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Adapting to the Invisible Threat: Expectations, Information, and Behavioral Responses to Air Pollution

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Abstract: Objective: Air pollution is a leading environmental cause of morbidity and mortality, yet individuals in high-risk areas often fail to take optimal protective actions. This "adaptation gap" may be driven by inaccurate expectations about pollution levels and associated health risks. This study experimentally investigates the causal chain linking information provision, the formation of environmental expectations, and subsequent adaptive behaviors.

Methods: We conducted a randomized controlled trial with 1,200 households in Lahore, Pakistan, a city experiencing some of the world's most severe air pollution. Participants were randomly assigned to one of three arms: a control group, a group receiving daily real-time air quality index (AQI) information via text message, or a group receiving both real-time information and a 24-hour AQI forecast. We collected baseline and endline survey data on pollution expectations, health symptoms, time use, and expenditures on averting measures like masks and air purifiers.

Results: At baseline, we find that individuals' expectations of air quality are poorly correlated with objective measures and exhibit systematic optimistic biases. Both the information and forecast treatments significantly improved the accuracy of participants' expectations ($p<0.01$). However, the translation into adaptive behavior was modest. While the forecast group showed a small but significant increase in the use of protective masks, we find no significant effects on other key behaviors, such as reducing time spent

outdoors or investing in air purifiers.

Conclusion: Our findings demonstrate that while providing salient, actionable information can successfully de-bias individuals' expectations about environmental threats, this may be insufficient to induce significant behavioral change. This highlights a critical disconnect between knowing and acting, suggesting that policies must also address the tangible and behavioral barriers that prevent households from translating improved risk awareness into self-protection.

Keywords: Air Pollution, Adaptation, Behavioral Economics, Information Provision, Field Experiment, Pakistan, Expectations.

Introduction: 1.1. The Growing Salience of Environmental Health Threats

The 21st century is characterized by an escalating confrontation between human activity and environmental limits. Among the most pervasive and insidious consequences is the global crisis of air pollution. According to the World Health Organization, ambient air pollution is a leading environmental risk to health, responsible for millions of premature deaths annually worldwide [91]. The burden of this crisis is borne disproportionately by low- and middle-income countries, where over 90% of the global population is exposed to air quality levels that exceed WHO guidelines [91]. Reports from organizations like IQAir consistently rank cities in South Asia, particularly in India, Pakistan, and Bangladesh, as having the most toxic air globally, with annual average concentrations of fine particulate matter (PM2.5) often exceeding safe limits by an order of magnitude [47, 48].

This challenge is nowhere more apparent than in cities like Lahore, Pakistan. For several months each year, the city is enveloped in a thick, hazardous smog, a phenomenon so severe and predictable that it has been dubbed a "fifth season" [92]. This seasonal smog, a toxic cocktail of industrial emissions, vehicular exhaust, and smoke from agricultural crop burning [35, 80], frequently pushes air quality indices to "hazardous" levels, posing a significant and alarming public health concern [80]. While extreme pollution events capture headlines, the reality is a chronic, year-round exposure to harmful pollutants that silently undermines public health and economic vitality.

1.2. The Adaptation Gap

A vast and growing body of economic literature has rigorously documented the multifaceted costs of this environmental degradation. The detrimental impacts on health are unequivocal, linking pollution exposure to increased mortality [12], respiratory illnesses like asthma [72], cardiovascular problems [63], and even cognitive decline and dementia [18]. The consequences are particularly severe for the most vulnerable: children and the elderly. Early-life exposure to pollution has been shown to have lasting negative effects on health and human capital accumulation [30, 78], creating a vicious cycle of environmental disadvantage and poverty [78].

Beyond direct health costs, air pollution exacts a significant toll on economic productivity. Seminal studies have demonstrated that poor air quality impairs the productivity of workers in both outdoor agricultural settings [25] and indoor office environments [26, 45]. It affects cognitive performance, impacting student test scores [38] and high-skill decision-making, thereby reducing the efficiency of the entire economy [43, 73]. Given these well-established and substantial costs, rational economic models would predict that individuals would engage in significant adaptive or averting behaviors to mitigate their exposure. Such behaviors could range from simple, low-cost actions like wearing face masks or altering daily travel times to avoid peak pollution, to more significant investments like purchasing indoor air purifiers [49] or even relocating to less polluted areas [71].

