CAN APPS MAKE AIR POLLUTION VISIBLE?

Learning about health impacts through 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 to 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 enable them to 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 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 through the app, 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 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 frequently shared air quality with others, learned about the Air Quality Index (AQI), and took measures to protect their health while using the app.

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

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Introduction

Air quality mobile applications (commonly called apps) provide information about real-time local air quality conditions to help individuals take action to protect their health against pollution. While these apps are increasingly common, we do not have a good understanding of their effectiveness at educating stakeholders about air pollution and at promoting behavioral change.

Air pollution affects people worldwide; poor air quality is ubiquitous and often invisible to the naked eye. The World Health Organization (WHO) states that air pollution is the single largest environmental health risk globally (UN WHO, 2014). The varied and numerous adverse health effects of air pollution to almost every organ and bodily system are well established through hundreds of research studies conducted across the world (Curtis, Rea, Smith-Willis, Fenyves, & Pan, 2006; Fenger, 2009; Katsouyanni et al., 2001; Landrigan et al., 2018; Pope & Dockery, 2006; Pope et al., 2018; Thurston et al., 2015)

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 (Kelly & Fussell, 2015). One reason for this lack of awareness is that air pollution is often imperceptible, and even when it is noticeable, people's perceptions can often be inaccurate (Semenza et al., 2008).

Real-time and localized information about poor air quality is now available in many cities, and can be disseminated easily through mobile apps to empower users to take protective action against harmful air quality. Air quality apps share similar features with apps for weather forecasts (Zabini, 2016), or health management (Free et al., 2013; Dorsey et al., 2017; Payne, Lister, West, & Bernhardt, 2015; Zhao, Freeman, Li, & Building, 2016). Indeed, weather apps like air quality apps, provide information about one's external environmental, and health apps provide information about health conditions and support health management. However, we know almost nothing about how users respond to the information provided in these apps. Furthermore, the success of air quality mobile apps hinges on their ability to effectively communicate the link between air pollution and health. Air pollution disproportionately affects young children, the elderly, pregnant women, asthmatics, heart and lung disease patients, and those with compromised immune systems (Brook et al., 2004; Mansfield 2006; Pope & Dockery, 2006). It is therefore especially important to understand how air quality information diffused through apps reaches these populations.

In this paper, we address the following research question: how effective are mobile apps at educating users about air pollution and promoting behavioral change? We build on behavior change theories to investigate whether intrinsic and/or extrinsic motivations can enhance users' engagement with air quality information provided through apps. We argue that knowledge of these motivations can help design more effective apps. In doing so, we employ the theory of issue engagement and complement it with the theory of planned behavior, which has been used to explain the link between intention and action.

To answer our research question, we developed an air quality app, AirForU, with a built-in research study. App users could access hourly air quality information and next-day air quality forecasts with data from the U.S. Environmental Protection Agency's (EPA) AirNow program. We tracked how users engaged with air quality information through the app and collected evidence of learning and behavior change through a survey of app users. Our analysis identifies 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 into the app's design can act as extrinsic motivations to engage with the information. Users reported that engaging with the app helped them learn about the impact of air pollution on health. They also reported adopting protective behaviors such as changing their outdoor exercise routines or closing windows during poor air quality episodes. The results of our study show that air quality apps are a promising tool to educate individuals about air quality particularly when users are intrinsically or extrinsically motivated, highlighting the need to build on these motivations to support learning through 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. The development of an app provides a platform that brings together students with different skills to work collaboratively on solutions to complex environmental problems and provides a direct experience of the challenges associated with promoting behavior change in a contested setting.

This paper is organized as follows. First, we review the theories used to explain how mobile apps can trigger behavior change. Second, we develop hypotheses on how to motivate users to engage with information provided in the app, as a precursor to behavior change. Third, we test our hypotheses on user engagement with data gathered through our air quality app, AirForU. Fourth, we present some anecdotal evidence of app use leading to behavior change. Finally, we provide recommendations to improve the effectiveness of air quality apps in general and offer a concluding discussion on using apps for active collaborative learning in academia.

Background

There is still very limited research on individual response to air quality information. 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), and 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 published on how people engage with real-time air quality information, what they learn from this information and the steps they take to protect their health in response to this information. Furthermore, no studies to the authors' knowledge look at individuals' response to air quality information specifically via mobile apps.

Mobile apps are a type of third-party software designed to run on mobile devices such as smartphones and tablets. These devices are intended to be always on and carried with their owner throughout the day (i.e., during normal daily activities) (Riley et al., 2011). Thus, mobile interventions have the capacity to interact with individuals at a much greater frequency than internet interventions delivered via laptop or desktop computers, and can even reach users while they are exhibiting a certain behavior (Riley et al., 2011).

Advances in mobile communication technologies could, in principle, improve the effectiveness of air quality communication by helping users learn about the link between air pollution and their health, and encouraging them to take action to protect themselves (i.e. change their behavior). Behavior change can be preventive, such as avoiding the 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 teaching others how to reduce their exposure to air pollution.

Mechanisms through which apps help users learn about air quality

What, then, are the mechanisms through which air quality apps facilitate individual learning and behavior change? The theory of planned behavior, which suggests that if you intend to do something, then you are likely to do it (Ajzen, 1991), is often used to understand behavior change (Armitage & Conner, 2001; Barnard-Brak, Burley, & Crooks, 2010; Conner & Armitage, 1998; Sunio & Schmöcker, 2017; Taylor & Todd, 1995; Zimmerman & Noar, 2005). Building on this theory, we can identify two main elements of 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. According to the theory of planned behavior, changes in beliefs and attitudes affect intentions and inform behavior (Carrington, Neville, & Whitwell, 2010).

In other words, realizing there is a problem helps people develop intentions to change their behavior to solve the problem. Thus, awareness of the negative impacts of air pollution on health is an important first step in motivating individual action.

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 order for individuals to effectively learn about air pollution (Saksena, 2011). An air quality app provides this by sharing real-time localized information about air quality, including alerts for high air pollution levels and predictions of future levels.

Similarly, the always-on connectivity provided by mobile apps allows users to receive specific information via notifications and continuously maintain access to real-time air quality information, which in turn can help users realize the importance of the problem. For example, this might be particularly salient for people who have asthma — by having access to air pollution levels during an asthma attack, individuals can better make the connection between air pollution and their health.

The second element is to give users *the ability to learn how to protect their health*. The ability to learn how to protect their 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, Yang, & Maher, 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).

