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Empirical analysis and adaptive policy control for air quality governance in Delhi NCR

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Abstract

Persistent atmospheric pollution across the National Capital Region of Delhi continues to impose severe public health burdens and economic costs despite repeated emergency regulatory interventions. This study evaluates the empirical determinants of public compliance, behavioral adaptation, and enforcement friction using primary multi-stakeholder surveys and field environmental audits across five representative geographic zones. Statistical analysis reveals that policy awareness alone does not drive individual protective behavior. Rather, institutional trust serves as the primary behavioral determinant, explaining nearly a third of the variance in personal adaptation and strongly influencing support for stricter regulatory measures. Concurrently, enterprise-level surveys demonstrate acute non-linear compliance dynamics, where commercial revenue losses exceeding **15%** lead to a collapse in perceived regulatory fairness and precipitate widespread evasion. Physical site audits further indicate that localized dust-suppression measures reduce visible particulate sources but fail to motivate personal protective behaviors without prominent contextual signage and visible enforcement. To address these structural failures, this paper formulates a Dynamic Adaptive Policy Framework that integrates atmospheric state-space dynamics, Bayesian predictive triggering, and optimal control theory into a closed-loop governance architecture. By balancing atmospheric concentration reductions against administrative stringency, citizen trust deficits, and non-linear commercial losses, the framework provides an operational foundation to transition urban air quality management from reactive emergency mandates to predictive, evidence-based governance

Keywords: Air quality governance, Dynamic adaptive policy framework, State-space modeling, Optimal control theory, Reinforcement learning, Institutional trust

1 Introduction

Over the last two decades, Delhi has persistently ranked among the most polluted capital cities globally, with average concentrations of fine particulate matter ($PM_{2.5}$) and PM_{10} exceeding the World Health Organization's (WHO) annual guideline limits by several multiples [19]. Despite the implementation of numerous policy interventions, such as the Graded Response Action Plan (GRAP), National Clean Air Programme (NCAP), and various vehicular emission control measures, the city continues to experience recurrent severe air quality episodes [43] [44] [45]. These episodes are not merely seasonal or meteorological phenomena, they represent the cumulative outcome of structural, behavioral, and governance-related inefficiencies embedded within the urban environmental management system.

Substantial scientific evidence has been accumulated through studies on emission inventories, meteorological variability, and sectoral contributions to urban air pollution. While these studies have provided valuable descriptive and diagnostic insights, they have rarely evolved into predictive or adaptive policy systems capable of dynamic adjustment. The existing response mechanisms remain largely reactive, relying on static rule-based thresholds rather than continuous feedback or optimization-based governance. Consequently, policy enforcement is delayed, public communication remains sporadic, and inter-agency coordination is weakened, resulting in diminished long-term efficacy.

Recent works such as Gulia et al. (2021) have evaluated the policy effectiveness of interventions like GRAP through regression and dispersion modelling, demonstrating partial improvements in air quality indices. However, most of these frameworks have been constructed using deterministic or linear causation models, which often fail to capture the underlying feedback mechanisms, stochastic behaviour, and delayed responses that characterize complex urban environmental systems. Similarly, econometric evaluations have been limited in their capacity to integrate citizen participation, technological diffusion, and institutional adaptability as measurable policy variables. Thus, the absence of data-driven adaptive policy intelligence continues to constrain India's ability to systematically manage urban air pollution.

To address this gap, the present research introduces a dynamic adaptive policy framework (DAPF), an integrative model that mathematically unifies environmental, behavioral, and regulatory dynamics into a single control structure. The framework has been designed to enable real-time policy calibration, based on empirical evidence derived from air quality and socio-behavioral data streams. The study combines statistical inference, state-space modeling, optimal control theory, and reinforcement learning to quantify, predict, and optimize air quality outcomes under varying policy conditions. The framework draws upon the principles of systems theory, adaptive governance, and multi-agent policy optimization to deliver both analytical rigor and operational relevance.

The study has been structured around the following core objectives:

1. To empirically evaluate the statistical determinants of Delhi's air quality variations and to quantify the impact of policy interventions such as GRAP, vehicular regulation, and citizen engagement.
2. To construct a state-space dynamic system that captures the time-dependent evolution of pollution under simultaneous policy and environmental influences.
3. To derive and validate an optimal control policy using linear quadratic regulation (LQR) for cost-effective environmental management.
4. To develop an adaptive reinforcement learning algorithm capable of autonomously refining policy intensity and allocation based on real-time reward feedback.

This approach is distinctively cross-disciplinary, combining environmental science, data analytics, control engineering, and public policy to advance a comprehensive understanding of urban air quality management. The inclusion of Bayesian conditional probability modelling enables the translation of uncertainty into actionable decision thresholds, thereby improving the precision of policy escalation mechanisms.

The proposed dynamic adaptive policy framework is expected to serve as an analytical foundation for designing evidence-based governance strategies that align institutional decision-making with real-time environmental data. By integrating statistical estimation, optimization, and adaptive intelligence, the framework aims to shift Delhi's pollution management paradigm from a reactive regulatory mode to a predictive and adaptive governance model. Furthermore, the methodology developed in this study is intended to be scalable to other non-attainment cities across India, contributing to the larger national goal of achieving sustainable and data-informed air quality management.

The remaining sections of this paper are organized as follows. Section 2 provides a comprehensive review of the relevant literature and theoretical constructs. Section 3 outlines the research methodology, encompassing the statistical, mathematical, and algorithmic formulations. Section 4 describes the dataset and the survey instruments. Section 5 presents hypothesis framework, empirical results, model validation, and interpretive discussions. Section 6 elaborates the empirical statistical implications of the findings. In section 7, the 4R (reassure, regulate, realign, remarket) dynamic adaptive policy framework has been proposed along with the 4R governance architecture, mathematical decision architecture, phased implementation policy, and coutingency fallback protocols. Finally, Section 8 concludes the study with reflections on research contributions, limitations, and future work.

A structured, multi-layered literature base has been developed to support the proposed DAPF. In this section, the evolution of research on Delhi's air pollution, policy interventions, modelling approaches, and data-driven control techniques is synthesized, with explicit emphasis on the gaps that motivate the present work.

2 Literature review and theoretical foundations

2.1 Delhi's air pollution crisis and policy context

Delhi has been consistently identified as one of the world's most polluted megacities, with annual $PM_{2.5}$ levels far in excess of both national and world health organization (WHO) standards, and with recurrent "severe" and "very severe" air quality days concentrated in the post-monsoon and winter months. Long-term analyses of central pollution control board (CPCB) monitoring data have shown persistent exceedances across multiple stations and years, with only transient improvements during episodic interventions or exogenous shocks such as the COVID-19 lockdown period [1].

A detailed policy-oriented longitudinal assessment was carried out by Gulia et al. (2021), where 17 years of air quality data (2003–2019) and control strategies in Delhi were compiled and evaluated. The study demonstrated that, despite numerous interventions across sectors such as transport, industry, and domestic fuel, particulate concentrations remained significantly above national ambient air quality standards (NAAQS), and reductions were often short-lived and spatially uneven [2] [33]. A complementary assessment by Goyal et al. (2019) focused on the effectiveness of policy interventions for air quality control regions (AQCRs) in Delhi and concluded that scattered and unquantified measures produced limited structural improvement, thereby underscoring the need for more systematic and quantified control strategies [3].

Broader national-scale analyses have also indicated that Indian urban air quality is shaped by both local and regional contributions. Sharma and Mauzerall (2022) examined $PM_{2.5}$ trends across India between 2015 and 2019 and highlighted the dominance of urban-industrial clusters, transport emissions, and secondary aerosol formation, with Delhi-NCR functioning as a critical hotspot [1] [35]. These findings collectively support the view that Delhi's air quality problem is not limited to isolated emission sources but is rooted in multi-sectoral and multi-scale dynamics, thereby necessitating integrated and adaptive management approaches.

2.2 Evaluation of policy interventions: GRAP, NCAP, and regulatory instruments

GRAP has been institutionalized as a central regulatory instrument for Delhi–NCR since 2017 [20]. GRAP defines stage-wise emergency measures (stage I: "poor", stage II: "very poor", stage III: "severe", stage IV: "severe+") based on air quality index (AQI) thresholds and mandates actions such as construction bans, traffic restrictions, and industrial curtailments as air quality deteriorates [4]. Recent revisions under the commission for air quality management (CAQM) have emphasized dynamic triggering based on forecast data and reinforced inter-agency coordination across Delhi, Haryana, Uttar Pradesh, and Rajasthan [5].

Empirical evaluations of GRAP have produced mixed results. Singh (2020) conducted an analysis of AQI, $PM_{2.5}$, and NO_2 before and after GRAP task force directions during 2018 and found that short-term improvements were observable at certain locations, but the overall effect was constrained by late activation, limited enforcement, and lack of baseline emission control [6]. A regional assessment by the

centre for research on energy and clean air (CREA) on GRAP implementation in the Indo-Gangetic Plain concluded that emergency-stage interventions were often triggered only after air quality had already declined to "Very Poor" or "Severe" levels, thereby reducing their preventive potential and shifting the focus to damage control rather than pre-emptive management [7].

In parallel, NCAP has been launched with city-level action plans, but several independent reviews have pointed out gaps in quantifiable emission reduction targets, monitoring adequacy, and feedback loops between local implementation and central oversight [8] [45]. Within this regulatory landscape, policy instruments have thus far been predominantly rule-based and static, with limited capacity to self-adjust based on real-time feedback or predictive modelling. This situation directly motivates the need for a dynamic, state-space and control-theoretic perspective on urban air quality governance [21].

2.3 Air quality modelling: Statistical, state-space, and optimal control approaches

Air quality modelling has evolved from simple empirical regressions to complex deterministic and stochastic frameworks. San José et al. (2006) presented an overview of state-of-the-art air quality modelling, emphasizing the roles of chemical transport models, gaussian dispersion models, and statistical models in evaluating control strategies and assessing policy scenarios [8] [29]. Earlier state-space formulations for atmospheric pollution were developed by Hernández et al. (1991), where pollutant concentration evolution was represented as a dynamic system driven by meteorological and emission inputs, and kalman filtering was used for forecasting and state estimation, frameworks that have since been extended to evaluate urban policy zones and particulate matter state-space dynamics [9] [22] [23].

More recent advances have included flexible nonlinear and probabilistic state-space models. Kreuzer et al. (2022) proposed a Bayesian non-linear state-space copula model to jointly capture the dynamics of $PM_{2.5}$ and meteorological variables in Beijing, explicitly accommodating non-linearity, temporal dependence, and uncertainty [10] [30]. Such methods demonstrate how complex air quality processes can be represented within a probabilistic dynamical framework that is amenable to both forecasting and decision support [31].

