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Enhancing public response to smog alerts: Evidence from Lahore

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Enhancing Public Response to Smog Alerts: Evidence from Lahore*

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Abstract

We collaborated with a government partner (Urban Unit) to develop *Smog Alert*, a smartphone application that provides residents of Lahore with real-time air quality information, next-day forecasts, alerts, and health advisories. We piloted the app with 300 respondents across 13 union councils. Thirty-nine percent of respondents downloaded the application during the survey. Respondents expressed substantial concern about air pollution and frequently undertook costly environmental actions, including contributing toward air purifiers for schools and signing a letter requesting stronger government enforcement. The pilot provides lessons for future app deployment and motivates further analysis of citizens' demand for government action.

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1 Introduction

Air pollution is a serious environmental threat to human well-being, with substantial consequences for mortality, morbidity, labor productivity, cognition, and welfare (Graff Zivin and Neidell 2013; Aguilar-Gomez et al. 2022). These costs are particularly acute in South Asia, which contains 37 of the 40 most polluted cities in the world (World Bank 2023). Pakistan is among the most polluted countries globally. Average fine-particulate concentrations are roughly five times the World Health Organization's guidelines, with considerably poorer air quality in the Punjab province (World Bank 2022). This pollution imposes large economic costs: World Bank estimates suggest that air pollution leads to economic losses equivalent to approximately 6.5 percent of Pakistan's GDP each year (World Bank 2022).

An important challenge with air pollution is that exposure varies across space and time and is not always readily observable. Individuals must therefore form expectations about environmental conditions—air quality in this case—when deciding whether to undertake costly protective actions. Timely and reliable information can improve these expectations and facilitate adaptation by allowing households to reduce exposure when pollution is high (Ahmad et al. 2026; Graff Zivin and Neidell 2013). This may include reallocating time between indoor and outdoor activities, wearing protective masks, or taking other precautions. More broadly, access to information may shape citizens' understanding of environmental risks and their preferences for responses to them.

A growing economics literature documents behavioral adaptation to air pollution and other environmental threats. Individuals can reduce their exposure through costly avoidance behaviors, including purchasing protective technologies and reallocating activities across time and space (Graff Zivin and Neidell 2013). Evidence from developing countries indicates that households place considerable value on reducing pollution exposure. In China, households' residential location choices (Freeman et al. 2019) and costly defensive investments such as air purifiers (Ito and Zhang 2020) reveal such value.

Households also value information that can help them respond to changes in environmental conditions. Our previous work in Lahore finds positive willingness to pay for air quality forecasts across two separate samples (Ahmad et al. 2026; Imtiaz et al. 2025). The effectiveness of avoidance depends not only on access to information but also on individuals' expectations about environmental conditions. When pollution varies over time and space, information such as forecasts can allow households to shift costly avoidance to periods in which its benefits are greatest. Consistent with

this mechanism, a nationwide air quality monitoring and disclosure program in China increased public awareness of pollution, avoidance of outdoor exposure, and expenditures on protective goods, with resulting health benefits (Barwick et al. 2024).

Informational constraints may be particularly important in developing countries, where severe pollution coexists with limited access to reliable and usable information and low levels of human capital. Incomplete information and inaccurate beliefs may limit households' ability to undertake protective actions even when they place high value on reducing exposure. Recent evidence from Dhaka shows that households systematically underestimate indoor air pollution. Providing monitors corrected these beliefs, but purifier use increased only among households given both monitors and purifiers (Chowdhury et al. 2025). These findings suggest that the benefits of pollution monitoring partially depend on whether the resulting data reach households in a form they can understand and process. Services that translate pollution data into actionable information, such as alerts, forecasts, and protective guidance, may complement investments in monitoring infrastructure.

Our earlier IGC-funded work in a low-middle-income neighborhood of Lahore provides direct evidence on these mechanisms, revealing that households value and change behavior in response to air quality information (Ahmad et al. 2026). We provided households with next-day air quality forecasts through text messages and found that forecast provision increased households' willingness to pay for protective masks and made them better align time spent indoors and outdoors with their expectations of air quality levels. Households also exhibited substantial willingness to pay to continue receiving air quality forecasts—41 percent of their total monthly mobile phone costs. Related work in a separate Lahore sample also finds high demand for accessible and reliable air quality information (Imtiaz et al. 2025). Together, these findings suggest that improving access to pollution information can help households make more informed decisions about exposure and facilitate welfare-enhancing adaptation.

In this project, we developed a smartphone application—*Smog Alert*—which builds on our previous work by moving from a single next-day forecast delivered through text messages toward a richer, localized, and continuously accessible air quality information system. Developed in partnership with the Urban Unit, an urban planning and management organization of the Government of Punjab, the application combines real-time air quality readings—from a network of monitors deployed by the Urban Unit across Lahore—with monitor-specific next-day forecasts and provides users with alerts, health guidance, historical trends, and spatial information on pollution. In contrast to our previous interventions, which provided forecasts without spatial granularity and through text mes-

sages, *Smog Alert* allows users to access regularly updated information from monitors across the city through a dedicated smartphone platform. The air quality forecasts included in the application draw on monitoring and weather data and automatically update twice daily as new data become available. The project extends our earlier research by examining the deployment of a substantially richer air quality information service in collaboration with a government partner—rather than a temporary service provided by researchers, as was the case in our previous work.

We further piloted *Smog Alert* along with an in-person survey of 300 low-middle-income households in Lahore. The survey elicited respondents' awareness and beliefs about air pollution, familiarity with the Air Quality Index (AQI), sources of and trust in air quality information, perceptions of government action, and interest in receiving additional information about the sources of Lahore's air pollution. It then introduced respondents to the application, giving them the option to install it on their own smartphones—117 respondents (39 percent) downloaded the app while 94 (31 percent) expressed an interest in downloading the app at a later stage.

We use the survey data to examine how respondents' baseline beliefs and attitudes correlate with app take-up and other costly forms of environmental engagement. Familiarity with the AQI emerges as the most consistent correlate of these behaviors. Respondents familiar with the AQI were more likely to download the application, sign a letter requesting government action, and contribute money toward air purifiers for schools. We caution that these relationships are descriptive associations rather than causal effects.

