less likely to respond to the exit survey. We therefore decided to also check the knowledge of AQI in the entry survey of the most active users at the time of the exit survey. Only 14% of those said they knew what AQI meant. Therefore, it seems that users learned about AQI while using the app. Similarly, the knowledge of the AQI range also improved from the entry to the exit survey.

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[Insert Table 5 About Here]

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Behavior change

There are several ways that users' engagement with an air quality app can influence their behavior. The first is for the user to adjust their location based on air quality information such as by exercising indoors rather than outdoors. The second one is to wear protective gear such as facemasks. The third one is to use air filters or air conditioning within the home. These behaviors are called "averting" behaviors, that is to say they reduce the exposure to air pollution (Dickie, 2017). Not all these behaviors are exclusive as app users could decide to undertake all of these.

As part of the feedback survey, we measured some behavioral changes. We made a list of all the health protective behaviors that app users could adopt and measured how many people adopted them (Table 6). Despite a low response rate of about 4% (N=103),[6] the data collected was crucial in understanding the usability of the app; the primary purpose of all AQI reporting programs is to change behavior to reduce the health risk associated with air pollution. There was a strong selection bias for respondents with a high engagement since over 70% of the respondents checked the app at least once a week and 18% checked it daily. The corresponding percentage for each measure indicated the proportion of 99 users that engaged in that action. The users could report the adoption of multiple measures hence the sum of measures (258)> 99. This was a one-time survey and adoption of measures was not tracked over time. The most common measures reported not exercising outdoors during high air pollution (21.7%), and closing windows (20.2%). The third type of measure related to the use of air filter and air conditioning and cleaning more often the filters of the air conditioning. Fewer people spoke with their doctor about air pollution (5.4%), planned for

[6] One of the reasons for the low response rate is because feedback was solicited almost two years after the app was launched by which time many of the users had disengaged from the app.

potential asthma attacks (5.4%), and wore a protective mask (4.4%). Finally, very few missed school of work based on the air quality information provided (1.6%).

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[Insert Table 6 about Here]

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In addition to the behavioral responses reported in the feedback survey, we collected some anecdotal evidence about behavior change. App users could provide feedback by leaving a comment on the app store or google play websites or by sending an email directly to the AirForU team. We received many emails from app users indicating the adoption of protective behaviors after obtaining information from the app such as planning their exercise routine at a time when air pollution levels were low, choosing to stay indoors and carrying their asthma medication when pollution levels are high. For example, one user said: “I use your app quite frequently and have found it invaluable in managing my asthma. Thank you for creating it and making it available on the App Store.” Another one wrote: “Thank you so much. I have been told by my Doctor not to go outside if it is too hot. Too hot means different things to different people. I have been house bound this summer because we have had many days that are over 100. This app will give me a great opportunity to enjoy taking a walk or spending time in my backyard. If there is anything I can do to help with your study please contact me. Now I know I can go out today without concern. Thank you again!” In addition, we found some people using the app to decide where to live. For example, one user said: “We moved one year ago to suburbs of Philadelphia and I used your app to carefully decide where to live.” We also received information from the XXXX Child Care Center that they used the app regularly to plan outdoor activities for children. In particular, they used the app during the periods of high air pollution due to fires. Based on information from the app, they made decisions about keeping the children indoors or letting them play outdoors and informing all the parents by email about the air pollution levels. Here is a quote from an email sent on Jun 29, 2017: "As you may know there are multiple fires in the surrounding areas. We will be monitoring the quality of the air throughout the day by using the xxxx AirForU app. Currently the air quality just went to the moderate level. When and if it reaches the level that is unhealthy for sensitive people we will engage in indoor play only. The level may remain in the safe range throughout the day but we are prepared the make adjustments to the daily schedule as needed. We will also monitor the air quality tomorrow." This information about the childcare use of the app was collected first hand by one of the authors who has a child enrolled in the childcare center.

In addition, we received many emails requesting more information about the type of air pollutants that was included in the app indicating an interest to learn more about air pollution. For example, one user emailed us: "I would like more detailed info. For instance, what is the pm 2.5, ozone, etc. If available, I would also like to know what types of particulates. Like pollen, types of dust, etc."

Some other anecdotal evidence was gathered about people using the information to discuss with businesses in their neighborhood. For example, one app user contacted a facility about their toxic releases based on the numbers provided in the app, which were taken directly from the US EPA Toxic Release Inventory. The company owning the facility, without disclosing its name, asked their lawyers to send us a letter questioning the public data we used and asking us to change the way we present it.[7] As a result, XXXX decided to remove the app from their app store, which was

[7] They argued that this was an air pollution app and therefore the public information we disclosed on total Toxic Releases from the surrounding facilities, should include exclusively air pollution data rather than waste, water and air pollution.

equivalent to temporarily shutting down the app since people who would delete it from their phone could not access it again from the app store. Fortunately, the data used for this project was gathered before the app was removed from the app store. While the result of this chain of events was not the one we were hoping for, it indicated that some users employed the information to pressure firms to reduce their pollution. It also shows that some companies do not like it when public information about their environmental performance is made easily accessible to a large audience. We also learned that while universities embrace the concept of action-oriented research, they might not yet be well equipped to implement it. The decision of the University was discussed with graduate students and they reflected on what should have been done to avoid it. This included being clearer in the app about the sources of the data and potentially bringing lawyers to the design team.

Therefore, overall, the evidence we have collected suggests that people improved their learning about air quality through the app. They seemed to discuss air quality often and adopted practices to protect their health. However, the engagement with the app was short lived since over 90% of the app visits dropped by the 12^{th} week after they downloaded the app. The first reason for this might be that the AQI information did not change much over time. For example, in Los Angeles, except when there was a major fire, the AQI was quite stable. It remained either in the Good (Green 0-50) or Moderate (Yellow 51-100) range. It is therefore possible that people learned about the average AQI, and decided that it was not high enough to warrant more attention or behavior change. When the AQI is moderate, only unusually sensitive people should consider taking action such as reducing prolonged or heavy outdoor exertion.

Interdisciplinary Team Learning

While the main objective of the program was to provide air quality information to app users, the development of the project was also a learning experience for the graduate students who developed the app.

Collaborative, action-oriented, and interdisciplinary education strategies are increasingly utilized to facilitate student learning. This project was conducted as part of the XXXX Leaders in Sustainability Program that focuses on collaborative, action-oriented learning and require graduate students to demonstrate leadership on a project related to sustainability.