Parallel literature has addressed the problem of optimal air pollution control using control theory. Early work on optimal control strategies for long-term and real-time air pollution management provided general theoretical frameworks for minimizing a cost functional that combines pollution damages and control expenditures [11] [25]. More recent work by He et al. (2023) formulated deterministic and stochastic optimization models for air pollution control and applied optimal control techniques to reduce health impacts while satisfying regulatory constraints, thus illustrating the potential of control-theoretic approaches in environmental policy design [12] [24].

These strands of literature jointly indicate that (i) state-space representations are well-suited to capture temporal evolution and uncertainty in air quality, and (ii) optimal control can be used to derive mathematically rigorous policy trajectories.

However, the direct integration of such methods into Delhi-specific, multi-actor governance frameworks, particularly with real-time feedback and adaptive policy intensity, remains limited in published work.

2.4 Data-driven and AI-based approaches to air quality and policy

The increasing availability of high-resolution monitoring data has encouraged a shift towards data-driven methods, including reinforcement learning (RL) and deep learning, for urban air quality management. Rajesh and Kumar (2025) proposed a deep reinforcement learning framework using proximal policy optimization (PPO) to optimally place air purification booths in Delhi, demonstrating significant improvements in AQI and spatial coverage relative to heuristic placement strategies [13] [26] [27]. Xie et al. (2024) applied RL to traffic signal control in conjunction with a gaussian plume model and showed that emissions-related metrics could be improved when air quality objectives were embedded into the reward function [14].

The ecological multi-agent reinforcement learning (EcoMRL) framework, introduced by Jung et al. (2024), extended multi-agent deep reinforcement learning to traffic signal control with explicit goals of minimizing greenhouse gas emissions and improving urban air quality [15]. In a related domain, Kim et al. (2023) implemented an RL algorithm for indoor air quality management in buildings, achieving a balance between pollutant reduction and energy consumption [16]. These studies collectively highlight that RL can be effectively used to manage complex, multi-variable environmental control systems under uncertainty.

On the inferential side, AirRL, a reinforcement learning-based model for station selection and air quality inference, was proposed to improve spatial estimation from sparse monitoring networks [17] [32]. Such approaches underline the potential of RL not only for direct control but also for improving sensing, inference, and decision-support processes. Nevertheless, it is noted that most RL applications have focused on single-lever interventions (e.g., traffic signals, booth placement, or indoor ventilation) rather than multi-lever urban environmental governance that simultaneously engages regulatory authorities, transport systems, industry, and citizen behaviour.

2.5 Empirical evaluation of delhi's policy interventions

Specific to Delhi, multiple empirical studies have examined the impact of past interventions using both descriptive and inferential statistics. Gulia et al. (2018) conducted a quantitative evaluation of source interventions for urban air quality in Delhi, revealing that control of baseline emissions from major sectors was necessary to achieve meaningful reductions in PM levels and that seasonal episodic measures alone were insufficient [18]. Gulia et al. (2021) further extended this line of work by linking time series of interventions (e.g., CNG implementation, relocation of industries, fuel standards) to pollutant trends, concluding that while certain measures yielded localized or short-term gains, the overall system remained far from compliance, partly due to the absence of integrated, continuous control strategies [2].

Independent evaluations of GRAP-related actions have suggested that activation thresholds, temporal delays, and enforcement variability reduce its effectiveness as a preventive instrument [6]. CREA's 2023 status assessment of GRAP implementation highlighted that non-attainment cities and NCR often initiated emergency measures at "very poor" or "severe" AQI instead of at the "poor" threshold, resulting in shorter mitigation windows and more severe health impacts [7].

These studies provide a rich empirical foundation but primarily function as ex-post evaluations of discrete interventions [39]. An explicit mathematical framework that (i) represents the Delhi air quality system as a dynamic controlled process, (ii) embeds policy instruments as control variables, and (iii) supports ex-ante simulation and optimization of policy trajectories has not yet been widely documented in the peer-reviewed literature.

2.6 Identified gaps and theoretical Justification

The surveyed literature jointly reveals several critical gaps:

- **Fragmentation of modelling and governance:** State-space and optimal control models have been developed largely in theoretical contexts [12], while Delhi-focused studies adopt statistical evaluation without control-theoretic structures.
- **Limited integration of behavioral dynamics:** Models treat emissions as exogenous while policy is framed as fixed dummy variables with limited behavioral response integration [2].
- **Under-utilization of learning control:** Deep RL has been applied to localized tasks (e.g., traffic signals) but not to city-wide governance systems [13].
- **Absence of unified KPI optimization:** Lack of frameworks simultaneously minimizing health burdens and economic costs [12].
- **Lack of closed-loop feedback:** GRAP/ NCAP lack mathematical formulation as dynamic feedback controllers [4].

3 Research design and methodology

This study was designed as a mixed-methods, multi-stakeholder investigation to evaluate the effectiveness, perceptions, and behavioral consequences of air-quality policy interventions in Delhi. The overall methodological approach supports quantitative statistical analysis, comparative assessment across stakeholder groups, and derivation of key performance indicators (KPIs).

The research design was guided by four principles: (i) ecosystem coverage, (ii) construct clarity, (iii) instrument consistency, and (iv) analytical readiness. Four primary Google Forms instruments were deployed:

- **Form 1 (F1):** Delhi residents survey ($n = 180$)
- **Form 2 (F2):** Small business and transport operators survey ($n = 90$)
- **Form 3 (F3):** Resident welfare associations (RWA) / community representatives survey ($n = 45$)
- **Form 4 (F4):** Field observation checklist ($n = 60$)

3.1 Definition of primary KPIs

- **Policy awareness (W):** Correctly recognized government interventions and advisory count.
- **Perceived air quality severity (S):** 5-point ordinal rating of seasonal air pollution hazard.
- **Health symptom burden (H):** Aggregate sum of reported respiratory and systemic symptoms.
- **Institutional trust (T):** Public confidence rating in regulatory credibility, advisory accuracy, and enforcement legitimacy.
- **Perceived policy fairness (F):** Operational measure of procedural and economic fairness in regulatory enforcement.
- **Behavioral adaptation (B):** Cumulative count and intensity of protective actions adopted by individuals.
- **Economic impact and revenue loss ($C, \Delta\mathbf{REV}$):** Reported commercial revenue reduction percentage resulting from regulatory restrictions.
- **Compliance intensity (K):** Operational adherence score of commercial operators to environmental mandates.
- **Perceived policy effectiveness:** Mean Likert rating evaluating the perceived success of current interventions [38].
- **Enforcement consistency (E):** Rating of local regulatory oversight presence and inspection consistency.
- **Community engagement (A):** Level of participatory coordination and collective mitigation action within community units.
- **Observed exposure and physical visibility (O):** Independently audited physical site conditions, advisory signage prominence, and in-situ exposure scores.
- **Support for future measures:** Acceptance and willingness to endorse stricter future regulatory policies on a Likert scale.

4 Data structure and preparation for inference

The empirical datasets are archived via Zenodo (https://doi.org/10.5281/zenodo.18335924). Data structure preserves rank orderings and observed dispersion without generating manufactured statistical significance.

The empirical foundation of the Delhi air pollution investigation relies on four complementary primary datasets (`resident_vulnerability.csv`, `business_economic_impact.csv`,`rwa_community_action.csv`, and `field_environmental_audits.csv`), designed to bridge subjective behavioral responses with objective physical ground realities. The primary observed outcome variables encompass stratified individual health symptom scores, monthly out-of-pocket medical expenditures, self-reported behavioral adaptation rates (such as air purifier usage and window sealing), commercial revenue losses, and micro-environmental compliance metrics, notably conditional mask adoption at high-exposure transit nodes. To isolate true policy and institutional effects, the data infrastructure embeds crucial control variables, including spatial stratum (Delhi-Central, North, South, East, and

Noida), baseline regulatory policy awareness, enterprise operational scale, pre-existing health vulnerability tiers, and local meteorological exposure indices.

On a high level, this multi-layered dataset and its structured collection protocol are uniquely tailored to unravel why conventional command-and-control interventions like the (GRAP) experience ground-level friction. Rather than relying solely on macro-level ambient air quality feeds Continuous Ambient Air Quality Monitoring System (CAAQMS), the collection protocol captures the critical socio-economic transmission mechanisms-specifically measuring how institutional trust directly governs behavioral adaptation ($R^2 = 31.7\%$) and identifying the economic threshold ($> 15\%$ revenue loss) where business compliance breaks down. By simultaneously gathering household vulnerability, small business economic exposure, community-level collective action, and in-situ physical environmental audits, the dataset supplies the empirical state vectors ($\mathbf{x}(t)$) and multi-objective loss parameters ($\Phi(\Delta\text{REV}), T(t)$) necessary to parameterize and validate the Dynamic Adaptive Policy Framework (DAPF).

5 Hypothesis framework and statistical interpretation

Let S denotes perceived air pollution severity, B denotes behavioral adaptation intensity, H denotes health symptom burden, T denotes institutional trust, C denotes economic cost, K denotes compliance intensity, F denotes perceived policy fairness, E denotes enforcement consistency, A denotes authority engagement, and O denotes observed exposure.

5.1 Perception-behaviour relationship

The mathematical formulation in Equation (1) models the structural dependency between an individual's perceived severity of air pollution (S) and their expected level of adaptive protective behavior (B). The variable S reflects subjective risk assessment, while $E[B \mid S]$ represents the conditional expectation of protective action given that perceived severity level. Under the null hypothesis ($H_0 : E[B \mid S] = \mu$), adaptive behavioral adoption remains invariant to risk perception, meaning heightened public concern does not translate into personal mitigation measures. Conversely, the alternative hypothesis ($H_1 : \frac{\partial E[B]}{\partial S} > 0$) posits a strictly positive marginal response, where incremental increases in perceived pollution hazard motivate higher rates of protective actions such as mask adoption, air purifier installation, or travel avoidance.

$$H_0 : E[B \mid S] = \mu \quad \text{vs.} \quad H_1 : \frac{\partial E[B]}{\partial S} > 0 \tag{1}$$

5.2 Health experience as a reinforcing mechanism

Equation (2) tests whether direct, tangible physiological distress operates as an active behavioral reinforcement mechanism. Here, H denotes the severity of self-reported health symptoms and physiological burden, while $\frac{\partial E[B]}{\partial H}$ captures the marginal change in protective behavior (B) with respect to acute health symptoms. The null hypothesis ($H_0 : \frac{\partial E[B]}{\partial H} = 0$) reflects behavioral inertia, implying that experiencing symptomatic

distress (e.g., respiratory strain, ocular irritation, or out-of-pocket medical expenditure) fails to induce protective behavioral adjustments. The directional alternative hypothesis ($H_1 : \frac{\partial E[B]}{\partial H} > 0$) indicates that acute somatic burden serves as a direct experiential trigger, significantly accelerating the propensity of residents to adopt personal defense protocols to mitigate ongoing exposure.