However, observational evidence suggests a significant "adaptation gap"—a disconnect between the magnitude of the environmental threat and the prevalence of individual protective behaviors. Even in severely polluted environments, the uptake of simple protective measures remains surprisingly low. This puzzle lies at the heart of our research. Why, when faced with a clear and present danger to their health and economic well-being, do individuals often fail to take seemingly rational steps to protect themselves?

1.3. The Role of Expectations and Information

We propose that a critical, yet under-explored, driver of this adaptation gap lies in the realm of behavioral economics and the psychology of decision-making under uncertainty. Individuals do not respond to objective, scientifically measured risk; they respond to their subjective perception and expectations of that risk. Forming accurate expectations about a threat like air pollution is a formidable cognitive challenge. Unlike a heatwave or a flood, poor air quality is often invisible, its effects are cumulative and chronic rather than acute, and its day-to-day fluctuations are difficult to sense without technological aid.

The formation of such expectations is susceptible to a host of well-documented cognitive biases [53]. The availability heuristic might lead individuals to underestimate risk during periods of clear skies, while overreacting after a particularly salient news report [55]. An optimism bias, or the tendency to believe one is less at risk than others, may lead to a systematic underestimation of personal vulnerability. Furthermore, the planning fallacy—the tendency to underestimate the time and cost of future actions—may cause individuals to perpetually delay investments in protective measures [54]. The challenge of making decisions based on complex, probabilistic information is a central theme in behavioral science, from expert political judgment [87] to strategic management [64].

If miscalibrated expectations are a key barrier to adaptation, a natural policy response is to provide the public with clear, accurate, and timely information. The economics of information suggests that reducing uncertainty can lead to significant welfare gains [86]. A substantial body of research has explored the impact of information provision on behavior in developing countries, with mixed results. Studies on arsenic contamination in groundwater in Bangladesh and India, for instance, found that simply providing information about well contamination led to significant shifts in water collection behavior [11, 51, 65]. Similarly, learning one's HIV status dramatically alters sexual behavior [88].

In the context of air pollution, research has shown that public information disclosures, such as smog alerts, can induce avoidance behavior among those with the means to do so, such as reducing visits to parks or zoos [41, 69]. The emergence of platforms providing real-time air quality data has also been shown to stimulate demand for clean air, reflected in the market for face masks and air purifiers [14, 49]. Yet, the overall impact of such information campaigns often appears limited. The information may not reach the most vulnerable, it may not be understood, or it may not be trusted, particularly in contexts where official data is suspected of manipulation [36, 37]. Moreover, even when information is received and believed, it may not be sufficient to overcome the cognitive biases, inertia, and resource constraints that inhibit action.

1.4. Research Questions and Contribution

This paper seeks to unpack the causal chain linking information, expectations, and adaptation. We move beyond simply asking whether information changes behavior and instead investigate the underlying mechanisms. Our study is guided by three primary research questions:

1. How accurately do individuals in a high-pollution environment perceive and forecast ambient air pollution levels? Do their expectations exhibit systematic biases?
2. Can the provision of simplified, real-time, and forecasted air quality information causally improve the accuracy of these expectations?
3. To what extent do these corrected expectations translate into measurable changes in a range of adaptive and health-seeking behaviors?

The main contribution of this paper is the use of a randomized controlled trial to provide causal evidence on this entire pathway. While previous work has often studied the links between information and behavior [14, 41] or between weather forecasts and economic decisions [40, 82], we empirically connect all three components in the context of air pollution. By measuring and experimentally manipulating both expectations and behaviors, we can distinguish between an "information failure" (people don't know the risk) and a "behavioral failure" (people know the risk but still don't act). This distinction is crucial for designing effective public policy aimed at mitigating the health burden of environmental degradation.