One of the benefits of interdisciplinary, collaborative and action oriented sustainability projects is to include several dimensions of learning. These potentially include physical and emotional or spiritual learning in addition to traditional intellectual learning (Shrivastava, 2017). First, the students learned from each other. The student engineers said that they enjoyed working with social scientists and management students, learned how to make technology accessible and usable by a large audience, but also learned rigorous social science techniques to test the effectiveness of the technology. The social science students said they learned the limitations that technology can put on some of the social theories they might have learned. Indeed, the success of the app was built on a complex chain of events; a glitch on any aspect could affect the whole operation. For example, if the server was not receiving air quality data properly due to an error on the coding or the agency from whom the data was obtained (the US EPA in this case), it affected the user being able to check air quality on the app. Furthermore, both engineers and social scientists learned about the difficulty in convincing people to care about air pollution and be engaged with the app for longer periods. In addition, they learned that sometimes, what seems a good idea on paper, does not work as well in the real life. For example while people express that historical data is needed to more fully interpret current air quality (Hubbell et al., 2018), they realized that people looked mostly at the current and future air quality data. In addition, while we thought people would be curious to look at the source of the pollution and therefore would look at the Toxic Release Inventory tab, only a few did.

In addition, because the development of the app was a research project and user data was collected and stored, students learned about the protocols to deal with such sensitive data. In recent times, there have many instances of data breaches and security risks because of private information becoming public. Data privacy and protection are an important aspect of conducting research through apps. The public are concerned about how their data is being used, managed and protected and were concerned whether apps were developed by reputable and legitimate sources (Dennison et al., 2013). Since sensitive information was obtained in the surveys, prior consent was obtained from all AirForU users. Great care was taken to anonymize all user data, store it on a protected server and limit access only to researchers. We adhered to IRB guidelines and best practices to protect user data.

Finally, students also learned the hard way that when information becomes strategic, companies might try to hide it or erase it. This is what happened when a company used lawyers to try to influence the type of information we provided in the app. The disappointment and stress related to the decision of the university to remove the app from their store, was also part of the emotional learning related to conducting action oriented research projects. While the other learning outcomes of this project are also possible in many different interdisciplinary research contexts, the environmental context can be quite polarized with stakeholders having very conflictual perspectives on what information to convey. They learned the risks associated with conducting interdisciplinary action oriented research in this context and potential ways to mitigate them.

Discussion

We learned several interesting things from developing an air quality app with a research study built into the app. With a traditional research study, it would not only have been challenging to recruit such a large number of participants but it also would have been very difficult to follow their engagement with air quality information for such a long duration (83 weeks). However, with the mobile app plateform this was accomplished relatively easily. Indeed, the results from the longer timeframe of the study brought important insights that would not have been observed in a short-term study.

First, we found that the theory of issue engagement is useful to complement the theory of planned behavior, which has been used to explain the link between intention and action. Indeed, one of the most important insights we gained with this study was a better understanding the motivations that explain engagement with air quality information. Users suffering from asthma, heart disease, lung disease or other conditions aggravated by air pollution were more engaged with the app compared to those who did not have these health conditions. In their research, Neidell (2004; 2006) found evidence that young children and the elderly protect their health against air pollution and our findings affirmed that partly but also identified other sensitive groups that engage with air quality information. This is an important finding since sensitive groups are most affected by air pollution, and contribute to the large health burden associated with air pollution. While engaging with this information does not ensure that these groups are engaging in risk-averting behaviors, it is the first step towards those behaviors. Another finding was that a high proportion of users, who regularly engage in outdoor activities, were more engaged with the app although their engagement was short-lived. Even healthy people are at risk if they engage in outdoor activities during episodes of poor air quality so air quality information can help them avoid exposure to unhealthy conditions. These findings are in line with the theory of issue involvement that emphasizes the importance of motivation as a driver of engagement with an issue. Therefore, we confirm our first hypothesis on the importance of intrinsic motivations to learn about air pollution through the app.

Second, we tested the effectiveness of extrinsic motivations through notifications, which remind the user of air pollution. We found that notifications were as important if not more than health conditions to drive engagement. Thus, we confirmed our second hypothesis. In addition, we found that notifications were particularly effective for those suffering from health conditions and in particular heart disease, lung disease and asthma. In other words, notifications and those two health conditions reinforced each other to drive engagement.

We measured two types of engagement, not only users' checking information on the app, but also sharing the information with other. Sharing air quality information is a social component of interacting with the information. We found similar impact of intrinsic and extrinsic motivations on these two measures although only the presence of heart disease and other health conditions and notifications were significant to induce social information sharing. This could be explained by the fact that fewer users shared the information than checked the app. This shows that for apps that seeking to promote a behavior change, one can enhance engagement by incorporating behavior change theory principles in the app's design (Michie & Johnston, 2012; Riley et al., 2011; West et al., 2012).

However, we found that both the intrinsic and extrinsic motivations were insufficient to counterbalance user disengagement in the long run. Weekly notifications sent via the app were effective at re-engaging users but even this re-engagement dropped over time. We learned that engagement with the app was high at first, but faded over time. After 12 weeks of downloading the app, engagement for most users had dropped by over 90%. Towards the end of the experiment (after 83 weeks), only about 5% of the initial users remained actively engaged with the app (defined as visiting the app at least once over a period of 5 weeks).

One possibility is that the lack of engagement over time could indicate that users have learned what they needed to know to take action. We investigated the link between user engagement and behavior change to answer this question. From the feedback survey, we learned that app users discussed air quality frequently and stated that they learned information about AQI and took measures to protect their health based on the information provided in the app. So overall the app succeeded in disseminating information about air quality levels and improving health protection.

The issue of long-term engagement is an important one for the apps beyond air quality apps. Thousands of apps already exist and new ones are being developed every day. How can we more effectively ensure engagement, especially in the long term? An important avenue for further research is to develop strategies to keep people more engaged over time. Some strategies to increase engagement are – using periodic reminders using different modes such as email, text or app alerts, the use of customized messages where the user can determine the air quality levels at which they would like to receive reminders and the use of gamification to encourage people to remain motivated.

Other features can be added to enhance engagement. Incorporating social media features that allow app users to share information with their friends and family easily through the app and send them invitations to download the app could increase recruitment and ongoing engagement. A two-way interface can be added in the app that allows users to be more active e.g. upload pictures of polluted areas. It is also possible that indoor air quality app might have a better potential than outdoor AQ apps. This is because with indoor air quality, some of the pollution is created by indoor sources, such as when cooking. So the app user can have direct control over the cause of the problem, by changing their cooking practices for example, rather than just about avoiding the problem (Bruce et al., 2015).

However, despite these attempts to engage users it is possible that mobile apps are still limited in their ability to induce long-term individual behavioral change. Researchers must consider that the use of apps can be irregular and only over the short-term (Dennison et al., 2013; Hebden et al., 2006). There is a fundamental question about what happens when app novelty effects fade or when information is repeated over time without much change (Asensio & Delmas, 2016). This is the challenge with air quality, which often remains in similar ranges. Users might therefore not find new information when they open the app. Once people have disengaged, and removed the app from their phone, it is harder to reach them when there are important air quality events such as fires.