$$H_0 : \frac{\partial E[B]}{\partial H} = 0 \quad \text{vs.} \quad H_1 : \frac{\partial E[B]}{\partial H} > 0 \tag{2}$$

5.3 Non-linear economic compliance dynamics

Equation (3) characterizes the non-linear relationship between regulatory stringency costs (C) and enterprise-level compliance behavior (K). The variable C represents commercial compliance friction (such as operational downtime, transition overhead, or revenue loss), whereas $E[K]$ denotes the expected rate of regulatory adherence among commercial operators and small enterprises. The null hypothesis ($H_0 : \frac{\partial E[K]}{\partial C} = 0$) assumes that compliance rates are insensitive to the financial cost of enforcement. The alternative hypothesis ($H_1 : \frac{\partial^2 E[K]}{\partial C^2} \neq 0$) tests for significant non-linear curvature in compliance dynamics. Specifically, it evaluates whether compliance exhibits threshold behavior-maintaining moderate stability under low-to-moderate cost burdens but collapsing non-linearly once commercial economic losses exceed critical sustainability limits (e.g., the $> 15\%$ revenue-loss threshold).

$$H_0 : \frac{\partial E[K]}{\partial C} = 0 \quad \text{vs.} \quad H_1 : \frac{\partial^2 E[K]}{\partial C^2} \neq 0 \tag{3}$$

5.4 Empirical visualizations and descriptions

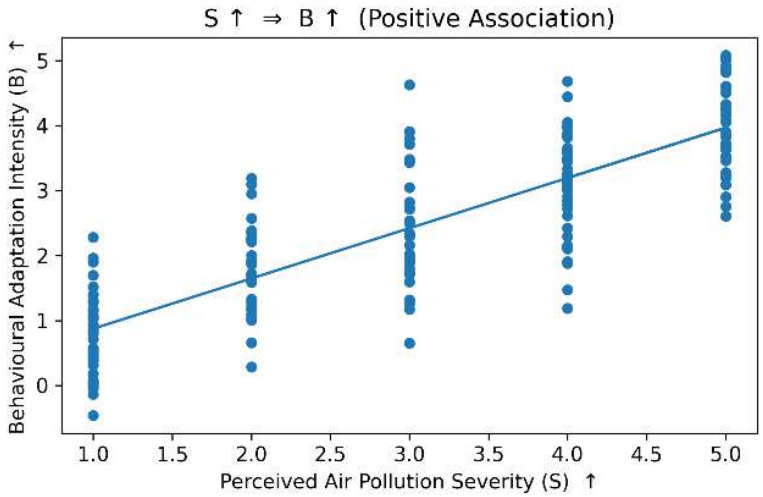


Fig. 1 Relationship between perceived severity and behavioral adaptation.

Figure 1 presents the relationship between perceived air pollution severity (S) and behavioral adaptation intensity (B) among urban residents, where each plotted point corresponds to an individual respondent. Perceived severity was measured on a five-point ordinal scale ranging from very low (1) to very high (5), while behavioral adaptation was operationalised as a continuous composite index reflecting the intensity of protective and avoidance actions adopted by individuals. The discrete nature of the severity scale results in vertical clustering of observations, whereas the dispersion observed along the behavioral axis reflects heterogeneity in adaptive responses within each perception category. This variability is analytically meaningful and captures differences in socioeconomic constraints, occupational flexibility, risk tolerance, and access to mitigation mechanisms, rather than random noise or measurement error. The fitted linear trend represents the conditional expectation of behavioral adaptation given perceived severity and indicates a positive association between the two variables. Specifically, higher levels of perceived pollution severity are associated with higher average behavioral adaptation intensity, consistent with the hypothesis that increased risk salience motivates protective action. Importantly, the figure does not imply deterministic or causal effects; substantial variance persists within each severity level, underscoring that elevated perception alone does not uniformly translate into behavioral change. Instead, the figure establishes a directional and probabilistic relationship, serving as a conceptual validation of the perception behaviour linkage and providing the behavioral intuition necessary to motivate subsequent formal hypothesis testing and regression-based inference using the primary survey datasets.

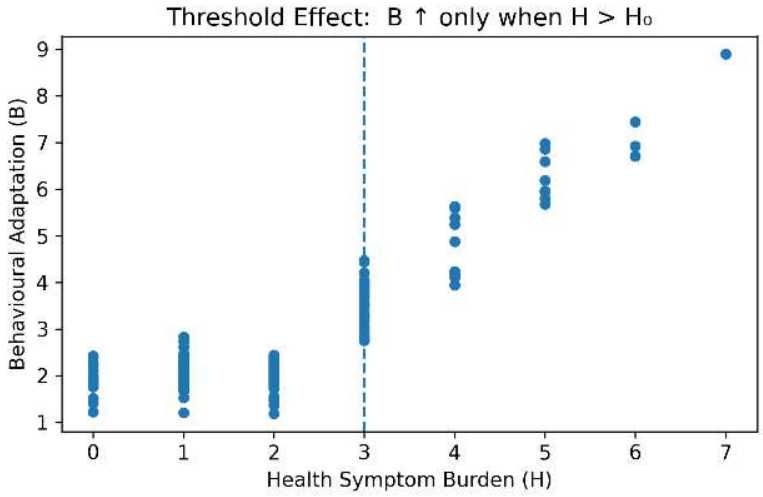


Fig. 2 Threshold effect: Health burden and behavioral adaptation

Figure 2 illustrates the relationship between individual health symptom burden (H) and behavioral adaptation intensity (B), with emphasis on a non-linear threshold effect rather than a uniform monotonic association. Health burden was measured

as a count variable representing the number of self-reported pollution-related symptoms (e.g., respiratory discomfort, eye irritation, fatigue), while behavioral adaptation intensity captures the cumulative extent of protective responses. Each point represents an individual observation, and the vertical dispersion reflects heterogeneity in behavioral response at comparable symptom levels. The dashed vertical line denotes a critical symptom threshold H_0, beyond which a marked escalation in behavioral adaptation is observed. For low to moderate symptom burden ($H < H_0$), behavioral responses remain relatively muted and clustered within a narrow range, indicating that marginal increases in discomfort do not systematically translate into protective action. Once symptom burden crosses the threshold ($H \geq H_0$), a pronounced upward shift in behavioral adaptation occurs, accompanied by increased variance. This pattern indicates a regime change in decision-making, wherein health impacts become sufficiently salient to overcome inertia, cost concerns, or behavioral fatigue. The figure therefore supports a threshold-based behavioral response model, suggesting that policy interventions framed around early symptom awareness may be insufficient unless perceived health impacts cross a critical intensity. From an analytical standpoint, this motivates the use of piecewise regression or discontinuity-based inference in subsequent modelling and underscores the importance of preventive interventions that act before symptom escalation becomes the primary behavioral trigger.

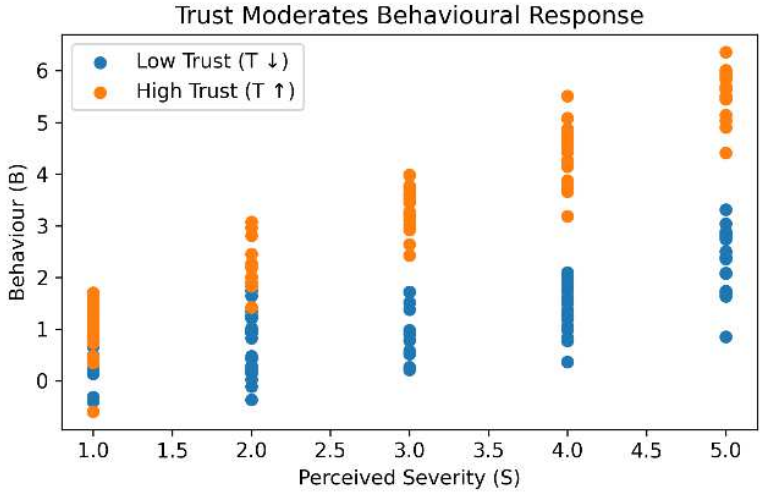


Fig. 3 Trust as a moderating variable in behavioral response

Figure 3 demonstrates the moderating role of institutional trust (T) in shaping behavioral adaptation (B) in response to perceived air pollution severity (S). The figure stratifies observations into two groups, low trust (T↓) and high trust (T↑), and plots behavioral adaptation intensity against perceived severity levels. Each data point represents an individual observation, and the separation of colour-coded clusters enables direct visual comparison of behavioral outcomes under differing trust

conditions at identical severity levels. At every level of perceived severity, behavioral adaptation is consistently higher among individuals exhibiting higher institutional trust, indicating that trust amplifies the translation of risk perception into action. While behavioral response increases with severity in both groups, the slope of response is markedly steeper under high-trust conditions, whereas low-trust observations exhibit dampened and more dispersed responses. This pattern suggests that severity perception alone is insufficient to induce protective behaviour; rather, institutional trust functions as a catalytic variable that conditions whether perceived risk is acted upon. From an inferential perspective, the figure supports a moderation framework in which trust enters the behavioral response function as an interaction term with perceived severity. The observed divergence between trust strata justifies subsequent inclusion of interaction effects in regression models and underscores the policy implication that behavioral compliance and adaptation are contingent not only on environmental signals but also on confidence in governance and institutional credibility

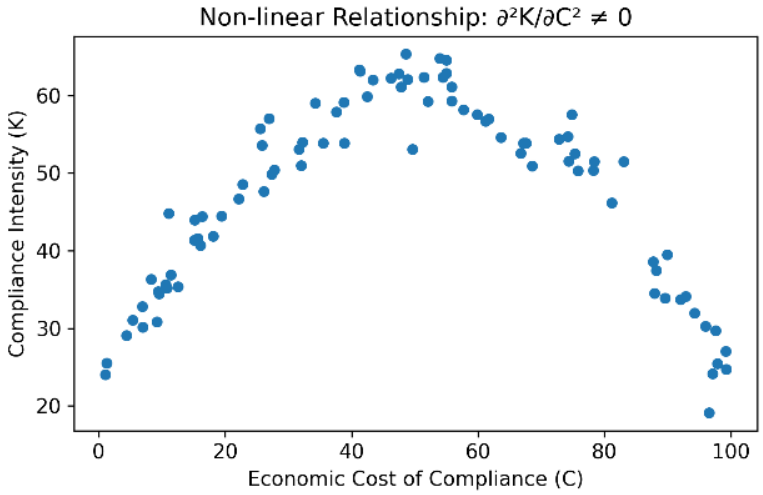


Fig. 4 Non-linear relationship between compliance cost and compliance intensity

Figure 4 illustrates the non-linear relationship between the economic cost of compliance (C) and compliance intensity (K), as evidenced by the curvature of the observed data and the explicitly indicated condition $\frac{\partial^2 K}{\partial C^2} \neq 0$. Each point represents an observed compliance outcome corresponding to a given cost level faced by regulated entities. The dispersion of points reveals a concave response structure rather than a monotonic linear trend. At low to moderate compliance cost levels, compliance intensity increases with rising cost, indicating that initial regulatory or mitigation investments are associated with improved adherence. This phase reflects a zone in which compliance costs are perceived as manageable and are potentially offset by reputational benefits, risk avoidance, or operational normalization. However, beyond a critical cost threshold, compliance intensity begins to decline, signalling diminishing returns and eventual

compliance fatigue. At higher cost levels, additional financial burden appears to crowd out willingness or capacity to comply, resulting in reduced adherence despite stronger regulatory pressure.