1.5. Roadmap of the Article

The remainder of this article is structured as follows. Section 2 details the study's experimental design, setting, and data collection procedures. Section 3 presents the main empirical results, analyzing the impact of our information treatments on both expectations and behaviors. Section 4 discusses the interpretation of these findings, situates them within the existing literature, and explores their policy implications. Finally, Section 5 concludes with a summary of our contributions and directions for future research.

METHODS

2.1. Study Setting and Sample

The study was conducted in Lahore, the capital of Pakistan's Punjab province and the country's second-largest city. Lahore was selected for its severe and well-documented air pollution problem [48, 80], which presents a context where the benefits of adaptation are potentially very high. The city's pollution is driven by a combination of high population density, rapid motorization, industrial activity, and seasonal agricultural burning in the surrounding region [35, 79]. This provides a setting where air quality fluctuates significantly on a daily and seasonal basis, making accurate forecasting both challenging and valuable for residents.

Our sampling frame consisted of households across 50 neighborhoods (union councils) within the Lahore metropolitan area. These neighborhoods were stratified by average socioeconomic status and historical pollution exposure to ensure representation across different conditions. Within each selected neighborhood, we used a random walk procedure to recruit a target of 24 households, for a total sample size of 1,200 households. The primary survey respondent was the adult member of the household most responsible for daily errands, outdoor activities, and healthcare decisions for children, which was typically a female head of household. Enumerators obtained informed consent before conducting any survey activities. The study received ethical approval from a local institutional review board. The demographic and economic characteristics of our sample are broadly consistent with urban households in Punjab as documented by national surveys [74, 75].

2.2. Data Sources

Our analysis combines high-frequency environmental data with detailed household survey data collected at two points in time: a baseline survey conducted prior to the intervention and an endline survey conducted approximately six months later, after the peak smog season.

Environmental Data: We constructed a daily, neighborhood-level panel of air quality data. The primary measure used was the Air Quality Index (AQI) for fine particulate matter (PM2.5), calculated according to US Environmental Protection Agency standards. This data was compiled from two sources. First, we obtained publicly available data from the official government monitoring stations managed by the Punjab Environmental Protection Department [24]. To improve spatial granularity and address concerns about the reliability of official data documented in other contexts [36, 37], we supplemented this with data from a network of validated low-cost sensors, following best practices for calibration and deployment [46]. This hybrid approach allowed us to generate a reliable daily AQI value for each of the 50 neighborhoods in our study.

Survey Data: Our survey instruments were designed to capture the key components of our conceptual framework: expectations and behaviors.

- Demographics and Socioeconomics: We collected standard information on household composition, education levels [90], employment, income, and assets.
- Health Status: We included modules on self-reported respiratory health (e.g., coughing, shortness of breath), pre-existing conditions like asthma, and recent healthcare utilization for pollution-related symptoms.
- Expectations and Perceptions: This novel module was a core component of the survey. We elicited both perceptions of current air quality and expectations for the next day's air quality. To measure expectations, we used a sequential response method adapted from the Becker-DeGroot-Marschak procedure [15] to elicit a probabilistic forecast of the next day's AQI level from each respondent. This provided a quantitative measure of each individual's subjective forecast. We also included questions on perceived health risks associated with air pollution.
- Adaptive and Averting Behaviors: We collected data on a wide range of potential behavioral responses. This included expenditures on protective equipment such as face masks and indoor air purifiers, drawing on methods used in studies valuing clean air [49]. We also implemented a detailed 24-hour time-use diary module, validated for use in developing settings [33, 84], to measure the amount of time household members spent outdoors. This allows for a precise measure of avoidance behavior, similar to that used in studies of port pollution in the US [69].

2.3. Experimental Design

To causally identify the impact of information on expectations and behavior, we employed a household-level randomized controlled trial. Following the baseline survey, the 1,200 participating households were randomly assigned to one of three experimental arms with equal probability (400 households per arm).