One area of great potential is to use air quality apps to raise general awareness and help the public contact other stakeholders such as local policy-makers or corporations through the app. In doing so, air quality apps can enhance business ethics. Through our app, one of the users did contact a facility to complain about their toxic releases. One hindering factor in enabling people to act on the issue of air pollution is that they do not know whom to contact or how to contact them (Wakefield, Elliott, Cole, & Eyles, 2001) and providing this information directly in the app could be another way to engage people. Information disclosure policies that gather and diffuse corporate pollution information have been shown to be effective (Delmas, Shimshack, & Montes-Sancho, 2010). With the diffusion of mobile apps and real-time localized information, such policies can be even more effective at influencing corporate behavior towards more sustainability.

We also found that apps are a promising platform to not only engage stakeholders through education and citizen science but also an opportunity for active collaborative learning in the academic domain.

The development of AirForU relied on the collaboration of scholars and professionals across a number disciplines – computer science and engineering students for the app development, environmental and business students for the content and research study design, business students for presentation of the environmental performance data (toxic release inventory data) and marketing and media professionals for recruiting and marketing. The entire project was an experiential learning experience and each team member built skills beyond their original area of expertise. Most importantly, they also faced first-hand the challenges associated with diffusing public data about pollution that some corporations might prefer to keep private.

Air pollution apps, such as AirForU could also be used in the classroom to help students realize the link between their health and the environment. This link is important but not experienced as much (Montiel, Delgado-Ceballos, & Ortiz-de-Mandojana, 2017).

Conclusion

In conclusion, in this research, we sought to understand the conditions under which sustainability mobile apps could educate stakeholders about air pollution issues and promote behavioral change. We developed an air quality app and studied the engagement of stakeholders with the information provided in the app. We measured two kinds of engagement. The first one was how many times users actually checked the app. The second one was whether they reported talking to someone about air pollution. We tested whether intrinsic and extrinsic motivations could enhance user engagement with the app. We found that engagement was higher for users with intrinsic motivations, such as those who are health conscious, either because they are suffering heart disease or other conditions aggravated by air pollution, or because they exercise often and want to keep this healthy lifestyle. Extrinsic motivations such as notifications were also effective. Indeed, users who allowed notifications were more likely to check the air quality on the app and on talking about air quality to others. Users also reported adopting behaviors to protect their health in response to the information provided in the app. However, engagement with the app was short lived since it faded significantly 12 weeks after users signed up for the app. This demonstrates the need for further research on how to keep users engaged over longer periods.

Ethical approval: All procedures performed in studies involving human participants were in accordance with the ethical standards of the institutional and/or national research committee and with the 1964 Helsinki declaration and its later amendments or comparable ethical standards. The study was approved by the IRB (Protocol ID #15-000215).

Informed consent: Informed consent was obtained from all individual participants included in the study.

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FIGURES

Figure 1. Engagement with air quality mobile application

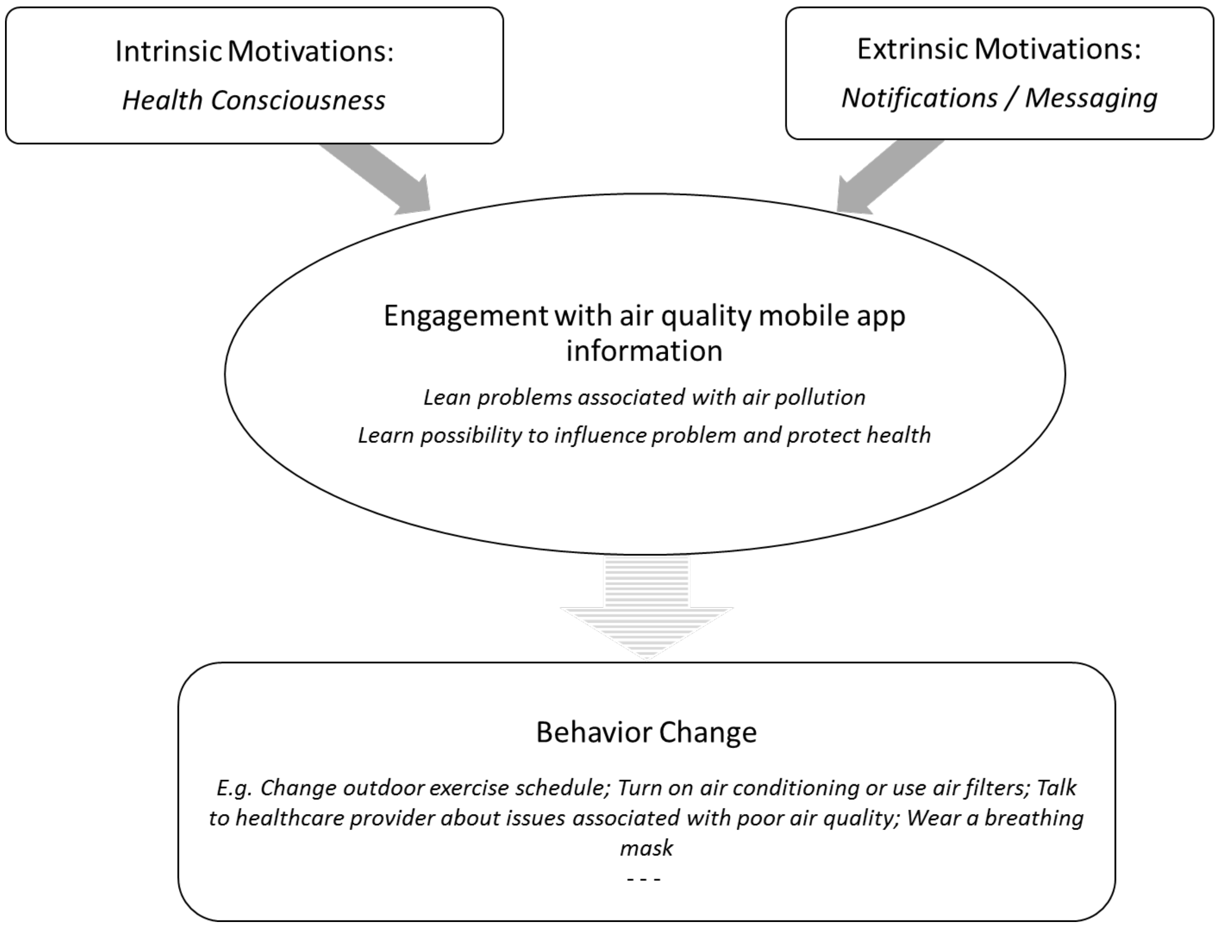


Figure 2: Air Quality Information - Historical Weekly AQI, Real-time AQI and Next-Day AQI