The survey included a separate preregistered experimental module examining how information about pollution sources shapes citizens' demand for government action. The analysis of this experiment is outside the scope of this report—we will present those findings separately at a later stage. In this report, we focus on the design and functionality of *Smog Alert*, the forecasting model embedded in it, its implementation through the household pilot, and descriptive evidence on air quality awareness and beliefs, app take-up, and the relationship between baseline beliefs and attitudes and costly environmental engagement.

2 The *Smog Alert* Application

Smog Alert integrates real-time data from the Urban Unit's air quality network of 18 monitors in Lahore with monitor-specific forecasts and advisories that help users interpret and respond to changing pollution conditions. We first describe the application's design and functionality, then

discuss the monitoring network that supplies the pollution data, and finally explain the forecasting model that generates predictions of next-day air quality.

2.1 App Design and Functionality

Smog Alert provides users with localized real-time readings and forecasts of ambient air pollution. The app currently draws data from the Urban Unit's 18 monitors distributed across Lahore and links each user to a specific monitoring location. If users enable location services, the app automatically identifies the nearest monitor, while users who do not enable location services can select a monitor manually. All users can switch between monitoring locations at any time. The home screen reports the distance to the selected monitor and the time of the most recent reading, allowing users to assess the spatial and temporal relevance of the information they receive. Figure 1 shows the main interface, including the $PM_{2.5}$-based AQI and next-day forecast, and monitor-selection functionality.

The app translates particulate pollution ($PM_{2.5}$) measurements into the Punjab Air Quality Index (AQI), which classifies air quality into seven categories ranging from Good (AQI 0–50) to Hazardous (AQI above 400). The home screen displays the current AQI along with its corresponding health-risk category, as well as temperature and relative humidity. The interface uses the colors associated with the Punjab AQI categories to make changes in pollution conditions easy to interpret. Users can select the information icon next to the current category to view the complete AQI scale and determine how current conditions compare to other pollution levels (Figure 2(a)). The home screen further displays the next-day AQI forecast for the user's selected location. Users can also view historical AQI over different time intervals and access a live map that displays their location and nearby monitors, along with each monitor's name and current AQI.

Smog Alert allows users to receive notifications when forecast pollution exceeds a specified threshold. By default, the app sets the alert threshold at the Unhealthy category (AQI 201–300), so users receive a notification when the forecast AQI for their selected monitor reaches 201 or higher. Users can change this threshold in the app according to their own preferences (Figure 2(b)). This feature allows users to receive salient information about poor air quality without requiring them to monitor the app continuously. The notification reports the predicted AQI with its corresponding category for the user's selected location and provides a recommended avoidance action based on the forecast pollution level. Figure 2(c) shows an example of such a notification.

Finally, the app provides information intended to help users interpret pollution readings and respond to elevated pollution levels. Its "Learn More" section provides information on $PM_{2.5}$ and its

health effects, the AQI and its interpretation, and recommended avoidance actions (Figure 3(a)). The health guidance and avoidance measures draw on the Punjab Environment Protection and Climate Change Department's (EPCCD) Health Advisory System for Critical Air Pollution Events (HAS-CAPEs), which provides AQI-specific recommendations for the general population and vulnerable groups (Environment Protection Department, Government of the Punjab 2022). The app makes these recommendations available to users through its information screens (Figures 3(b) & 3(c)).

2.2 Air Quality Monitoring Network

Smog Alert draws its real-time pollution data from the Urban Unit's air quality monitoring network. With support from the University of Chicago's Energy Policy Institute (EPIC) Air Quality Fund, the Urban Unit installed 160 $PM_{2.5}$ monitors across 14 cities in Pakistan, creating the country's largest open-access, real-time particulate pollution monitoring network (EPIC Air Quality Fund 2025). Eighteen of these monitors are located across Lahore, providing the spatial coverage for the app.

The Urban Unit provides *Smog Alert* with access to real-time monitor-level measurements through its application programming interface (API), which the app converts into the corresponding Punjab AQI using the standard AQI conversion formula—a linear interpolation between the relevant $PM_{2.5}$ and AQI breakpoints—using Punjab's AQI thresholds (U.S. Environmental Protection Agency 2024; Environmental Protection Agency, Punjab 2025). As described earlier, the app assigns users who enable location services to the nearest monitor while allowing all users to select any available monitoring location manually. The spatial coverage allows the app to show pollution levels at different locations in Lahore rather than a single citywide measure.

The Urban Unit's monitors also provide the data required to construct the air quality forecasts delivered through the app. We use recent monitor-level pollution measurements together with meteorological data to generate location-specific predictions of next-day air quality.

2.3 Air Quality Forecasting

Smog Alert provides monitor-specific forecasts of next-day air quality. We use a LASSO model to predict next-day $PM_{2.5}$ concentrations for each monitoring location using recent pollution measurements from the Urban Unit's monitor network and historical meteorological data from Open-Meteo (Zippenfenig 2023). The model uses information across monitoring locations to capture spatial and

temporal patterns in pollution while generating a separate forecast for each monitor.

The forecasting pipeline generates updated predictions twice each day, at 4 p.m. and 11 p.m. The app converts the resulting $PM_{2.5}$ forecasts into the corresponding Punjab AQI using the conversion described in Section 2.2 and displays the next-day AQI and its associated category for the user's selected monitoring location. These forecasts also determine whether the app sends the air quality alert notifications described in Section 2.1.

3 Pilot Household Survey

The pilot household survey examined how households in Lahore understand and respond to air pollution and how they engage with *Smog Alert*. The survey measured respondents' knowledge and perceptions of air pollution, access to and trust in air quality information, pollution avoidance behavior, and demand for air quality information. It also examined app take-up and other forms of environmental engagement.

3.1 Survey Design and Sample

We conducted an in-person household survey in Shalamar tehsil, Lahore, from July 15 to July 24, 2026. Research Solutions, a Lahore-based survey firm, administered the survey in Urdu using trained enumerators. The final sample consisted of 300 respondents across 30 randomly selected geographic sampling points spanning 13 union councils within Shalamar tehsil, with ten respondents surveyed around each sampling point. Starting from each sampling point, enumerators followed a left-hand rule, proceeding on the left side of their route and skipping five housing units between approached households.