As such, an app that provides predictions of future air quality levels alongside tips to reduce harmful exposure can help users improve their perception of behavioral control. In our app, we ensured that users could easily access health tips to minimize exposure. Some examples 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.

In addition, *the time between intention and action can be reduced with air quality 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).

Here we argue that the effectiveness of these two elements, learning about the problem and learning about solutions, is enhanced when users are more deeply engaged with the information provided by an air quality app. 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 people are 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. Engagement can be individual, such as opening the app to seek information, or it can be social, such as sharing the information in the app with others. These two types of engagement help users better comprehend, contextualize and retain the information before adopting protective behavior.

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 (Van 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 health consciousness of the user and the availability of engagement reminders. 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). Deci and 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, health consciousness, represents an intrinsic motivation, which is regulated from within the user. The second, notifications from the app, is extrinsic motivation, and is regulated from an external source (the 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 thus lead to behavior change. Behavior change might be more likely for health-conscious users, and those who receive notifications. In other words, engagement may be enhanced with intrinsic and extrinsic motivations. While intrinsic and extrinsic motivations could act independently, they might also interact and enhance each other. Similarly, it is possible that engagement with the app enhances health consciousness, and that those who change their behavior decide to engage further with the app.

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[Insert Figure 1 About Here]

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In this paper, we first develop and 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 using a survey of app users and other anecdotal evidence. 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.

Health consciousness and engagement

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

Environmental harm and human health are often closely linked (Delmas & Colgan, 2018). 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 out pollution information and engage with the information they find. For example, individuals with asthma and other sensitive groups usually seek more information about the health effects of pollution than those who are less sensitive (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. Learning is both cognitive and emotional (Montiel, Antolin-Lopez, & Gallo, 2018)—the emotional learning linked to the pain caused by higher pollution could facilitate cognitive learning. Thus, those who are health conscious are also more likely to learn about air pollution, and 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. 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). Importance and relevance is key— without these factors notification use can have an inverse effect. In the case of air pollution, we argue that notifications can effectively direct the attention of the user to the information presented in the app provided that the frequency of these notifications is low. In this case, 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.

Method

AirForU Development and Features

To test our hypotheses, we developed an air quality app that was available and free to the public on both iPhones and Android devices (together these devices heavily dominate the smartphone market (Statista, 2017)). 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 UCLA Health brand in Google Play (for Android devices) and the App Store (for iPhones).

The app's air quality data is obtained from US EPA AirNow website and includes real-time hourly updates of air quality as well as next-day Air Quality Index (AQI) forecasts. The air quality information is gathered from monitoring stations throughout the nation and supplemented with modeled predictions. The AQI communicates how clean or polluted the outdoor air is along with any associated health risks. Air quality is reported on a scale of 0-500. 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).

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 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 toxicity 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 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.

Recruitment strategy

A number of avenues (social media, newsletters, websites, and flyers) were used to diffuse the app. The UCLA Health Media and Marketing team provided support in marketing the app and recruiting users through their health network. Collaborating with UCLA 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

The development team was an interdisciplinary group spanning business, social science, and engineering disciplines and comprised of five students, a postdoctoral researcher and a faculty member. All were interested in exploring the use of information technologies to solve environmental problems, and some were part of the Leaders in Sustainability graduate program at UCLA. Collectively, the team also partnered with the UCLA Health marketing department to develop and promote the app.

Sample

First-time users were asked to complete an intake survey before they were able to access information within the app (See Appendix 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.

Results from the intake survey are provided in Appendix 3. Overall 55% of the users were male and 45% female. The percentage of females is therefore slightly below the US average, which is 50.8%.[i] 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: (1) how many times users checked the app, and (2) how often users reported sharing air quality information with others (measured through short daily survey questions).

Users checking the app

We generated a variable called *check air pollution app* to represent the number of times a user opened AirForU each week. For AirForU, the only "critical" objective is to check air quality (either current or forecasted), so the first screen the user views shows this information.

We did not use the duration of the app visit as a measure of engagement, although that is the norm for measuring engagement for many apps, since a visit may last only a few seconds yet the user might have accessed "critical" content i.e. air quality information and be "satisfied" with the information. Hence, engagement is defined as opening the app. Table 1 provides a summary of all the views of the pages from its launch in October 2015 through until the end of the study period in June 2017. The app was opened 66,000+ times and air quality information (combination of real-time AQI, next-day AQI forecasts and historical AQIs) was accessed 164,000+ times. The majority of the views were for the hourly air quality information screen. The second most frequented screen was the health information corresponding to the AQI levels. The other tabs were accessed less frequently. On average, since its launch, the app was accessed 107 times per day and 753 times per week.

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[Insert Table 1 About Here]

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Overall engagement (measured as total app visits) dropped by 90% after 12 weeks of accessing the app (Figure A4 in Appendix 4). This indicates that either users learn enough during that time, or that we need other strategies to engage users beyond this period. The majority of app visits for each user (~75%) occurred within this period.

Users sharing air quality information with others

The second type of engagement we measured is how frequently users shared air quality information with others. This measure 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 could have talked about air pollution with family, friends, healthcare professionals, 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 talking to a doctor could result in a user getting access to medication for asthma or other health problems related to air pollution.

Although we do not have a reference point to compare frequency of air quality discussions as a result of the app to that 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 as result of checking the app. 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 pre-existing health problems identified by the users and through their frequency of outdoor exercise. The first variable, *user health*, represents whether the users reported any of the following health conditions: heart disease, lung disease, asthma, allergies and other health conditions that are exacerbated by poor air quality (eczema, bronchitis, migraine headaches, autoimmune disorders, COPD, sinus and rhinitis to name a few). The second variable, *child health,* represents whether the users reported that their children were suffering from any of the conditions listed above. 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.[ii] We control for users' *gender*, *age,* and whether they have *children*. In addition, we control for the *number of weeks* to account for the time since the app was first downloaded by the user.

Descriptive statistics are provided in Table 2 below and more details about the variables is in Appendix 3.

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[Insert Table 2 About Here]

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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 throughout the study period of 83 weeks.

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 and shows signs of over dispersion,[iii] we use a Negative Binomial panel model with random effects.

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

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

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 $x_{1it}, x_{2it} \dots .\ x_{nit}$. The independent variables include *user health, child health, exercise*, 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).[iv] A correlation table can be found in Appendix 6.

Results

Table 3 presents the regression results with *check air pollution app* as the dependent variable and Table 4 uses *talk to someone* as the dependent variable. Column 1 provides the full model, and columns 2 to 6 show interactions between the independent variables.