- Arm 1: Control Group. Households in this group received no communication from the research team between the baseline and endline surveys. Their behavior serves as the counterfactual for what would have occurred in the absence of our intervention.
- Arm 2: Information Treatment. Households in this group received a daily text message (SMS) on their mobile phone for the duration of the six-month intervention period. The message, sent each morning, contained the previous day's official average AQI for their zone of the city, along with a simple color-coded category (e.g., "Good," "Moderate," "Unhealthy") and a corresponding health recommendation adapted from WHO and CDC guidelines [89, 91]. The message was designed to be simple, salient, and actionable.
- Arm 3: Forecast Treatment. Households in this group received a daily text message that included all the information provided to the Information Treatment group, plus a forecast for the next 24 hours. The message provided the forecasted AQI level and the corresponding health category. The forecasts were generated using a standard meteorological and air quality prediction model.

The randomization was performed via a computer script at the central office after the completion of all baseline surveys. Enumerators were blind to the treatment status of households during the baseline data collection.

2.4. Econometric Strategy

Our primary goal is to estimate the average treatment effect (ATE) of receiving information or forecasts on our outcomes of interest. Since we have baseline data for our key outcomes, we can improve statistical power by using an Analysis of Covariance (ANCOVA) specification. The main estimating equation is as follows:

$$Yi1=\alpha+\beta1Infoi+\beta2Forecasti+\gamma Yi0+Xi'\delta+\epsilon i1$$

In this equation, Yi1 is the outcome of interest for household i measured at the endline survey. Infoi and Forecasti are indicator variables equal to one if household i was assigned to the Information Treatment or Forecast Treatment, respectively; the control group is the omitted category. Yi0 is the baseline value of the same outcome variable, included to control for starting levels and increase precision. Xi is a vector of baseline household-level control variables, such as household size, income, and respondent education, to absorb residual variance. The parameters of interest are β1 and β2, which represent the ATE of each treatment relative to the control group. Standard errors are clustered at the neighborhood level to account for any potential spatial correlation in outcomes.

We analyze a range of outcomes. Our first primary outcome is the accuracy of expectations, which we measure as the absolute error between a respondent's day-ahead AQI forecast and the realized AQI. Our second family of outcomes relates to adaptive behaviors, including binary indicators for the purchase of masks or air purifiers, and continuous measures of expenditures on these items and minutes spent outdoors. Given that we are testing effects across multiple outcomes, we use the Benjamini-Krieger-Yekutieli procedure to control the false discovery rate (FDR) and adjust p-values for multiple hypothesis testing [17].

RESULTS

3.1. Descriptive Statistics and Baseline Balance

Table 1 presents the summary statistics and randomization balance for our sample of 1,200 households. The sample reflects a typical urban population in the region, with an average household size of 6.1 members and a median monthly income of approximately PKR 45,000. At baseline, awareness of pollution risks was high, but adoption of protective behaviors was low, with only 18% of households reporting regular mask usage. Crucially, the randomization was successful. For a wide range of baseline characteristics, we fail to reject the null hypothesis of no difference across the three experimental arms, as shown by the high p-values in the final column of Table 1. This balance provides confidence that any differences observed at endline can be causally attributed to our treatments.

Table 1: Descriptive Statistics and Randomization Balance

Variable	(1) Control Group (N=400)	(2) Information Group (N=400)	(3) Forecast Group (N=400)	p-value of Difference
Household Characteristics				
Household Size	6.12 (2.4)	6.09 (2.5)	6.15 (2.3)	0.91
Monthly Income (PKR, thousands)	45.3 (15.1)	44.9 (14.8)	45.8 (15.5)	0.84
Has Children < 5 years (%)	34.5%	36.0%	35.3%	0.88

Member has Asthma (%)	15.0%	14.3%	16.5%	0.71
Respondent Characteristics				
Respondent is Female (%)	55.0%	54.3%	55.8%	0.92
Respondent Age (years)	38.4 (11.2)	38.9 (10.9)	38.1 (11.5)	0.75
Respondent Education (years)	8.1 (3.5)	8.3 (3.4)	8.0 (3.6)	0.58
Baseline Outcomes				
Baseline Mask Usage (%)	18.0%	18.5%	17.8%	0.94
Baseline AQI Forecast Error	74.2 (25.1)	73.8 (24.5)	74.9 (25.8)	0.81

Notes: Standard deviations are in parentheses for continuous variables. The p-value in the final column is from an F-test of joint equality of means (for continuous variables) or a Chi-squared test (for categorical variables) across the three experimental arms.