Eligible respondents had to be at least 18 years old, have access to a smartphone, and consent to learning more about and potentially installing *Smog Alert*. Enumerators obtained respondents' informed consent before administering the survey.

3.2 Survey Measures and App Introduction

The survey collected information on respondents' socioeconomic characteristics, beliefs and attitudes about air pollution, and access to air quality information. We asked respondents whether they thought Lahore's air quality had improved, worsened, or stayed the same compared to five years earlier, how much attention they paid to air quality, and what they considered the most im-

portant source of air pollution. We also elicited whether respondents had heard of the Air Quality Index (AQI), their trust in official air quality information, their perceptions of government action on air pollution, and their interest in receiving additional information about the sources of Lahore's air pollution. The survey also recorded whether any household member had experienced breathing or respiratory issues during smog or high-pollution days in the previous 12 months.

Enumerators introduced respondents to *Smog Alert*, demonstrated its main features, and gave them an opportunity to install the app during the interview. Respondents who did not install it immediately could take a QR code and indicate that they intended to install it later. We recorded respondents' app take-up and measured two forms of costly environmental engagement: 1) signing a letter to the Urban Unit requesting stronger government enforcement against air pollution; and 2) contributing any portion of a PKR 500 endowment toward air purifiers for schools.

We use these measures to provide descriptive evidence on engagement with *Smog Alert* and costly environmental actions and to examine how respondents' baseline beliefs and attitudes correlate with these behaviors.

Table 1 summarizes key characteristics of the survey sample, including respondents' demographic and household characteristics, awareness of air quality, beliefs about major pollution sources, and measures of costly environmental engagement.

4 Descriptive Findings

This section presents descriptive evidence from the household pilot. We first examine take-up of *Smog Alert* and patterns of subsequent app use. We then describe respondents' baseline beliefs and attitudes about air pollution and examine how these measures correlate with app take-up and costly environmental actions.

4.1 App Take-Up and Usage

Of the 300 respondents, 211 (70 percent) either downloaded *Smog Alert* during the survey or expressed interest in downloading it later—117 (39 percent) downloaded the app during the survey, while 94 (31 percent) took a QR code to download it later. We complement these measures with usage analytics captured by the app to see how users engaged with *Smog Alert* after installing it on their phones.

A technical issue with the app's analytics during the pilot prevented us from tracking app use

initially. The app did not correctly record anonymous usage before July 24. After we resolved this issue, the analytics data captured activity from 27 users, including 16 users whose activity we could link to the survey and 11 anonymous users. We treat these data as descriptive of observed engagement with the app rather than as a complete measure of usage among respondents who downloaded it.

Figure 4 summarizes app take-up and observed engagement during the pilot. Since self-reported downloads and tracked usage come from different data sources, the 27 tracked users are not necessarily a subset of the 117 respondents who downloaded the app during the survey. The analytics data exclude app test-runs during the survey and observations affected by the anonymous-tracking issue mentioned earlier.

We explore how tracked users engaged with different parts of *Smog Alert*. Figure 5 shows counts of views across the app's screens. The Home Screen accounted for most observed screen activity, followed by the Settings and Onboarding screens. We observed modest activity on the Learn More screen.

Users infrequently interacted with the app's next-day forecast feature. We recorded six visits to the forecast tab, all from two of the 16 respondents whose app activity we could link to the survey. These numbers are too small to infer how users consume forecasts, but they reveal users rarely engaged with this feature. A possible reason may be that users can see the forecasts on the home screen, which may preclude them from tapping the feature to get further details.

4.2 Air Pollution Beliefs and Environmental Engagement

Respondents expressed substantial concern about Lahore's air pollution. Figure 6 shows how respondents perceived changes in the city's air quality compared to five years earlier. The vast majority reported that air quality had become much worse, while nearly all remaining reported that it had become worse. Very few thought that air quality had stayed the same.

Respondents attributed most of Lahore's air pollution to vehicles and industry. As shown in Figure 7, respondents attributed an average of 40.8 percent of air pollution to vehicles and 38.3 percent to industry versus 10.7 percent to crop burning and 10.3 percent to other sources.

We also elicited two forms of costly environmental engagement. As reported in Table 1, 76 percent of respondents contributed some portion of their PKR 500 endowment toward air purifiers for schools, with an average contribution of PKR 295; 47 percent of respondents signed the letter requesting stronger government enforcement against air pollution.

We next examine how respondents' baseline beliefs and attitudes correlate with these forms of environmental engagement. Table 2 reports associations with app take-up, signing the enforcement letter, and contributions to the air-purifier fund. Each estimate comes from a separate regression of an engagement outcome on a standardized baseline belief or attitude. Because app take-up occurred before the experimental module, while letter signing and donations occurred afterward, the latter regressions include treatment-arm fixed effects. All specifications also include sampling-point fixed effects. We interpret these estimates as descriptive associations rather than causal effects.

Several patterns stand out. Prior awareness of the AQI is positively associated with all three forms of engagement. A 1 standard-deviation (S.D.) increase in prior AQI awareness was associated with a 21.6 percentage-point increase in app take-up, a 20.9 percentage-point increase in letter signing, and a PKR 70.3 increase in contributions to the air-purifier fund. Interest in receiving a source-apportionment report and identifying vehicles as the leading source of air pollution are both positively associated with app take-up and donations.

A 1 S.D. increase in reported attention to air quality was associated with a 19.2 percentage-point decrease in app take-up, a 12.6 percentage-point decrease in letter signing, and a PKR 56.6 decrease in contributions to the air-purifier fund. Trust in official air quality information is negatively associated with donations, while perceiving the government as serious about addressing air pollution is positively associated with donations. Figure 8 presents these relationships as standardized partial correlations, allowing the magnitude of the associations to be compared across outcomes.