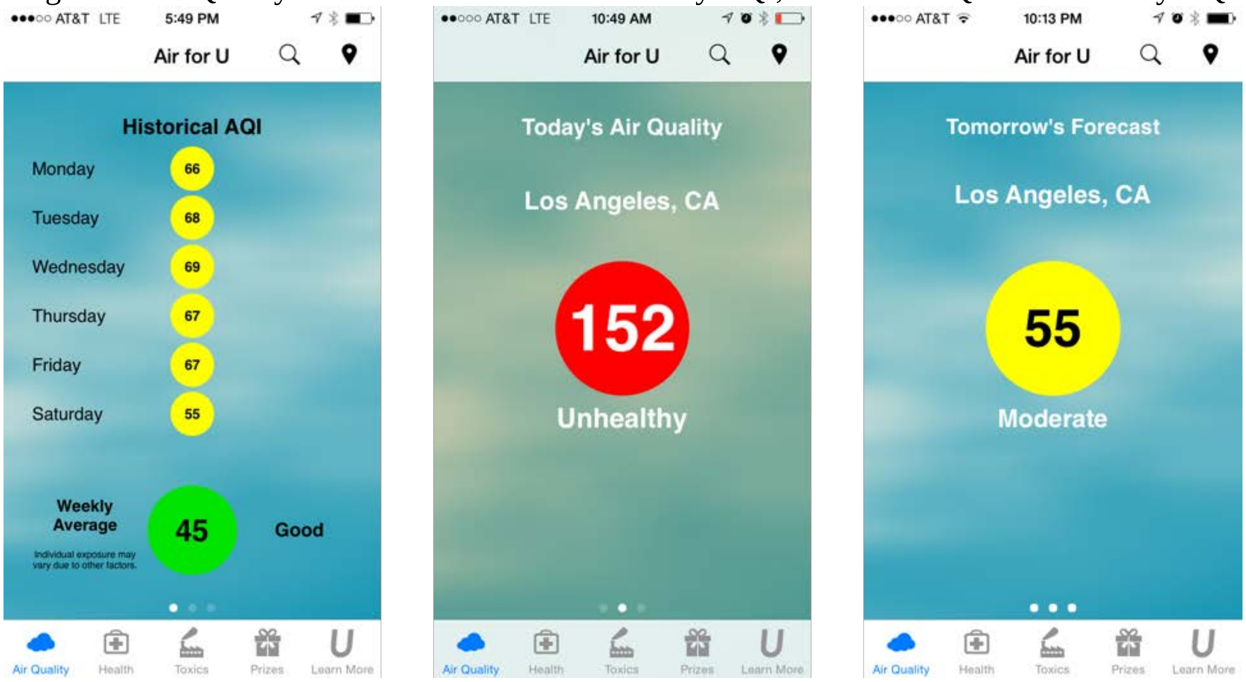


Figure 3: AirForU Screenshots with Health information based on EPA-designated AQI levels

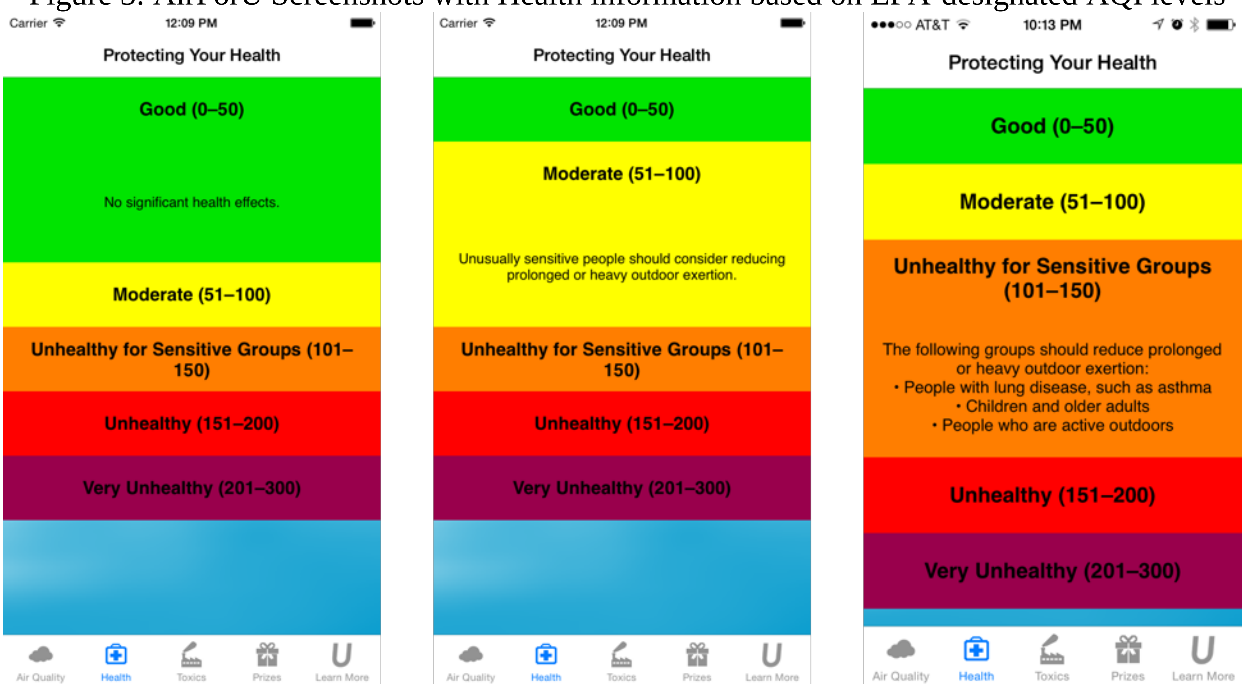


Table 1: App usage summary over the duration of the study

App tabs	Information Content	# Views	Percentage
Air Quality	Changes hourly	164,196	56%
Health	Static	87,547	30%
Toxic Release Inventory	Changes based on current location and zip code	23,286	8%
Prizes	Changes daily based on response to behavioral questions	12,328	4%
Learn More	Static	4,594	1%
Total		291,951	100%

Table 2: Descriptive Statistics

	Mean	SD	Min	Max
Dependent Variables				
Check air pollution app	0.406	2.247	0	117
Talk to someone about air pollution	0.033	0.295	0	7
Independent Variables				
Heart Disease	0.141	0.348	0	1
Lung Disease	0.037	0.189	0	1
Asthma	0.154	0.361	0	1
Allergies	0.332	0.471	0	1
Other health conditions affected by air quality	0.044	0.205	0	1
Children Asthma	0.065	0.247	0	1
Children Allergies	0.123	0.328	0	1
Children other health conditions	0.057	0.232	0	1
Exercise	4.04	1.43	1	6
Notifications	0.420	0.494	0	1
Control variables				
Female	0.447	0.497	0	1
Age	3.03	1.15	1	5
Children	0.350	0.477	0	1
Knowledge of AQ	0.097	0.296	0	1
Number of weeks since download	34.7	22.4	1	83