Users with pre-existing health conditions were more engaged with the app than those that did not have health conditions (i.e. about 1-2 additional app visits per week for every user with health conditions). This is an important finding because these are the groups that are more adversely impacted by air pollution. Users who exercise outdoors frequently compared to those that do not exercise frequently were more engaged, although this effect was smaller than for those with health conditions (a coefficient of 0.047 vs. 0.17). This is an important finding because those who exercise outdoors frequently have a higher exposure to pollution than those who do not and are thus more vulnerable to the health effects of air pollution. Similarly, users with children with health conditions were more likely to engage with the app than users without children or users with children without health conditions. 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 resulted in about 2-3 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.

The control variables provide more insight into engagement. older users were more likely to engage with the app compared to younger users. 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, gender and knowledge of air quality were not a significant predictor of engagement.

To determine if the extrinsic and intrinsic motivations helped users remain engaged over longer time frames, we present additional analysis (Table 3, columns 2, 3, 4 and 5)): models with interactions between the independent variables and the variable representing the number of weeks since download. Overall, these interactions show that health conscious users as well as those who receive notifications are more engaged over time than those who are not health conscious or did not receive notifications. The exception is the interaction between the variable child health and notifications, which is negative but only significant at the 10% level.

In order to understand whether the intrinsic and extrinsic motivations build on each other, we conducted interactions between user health, child health, exercises and notifications (presented in Table 3, columns 6, 7 and 8). The results show that the interactions are significant, insignificant or negative. For example, the interaction term between user health and notifications is insignificant, while the interaction between exercise and notifications is negative. This may be explained by the fact that health conscious people think enough about their health - they do not need extra reminders and may even find them annoying. This suggests that notifications should be used with caution as their overuse could backfire. Conversely, the term for notifications interacted with children's health is positive, indicating that users who have children with health conditions use the notifications as a reminder to engage with the app.

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[Insert Table 3 & 4 About Here]

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The factors that were most likely to encourage users to talk to someone about air pollution are provided in Table 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. The interactions between the independent variables and the number of weeks are positive (except for the exercise variable), but only at the 10% level. The interactions between the independent variables are insignificant in this case. So, generally speaking, the results including the variable of talking to others about air pollution go in the same direction as the results with checking the app as the dependent variable. However, in the former case, there is less significance for some of the interactions. This might be explained by the fact that there are fewer people who talk to others about air pollution than those who simply check the app.

Users Behavioral Responses

To get a comprehensive picture of the impact of user engagement on behavior, we investigated other behavioral responses to the information provided in the app through a feedback survey towards the end of our study period.[v] 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.

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 99 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 relevant. 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%).

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 less than 10% claimed to know about AQI, this 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 know that the respondents in the feedback survey were more actively engaged with the app, so we decided to check the knowledge of AQI in the entry survey of the most active users to make a fair comparison with the feedback survey responses. Still, less than 14% initially said they knew what AQI meant. Users' knowledge of the AQI range similarly improved between the entry and exit surveys. Therefore, it is reasonable to conclude that users learned about AQI while using the app.

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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 could influence their protective behavior. For example, users could adjust their location based on air quality information such as exercising indoors rather than outdoors. Users could also wear protective gear such as facemasks. Furthermore, they could use air filters with air conditioning within the home. These behaviors are called "averting" behaviors, meaning they reduce the users' exposure to air pollution (Dickie, 2017).

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=99),[vi] the data collected was crucial in understanding the usability of the app. 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 indicates the proportion of the 99 users that engaged in that action. The users could report the adoption of multiple measures, hence the sum of the measures is greater than the number of respondents. The two most common measures reported were: not exercising outdoors during high air pollution (21.7%), and closing windows (20.2%). The third most popular measure related to the use of air filters (including increasing frequency of cleaning filters) and air conditioning. Fewer people spoke with their doctor about air pollution (5.4%), planned for 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 UCLA 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 UCLA 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 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.”

Other anecdotal evidence showed some people using information provided by the app to discuss pollution with businesses in their neighborhood. For example, one app user was surprised to learn that a neighboring business produced a high level of toxic releases. While the information in the app came from the U.S. EPA Toxic Release Inventory, and was publicly available on the U.S. EPA website, the app user discovered it via the app because of her interest in the health impact of air pollution.

Therefore, overall, the evidence we 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 12th 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.

In summary, we developed an air quality app and studied user engagement with information provided in the app. We measured two kinds of engagement: (1) how many times users checked the app and (2) whether users reported talking to others about air pollution. We also tested whether intrinsic and extrinsic motivations could enhance user engagement with the app. We found that engagement was highest for users with intrinsic motivations, such as those who are health conscious, either because they are suffering from a condition aggravated by air pollution, or because they exercise often as part of a 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 talk 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.

Discussion

Our app based research design proved to be fruitful to help us understand how apps can help stakeholders learn about sustainability. In a more 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 platform 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 from this study was a better understanding of the motivations that explain engagement with air quality information. Users suffering from asthma, heart disease, lung disease or other conditions aggravated by air pollution, either directly or through their children, were more engaged with the app compared to those who did not have these health conditions. Our findings in part affirm those of Neidell (2004; 2006), who found evidence that young children and the elderly protect their health against air pollution. However, our study 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 sensitive groups are fully adopting risk-averting behaviors, engagement is the first step.

Another finding was that a high proportion of users who regularly partake in outdoor activities were more engaged with the app. 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, which 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 to check air pollution levels. We found that notifications were as important (if not more so) as health conditions in driving engagement. Thus, we confirmed our second hypothesis.

We also found that intrinsic and extrinsic motivations could work together to facilitate engagement, but that they could also work against each other. This is consistent with the behavioral economics literature that has shown how activating some motivations, such as altruistic motivations, can be counterproductive in some contexts (Gneezy, Meier, and Rey-Biel, 2011).

We measured two types of engagement: frequency of users checking information on the app, and whether users share air quality information with others. Sharing air quality information is a social component of interacting with the information. It is one-step further towards behavior change than simply checking the app. We found that intrinsic and extrinsic motivations had a similar impact on these two measures. This shows that for apps 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. 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 for apps beyond just those dealing with air. 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 engaged over time. Some strategies to increase engagement are – the use of periodic reminders through 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 (Dennison, Morrison, Conway, & Yardley, 2013; Cafazzo, Casselman, Hamming, Katzman, & Palmert, 2012).

Other features can also be added to enhance engagement. Incorporating social media features that allow users to share information with their friends and family easily through the app, including sending them invitations to download the app, could increase recruitment and ongoing engagement (Singh et al., 2016). A two-way interface could also 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 air quality apps. This is because with indoor air quality, some of the pollution is created by indoor sources, such as when cooking.