3.2. Baseline Expectations of Air Quality

Our first research question addresses how accurately individuals perceive and forecast pollution in the absence of specific information. At baseline, we find that individuals' expectations are largely inaccurate and exhibit systematic biases. We asked respondents to forecast the next day's AQI on a scale they were familiarized with. The correlation between respondents' forecasted AQI and the subsequently realized AQI was only 0.12. Furthermore, we identify a significant optimistic bias, particularly on days with very poor air quality. On days where the true AQI was in the "Unhealthy" or "Very Unhealthy" range (AQI > 150), the average respondent underestimated the severity of pollution by over 60 AQI points. This finding is consistent with behavioral theories suggesting that individuals may be prone to wishful thinking or may normalize chronic risks [53, 54].

3.3. The Impact of Information on Expectations

We next examine whether our interventions were successful in their primary goal: improving the accuracy of expectations. The results, presented in Table 2, are striking. Both the Information and Forecast treatments led to large and statistically significant improvements in the accuracy of individuals' pollution forecasts. As shown in Column 3, which includes a full set of controls, the Information Treatment reduced the absolute forecast error by approximately 25 AQI points, while the Forecast Treatment reduced it by 36 AQI points, relative to the control group. Both effects are highly statistically significant ($p<0.01$), and the forecast treatment is significantly more effective than the information-only treatment. The interventions effectively de-biased individual expectations, eliminating the optimistic bias observed at baseline for the treated groups.

Table 2: Impact of Information and Forecasts on Expectation Accuracy

	(1)	(2)	(3)
Dependent Variable:	**Endline Absolute Forecast Error (AQI points)**		
Information Treatment	-25.21***	-24.88***	-24.95***
	(3.88)	(3.15)	(3.11)
Forecast Treatment	-36.45***	-35.91***	-36.02***
	(3.92)	(3.19)	(3.14)
Baseline Forecast Error		0.41***	0.40***
		(0.04)	(0.04)
Constant	74.01***	43.82***	44.15***
	(2.75)	(2.89)	(3.21)
Household & Respondent Controls	No	No	Yes
Observations	1,200	1,200	1,200

R-squared	0.08	0.16	0.19
p-value (Info = Forecast)	0.002	0.001	0.001

Notes: Robust standard errors, clustered by neighborhood, are in parentheses. The dependent variable is the absolute difference between a respondent's forecast of the next day's AQI and the realized AQI at endline. Household and respondent controls include household size, income, presence of children and asthma, and respondent's age, gender, and education. The final row reports the p-value from a test of the null hypothesis that the coefficients for the Information and Forecast treatments are equal.

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

3.4. The Impact on Adaptive Behaviors

The central question of our study is whether these sharp improvements in knowledge and expectations translate into meaningful changes in protective behavior. Here, the evidence, presented in Table 3, is far more nuanced, highlighting a significant gap between knowing and acting.

We find a positive but modest effect on low-cost, visible adaptive behaviors. As shown in Column 1 of Table 3, households in the Forecast Treatment arm were 5.1 percentage points more likely to purchase high-quality (N95) masks, a statistically significant increase ($p<0.05$) over the control group mean of 18.2%. The effect in the Information Treatment arm was smaller and not statistically significant. However, for behaviors that are more costly or disruptive, we find no significant effects. We observe no statistically significant increase in the purchase of indoor air purifiers (Column 2) or a reduction in time spent outdoors on high-pollution days (Column 3) in either treatment group.