Table 3: Drivers of Users' Engagement with App

	First 12 weeks	*83 weeks*	*First 12 weeks*	*83 weeks*
	Check App	**Check App**	**Talk to Someone About AP**	**Talk to Someone About AP**
Independent variables				
Heart Disease	0.44***	0.51***	0.52**	0.68**
	(0.11)	(0.14)	(0.23)	(0.30)
Lung Disease	-0.14	-0.08	-0.29	-0.20
	(0.17)	(0.19)	(0.27)	(0.29)
Asthma	0.03	0.09	0.08	0.11
	(0.11)	(0.13)	(0.16)	(0.18)
Allergies	0.12	0.17*	0.06	0.15
	(0.08)	(0.09)	(0.14)	(0.15)
Other health conditions	0.60***	0.96***	0.71**	1.18***
	(0.20)	(0.27)	(0.28)	(0.39)
Children Asthma	0.18	0.55**	-0.06	0.21
	(0.19)	(0.26)	(0.27)	(0.36)
Children Allergies	-0.11	-0.19	0.32	0.15
	(0.14)	(0.18)	(0.25)	(0.29)
Children other health conditions	0.18	0.11	0.19	0.29
	(0.16)	(0.20)	(0.32)	(0.42)
Exercise	0.04*	0.04	0.03	0.05
	(0.03)	(0.03)	(0.05)	(0.05)
Notifications	0.69***	0.76***	0.74***	0.86***
	(0.07)	(0.09)	(0.15)	(0.18)
Control variables				
Female	0.14**	0.09	0.12	0.04
	(0.07)	(0.09)	(0.14)	(0.17)
Age	0.07**	0.13***	0.02	0.10
	(0.03)	(0.04)	(0.06)	(0.09)
Children	0.01	0.08	0.02	0.01
	(0.10)	(0.12)	(0.21)	(0.23)
Knowledge of AQ	0.06	0.22	0.16	0.37
	(0.11)	(0.15)	(0.21)	(0.28)
Number of weeks since download	-0.24***	-0.06***	-0.16***	-0.05***
	(0.01)	(0.01)	(0.01)	(0.01)
Constant for check app	0.47***	-0.84***	-2.33***	-3.54***
	(0.16)	(0.19)	(0.33)	(0.51)
Observations	32,384	152,302	32,384	152,302
N	2,740	2,740	2,740	2,740

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

Table 4: App users' responses for their experience with the AirForU app

	% of respondents who agreed (somewhat agree, agree or selected strongly agree) on a 7 point Likert scale	N
Is the air quality information on AirForU easy to understand?	84.5%	103
Do you find the air quality information relevant to you?	80.5%	103
Did the air quality information on AirForU help you protect your health against air pollution?	69.2%	103
Did the AirForU app help you learn more about the health impact of air pollution?	59.3%	103

Table 5: Pre/post learning of AQI among app users

	Intake Survey (N=2740)	Actively engaged app users (N=218)	Feedback Survey (N=99)
Knowledge of AQI			
Yes	9.7%	13.8%	70.1%
No	90.3%	86.2%	29.6%
Knowledge of AQI range[a]			
Yes	9.4%	13.0%	97.1%
No	90.6%	87.0%	2.9%

[a]N is based on those who responded yes to knowledge of AQI

Table 6: Adoption of health protecting behaviors based on the information provided in the AirForU app as measured in the feedback survey (N=99)

Health Protective Behavior	Percentage	Number
Change your outdoor exercise schedule	21.7%	56
Close windows during poor air quality episodes	20.2%	52
Use an air filter/purifier	14.0%	36
Clean or change filters in your air conditioner more frequently	12.4%	32
Use your air conditioner more frequently	12.0%	31
Talk to your healthcare provider about issues associated with poor air quality	5.4%	14
Plan for potential asthma attacks	5.4%	14
Wear a breathing mask	4.4%	11
Other	3.2%	8
Missed school or work	1.6%	4
Total	100%	258

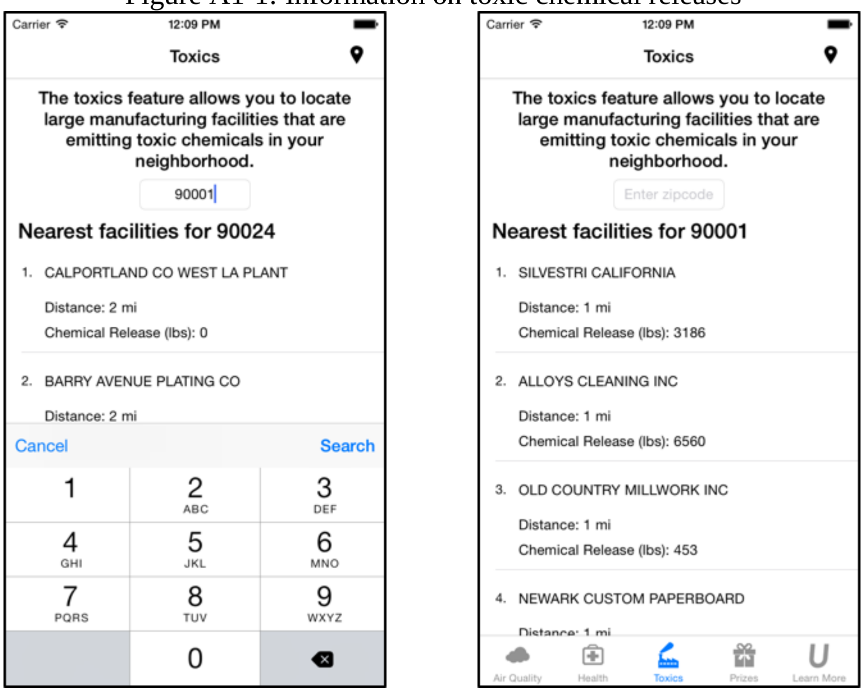
APPENDIX

Appendix 1: Additional AirForU App Features

Toxics Tab

The toxics tab is another unique feature of the *AirForU* app. Through this feature, users can obtain information about large industrial facilities that release toxic chemicals into the environment. This data is obtained from EPA's Toxic Release Inventory (TRI), which provides data on toxic chemical releases by all large manufacturing facilities in the US on an annual basis. Based on a zip code entered by the user or the user's current location, the 10 closest facilities are listed based on the center of the zip code. The number of pounds of chemicals released are listed per facility (Figure A1).