5 Conclusion and Next Steps

We collaborated with the Urban Unit, our government partner in Punjab, to develop and pilot *Smog Alert*, a citizen-facing smartphone application that provides residents of Lahore with real-time air quality readings, alerts, next-day forecasts, and health and avoidance advisories. We integrated the application into an in-person household pilot with 300 respondents across 13 union councils in Lahore, allowing us to assess initial app take-up and usage while documenting respondents' awareness of and beliefs about air pollution and their engagement with costly environmental actions.

The pilot provides several preliminary insights into how respondents engage with air quality information. Thirty-nine percent of respondents downloaded *Smog Alert* and another 31 percent expressed interest in downloading it later, indicating meaningful initial take-up of and interest in the app. Respondents also expressed serious concern about Lahore's air pollution and attributed

most of it to vehicles and industry. Beyond these stated beliefs, many respondents took costly environmental actions: 76 percent contributed some of their endowment toward air purifiers for schools and 47 percent signed a letter requesting stronger government enforcement. Familiarity with the AQI emerged as the most consistent correlate of these behaviors, with respondents who had heard of the AQI more likely to download the application, sign the enforcement letter, and contribute to the air purifier fund.

The pilot also revealed several limitations that inform the next stage of the project. A technical issue with the application's analytics system prevented us from tracking app usage during part of the pilot. The relatively small sample of 300 respondents also limits our ability to examine heterogeneity in beliefs and engagement across demographic groups. The reported associations between baseline beliefs and environmental engagement are descriptive and should not be interpreted as causal effects. The pilot nonetheless identified where we can improve the app's analytics, deployment protocol, and evaluation design.

Our next step involves analyzing and writing up the preregistered experimental module embedded in the household survey. The experiment will allow us to examine how information about the sources of Lahore's air pollution shapes respondents' beliefs and their demand for government action. Evidence that better information increases such demand could help motivate policy efforts to regulate sources of air pollution. Together with the implementation lessons and descriptive evidence presented here, this analysis can inform the design of future research and potential efforts to expand access to timely, accessible, and reliable air quality information. We envision pursuing such efforts in collaboration with government and policy stakeholders, including the Urban Unit.

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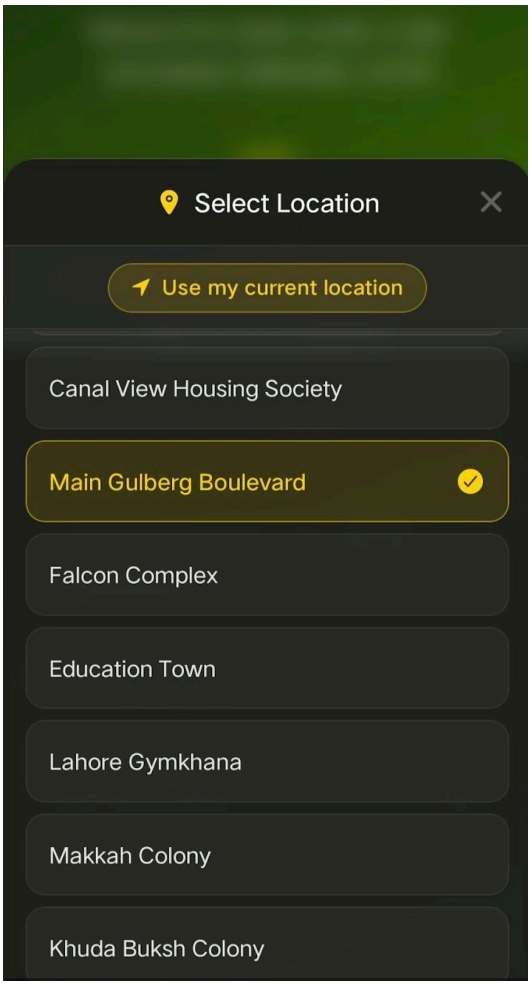
Figures