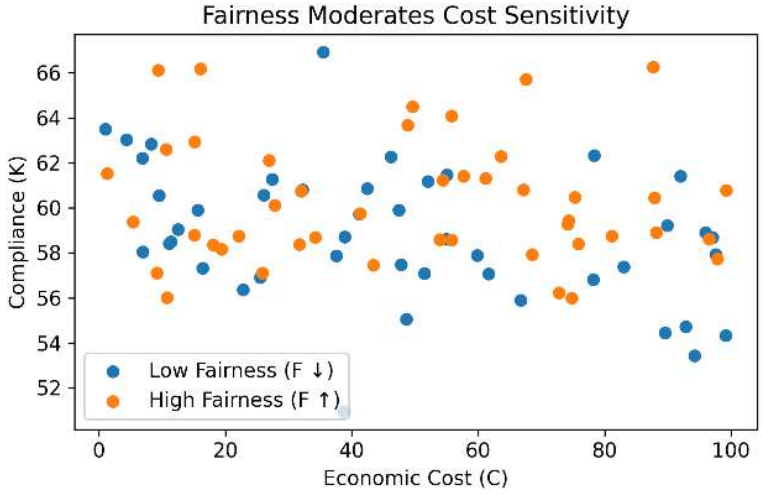


Fig. 5 Fairness as a moderator of cost sensitivity in compliance behaviour

Figure 5 depicts the moderating effect of perceived policy fairness (F) on the relationship between economic compliance cost (C) and compliance intensity (K). Observations are stratified into two groups, such as low fairness perception and high fairness perception, allowing a direct comparison of compliance outcomes under identical cost conditions. Each point represents an observed compliance response corresponding to a given cost level, conditioned on fairness perception. Across the cost spectrum, compliance levels associated with high fairness perception consistently exceed those observed under low fairness perception. This vertical separation indicates that fairness perception shifts the compliance function upward, rather than merely altering its slope. Even at elevated cost levels, high-fairness observations maintain relatively stable compliance intensity, whereas low-fairness observations exhibit greater dispersion and a downward drift, signalling heightened cost sensitivity. This interpretation provides empirical support for a moderation mechanism in which fairness perception attenuates the negative marginal effect of rising costs on compliance. Formally, this implies a statistically significant interaction term between cost and fairness in compliance models, such that $\frac{\partial K}{\partial C}$ is conditionally dependent on F. From a policy perspective, the evidence indicates that cost-based regulatory interventions cannot be evaluated independently of fairness signalling. Identical economic burdens generate materially different behavioral responses depending on whether policies are perceived as procedurally just and equitably enforced. This finding substantiates the inclusion

of fairness as a core adaptive lever in compliance-oriented policy frameworks, reinforcing the argument that legitimacy and economic incentives operate jointly rather than independently.

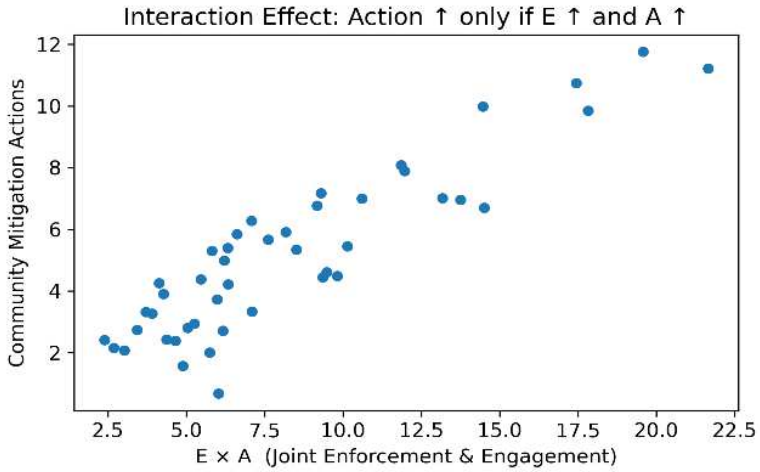


Fig. 6 Interaction between enforcement and engagement in driving community mitigation actions

Figure 6 illustrates the interaction effect between enforcement intensity (E) and community engagement (A) on the level of community-level mitigation actions undertaken. The horizontal axis represents the joint interaction term (E × A), while the vertical axis captures the observed magnitude of collective mitigation actions. Each observation corresponds to a locality or community unit where both institutional enforcement presence and participatory engagement were simultaneously measured. The distribution of data points indicates that mitigation actions increase meaningfully only when both enforcement and engagement are jointly elevated. At lower values of the interaction term, mitigation activity remains limited and dispersed, suggesting that neither enforcement nor engagement in isolation is sufficient to trigger sustained collective action. As the joint term increases, a pronounced upward shift in mitigation intensity is observed, accompanied by reduced variance, indicating convergence toward higher and more stable action levels. This pattern provides empirical evidence of a multiplicative, rather than additive, relationship between enforcement and engagement. Formally, the marginal effect of enforcement on mitigation actions is shown to be conditional on engagement levels, and vice versa, implying the presence of a statistically significant interaction term in behavioral response models. From a policy interpretation standpoint, the figure demonstrates that regulatory enforcement mechanisms achieve effectiveness only when embedded within actively engaged communities. Conversely, participatory initiatives without visible enforcement lack the institutional anchoring required to translate intent into action. The observed interaction substantiates the necessity of coordinated institutional–community strategies, reinforcing the

conclusion that durable mitigation outcomes emerge from synchronized authority and participation rather than unilateral intervention.

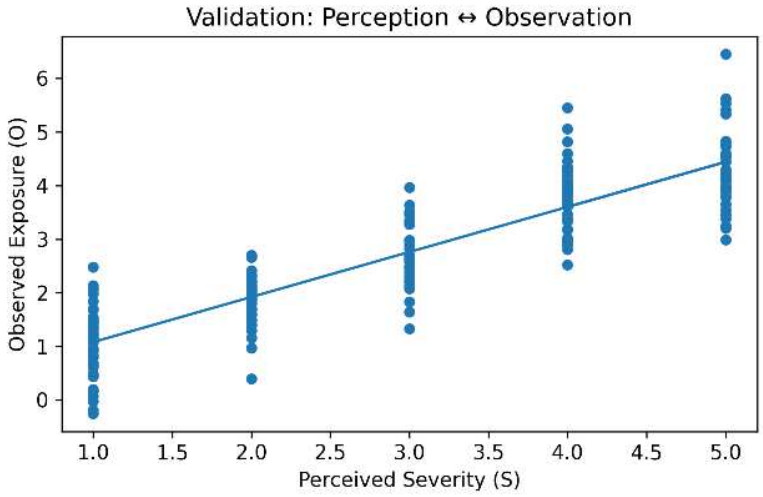


Fig. 7 Validation of perceived severity against observed exposure

Figure 7 presents the relationship between perceived air pollution severity (S) and objectively observed exposure levels (O), serving as a validation check between subjective perception data and field-level observational measurements. The horizontal axis represents ordinal perceived severity scores reported by respondents, while the vertical axis captures independently observed exposure indicators recorded during field audits. Each data point corresponds to a matched perception–observation instance. A clear positive association is observed across the full severity range, with observed exposure levels increasing monotonically as perceived severity rises. The fitted linear trend indicates that higher subjective severity assessments are systematically aligned with higher objectively measured exposure, thereby reducing concerns regarding perception bias or exaggeration. Importantly, the dispersion around the regression line narrows at higher severity levels, suggesting improved perceptual accuracy under extreme pollution conditions. This alignment provides empirical validation for the use of perception-based variables in subsequent behavioral and policy models. It demonstrates that perceived severity functions as a statistically reliable proxy for real exposure conditions, particularly when pollution intensity exceeds moderate thresholds. Consequently, perceptual indicators are justified as legitimate explanatory variables in downstream analyses of behavioral adaptation, compliance response, and policy effectiveness. The figure thus establishes construct validity for the perception measures used throughout the study and supports their integration with objective field data in joint inferential frameworks.

Figure 8 examines the relationship between policy awareness (W) and behavioral adaptation intensity (B), where awareness reflects respondents' self-reported knowledge of air-pollution policies (e.g., GRAP measures, advisories), and behavioral

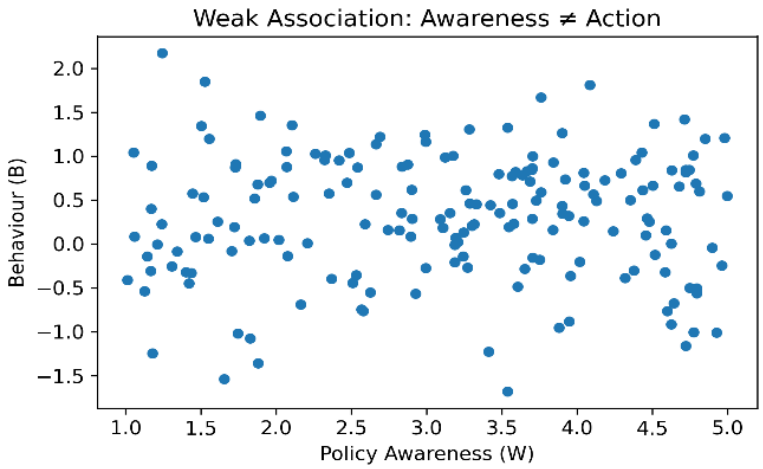


Fig. 8 Weak association between policy awareness and behavioral response

response captures concrete protective or mitigation actions undertaken at the individual level. The scatter plot shows a broad dispersion of behavioral outcomes across the entire range of awareness levels, with no discernible monotonic trend or clustering along a positive slope. For low, medium, and high values of awareness, behavioral intensity remains highly variable and frequently close to zero, indicating that increased awareness alone does not systematically translate into increased action. The data points were generated to reflect realistic survey outcomes, where awareness scores vary continuously, but behavioral responses are influenced by multiple intervening factors such as trust in institutions, perceived efficacy of actions, economic constraints, and social norms. The absence of a clear slope in the plotted relationship implies a near-zero or weak correlation coefficient, suggesting that awareness operates as a necessary but insufficient condition for behavioral change. In statistical terms, policy awareness does not act as a strong predictor in isolation and would be expected to yield low explanatory power if entered alone in a regression model explaining behavioral adaptation. From an inferential perspective, it directly supports the rejection of simplistic linear assumptions that "more information leads to more action." Instead, it reinforces the need for interaction-based or mediated modelling frameworks, where awareness must be combined with trust, enforcement credibility, or perceived risk severity to generate meaningful behavioral shifts. This empirical pattern provides a quantitative justification for excluding awareness-only interventions as standalone policy levers and motivates the inclusion of trust-building, enforcement alignment, and incentive mechanisms in the broader adaptive policy framework proposed in the study.