Figure A1-1: Information on toxic chemical releases



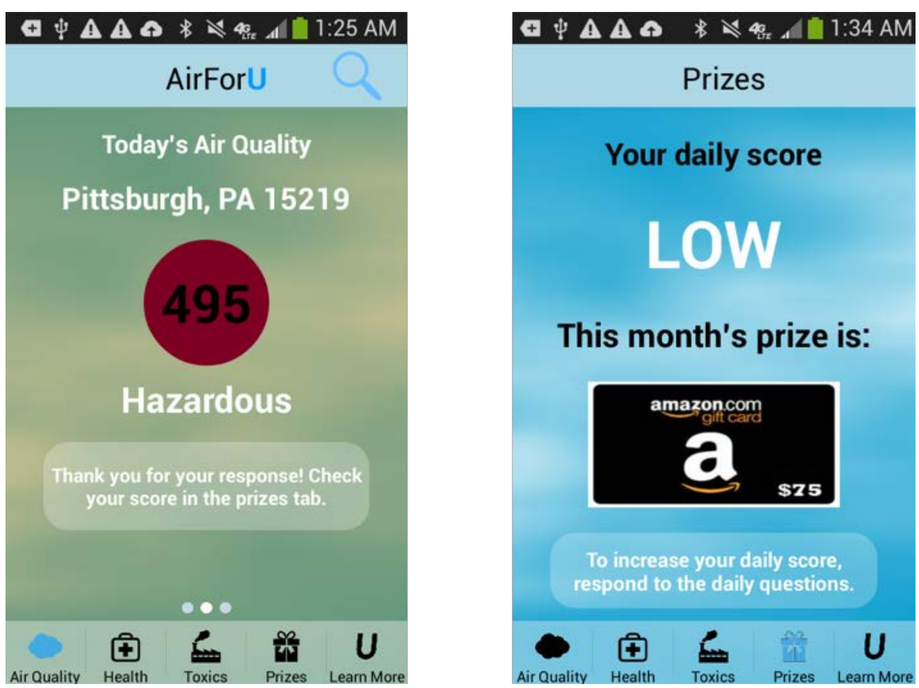
The toxics feature provides another dimension to air pollution. The AQI is based only on criteria pollutants and does not take into consideration other chemicals. Although TRI data is based on total environmental releases (air, water and land), the majority of these chemicals are discharged into the air so adding this feature provides a more comprehensive view of the pollutants in our atmosphere by highlighting local non-criteria pollutant sources. The TRI is also an informational program; its success relies on awareness among the public which hopefully results in better environmental performance by large industrial facilities. This feature increases awareness of toxic releases in local communities. An added note: this data is annual so it is static relative to the AQI data.

Prizes Tab

Another feature incorporated into the application is the use of monthly giveaways to users as a means of incentivizing engagement with the application. While there is a lot of variation reported among studies in literature, financial incentives do have an effect on the performance of a number of tasks (Camerer & Hogarth, 1999). Financial incentives may not be important for those with intrinsic motivation to respond to the behavioral questions but it might have an effect on other users.

The prizes tab displays the user's personal score that changes daily, based upon the response to the daily behavioral questions that appear on the AQ home screen. If they respond to all the questions, they get a high score and if they respond only to 1 or 2 questions they get a medium score and if they don't respond to any they get a low score reflected in the prizes tab immediately (A2). Prizes are awarded monthly ($75 Amazon gift cards) and the winner is selected based on a raffle conducted for users that score the top third of the maximum number of "high" and "medium" scores over a monthly time period.

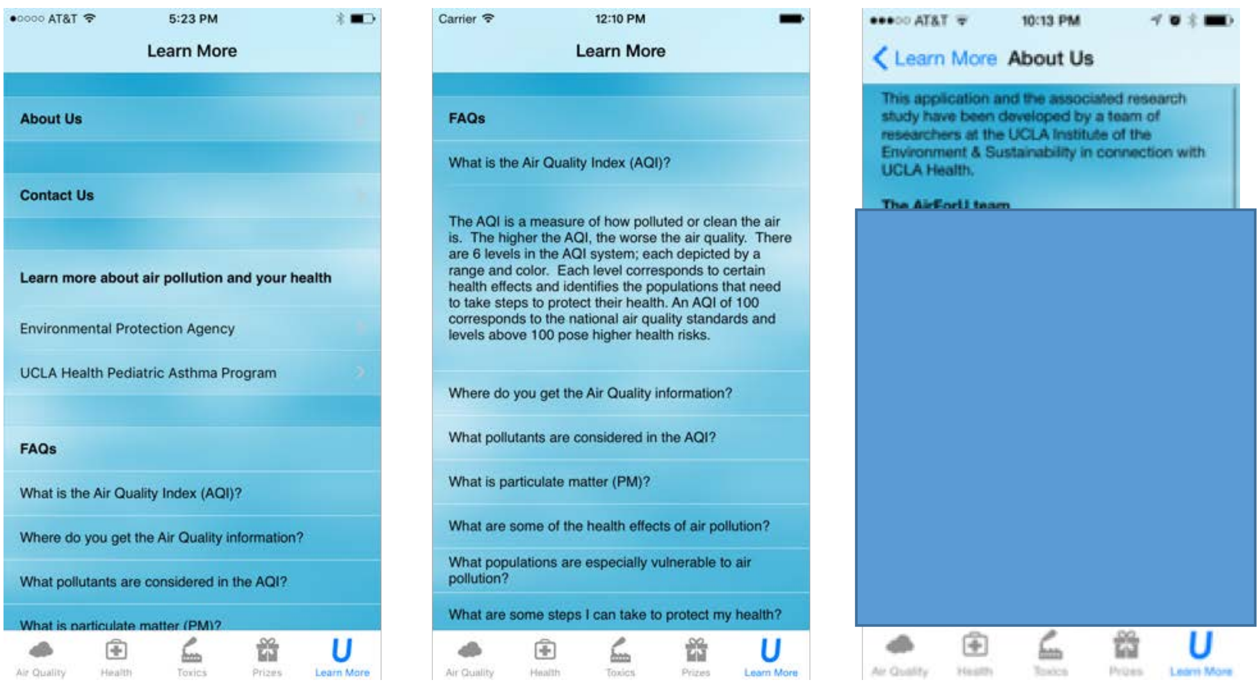
Figure A1-2: The daily score is updated on the prizes tab based on response to the behavioral questions presented in the AQ tab



Learn More Tab

The last tab contains general information about air quality in the form on external links and frequently asked questions (FAQs) about air quality (Figure A3). Links to the EPA's AirNow page (www.airnow.gov) and UCLA Health's Pediatric Asthma Program ([https://www.uclahealth.org/mattel/pediatric-pulmonology/asthma-program)](https://www.uclahealth.org/mattel/pediatric-pulmonology/asthma-program) redirect users to these websites for additional information. Contact information and information about the researchers can also be found in this tab (Figure A3).