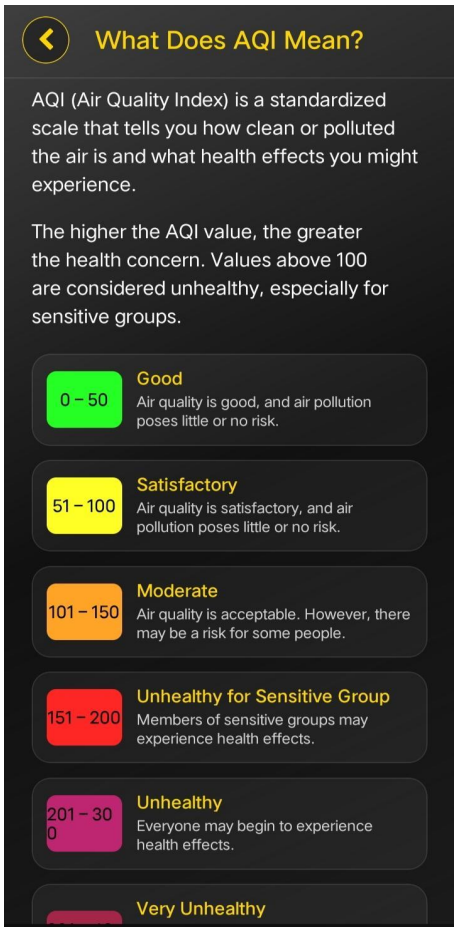


(a) Home screen

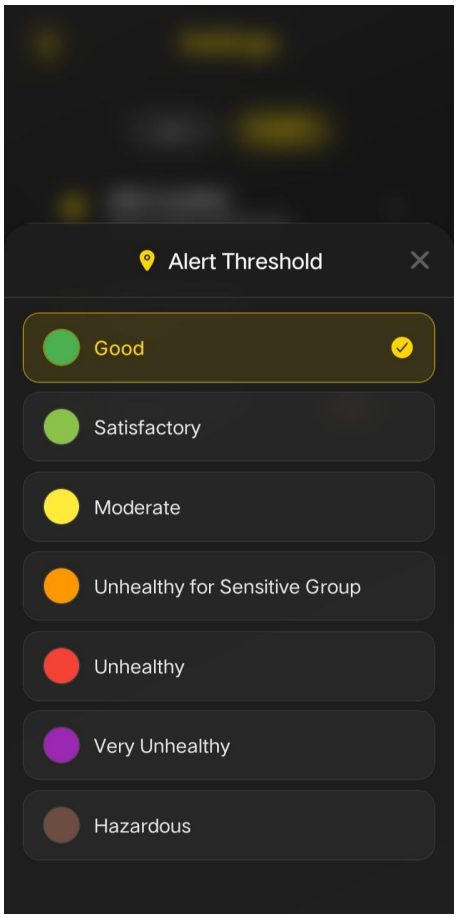


(b) Monitor selection

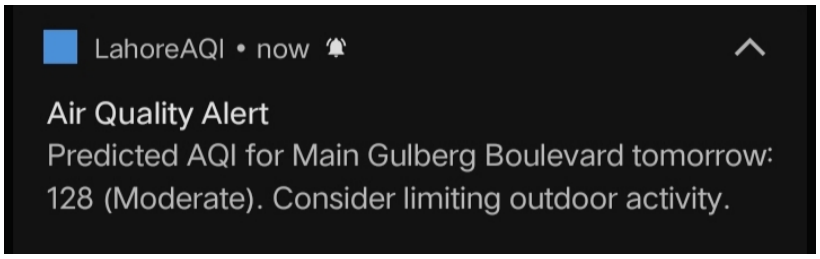
Figure 1: Real-time air quality and forecasts. Panel (a) shows the *Smog Alert* home screen, which displays current air quality and the next-day forecast for the selected monitoring location. Panel (b) shows the interface through which users can select a monitoring location.



(a) Punjab AQI categories

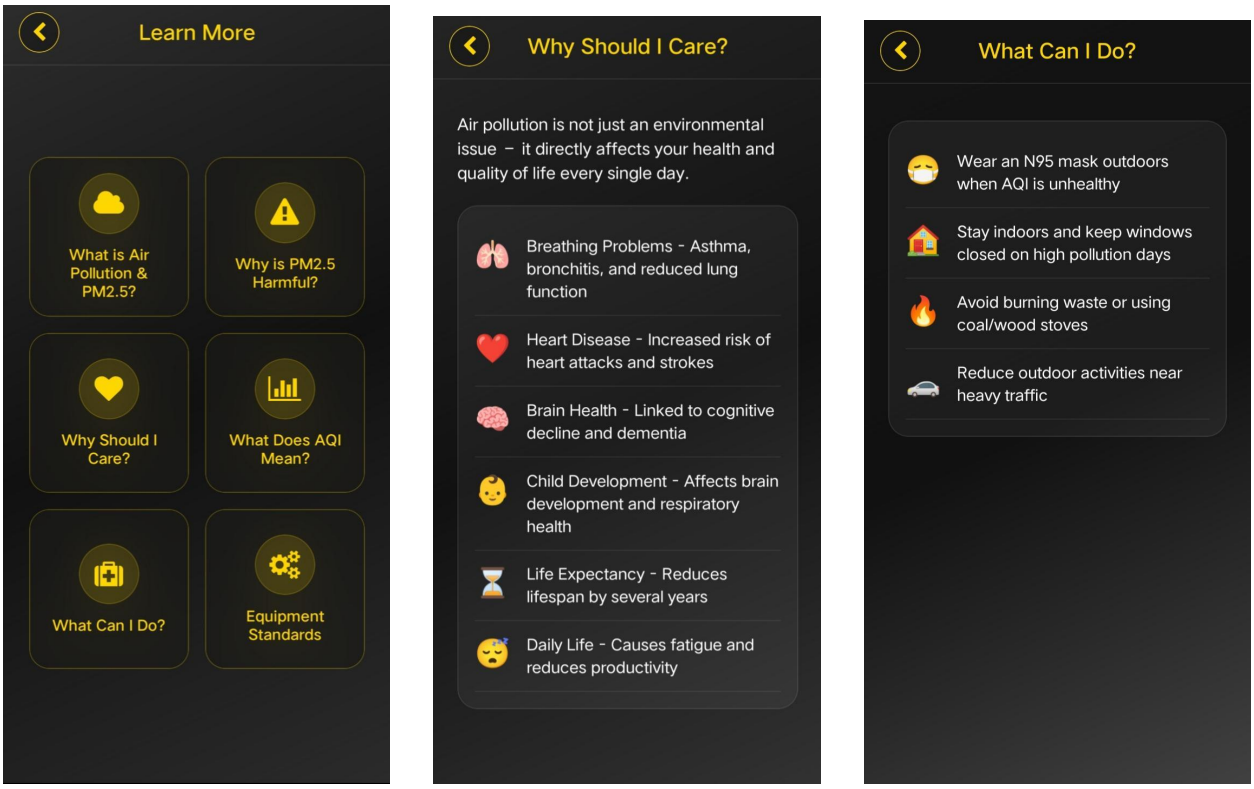


(b) Alert settings



(c) Air quality alert

Figure 2: AQI interpretation and air quality alerts. Panel (a) shows the Punjab AQI categories presented in the app. Panel (b) shows the interface through which users can customize the AQI threshold that triggers an alert. Panel (c) provides an example of an air quality alert, which reports the predicted AQI with its corresponding category and provides a recommended avoidance action.



(a) Information menu (b) Health advisory (c) Protective actions

Figure 3: Health information and protective actions. Panel (a) shows the app's "Learn More" menu. Panel (b) shows health guidance associated with different levels of air pollution. Panel (c) provides recommended actions that users can take to reduce pollution exposure.