Thus, the app user may have more direct control in addressing the root cause of the problem, by changing their cooking practices for example, rather than just 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, Morrison, Conway, & Yardley, 2013; Hebden, Hons, Cook, Hons, & Ploeg, 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 encouraging 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 of 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, which potentially includes 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, and, in addition to learning how to make technology accessible to and usable by a large audience, they were exposed to rigorous social science techniques to test the effectiveness of the technology. Similarly, the social science students said they learned the limitations that technology can put on some of the social theories they were familiar with. Indeed, the success of the app was built on a complex chain of events; a glitch on any aspect could have affected the whole operation.

Most importantly, the students faced first-hand the challenges associated with diffusing public data about pollution that some corporations might prefer to keep private. Indeed, students 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. After one app user contacted a facility about their toxic releases based on the numbers provided in the app (which were taken directly from the publicly available 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 presented it.[vii] As a result, UCLA Health decided to remove the app from the app store, which was equivalent to temporarily shutting down the app since people who deleted 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. While the result of this chain of events was not ideal, it indicated that some users employed the information to pressure firms to reduce their pollution and 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 to delist the app was discussed with the team of graduate students, who then reflected on what could have been done to avoid this outcome. Some solutions included being clearer in the app about the sources of the data and potentially bringing lawyers to the design team.

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 especially polarizing with stakeholders having conflicting perspectives on what information to convey. Ultimately, the students involved learned the risks associated with conducting interdisciplinary action-oriented research around sustainability, and were equipped with ideas to mitigate future challenges.

Conclusion

In this research, we sought to understand the conditions under which mobile apps could educate stakeholders about air pollution issues and promote behavioral change.

One recognized avenue to help individuals learn about sustainability is to assist them in make the link between the natural environment and their health (Asensio & Delmas, 2015). This link is important but little discussed (Montiel, Delgado-Ceballos, & Ortiz-de-Mandojana, 2017). We found that air quality apps can be used to educate stakeholders about sustainability by helping them more effectively make that link. Indeed, air quality apps possess unique features that can make air pollution not only more visible, but also more relevant to individuals by linking it to their personal health. Air quality app users can "see" local levels of air pollution in real time, learn how these levels can affect their health, and therefore take immediate actions to protect their health. In other words, air quality apps can make air pollution visible and actionable.

However, user engagement with the information provided through the app is a necessary condition to realize the link between air quality and personal health, and to trigger behavior change. Specifically, air quality apps are useless if users do not open them regularly. We found that such engagement is facilitated when users are motivated either intrinsically because they care about their health, or extrinsically because notifications prompt them to look at the information. It is important to identify these motivations because they can be used to target stakeholders who will be most responsive to air pollution information, or to devise strategies to sensitize other stakeholders to health issues. It is also important to understand the interactions between intrinsic and extrinsic motivations as in some cases they can act against each other. In sum, it is possible to enhance user engagement with information by incorporating behavior change theory principles in the app's design. We found that the theory of issue involvement was particularly useful to complement the theory of planned behavior and guide the development of effective air quality apps.

There is a variety of stakeholders, such as consumers, employees or even students, who can be educated through apps about the link between the natural environment and health. For example, we have seen the development of apps that target consumers by providing information about the health impact of different types of food based on the chemical products they contain. Such information can help consumers make healthier and more environmentally friendly choices at the grocery store (Montiel, Delgado-Ceballos, & Ortiz-de-Mandojana, 2017). In the workplace, there are now wellness apps that enables employees track their exposure to air or noise pollution, help them reduce their exposure, and provide this information to employers.[viii] In the classroom, air quality apps could be also used to help students realize the link between their health and the environment.