Figure A1-3: The Learn More tab contains additional AQ information and contact information



Appendix 2. AirForU Intake Survey

Please provide your email address: _________________

Please provide your phone number (e.g. 1234567890): _________________

Please provide your 5-digit area zip code (e.g. 12345): _________________

How old are you? 18-24 years; 25-30 years; 31-50 years; 51-64 years; 65 years or more

What is your gender? Male; Female

Do you have any of the following conditions? (You may select more than one) Heart disease; Lung disease; Asthma; Outdoor Allergies; None; Other conditions affected by air quality. Please specify. ________________

Are any members of your household under the age of 18? Yes; No

(If yes to above question) Do they have any of the following conditions? (You may select more than one) Heart disease; Lung disease; Asthma; Outdoor Allergies; None; Other conditions affected by air quality. Please specify. ________________

Approximately, how often do you exercise outdoors? Once a year or less; Several times a year; A few times a month; 1-2 times a week; 3-4 times a week; 5 or more times a week

The following questions provide us with a better understanding of the public's knowledge of air quality. Please answer truthfully

Do you know the typical daily Air Quality Index (AQI) in the area where you live? Yes; No

(If yes to above question) What is the typical range of the Air Quality Index (AQI) in the area where you live? 0-50; 51-100; Above 100

What is PM2.5? Air quality after 2 pm; Particulate matter with a diameter less than 2.5 micrometers; Performance measurements standards for air quality equipment; Powdered metallics with a diameter less than 2.5 micrometers; I don't know

Appendix 3. Intake Survey Results

Table A3: Summary Statistics for App Users (N=2,740)

Survey Questions and Response Options in App Intake Survey	Question Wording	Coding for Regression Analysis	N	%
Gender				
Female	What is your gender?	Female (1)	1226	44.7
Male		Male (0)	1514	55.3
Age				
18-24 years	How old are you?	18-24 years (1);	357	13.02
25-30 years		25-30 years (2)	387	14.12
31-50 years		31-50 years (3);	1144	41.77
51-64 years		51-64 years (4);	531	19.37
65 years or older		65 years or more (5)	321	11.71
Health Conditions				
Heart Disease	Do you have heart disease?	Yes (1); No (0)	385	14.1
Lung Disease	Do you have lung disease?	Yes (1); No (0)	102	3.72
Asthma	Do you have asthma?	Yes (1); No (0)	421	15.4
Allergies	Do you have allergies?	Yes (1); No (0)	909	33.2
Other Health Conditions	Do you have other health conditions affected by air quality?	Yes (1); No (0)	121	4.41
Children (<18 yrs.) living in Home	Are any members of your household under the age of 18?	Yes (1); No (0)	959	35.0
Children Health Conditions	If Children = yes;			
Heart Disease	Do they have asthma?	Yes (1); No (0)	113	11.8
Lung Disease	Do they have allergies	Yes (1); No (0)	18	1.88
Asthma	Do they have heart and/or lung disease or other	Yes (1); No (0)	179	18.7
Allergies	Do they have asthma?	Yes (1); No (0)	337	35.1
Other Health Conditions	Do they have other health conditions affected by air quality?	Yes (1); No (0)	32	3.34
Frequency of Outdoor exercise				

Survey Questions and Response Options in App Intake Survey	Question Wording	Coding for Regression Analysis	N	%
Once a year or less	Approximately, how often do you exercise outdoors??	Once a year or less (1)	163	5.95
Several times a year		Several times a year (2)	269	9.82
A few times a month		A few times a month (3)	491	17.93
1-2 times a week		1-2 times a week (4)	656	23.95
3-4 times a week		3-4 times a week (5)	686	25.05
5 or more times a week		5 or more times a week (6)	474	17.31
Knowledge of $PM_{2.5}$	**What is** $PM_{2.5}$?			
Air quality after 2 pm (Wrong)		Wrong (0)	24	1.15
Particulate matter with a diameter less than 2.5 µm (Correct)		Correct (1)	810	38.68
Performance measurements standards for air quality (Wrong)		Wrong (0)	45	2.15
Powdered metallics with a diameter less than 2.5 µm (Wrong)		Wrong (0)	33	1.58
I don't know (Wrong)		Wrong (0)	1182	56.45
Knowledge of AQI	Do you know what the Air Quality Index (AQI) is?			
Yes		Yes (1)	266	9.70
No		No (0)	2474	90.30
Knowledge of AQI Range	If AQI=yes; Do you know the typical daily Air Quality Index (AQI) in the area where you live?			
0-50 (Correct)		Correct (1)	135	4.93
51-100 (Correct)		Correct (1)	122	4.45
>100 (Wrong)		Wrong (0)	2483	90.22

To assess user's knowledge of air quality, we developed two questions in the intake survey, one about AQI and one about $PM_{2.5}$. As a reference, the average AQI in Los Angeles is about 60 and the mean AQI of California is about 40 (see http://www.usa.com/los-angeles-ca-air-quality.htm). We coded all the responses above 100 as wrong since the average for Los Angeles and California are lower than that and the majority of our users were based in California.