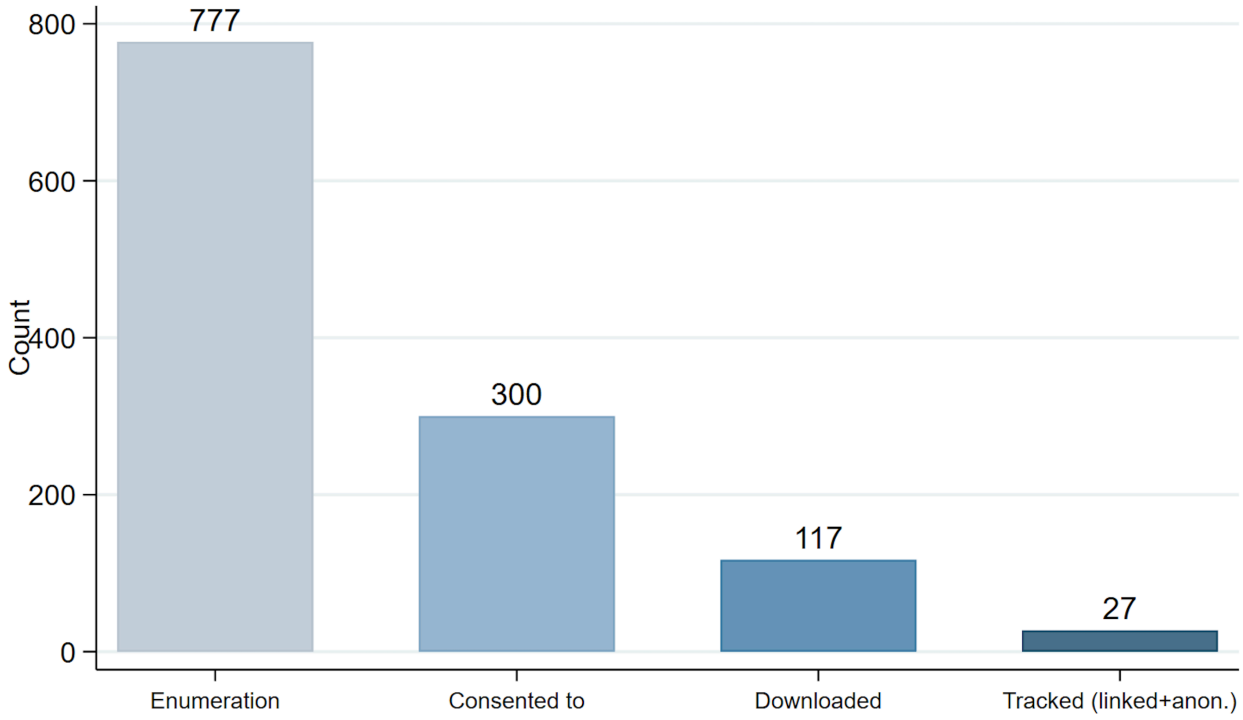


Figure 4: App take-up and observed engagement during the pilot. The 27 tracked users comprise 16 respondents who opted to link their app activity to their survey record and 11 anonymous users. Self-reported downloads and tracked usage come from different data sources, so the 27 tracked users are not necessarily a subset of the 117 respondents who downloaded the app during the survey.

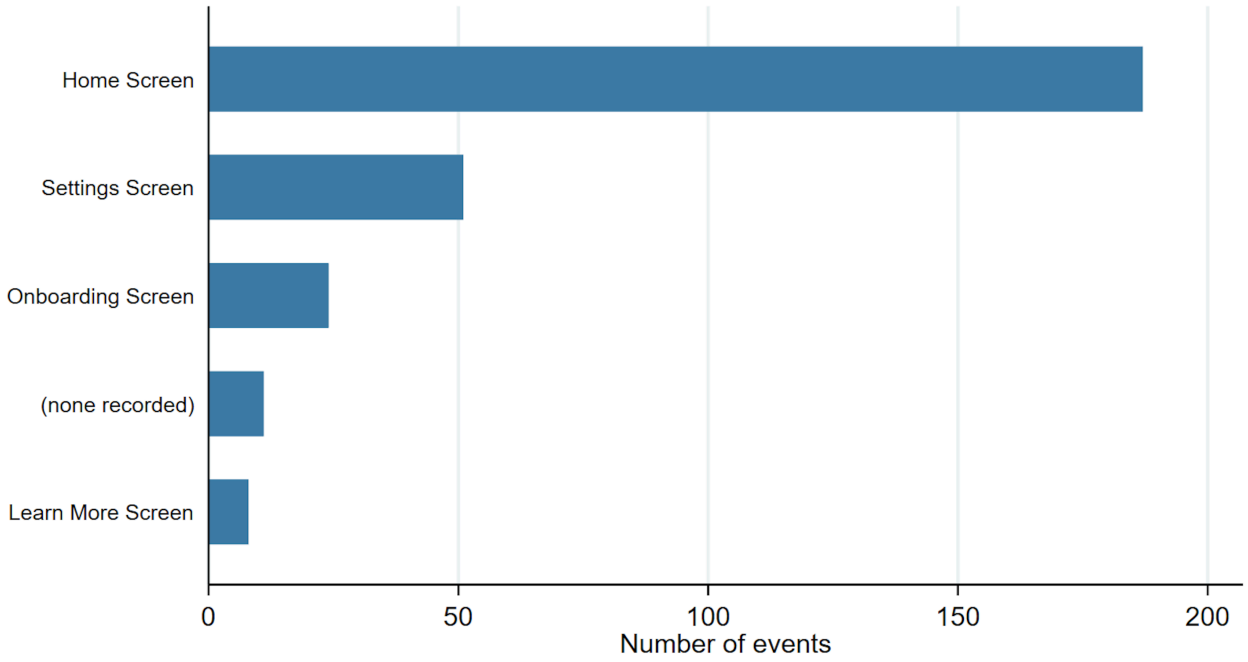


Figure 5: Recorded screen visits by tracked users. We exclude notification-open events because their screen tags may not reliably identify the screen visited.