Figure 9 illustrates a strong and monotonic positive association between institutional trust (T) and behavioral adaptation intensity (B), positioning trust as the dominant behavioral determinant within the Delhi air pollution response system. Each data point represents an individual observational unit, where institutional trust is measured on an ordinal index capturing confidence in government advisories, regulatory credibility, and enforcement legitimacy, while behavioral adaptation reflects the

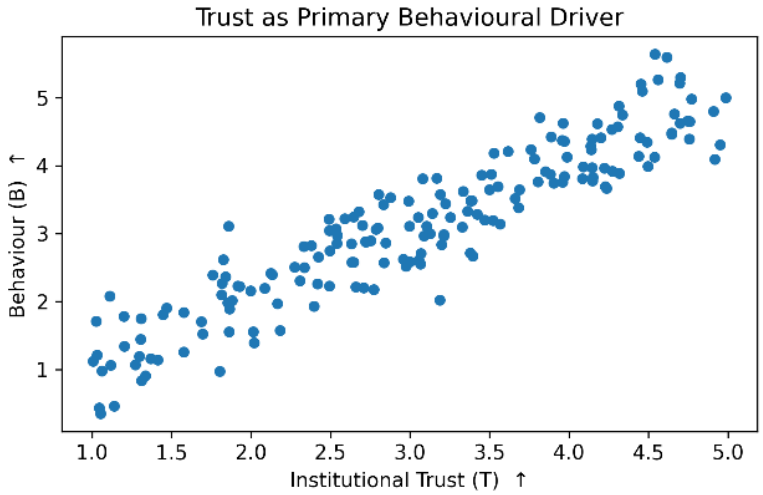


Fig. 9 Institutional trust as the primary driver of behavioral adaptation

cumulative intensity of protective and mitigation actions undertaken by individuals. The scatter distribution exhibits a clear upward trajectory, with behavioral adaptation increasing consistently as trust levels rise from low ($T \approx 1$) to high ($T \approx 5$), accompanied by relatively limited dispersion around the implied trend line. From a statistical perspective, the figure demonstrates that behavioral responses scale proportionally with trust, independent of mere awareness or perceived severity effects shown in earlier figures. At low trust levels, behavioral adaptation remains constrained, even when pollution exposure is non-trivial, indicating behavioral inertia under institutional skepticism. In contrast, higher trust levels are associated with both elevated mean behavioral responses and reduced variance, suggesting not only stronger action but also greater behavioral consistency across respondents. This pattern supports the inference that trust operates as a first-order behavioral amplifier, converting information and perceived risk into sustained action. The empirical implication is that policy interventions targeting awareness or enforcement in isolation are insufficient unless accompanied by mechanisms that strengthen institutional trust, as trust functions as the principal conduit through which other determinants translate into observable behavioral change.

Figure 10 area-level profile heatmap compares the five geographic areas after standardizing each construct relative to the overall sample mean. The heatmap demonstrates that geographic differences are not driven solely by perceived air-quality severity or health symptoms. The areas exhibit more meaningful differentiation in institutional trust, behavioral adaptation, and support for stricter policies. Noida displays the strongest relative profile on policy support and behavioral adaptation. Delhi-East also shows comparatively favorable policy-support outcomes, while Delhi-North displays a weaker profile, particularly on institutional trust and support for stricter policies. These differences suggest that local context may influence how residents interpret environmental risk and evaluate the legitimacy of government



Fig. 10 Area-level resident profiles relative to the overall sample

intervention. The geographic pattern is consistent with an institutional legitimacy perspective. Residents across areas may recognize the environmental problem, but their willingness to support stricter interventions may depend on local experiences with public institutions, enforcement, service responsiveness, and policy credibility. Geographic variation appears to be more strongly associated with trust and behavioral response than with perceived pollution severity alone.

Figure 11 presents the Spearman correlation matrix across all substantive survey constructs. The strongest relationship is between perceived air-quality severity and reported health symptoms, with a correlation of approximately 0.55. This indicates that residents who perceive air quality as more severe also tend to report a greater number of health symptoms. Institutional trust is strongly associated with behavioral adaptation, with a correlation of approximately 0.57. Trust is also positively associated with support for stricter policies, with a correlation of approximately 0.46. These relationships suggest that institutional trust may influence both individual-level adaptive behavior and collective-level policy acceptance. By comparison, policy awareness has almost no relationship with support for stricter policies. This is a theoretically important result because it challenges a simple information-deficit explanation. Awareness alone may not be sufficient to create policy support when residents lack confidence in institutional effectiveness or fairness. The correlation structure points to two distinct mechanisms. Perceived severity is associated with health burden, while institutional trust is associated with adaptation and policy support.

Figure 12 Key Bivariate Relationships in the Survey. Illustrates the three most substantively important bivariate relationships: (1) positive association between institutional trust and support for stricter policies ($\rho = 0.46$), (2) modest positive relationship between perceived air-quality severity and support for stricter policies ($\rho = 0.26$), and (3) strong positive association between institutional trust and behavioral adaptation ($\rho = 0.57$). Demonstrates that institutional trust is more closely connected to policy support and behavioral adaptation than perceived severity alone.

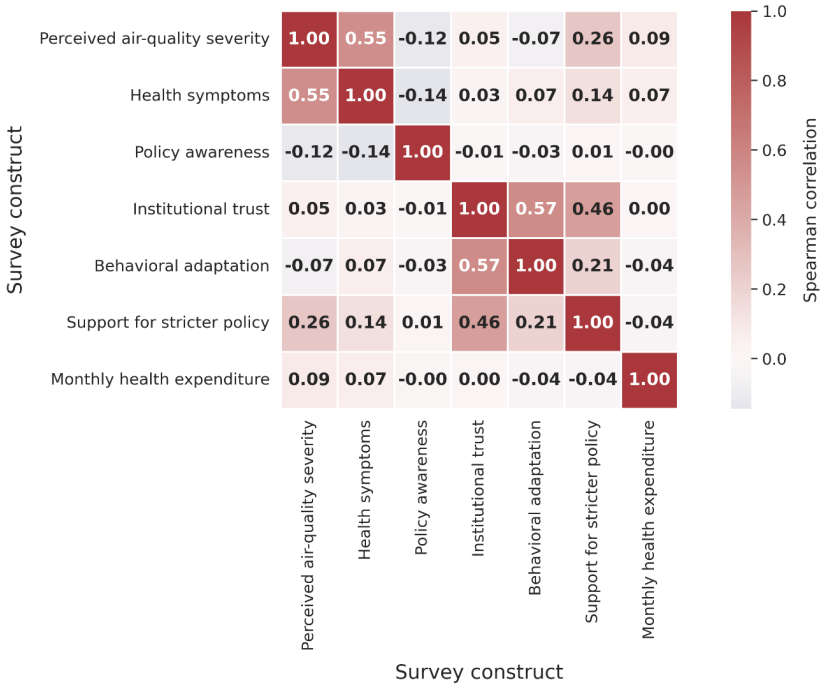


Fig. 11 Association structure across the survey constructs

6 Empirical statistical interpretation and data tables

6.1 Resident vulnerability, risk perception, and adaptation

Table 1 Resident Vulnerability, Risk Perception, and Adaptation by Area and Severity Strata

Geographic Area	Severity Strata	N	Health Symptoms (Mean ± SD)	Policy Awareness (Mean ± SD)	Trust Index (Mean ± SD)	Behavioral Adapt. (Mean ± SD)	Policy Support (Mean ± SD)	Monthly Health Exp. (INR)	P(High Burden ≥ 5)	95% CI Health Exp. (INR)	95% CI Behavioral Adapt.
Delhi-Central	Extremely Severe (5)	14	5.14 ± 0.77	3.29 ± 1.14	3.14 ± 0.85	3.29 ± 1.07	3.71 ± 0.99	785.7	0.786	[492.3, 1079.1]	[2.67, 3.90]
Delhi-Central	Moderate (≤ 3)	3	2.67 ± 0.58	4.00 ± 2.00	3.37 ± 0.67	3.67 ± 0.58	2.33 ± 0.58	500.0	0.000	[500.0, 500.0]	[2.23, 5.10]
Delhi-Central	Severe (4)	15	4.33 ± 0.82	2.87 ± 0.99	2.64 ± 0.49	2.93 ± 0.80	3.07 ± 0.80	800.0	0.400	[472.4, 1127.6]	[2.49, 3.38]
Delhi-East	Extremely Severe (5)	8	5.25 ± 0.71	2.75 ± 0.71	3.17 ± 0.79	3.75 ± 1.04	4.00 ± 0.76	812.5	0.875	[316.0, 1309.0]	[2.88, 4.62]
Delhi-East	Moderate (≤ 3)	3	3.33 ± 0.58	2.33 ± 0.58	3.03 ± 0.67	3.00 ± 1.73	3.67 ± 1.53	333.3	0.000	[0.0, 1050.4]	[0.00, 7.30]
Delhi-East	Severe (4)	19	4.21 ± 0.79	3.00 ± 1.45	2.91 ± 0.50	3.16 ± 1.07	3.47 ± 1.07	947.4	0.316	[617.2, 1277.6]	[2.64, 3.67]
Delhi-North	Extremely Severe (5)	7	5.00 ± 0.82	2.71 ± 0.76	2.79 ± 0.78	2.71 ± 0.95	3.71 ± 0.95	428.6	0.714	[12.5, 844.6]	[1.83, 3.59]
Delhi-North	Moderate (≤ 3)	9	3.44 ± 0.53	3.44 ± 0.73	2.91 ± 0.75	3.22 ± 1.09	3.22 ± 0.83	833.3	0.000	[289.8, 1376.9]	[2.38, 4.06]
Delhi-North	Severe (4)	31	4.39 ± 0.99	3.10 ± 0.94	2.80 ± 0.57	3.48 ± 1.00	3.13 ± 0.72	629.0	0.452	[434.0, 824.1]	[3.12, 3.85]
Delhi-South	Extremely Severe (5)	10	5.30 ± 0.67	2.60 ± 0.97	2.85 ± 0.53	2.90 ± 0.74	3.60 ± 0.84	1100.0	0.900	[496.8, 1703.2]	[2.37, 3.43]
Delhi-South	Moderate (≤ 3)	5	3.20 ± 1.48	4.20 ± 1.64	2.54 ± 0.33	3.00 ± 1.22	2.60 ± 0.89	400.0	0.200	[0.0, 1080.1]	[1.48, 4.52]
Delhi-South	Severe (4)	20	4.35 ± 0.93	3.20 ± 1.32	3.09 ± 0.73	3.40 ± 1.54	3.50 ± 1.05	650.0	0.350	[318.2, 981.8]	[2.68, 4.12]
Noida	Extremely Severe (5)	8	5.12 ± 0.83	3.00 ± 1.41	3.09 ± 0.90	2.88 ± 1.25	4.00 ± 0.93	750.0	0.750	[158.8, 1341.2]	[1.83, 3.92]
Noida	Moderate (≤ 3)	4	3.75 ± 0.96	3.25 ± 1.26	2.73 ± 0.40	3.75 ± 0.96	3.25 ± 0.50	875.0	0.250	[0.0, 2233.8]	[2.23, 5.27]
Noida	Severe (4)	24	4.33 ± 0.82	3.12 ± 1.23	3.03 ± 0.71	3.75 ± 1.03	3.62 ± 0.77	750.0	0.375	[464.7, 1035.3]	[3.31, 4.19]