Appendix 4. User engagement over time

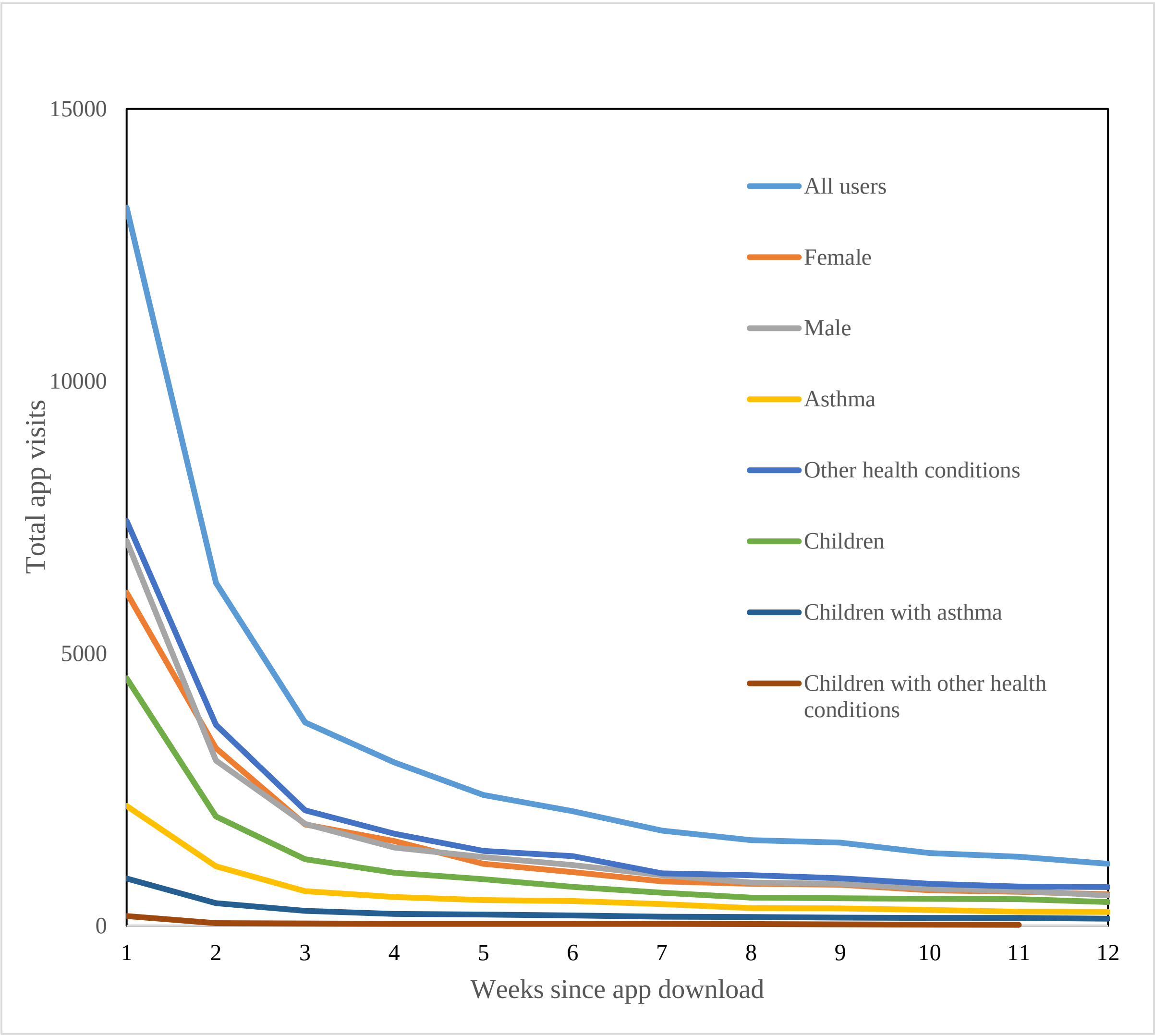


Figure A4: User Engagement drops sharply in the first 12 weeks of downloading the app

Appendix 5. Number of active users

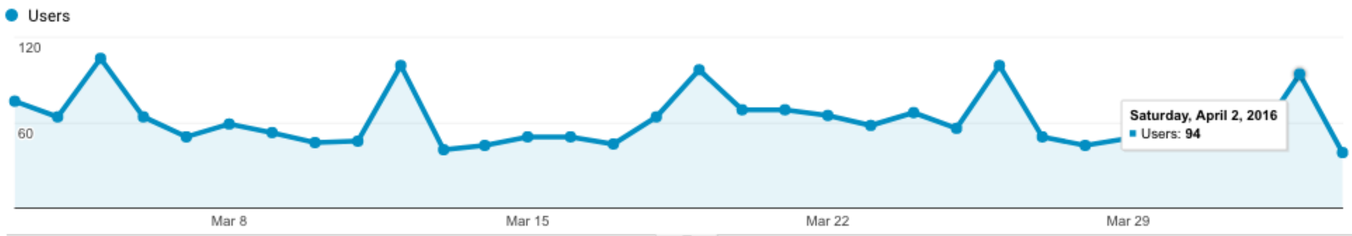


Figure A5: Number of active users on a daily basis for March-April 2016 from Google Analytics. Spikes correspond to Saturdays when notifications were sent to app users.

Appendix 6: Exploring Interaction effects for notifications

Table A6: Engagement measured through the number of weekly app visits (i.e. variable check app) for 83 weeks i.e. duration of the study with interaction terms in the model

Dependent Variable: Check App	Notification X Heart Disease	Notification X Lung Disease	Notification X Asthma
Interaction Term	-0.96***	0.68*	0.44*
	(0.31)	(0.38)	(0.24)
Independent variables			
Heart Disease	0.60***	0.48***	0.47***
	(0.15)	(0.14)	(0.14)
Lung Disease	0.05	-0.50*	-0.09
	(0.19)	(0.30)	(0.19)
Asthma	0.10	0.08	-0.16
	(0.13)	(0.13)	(0.19)
Allergies	0.19**	0.16*	0.18*
	(0.09)	(0.09)	(0.09)
Other health	0.98***	0.95***	0.97***
	(0.27)	(0.28)	(0.27)
Children Asthma	0.54**	0.55**	0.61**
	(0.26)	(0.26)	(0.26)
Children Allergies	-0.20	-0.18	-0.21
	(0.18)	(0.18)	(0.18)
Children other health	0.07	0.12	0.10
	(0.19)	(0.20)	(0.20)
Exercise	0.05	0.05	0.05
	(0.03)	(0.03)	(0.03)
Notifications	0.79***	0.73***	0.68***
	(0.09)	(0.09)	(0.09)
Control variables			
Female	0.09	0.08	0.06
	(0.09)	(0.09)	(0.09)
Age	0.13***	0.13***	0.13***
	(0.04)	(0.04)	(0.04)
Children	0.09	0.08	0.09
	(0.12)	(0.12)	(0.12)
Knowledge of AQ	0.23	0.23	0.20
	(0.15)	(0.15)	(0.15)
Number of weeks since download	-0.06***	-0.06***	-0.06***
	(0.01)	(0.00)	(0.01)
Constant for check app	-0.88***	-0.82***	-0.79***
	(0.19)	(0.18)	(0.19)
Observations	152,302	152,302	152,302
N	2740	2740	2740

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

Appendix 7: Correlation Table

		1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17
1	Check app	1																
2	Talk to someone about AP	0.616	1.000															
3	Knowledge of AQ	0.012	0.020	1.000														
4	Heart Disease	0.003	0.011	0.056	1.000													
5	Lung Disease	0.022	0.014	0.034	0.028	1.000												
6	Asthma	0.027	0.011	0.022	-0.112	0.151	1.000											
7	Allergies	0.017	0.011	-0.023	-0.224	0.043	0.305	1.000										
8	Other health conditions	0.077	0.070	-0.023	-0.073	0.060	-0.004	-0.012	1.000									
9	Children asthma	0.045	0.033	0.019	-0.092	0.011	0.293	0.122	-0.020	1.000								
10	Children allergies	0.021	0.028	0.004	-0.099	-0.029	0.106	0.274	-0.017	0.451	1.000							
11	Children other health	0.001	0.014	0.031	0.314	0.022	-0.052	-0.091	0.043	0.024	0.017	1.000						
12	Notifications	0.062	0.041	-0.028	-0.285	0.052	0.097	0.121	0.001	0.081	0.067	-0.140	1.000					
13	Female	0.018	0.003	-0.039	-0.136	0.013	0.124	0.157	0.044	0.084	0.086	-0.037	0.068	1.000				
14	Age	0.035	0.018	0.018	0.048	0.183	0.023	0.023	0.126	-0.035	-0.058	-0.005	0.007	-0.104	1.000			
15	Children	0.007	0.015	0.006	-0.046	-0.088	-0.005	-0.008	-0.061	0.356	0.520	0.340	0.024	0.009	-0.131	1.000		
16	Exercise	-0.006	-0.006	0.059	-0.019	-0.027	-0.049	-0.019	-0.017	-0.047	-0.047	-0.021	0.040	-0.072	0.123	-0.065	1.000	
17	Number of weeks	-0.150	-0.084	-0.003	0.024	-0.017	-0.033	-0.020	-0.015	-0.020	-0.012	-0.006	0.012	-0.044	0.043	-0.019	0.030	1.000