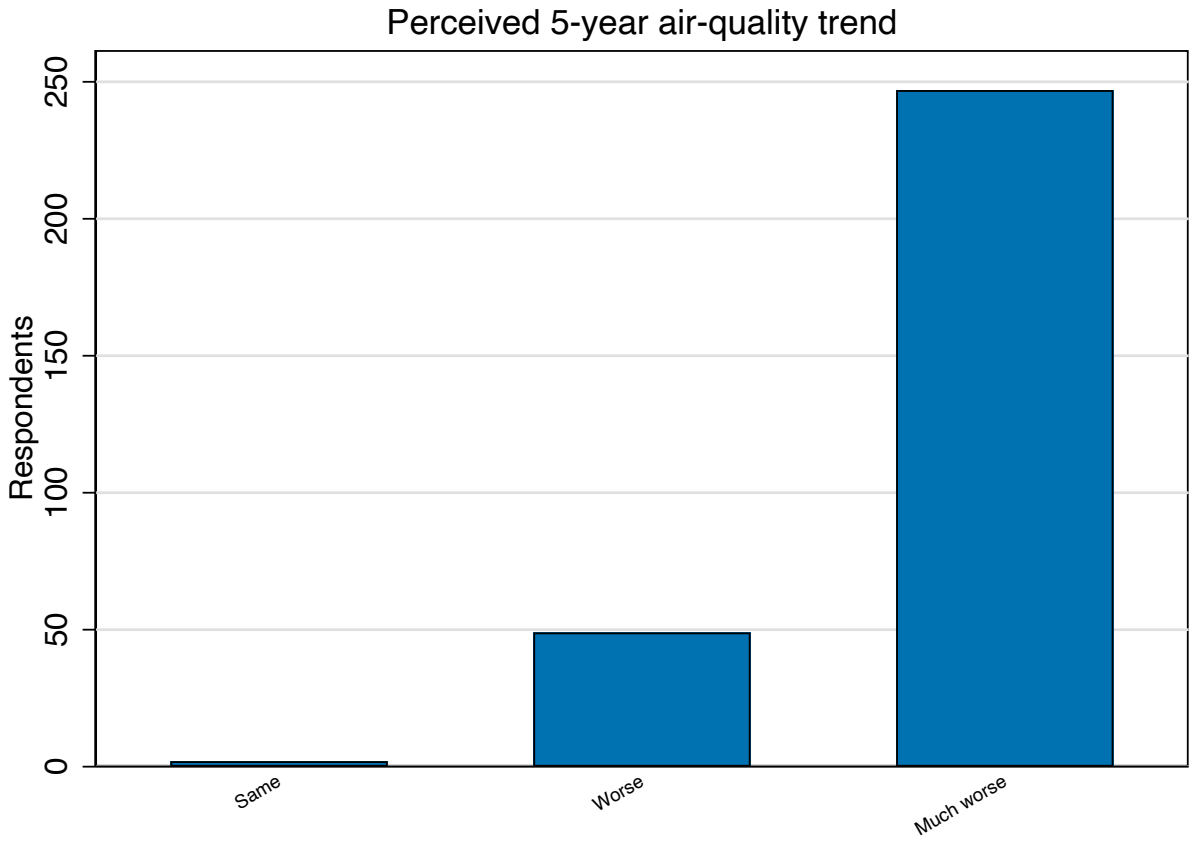


Figure 6: Perceived change in Lahore's air quality compared to five years earlier.

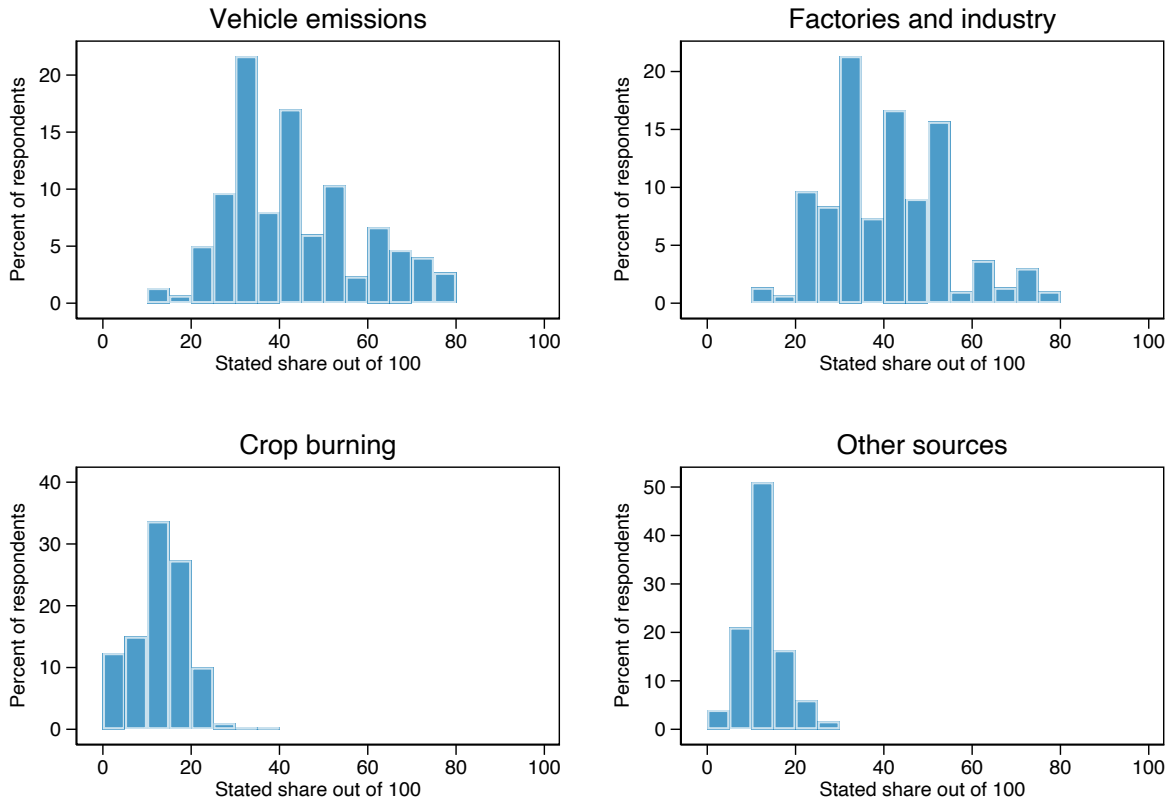


Figure 7: Respondents' beliefs about the sources of Lahore's air pollution.