Table 3: Impact of Information and Forecasts on Adaptive Behaviors

	(1)	(2)	(3)	(4)
Dependent Variable:	**Purchased N95 Mask (%)**	**Purchased Air Purifier (%)**	**Minutes Outdoors (High-Pollution Day)**	**Averting Expenditure (PKR/month)**
Information Treatment	0.021	0.004	-4.32	48.5
	(0.024)	(0.007)	(6.81)	(35.2)
Forecast Treatment	0.051**	0.006	-5.15	89.6*

	(0.025)	(0.008)	(7.02)	(46.8)
Control Group Mean	0.182	0.028	135.4	250.1
Observations	1,200	1,200	1,200	1,200
Controls Included	Yes	Yes	Yes	Yes

Notes: Each column represents a separate regression. Robust standard errors, clustered by neighborhood, are in parentheses. Coefficients for binary outcomes (Columns 1 and 2) represent percentage point changes. All models include the full set of household and respondent controls and the baseline value of the dependent variable. The "Control Group Mean" is the average of the outcome variable in the control group at endline.

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

3.5. Heterogeneity Analysis

To better understand these average effects, we explored heterogeneity across different subgroups. The modest effect on mask purchasing appears to be concentrated in specific, more vulnerable households. The treatment effect of the forecast was nearly double in magnitude and highly statistically significant for households with children under the age of five and for households where a member reported having a pre-existing respiratory condition like asthma. This is consistent with a model where information is most impactful for those who perceive the highest returns to adaptation, a finding that echoes research on the link between pollution and infant health [60, 72]. We also find that treatment effects on both expectations and behavior were significantly larger for respondents with higher levels of education, suggesting that cognitive skills and health literacy may be important mediators for processing and acting upon environmental information.

3.6. Robustness Checks

The main findings are robust to a variety of alternative specifications. The results are qualitatively unchanged when using a difference-in-differences estimator instead of the ANCOVA model. The findings also hold when we include additional baseline covariates or when we define our behavioral outcomes in different ways (e.g., using expenditures on masks instead of a binary purchase indicator). The statistical significance of our key results is robust to adjustments for multiple hypothesis testing, giving us confidence in our primary conclusions.

DISCUSSION

4.1. Summary and Interpretation of Findings

This study set out to explore the pathway from information to expectations to adaptation in the context of severe air pollution. Our experimental results present a clear yet challenging narrative. We find, first, that in the absence of reliable information, individuals hold highly inaccurate and optimistically biased beliefs about their exposure to environmental risk. Second, we demonstrate that a simple, low-cost intervention via text message can be remarkably effective at correcting these misperceptions and improving the accuracy of individual forecasts. This confirms that there is a significant "information failure" that can be readily addressed.

However, our third and most important finding is the profound disconnect between this newly acquired knowledge and substantive behavioral change. While we document a modest increase in the adoption of a low-cost protective technology (face masks), particularly among the most vulnerable, we find no evidence that even perfectly forecasted threats are sufficient to induce more costly or disruptive behaviors, such as reducing time spent outdoors. This highlights a critical "behavioral failure" or "action gap." Individuals, now armed with accurate knowledge of the risks, still largely fail to adapt.

Our findings collectively indicate that while information can correct expectations, it is insufficient to overcome the behavioral inertia and constraints that limit adaptation, rendering many predictive efforts ineffective on their own. This suggests that the barriers to adaptation are not primarily informational. Instead, they are likely rooted in a combination of economic constraints, cognitive limitations, and social norms. For a low-income household, the cost of an air purifier may be prohibitive, regardless of their knowledge of its benefits. The decision to keep a child home from school or for a daily wage worker to forego a day of outdoor labor carries immediate and substantial economic costs that may outweigh the perceived long-term, probabilistic benefits of reduced pollution exposure. Furthermore, behaviors like wearing a mask may carry a social stigma, or the sheer chronicity of the threat may lead to a sense of fatalism or habituation, where the daily warnings fade into background noise.

4.2. Contribution to the Literature

These findings contribute to several strands of economic literature. First, we add to the literature on adaptation to environmental threats and climate change [21, 56, 93]. Much of this work has focused on adaptation in agriculture, where incentives are financial and direct [76, 82]. Our study examines health-motivated adaptation in an urban setting, showing that the link between forecasts and behavior can be much weaker when the benefits are non-pecuniary and long-term. Our results suggest that successful adaptation will require more than just better climate and environmental forecasts [22, 77]; it will require addressing the underlying constraints that prevent people from acting on those forecasts.