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

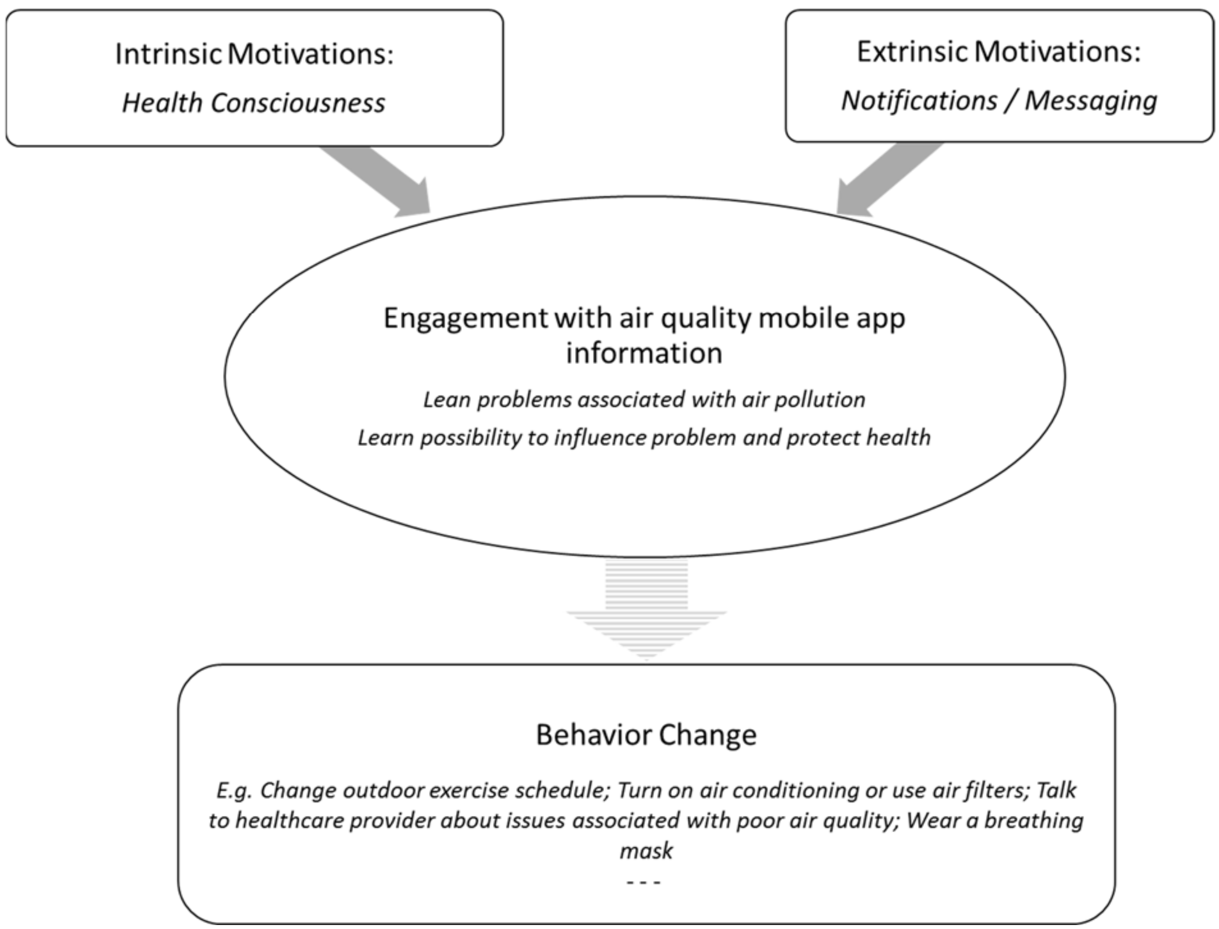


Figure 2: Air Quality Information - Historical Weekly AQI, Real-time AQI and Next-Day AQI

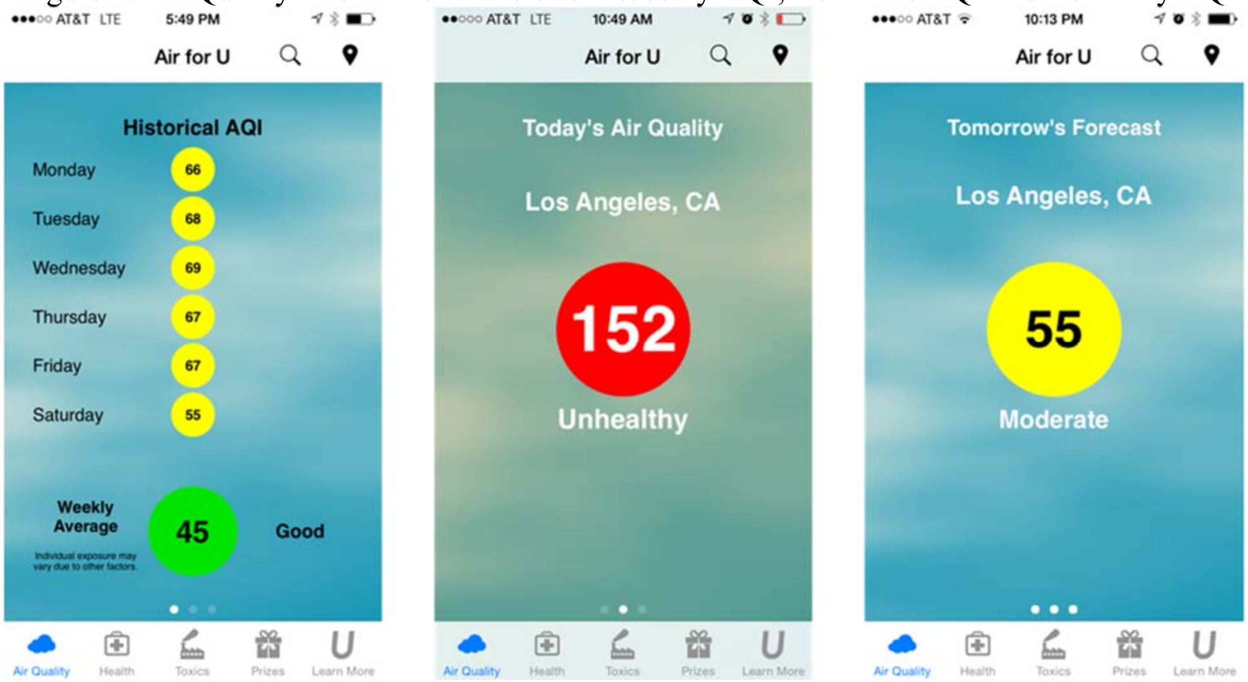
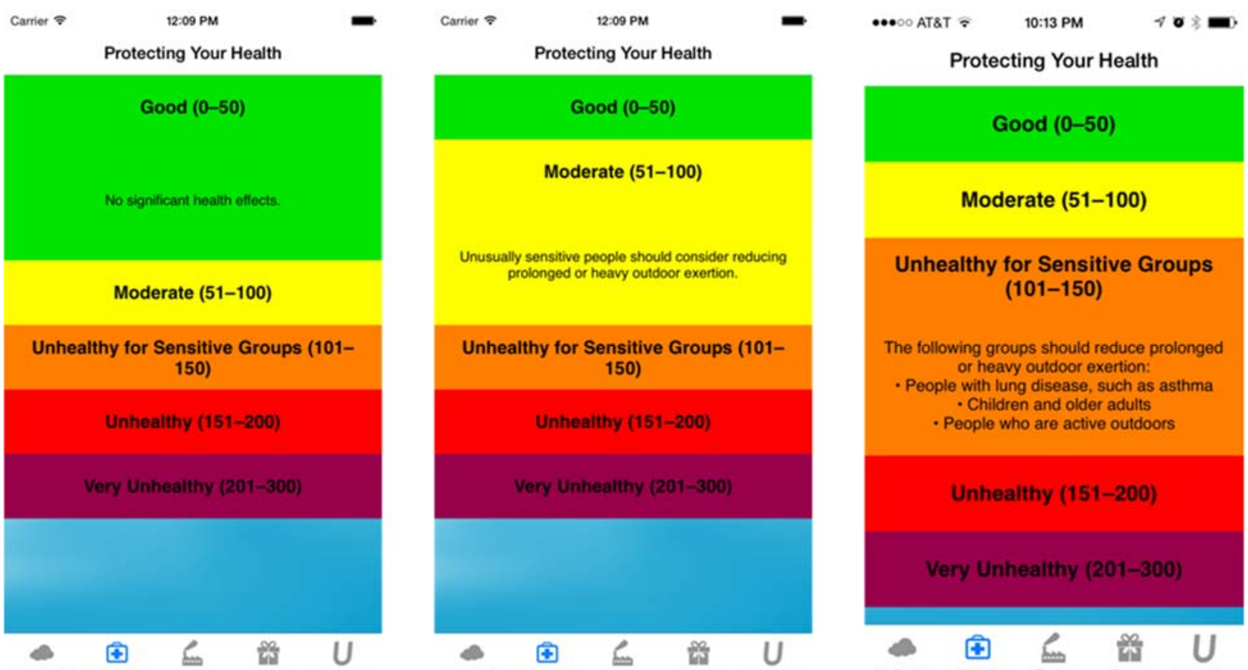