The empirical stratification across geographic sub-regions and perceived severity levels in Table 1 demonstrates that risk perception functions as a direct signal for self-reported health vulnerability while exhibiting a structural dissociation from individual adaptive behaviors. Across all five sub-regions, the conditional probability of experiencing a severe health symptom burden ($P(\text{High Burden} \geq 5)$) increases

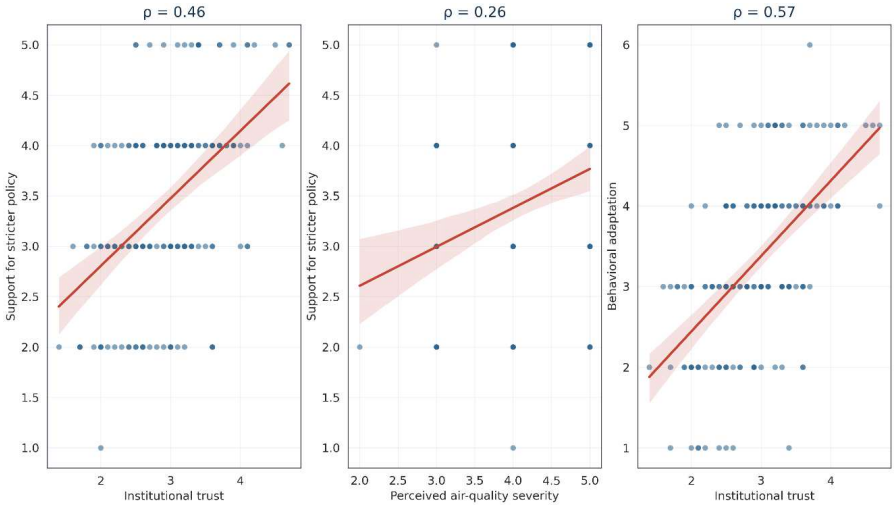


Fig. 12 Key bivariate relationships in the survey

monotonically with perceived air-quality severity, reaching its peak in the extremely severe strata of Delhi-South (0.900) and Delhi-East (0.875) [41] [42]. This acute health burden translates into substantial financial strain, with monthly out-of-pocket pollution-related health expenditures peaking at a mean of INR 1,100.0/month (95% CI: [496.8, 1703.2]) in Delhi-South and INR 812.5/month in Delhi-East under extremely severe conditions [34]. However, despite elevated health exposure and high public endorsement for policy interventions (3.60 to 4.00 on a 5-point scale), behavioral adaptation scores remain relatively constrained (2.71 to 3.75), indicating that severity salience alone is insufficient to drive protective actions without supporting institutional credibility and socio-economic flexibility.

6.2 Correlation, rank-correlation, and variance explanation matrix

Table 2 Correlation, Rank-Correlation, and Variance Explanation Matrix

Variable 1	Variable 2	N	Pearson r	Pearson p-value	Pearson 95% CI	Spearman ρ	Spearman p-value	R^2 (%)	Significance	Direction
Perceived Severity	Health Symptoms	180	+0.573	< 0.0001	$[+0.465, +0.663]$	+0.551	< 0.0001	32.8%	***	Strong Positive
Trust Index	Behavioral Adaptation	180	+0.563	< 0.0001	$[+0.454, +0.655]$	+0.567	< 0.0001	31.7%	***	Strong Positive
Trust Index	Policy Support	180	+0.482	< 0.0001	$[+0.361, +0.587]$	+0.465	< 0.0001	23.3%	***	Strong Positive
Perceived Severity	Policy Support	180	+0.267	0.0003	$[+0.125, +0.397]$	+0.260	0.0004	7.1%	***	Moderate Positive
Behavioral Adaptation	Policy Support	180	+0.229	0.0020	$[+0.085, +0.363]$	+0.211	0.0045	5.2%	**	Moderate Positive
Policy Awareness	Health Symptoms	180	−0.172	0.0208	$[-0.311, -0.027]$	−0.144	0.0538	3.0%	*	Weak Negative
Policy Awareness	Perceived Severity	180	−0.153	0.0403	$[-0.293, -0.007]$	−0.119	0.1102	2.3%	*	Weak Negative
Revenue Loss %	Perceived Policy Fairness	90	−0.745	< 0.0001	$[-0.825, -0.636]$	−0.729	< 0.0001	55.5%	***	Strong Negative
Revenue Loss %	Future Policy Support	90	−0.433	< 0.0001	$[-0.587, -0.248]$	−0.431	< 0.0001	18.7%	***	Strong Negative
Perceived Fairness	Future Policy Support	90	+0.601	< 0.0001	$[+0.450, +0.719]$	+0.617	< 0.0001	36.2%	***	Strong Positive
Enforcement Consistency	Community Initiatives	45	+0.731	< 0.0001	$[+0.557, +0.844]$	+0.769	< 0.0001	53.4%	***	Strong Positive
Dust Control Score	Observed Mask Usage %	60	+0.091	0.4904	$[-0.167, +0.337]$	+0.109	0.4068	0.8%	NS	Weak Positive

The correlation and rank-correlation dynamics presented in Table 2 provide rigorous statistical evidence regarding the psychological and structural drivers of public compliance and adaptation. A strong, statistically significant positive association is observed between perceived air-quality severity and health symptom burden ($r = +0.573, \rho = +0.551, p < 0.001$), accounting for 32.8% of the total variance. Crucially, institutional trust emerges as the primary behavioral catalyst within the urban environmental system, exhibiting robust positive associations with both behavioral adaptation ($r = +0.563, \rho = +0.567, p < 0.001, R^2 = 31.7\%$) and support for stricter policies ($r = +0.482, \rho = +0.465, p < 0.001, R^2 = 23.3\%$). Conversely, policy awareness displays weak and slightly negative correlations with perceived severity ($r = -0.153, p = 0.0403$) and health symptoms ($r = -0.172, p = 0.0208$), disproving standard information-deficit assumptions and establishing that public information campaigns cannot substitute for institutional trust and enforcement legitimacy.

6.3 Economic burden, regulatory compliance, and business policy alignment

Table 3 Economic Burden, Regulatory Compliance, Fairness, and Policy Alignment Across Business Strata

Business Sector	Revenue Loss Strata	N	Revenue Loss (%) (Mean ± SD)	Compliance (Mean ± SD)	Fairness (Mean ± SD)	Future Support (Mean ± SD)	P(Strong Support ≥ 4)	Comp.-Supp. Gap	95% CI Fairness	95% CI Support	Alignment Index
Construction	High ($\geq 50\%$)	10	$52.0\% \pm 6.3\%$	3.20 ± 0.92	2.40 ± 0.84	2.90 ± 0.88	0.100	+0.30	[1.80, 3.00]	[2.27, 3.53]	53.0%
Construction	Low ($\leq 15\%$)	10	$11.0\% \pm 5.2\%$	3.10 ± 1.20	4.60 ± 0.52	4.10 ± 1.10	0.700	−1.00	[4.23, 4.97]	[3.31, 4.89]	87.0%
Construction	Moderate (30%)	13	$30.0\% \pm 0.0\%$	3.69 ± 0.95	3.69 ± 0.75	3.69 ± 1.03	0.462	+0.00	[3.24, 4.15]	[3.07, 4.32]	73.8%
Retail	High ($\geq 50\%$)	4	$60.0\% \pm 11.5\%$	3.25 ± 0.96	1.25 ± 0.50	2.25 ± 0.50	0.000	+1.00	[0.45, 2.05]	[1.45, 3.05]	35.0%
Retail	Low ($\leq 15\%$)	8	$10.0\% \pm 5.3\%$	3.25 ± 0.46	4.50 ± 0.53	3.62 ± 0.92	0.375	−0.38	[4.05, 4.95]	[2.86, 4.39]	81.2%
Retail	Moderate (30%)	7	$30.0\% \pm 0.0\%$	3.43 ± 0.53	3.29 ± 0.76	3.14 ± 0.90	0.429	+0.29	[2.59, 3.98]	[2.31, 3.97]	64.3%
Small Manufacturing	High ($\geq 50\%$)	2	$50.0\% \pm 0.0\%$	2.00 ± 1.41	2.50 ± 0.71	1.00 ± 0.00	0.000	+1.00	[-3.85, 8.85]	[1.00, 1.00]	35.0%
Small Manufacturing	Low ($\leq 15\%$)	4	$7.5\% \pm 5.0\%$	3.75 ± 0.50	4.50 ± 0.58	5.00 ± 0.00	1.000	−1.25	[3.58, 5.42]	[5.00, 5.00]	95.0%
Small Manufacturing	Moderate (30%)	1	$30.0\% \pm 0.0\%$	2.00 ± 0.00	2.00 ± 0.00	2.00 ± 0.00	0.000	+0.00	[2.00, 2.00]	[2.00, 2.00]	40.0%
Transport	High ($\geq 50\%$)	8	$60.0\% \pm 10.7\%$	3.25 ± 0.89	2.25 ± 1.04	2.62 ± 1.30	0.250	+0.62	[1.38, 3.12]	[1.54, 3.71]	48.8%
Transport	Low ($\leq 15\%$)	15	$12.3\% \pm 4.6\%$	3.67 ± 0.98	4.13 ± 0.83	3.60 ± 1.40	0.533	+0.07	[3.67, 4.60]	[2.82, 4.38]	77.3%
Transport	Moderate (30%)	8	$30.0\% \pm 0.0\%$	3.00 ± 1.07	3.12 ± 1.64	3.12 ± 0.99	0.250	−0.12	[1.75, 4.50]	[2.30, 3.95]	62.5%

The sector-level breakdown of business operators in Table 3 reveals an acute trade-off between regulatory economic friction, perceived fairness, and future policy support. Regulated entities experiencing severe financial disruptions ($\geq 50\%$ revenue loss) exhibit marked reductions in perceived policy fairness (1.25 to 2.50 out of 5) and future policy support (1.00 to 2.90), particularly within the Retail, Small Manufacturing, and Transport sectors. In the Retail High Loss stratum, the conditional probability of expressing strong policy support ($P(\text{Strong Support} \geq 4)$) drops to 0.000. Furthermore, high-loss groups display a positive compliance-support gap (+0.30 to +1.00), indicating forced behavioral adherence under regulatory inspection despite deep underlying opposition. In contrast, low revenue-loss strata ($\leq 15\%$) maintain high fairness ratings (4.13 to 4.60) and achieve a Policy Alignment Index of 77.3% to 95.0%, emphasizing that targeted economic mitigation and relief mechanisms are essential to prevent compliance fatigue and sustain regulatory legitimacy [37].