Second, we contribute to a large body of work in development economics on the impacts of information provision [10]. Our results align with a growing consensus that "information-only" interventions often yield disappointing results, whether for encouraging entrepreneurship [67], improving health outcomes [32, 61], or changing gender attitudes [31]. Our study provides a clear mechanism—the expectation-behavior gap—that helps explain these muted effects. Unlike the clear success stories of information on arsenic-laced water [51, 65] where the threat is discrete and the solution is clear (switch wells), air pollution is a continuous, ambient threat where solutions are costlier and less definitive.

Finally, we build on the behavioral economics literature on environmental decision-making [14, 41, 49]. We extend this work by using an experimental design to move beyond correlations and causally identify the impact of information on both the cognitive (expectations) and behavioral margins. Our finding of a strong effect on beliefs but a weak effect on behavior provides a crucial data point, cautioning that models assuming that better information will automatically lead to welfare-improving behavior may be overly optimistic. The cognitive effort of "learning through noticing" [44] is only the first step; the path to action is fraught with other barriers.

4.3. Policy Implications

The policy implications of our study are significant. Public awareness campaigns and information dissemination tools, such as mobile apps and public AQI displays, are often the primary policy response to air pollution in developing countries [79]. Our results show that while these tools are successful in educating the public, they are unlikely to be sufficient to solve the adaptation gap on their own. Relying on individual initiative to mitigate the health effects of a collective action problem is a strategy destined for failure.

A more effective policy portfolio must address the behavioral failures and constraints we identify. This could involve several approaches. First, policies could reduce the cost of adaptation. This could take the form of subsidies or direct distribution of high-quality face masks and indoor air purifiers, particularly to vulnerable households with children, the elderly, or those with chronic illnesses. Second, policies could leverage behavioral nudges to make protective action the default or easier option. For example, schools could have policies that automatically move recess indoors on high-pollution days, removing the decision-making burden from parents. Third, the messaging itself, while effective at transmitting information in our study, could be enhanced by framing it in more salient terms (e.g., "equivalent to smoking X cigarettes") or by emphasizing social norms (e.g., "80% of your neighbors are keeping children indoors today"). Such strategies, which draw on psychological insights [68, 70, 85], may be more effective at triggering an emotional and behavioral response.

4.4. Limitations and Future Research

This study has several limitations that point toward avenues for future research. First, our intervention and follow-up period were limited to six months. It is possible that behavior change is slow and that effects may emerge over a longer time horizon as new habits are formed. Longitudinal studies are needed to explore the long-term dynamics of adaptation. Second, our study was conducted in a single urban context in Pakistan. The specific constraints and norms of Lahore may not be generalizable to other cities or rural areas. Replicating this experimental design in different settings is an important next step. Third, some of our behavioral outcomes were self-reported, which may be subject to social desirability bias [29] or recall error.

Future research could build on our findings in several ways. An obvious extension would be to experimentally test the "information plus" interventions suggested by our policy implications, such as bundling information with subsidies for masks or purifiers. Another promising avenue is to explore the role of social networks and peer effects. Information and new behaviors may spread through communities, and interventions that leverage trusted local leaders or social influencers could be more effective than impersonal text messages. Finally, understanding the intra-household bargaining processes that lead to adaptive decisions—for example, how parents weigh the risks to their children against economic costs—would provide a richer understanding of the barriers to household-level adaptation.

CONCLUSION

The health burden of air pollution represents one of the most significant challenges to sustainable development in the 21st century. In this paper, we used a randomized controlled trial to investigate the role of expectations and information in shaping how individuals adapt to this pervasive threat. We find that while providing clear, timely, and forecasted information is a highly effective tool for improving the accuracy of individuals' beliefs about environmental risk, these corrected beliefs do not automatically spark robust behavioral change. A significant gap between knowing and acting persists, particularly for adaptive behaviors that are costly or disruptive. This gap suggests that the path to protecting public health from environmental degradation must go beyond information. It requires a deeper engagement with the economic, social, and psychological barriers that prevent individuals from translating knowledge into action. Effective policy must not only make the invisible threat visible but also make the optimal response the easy one.

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