Figure 3: AirForU Screenshots with Health information based on EPA-designated AQI levels



Tables

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				
User health	0.707	0.757	0	4
Child health	0.248	0.555	0	4
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
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 checking the App

VARIABLES	(1) Check app	(2) Check app	(3) Check app	(4) Check app	(5) Check app	(6) Check app	(7) Check app	(8) Check app
User health	0.170***	0.043	0.169***	0.170***	0.171***	0.128***	0.173***	0.173***
	(0.027)	(0.036)	(0.027)	(0.027)	(0.027)	(0.039)	(0.027)	(0.027)
Children health	0.061*	0.063*	0.112**	0.061*	0.060*	0.064*	-0.024	0.060*
	(0.033)	(0.033)	(0.044)	(0.033)	(0.033)	(0.033)	(0.046)	(0.033)
Exercise	0.047***	0.047***	0.047***	0.008	0.047***	0.047***	0.047***	0.121***
	(0.009)	(0.009)	(0.009)	(0.012)	(0.009)	(0.009)	(0.009)	(0.013)
Notifications	0.890***	0.891***	0.890***	0.890***	0.642***	0.844***	0.857***	1.477***
	(0.026)	(0.026)	(0.026)	(0.026)	(0.035)	(0.041)	(0.029)	(0.080)
Female	0.010	0.008	0.010	0.008	0.010	0.005	0.008	0.015
	(0.026)	(0.026)	(0.026)	(0.026)	(0.026)	(0.026)	(0.026)	(0.026)
Age	0.297***	0.298***	0.297***	0.296***	0.299***	0.297***	0.296***	0.294***
	(0.012)	(0.012)	(0.012)	(0.012)	(0.012)	(0.012)	(0.012)	(0.012)
Knowledge of AQ	0.022	0.024	0.023	0.022	0.016	0.022	0.025	0.027
	(0.044)	(0.044)	(0.044)	(0.044)	(0.044)	(0.044)	(0.044)	(0.044)
Number of weeks since download	-0.065***	-0.069***	-0.065***	-0.074***	-0.074***	-0.065***	-0.065***	-0.065***
	(0.001)	(0.001)	(0.001)	(0.002)	(0.001)	(0.001)	(0.001)	(0.001)
User health * Number of weeks		0.007***						
		(0.001)						
Children health * Number of weeks			-0.003*					
			(0.002)					
Exercise * Number of weeks				0.002***				
				(0.000)				
Notifications * Number of weeks					0.014***			
					(0.001)			
User health * Notifications						0.078		
						(0.053)		
Children health * Notifications							0.172***	
							(0.065)	
Exercise * Notifications								-0.142***
								(0.018)
Constant	-2.161***	-2.087***	-2.171***	-1.992***	-2.015***	-2.132***	-2.143***	-2.462***
	(0.060)	(0.061)	(0.060)	(0.069)	(0.061)	(0.063)	(0.060)	(0.071)
Observations	152,322	152,322	152,322	152,322	152,322	152,322	152,322	152,322
Number of users	2,740	2,740	2,740	2,740	2,740	2,740	2,740	2,740

Standard errors in parentheses, *** p<0.01, ** p<0.05, * p<0.1

Table 4: Drivers of Users Talking about Someone about Air Pollution

VARIABLES	(1) Talk about AP	(2) Talk about AP	(3) Talk about AP	(4) Talk about AP	(5) Talk about AP	(6) Talk about AP	(7) Talk about AP	(8) Talk about AP
User health	0.419***	0.093	0.421***	0.420***	0.411***	0.541***	0.413***	0.415***
	(0.097)	(0.106)	(0.097)	(0.097)	(0.097)	(0.130)	(0.097)	(0.097)
Children health	0.333***	0.357***	0.191	0.340***	0.326***	0.343***	0.184	0.322***
	(0.114)	(0.116)	(0.123)	(0.115)	(0.115)	(0.115)	(0.154)	(0.115)
Exercise	0.052*	0.048	0.048	0.073**	0.044	0.046	0.060*	0.074
	(0.031)	(0.032)	(0.032)	(0.034)	(0.032)	(0.032)	(0.032)	(0.046)
Notifications	0.680***	0.673***	0.677***	0.686***	0.364***	0.834***	0.614***	0.841***
	(0.086)	(0.087)	(0.086)	(0.086)	(0.094)	(0.139)	(0.098)	(0.260)
Female	-0.092	-0.106	-0.110	-0.096	-0.099	-0.081	-0.077	-0.087
	(0.090)	(0.091)	(0.091)	(0.090)	(0.091)	(0.091)	(0.091)	(0.091)
Age	0.146***	0.152***	0.140***	0.147***	0.147***	0.147***	0.149***	0.143***
	(0.041)	(0.042)	(0.042)	(0.041)	(0.042)	(0.041)	(0.041)	(0.042)
Knowledge of AQ	0.208	0.218	0.218	0.194	0.166	0.216	0.240*	0.209
	(0.142)	(0.144)	(0.144)	(0.142)	(0.141)	(0.142)	(0.145)	(0.142)
Number of weeks since download	-0.061***	-0.075***	-0.064***	-0.055***	-0.075***	-0.061***	-0.061***	-0.061***
	(0.001)	(0.002)	(0.001)	(0.004)	(0.002)	(0.001)	(0.001)	(0.001)
User health * Number of weeks		0.021***						
		(0.003)						
Children health * Number of weeks			0.011***					
			(0.003)					
Exercise * Number of weeks				-0.001*				
				(0.001)				
Notifications* Number of weeks					0.022***			
					(0.003)			
User health * Notifications						-0.250		
						(0.178)		
Children health * Notifications							0.289	
							(0.205)	
Exercise * Notifications								-0.040
								(0.061)
Constant	-0.264	-0.004	-0.165	-0.356	-0.006	-0.328	-0.282	-0.346
	(0.223)	(0.227)	(0.226)	(0.230)	(0.227)	(0.227)	(0.223)	(0.254)
Observations	152,322	152,322	152,322	152,322	152,322	152,322	152,322	152,322
Number of users	2,740	2,740	2,740	2,740	2,740	2,740	2,740	2,740

Standard errors in parentheses, *** p<0.01, ** p<0.05, * p<0.1

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 of responses	Number of responses
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

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.