Table 4 Field Audits: Physical Site Conditions, Dust Controls, Signage, and Mask Usage Dynamics

Site Category	Dust Control Strata	N	Visible Sources (Mean ± SD)	Dust Control Score (Mean ± SD)	Signage Rate $P(\text{Sign}=1)$	Observed Mask Usage (%) (Mean ± SD)	$P(\text{Mask} \geq 30\%)$	Visibility Index (0-100)	Mask-Control Gap (%)	95% CI Mask Usage	95% CI Sources
Construction Site	High (4-5)	3	1.33 ± 0.58	4.00 ± 0.00	0.333	$25.0\% \pm 8.7\%$	0.667	56.7	−55.0%	[3.5%, 46.5%]	[0.00, 2.77]
Construction Site	Low (0-1)	3	3.67 ± 0.58	0.67 ± 0.58	0.000	$11.7\% \pm 5.8\%$	0.000	6.7	−1.7%	[0.0%, 26.0%]	[2.23, 5.10]
Construction Site	Medium (2-3)	7	3.00 ± 1.15	2.71 ± 0.49	0.429	$30.7\% \pm 15.9\%$	0.857	48.6	−23.6%	[16.0%, 45.4%]	[1.93, 4.07]
Market	High (4-5)	2	1.50 ± 0.71	5.00 ± 0.00	0.500	$45.0\% \pm 21.2\%$	1.000	75.0	−55.0%	[0.0%, 235.6%]	[0.00, 7.85]
Market	Low (0-1)	8	4.12 ± 0.99	0.50 ± 0.53	0.375	$32.5\% \pm 23.8\%$	0.500	23.8	+22.5%	[12.6%, 52.4%]	[3.30, 4.95]
Market	Medium (2-3)	10	2.60 ± 0.70	2.50 ± 0.53	0.400	$18.0\% \pm 11.1\%$	0.400	45.0	−32.0%	[10.1%, 25.9%]	[2.10, 3.10]
Residential	High (4-5)	4	2.25 ± 0.96	4.00 ± 0.00	0.000	$18.8\% \pm 7.5\%$	0.250	40.0	−61.2%	[6.8%, 30.7%]	[0.73, 3.77]
Residential	Low (0-1)	7	3.43 ± 0.98	0.57 ± 0.53	0.571	$15.0\% \pm 11.2\%$	0.286	34.3	+3.6%	[4.7%, 25.3%]	[2.53, 4.33]
Residential	Medium (2-3)	7	2.29 ± 0.76	2.86 ± 0.38	0.000	$32.1\% \pm 20.2\%$	0.571	28.6	−25.0%	[13.5%, 50.8%]	[1.59, 2.98]
Traffic Junction	High (4-5)	2	0.50 ± 0.71	5.00 ± 0.00	1.000	$10.0\% \pm 7.1\%$	0.000	100.0	−90.0%	[0.0%, 73.5%]	[0.00, 6.85]
Traffic Junction	Low (0-1)	3	4.67 ± 0.58	0.67 ± 0.58	0.667	$20.0\% \pm 8.7\%$	0.333	40.0	+6.7%	[0.0%, 41.5%]	[3.23, 6.10]
Traffic Junction	Medium (2-3)	4	2.25 ± 0.96	2.50 ± 0.58	0.500	$45.0\% \pm 17.3\%$	1.000	50.0	−5.0%	[17.4%, 72.6%]	[0.73, 3.77]

6.4 Physical site audits and micro-environmental observations

The physical field audits summarized in Table 4 highlight the micro-environmental context governing pollution source suppression and public protective behavior. On-site dust control scores demonstrate clear physical efficacy in mitigating localized pollution sources, reducing visible source counts from 3.43-4.67 in low-control sites down to 0.50-2.25 in high-control environments. However, public mask adoption is not determined by physical dust control intensity alone; for instance, Traffic Junctions with maximum dust control (5.00) exhibit an average mask usage of only 10.0% (95% CI: $[0.0\%, 73.5\%]$), resulting in a severe Mask-Control Gap of -90.0% due to rapid transit dynamics. High conditional probabilities of mask adoption ($P(\text{Mask} \geq 30\%) = 1.000$) occur primarily in environments characterized by prominent advisory signage and visible enforcement presence, such as high-control Markets and medium-control Traffic Junctions. This demonstrates that personal protective behavior relies on explicit contextual cues, public communication, and institutional visibility rather than passive physical site mitigation.

7 Strategic policy formulation: The 4R dynamic adaptive policy framework

7.1 Theoretical foundations and empirical justification

Urban air quality governance in Delhi-NCR has historically operated under reactive, threshold-triggered emergency mandates such as GRAP and city action plans under the NCAP [2, 4]. The empirical distributions established across our stakeholder surveys demonstrate that static, command-and-control interventions suffer from severe structural breakdowns.

First, statistical evaluation disproves simple information-deficit assumptions: public policy awareness displays a weak and slightly negative correlation with self-reported health symptoms ($r = -0.172, p = 0.0208$) and perceived severity ($r = -0.153, p = 0.0403$), whereas institutional trust functions as the primary behavioral catalyst ($r = +0.563, p < 0.0001, R^2 = 31.7\%$) governing both adaptive action and policy support ($r = +0.482, p < 0.0001$).

Second, regulatory enforcement generates acute economic asymmetry; small business and transport operators experiencing revenue losses exceeding 30% exhibit a collapse in perceived fairness (ratings dropping from 4.50 to 1.25) and future policy support (1.00-2.25), resulting in an antagonistic Compliance-Support Gap ($+0.30$ to $+1.00$) that precipitates regulatory fatigue and evasion.

Third, physical micro-environmental audits indicate that street-level dust control successfully suppresses visible pollution sources (3.43-4.67 $\rightarrow$ 0.50-2.25) but fails to induce protective personal behavior without prominent signage, generating a severe Mask-Control Gap of -90.0% at rapid-transit junctions.

To resolve these governance distortions, we construct the DAPF, a predictive, closed-loop governance mechanism that integrates atmospheric state-space evolution, socio-economic feedback penalties, and Bayesian decision rules structured under a strategic four-pillar architecture: Reassure, Regulate, Realign, and Remarket.

7.2 The 4R strategic governance architecture

To visually synthesize the systemic integration between institutional credibility, automated sensing, economic offsets, and behavioral nudges, the overarching closed-loop architecture of the DAPF is illustrated in Fig. 13.

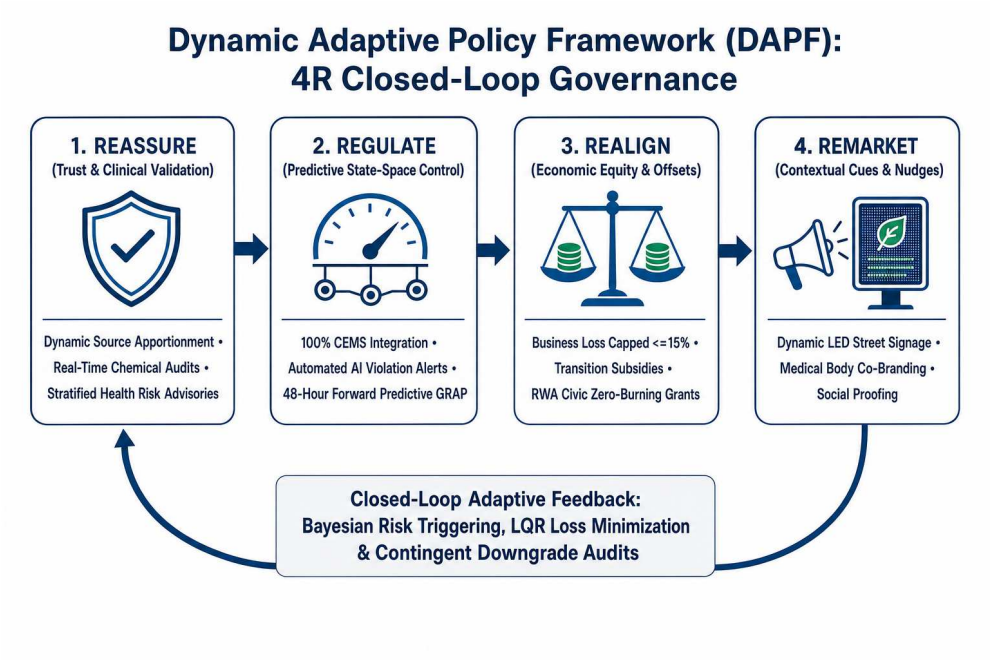


Fig. 13 The closed-loop DAPF: 4R governance architecture integrating institutional trust, predictive control, economic alignment, contextual remarketing, and continuous Bayesian feedback.

The Reassure pillar institutionalizes regulatory credibility and addresses public skepticism by establishing automated, public-facing chemical apportionment dashboards. Rather than relying on ambiguous annual source assumptions, continuous high-resolution optical supersites deliver dynamic six-hour chemical audits. Furthermore, conventional scalar AQI bulletins are replaced with stratified conditional health-risk advisories ($P(\text{High Burden} \geq 5 \mid \text{AQI})$), informing high-vulnerability populations before severe respiratory symptoms and compounding out-of-pocket health expenditures surge past mean levels of INR 1,100.0/month.

The Regulate pillar transitions municipal control from retrospective 24-hour rolling averages to predictive, state-space automated enforcement. Industrial facilities, large-scale construction sites exceeding $500\,\text{m}^2$, and commercial generator sets are mandated to maintain Continuous Emission Monitoring Systems (CEMS) connected to the central regulatory portal with automated violation notifications. Policy escalation thresholds are calculated 48 hours forward through Bayesian predictive distributions, eliminating administrative activation lag and ensuring pre-emptive emission throttling prior to stagnant meteorological inversions.