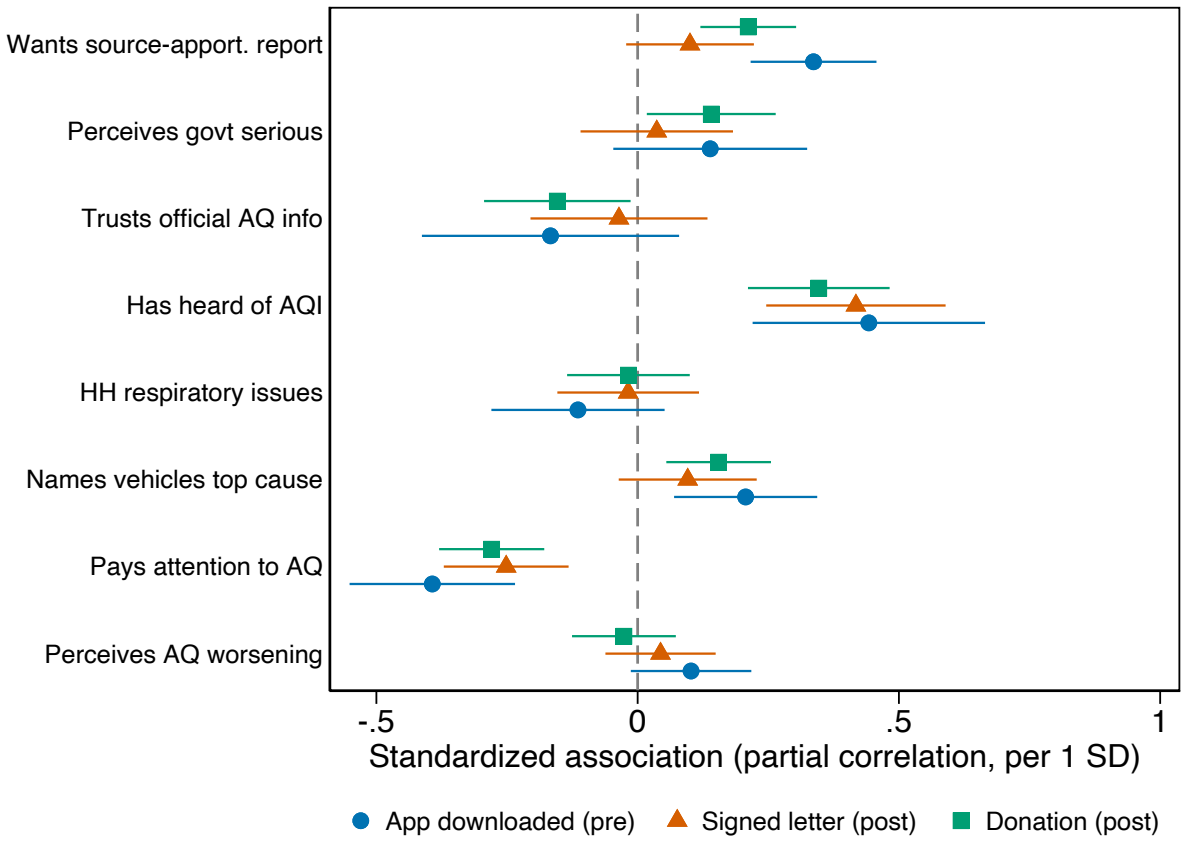


Figure 8: Associations between baseline beliefs and attitudes and environmental engagement. Estimates are partial correlations from regressions with standardized predictors and outcomes.

Tables

Table 1: Sample characteristics and survey measures

	Mean	SD	Median	Min	Max	N
Age (years)	36.41	8.27	36	19	57	300
Female	0.33	0.47	0	0	1	300
Education (years)	10.72	2.24	10	0	16	300
Household size	5.96	1.22	6	3	9	300
Rooms in dwelling	2.88	0.74	3	1	5	300
Monthly household income (PKR thousands, midpoint)	59.54	20.79	50	30	120	281
Hours outdoors, typical day	7.08	3.83	8	0	14	300
Household respiratory issues, last 12 months	0.17	0.37	0	0	1	300
Has heard of AQI	0.59	0.49	1	0	1	300
Pays attention to air quality (1-5)	2.85	0.80	3	2	5	300
Prior belief: vehicles (out of 100)	40.75	14.99	40	10	80	300
Prior belief: industry (out of 100)	38.25	13.34	40	10	80	300
Prior belief: crop burning (out of 100)	10.74	6.21	10	0	40	300
Prior belief: other sources (out of 100)	10.26	4.83	10	0	30	300
Donation (PKR)	295.00	202.72	300	0	500	300
Donated any amount	0.76	0.43	1	0	1	300
Signed enforcement letter	0.47	0.50	0	0	1	300
Top enforcement priority: vehicles	0.70	0.46	1	0	1	300

Notes: Binary variables equal one when the indicated condition holds and zero otherwise. We construct monthly household income using the midpoint of the reported income category. Prior beliefs about pollution sources measure the share of Lahore's air pollution that respondents attribute to each source and sum to 100. Respondents allocated donations from a PKR 500 endowment toward air purifiers for schools.

Table 2: Associations between beliefs, attitudes, and environmental engagement

Belief or attitude (per 1 SD)	App downloaded (pp)	Signed letter (pp)	Donation (PKR)
Perceives air quality worsening	5.0*	2.2	-5.3
	(2.9)	(2.7)	(10.3)
Pays attention to air quality	-19.2***	-12.6***	-56.6***
	(3.9)	(3.0)	(10.4)
Names vehicles as top cause	10.1***	4.8	31.4***
	(3.4)	(3.4)	(10.4)
Household respiratory issues	-5.6	-0.9	-3.6
	(4.1)	(3.5)	(12.1)
Has heard of AQI	21.6***	20.9***	70.3***
	(5.5)	(4.4)	(14.0)
Trusts official air quality information	-8.1	-1.8	-31.2**
	(6.1)	(4.3)	(14.5)
Perceives government as serious	6.8	1.8	28.6**
	(4.6)	(3.7)	(12.8)
Wants source-apportionment report	16.4***	5.0	42.9***
	(3.0)	(3.1)	(9.5)

Notes: Each cell reports a separate regression of the indicated outcome on the standardized belief or attitude measure. App download and letter-signing coefficients are percentage-point changes associated with a one-standard-deviation increase in the belief or attitude measure. Donation coefficients are in PKR. All specifications include sampling-point fixed effects. Letter-signing and donation specifications also include treatment-arm fixed effects. Robust standard errors are in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.



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