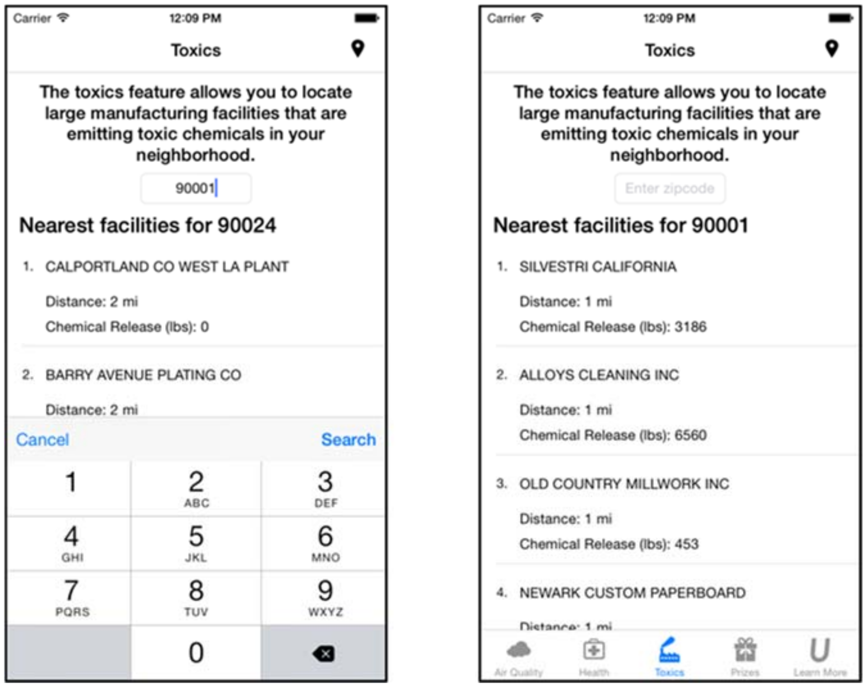
AQIs are provided by zip code from AirNow. Each time the user searches by city, the data is first converted to a zip code and then the zip code is checked against the AirNow AQI data. When the user searches by current location, the latitude/longitude is converted to a zip code within the server and checked 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.

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.

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.

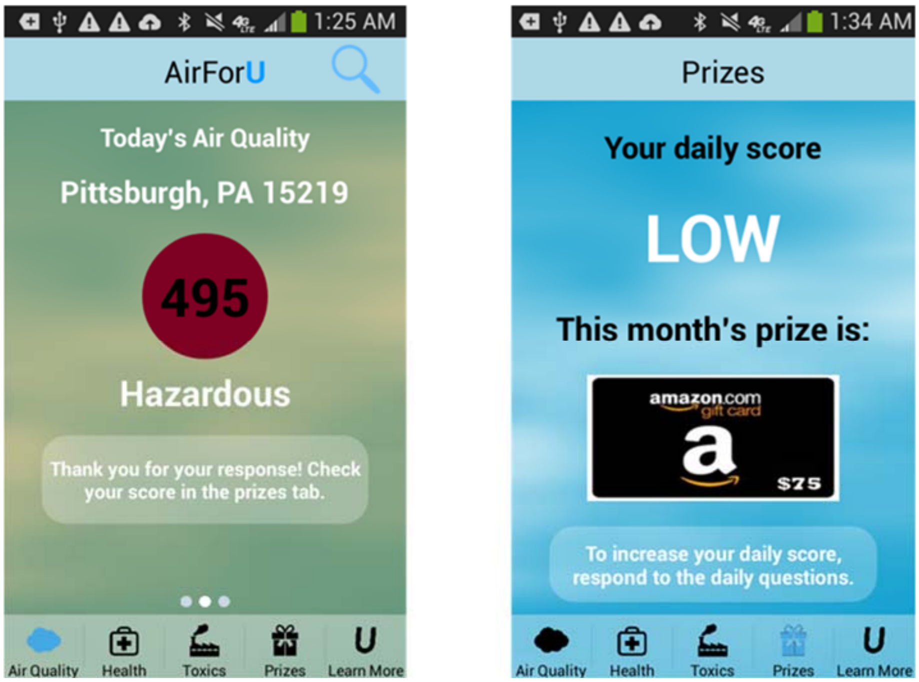
Prizes Tab

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.

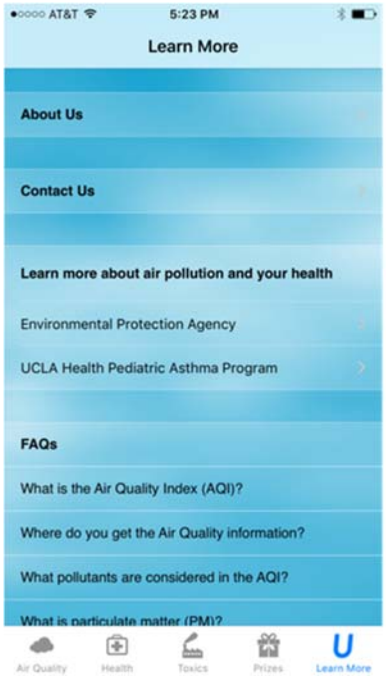
Figure A1-2: The daily score is updated on the prizes tab based on response to the behavioral questions presented in the AQ tab



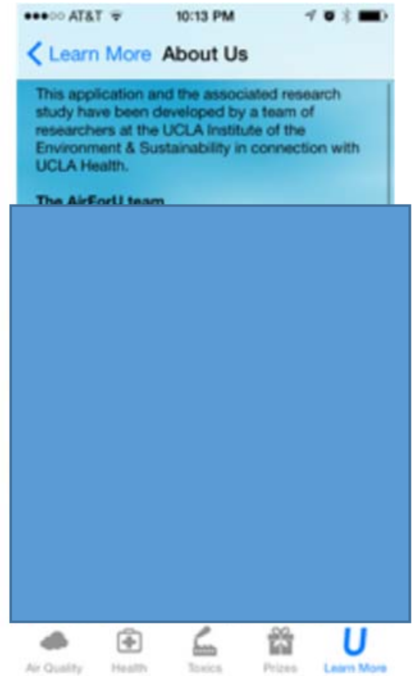
Learn More Tab

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) 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


5:23 PM
Learn More
About Us
Contact Us
Learn more about air pollution and your health
Environmental Protection Agency
UCLA Health Pediatric Asthma Program
FAQs
What is the Air Quality Index (AQI)?
Where do you get the Air Quality information?
What pollutants are considered in the AQI?
What is particulate matter (PM)?
Air Quality
Health
Toxics
Prizes
Learn More


Carrier
12:10 PM
Learn More
FAQs
What is the Air Quality Index (AQI)?
The AQI is a measure of how polluted or clean the air is. The higher the AQI, the worse the air quality. There are 6 levels in the AQI system; each depicted by a range and color. Each level corresponds to certain health effects and identifies the populations that need to take steps to protect their health. An AQI of 100 corresponds to the national air quality standards and levels above 100 pose higher health risks.
Where do you get the Air Quality information?
What pollutants are considered in the AQI?
What is particulate matter (PM)?
What are some of the health effects of air pollution?
What populations are especially vulnerable to air pollution?
What are some steps I can take to protect my health?
Air Quality
Health
Toxics
Prizes
Learn More


10:13 PM
Learn More
About Us
This application and the associated research study have been developed by a team of researchers at the UCLA Institute of the Environment & Sustainability in connection with UCLA Health.
Air Quality
Health
Toxics
Prizes
Learn More

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

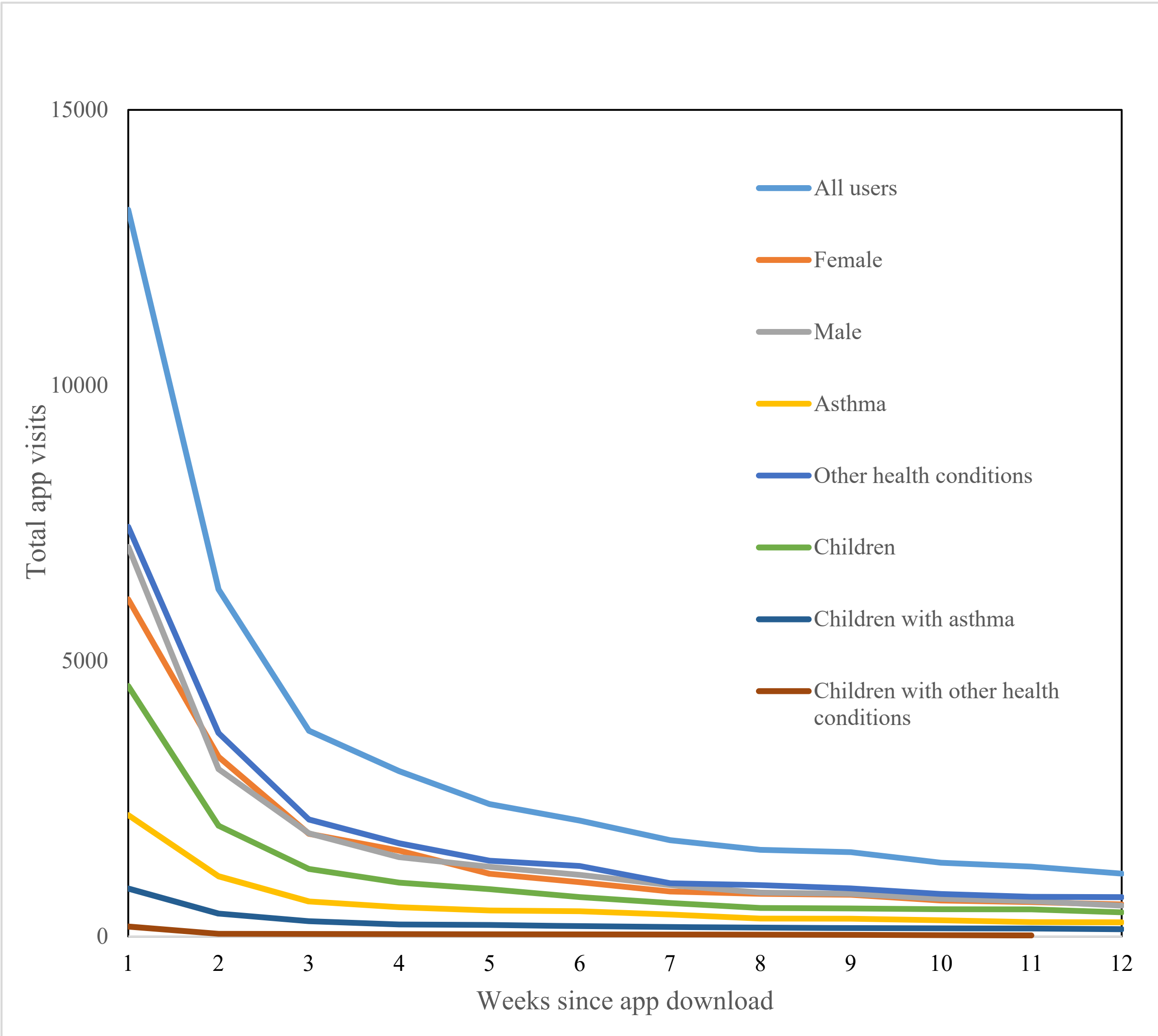
Appendix 3. Summary Statistics for App Users (N=2,740)

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	Approximately, how often do you exercise outdoors??			
Once a year or less		Once a year or less (1)	163	5.95

Survey Questions and Response Options in App Intake Survey	Question Wording	Coding for Regression Analysis	N	%
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



Appendix 5: Correlation Table

		1	2	3	4	5	6	7	8	9	10
1	Check app	1.000									
2	Talk about AP	0.615	1.000								
3	User health	0.050	0.039	1.000							
4	Children health	0.032	0.036	0.211	1.000						
5	Exercise	-0.006	-0.006	-0.055	-0.062	1.000					
6	Notifications	0.062	0.041	-0.001	0.020	0.040	1.000				
7	Female	0.019	0.003	0.106	0.074	-0.071	0.068	1.000			
8	Age	0.035	0.018	0.126	-0.051	0.123	0.007	-0.103	1.000		
9	Knowledge of AQ	0.012	0.020	0.025	0.022	0.059	-0.028	-0.039	0.018	1.000	
10	Number of weeks since download	-0.150	-0.084	-0.025	-0.019	0.030	0.012	-0.044	0.043	-0.003	1.000

[i] https://www.census.gov/quickfacts/fact/table/US/LFE046217
[ii] We asked additional questions about knowledge of air quality that are reported in Appendix 3.
[iii] The variance of the dependent variable *Open app* is 4.87766, that is to say about 12 times superior to the mean of 0.3887728. The variance of the dependent variable *Talk to someone about air pollution* is .0871683 that is about 2.6 time superior to the mean of 0.0329143.
[iv] Variance Inflated Factor = 1.26
[v] 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.
[vi] 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.
[vii] They argued that this was an air quality 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.
[viii] https://phys.org/news/2019-03-canairy-app-tracks-outdoor-workers.html