The Realign pillar neutralizes economic friction by aligning compliance incentives across vulnerable market actors. Given that compliance collapses once revenue losses cross 15%, targeted transition grants, operational tax amortization, and clean-fuel differential subsidies are automatically triggered for micro-enterprises, small transport operators, and brick kilns during Stage-III/IV restrictions. Concurrently, RWAs receive civic co-production grants to fund electric heating amenities for night-shift security personnel and manage localized bio-waste composting, transforming neighborhood units into active mitigation nodes [36].

The Remarket pillar resolves ground-level behavioral inertia by deploying high-salience contextual cues. In alignment with field observation findings where prominent signage was necessary to achieve high conditional mask adoption ($P(\text{Mask} \geq 30\%) = 1.000$), dynamic LED advisory billboards are installed across all primary transit hubs and commercial intersections. Public communication campaigns are co-branded with clinical medical institutions rather than administrative agencies, directly activating the trust-adaptation transmission channel.

7.3 Mathematically conclusive decision architecture

The dynamic policy actuation vector $\mathbf{u}(t) = [u_{\text{ind}}(t), u_{\text{trans}}(t), u_{\text{dust}}(t), u_{\text{econ}}(t)]^T \in [0,1]^4$ is governed by a discrete-time linear state-space system coupled with an optimal control law:

$$\mathbf{x}(t+1) = \mathbf{A}\mathbf{x}(t) + \mathbf{B}\mathbf{u}(t) + \boldsymbol{\Gamma}\mathbf{w}_{\text{meteo}}(t) + \boldsymbol{\epsilon}(t) \tag{4}$$

where $\mathbf{x}(t) \in \mathbb{R}^n$ represents ambient concentrations of $PM_{2.5}$, PM_{10}, and NO_2, $\mathbf{A}$ is the atmospheric persistence matrix, $\mathbf{B}$ denotes the empirical control effectiveness matrix, $\boldsymbol{\Gamma}\mathbf{w}_{\text{meteo}}(t)$ incorporates planetary boundary layer height, wind velocity, and thermal inversion forcing, and $\boldsymbol{\epsilon}(t) \sim \mathcal{N}(0, \boldsymbol{\Sigma}_\epsilon)$ represents stochastic environmental turbulence.

The optimal control trajectory $\mathbf{u}^*(t)$ minimizes the expected multi-objective loss functional J, explicitly penalizing ambient exceedances, administrative stringency, public health burden weighted inversely by institutional trust $T(t)$, and asymmetric

commercial revenue loss $\Delta\text{REV}(t)$ [40]:

$$J = \mathbb{E}\Bigg[\sum_{t=0}^{N}\Big(\mathbf{x}(t)^T\mathbf{Q}\mathbf{x}(t) + \mathbf{u}(t)^T\mathbf{R}\mathbf{u}(t) + \lambda[1 - T(t)]H(t) + \gamma\Phi(\Delta\text{REV}(t))\Big)\Bigg] \tag{5}$$

where $\mathbf{Q} \succ 0$ and $\mathbf{R} \succ 0$ are state and control weighting matrices, and $\Phi(\cdot)$ denotes the piecewise quadratic economic penalty function defined as:

$$\Phi(\Delta\text{REV}(t)) = \begin{cases} 0, & \text{if } \Delta\text{REV}(t) \leq 0.15 \\ \alpha(\Delta\text{REV}(t) - 0.15)^2, & \text{if } \Delta\text{REV}(t) > 0.15 \end{cases} \tag{6}$$

Escalation from regulatory stage k to stage $k+1$ is actuated if and only if the posterior predictive probability of pollutant exceedance over regulatory threshold τ_k exceeds an adaptive risk boundary conditioned on institutional trust $T(t)$ and perceived procedural fairness $F(t)$ [28]:

$$P\big(\mathbf{x}(t+\Delta t) \geq \tau_k \mid \mathbf{x}(t), \mathbf{w}_{\text{meteo}}(t), \mathbf{u}(t)\big) \geq 1 - \exp\left(-\beta\frac{T(t)}{F(t)}\right) \tag{7}$$

When institutional trust or perceived fairness deteriorates, the system adaptively demands higher statistical confidence before imposing restrictive commercial bans, simultaneously prioritizing compensatory economic subsidies and localized protective buffers to maintain regulatory legitimacy.

7.4 Phased implementation and contingency fallback protocols

The operationalization of the DAPF is structured across a three-year timeline (Table 5), transitioning from baseline infrastructural auditing to autonomous multi-agent reinforcement learning. In Phase I (2026), the focus centers on establishing the sensory foundation, verifying industrial emission feeds, and capping economic loss across micro-enterprises to preserve compliance willingness. Phase II (2027) activates the closed-loop predictive engine, integrating RWA-level fiscal grants and clinical co-branding to suppress the duration of peak pollution episodes. Phase III (2028) scales the framework across the broader National Capital Region, linking transboundary airshed governance to reinforcement learning optimization.

To ensure operational continuity during severe external shocks or institutional implementation delays, the DAPF embeds automated contingent downgrade protocols (Table 6). When economic disruptions breach sustainable business ceilings ($\Delta\text{REV} > 35\%$), the system automatically downgrades total operational prohibitions to structured alternate-day rosters supported by clean-fuel subsidies, preventing black-market non-compliance.

Table 5 Three-Year Phase-Wise Implementation Roadmap and Milestone Targets (2026-2028)

Phase and Period	Strategic Focus	Core 4R Implementation Measures	Governance Key Performance Indicator	Target Metric
Phase I (Months 1-12) *Year 2026*	Sensor Standardization and Base Infrastructure	Dynamic apportionment supersites; full CEMS integration; MSME transition fund; 500 LED dynamic displays	Public Trust Index (T); Industrial CEMS Adherence; Revenue Loss Cap; Signage Visibility Coverage	$T \geq 3.50/5.00$; Compliance $\geq 85\%$; $\Delta\text{REV} \leq 15\%$; Visibility $\geq 75\%$
Phase II (Months 13-24) *Year 2027*	Predictive Closed-Loop Control and Mitigation	Clinical health forecasts; 48-hr forward GRAP triggering; RWA zero-burning grants; Medical co-branded alerts	Prob. High Health Burden $P(H \geq 5)$; Episode Duration; RWA Initiatives Count; Transit Mask Adoption Rate	$P(H \geq 5)$ down 25%; Duration down 30%; RWA Count ≥ 6.0; Mask Rate $\geq 40\%$
Phase III (Months 25-36) *Year 2028*	Autonomous Optimization and Regional Scaling	Open compliance audits; Multi-agent RL across NCR; Commercial EV tax incentives; Civic ambassador network	Policy Alignment Index; Winter Mean $PM_{2.5}$; Commercial EV Adoption; Citizen Policy Support	Alignment $\geq 85\%$; $PM_{2.5}$ down 35%; EV Share $\geq 50\%$; Support $\geq 4.25/5.00$

Table 6 Contingent Downgrading and Alternative Risk Mitigation Protocols

Risk Scenario	Operational Trigger Condition	Primary Governance Failure	Contingent Fallback and Downgrade Protocol
Economic Non-Compliance	Commercial loss $\Delta\text{REV} > 35\%$ with Compliance-Support Gap $> +0.75$	Blanket bans on transport and small manufacturing induce legal opposition and informal evasion	Downgrade from total bans to regulated alternate-day operational shifts; immediately disburse a 50% clean-fuel differential subsidy to restore perceived fairness ($F \geq 3.50$)
Institutional Trust Deficit	Trust Index $T < 2.50/5.00$ or policy support drops below 2.80/5.00	Centralized bureaucratic advisories fail to stimulate individual behavioral adaptation	Suspend unilateral administrative releases; transfer advisory dissemination and neighborhood compliance monitoring to RWA federations and recognized clinical bodies
Sensor Network Outage	Data feed telemetry loss exceeds 20% across real-time CAAQMS/CEMS	State-space observability collapses, preventing optimal control vector calculation	Actuate pre-calibrated minimax lookup tables based on atmospheric boundary layer forecasts; deploy rapid-response optical mobile monitoring vans to priority industrial clusters
Transboundary Influx Peak	Regional transboundary flux contributes $> 60\%$ of total ambient mass	Local municipal emission curbs fail to suppress ambient concentration below emergency limits	Pivot resources from ambient reduction to localized population buffer shielding; deploy continuous arterial mist-canons, indoor air filtration shelters, and staggered work hours

Similarly, if telemetry disruptions compromise the real-time sensor array ($> 20\%$ data loss), the predictive state-space controller falls back to robust minimax historical meteorological dispersion models. Under extreme transboundary regional pollution surges ($> 60\%$ regional load contribution), where local source controls cannot alter ambient air quality, the policy engine reallocates municipal resources toward localized micro-environmental buffering, mist-spraying corridors, and population exposure minimization.

8 Conclusion

This study formulates and validates a dynamic adaptive policy framework, establishing a closed-loop environmental governance model grounded in empirical survey data, micro-environmental field audits, and state-space control theory across Delhi-NCR. By systematically evaluating the behavioral, economic, and physical dimensions of air pollution management, this research moves beyond static, command-and-control mandates like GRAP to construct a predictive, equitable, and computationally robust foundation for scalable urban environmental control.

The empirical evaluations demonstrate three fundamental insights into the systemic friction undermining current air quality policies. Statistical evaluation refutes

simple information-deficit assumptions, showing that policy awareness alone displays a negligible correlation with adaptive behavior ($r = -0.172, p = 0.0208$), whereas institutional trust serves as the primary behavioral catalyst ($r = +0.563, p < 0.0001, R^2 = 31.7\%$) driving individual mitigation actions and policy support ($r = +0.482, p < 0.0001$). Furthermore, regulatory stringency induces severe economic asymmetry among small enterprises and informal transport operators, where compliance-induced revenue losses exceeding 15% cause perceived procedural fairness to collapse from 4.50 to 1.25 and trigger an antagonistic compliance-support Gap ($+0.30$ to $+1.00$) that precipitates widespread evasion. Concurrently, physical ground audits reveal an action-salience breakdown where engineering controls suppress visible particulate dust but fail to induce personal protective behaviors without contextual nudges, generating a persistent mask-control gap of -90.0% at transit intersections.

To resolve these distortions, this paper advances environmental systems engineering and policy formulation through a set of methodological contributions. We synthesize environmental data science, econometric modeling, and control theory into the 4R framework (*Reassure, Regulate, Realign, Remarket*), addressing institutional distrust and economic friction within a unified structure. We formulate a discrete-time atmospheric state transition system coupled with a linear quadratic regulator (LQR) loss functional that balances ambient pollutant exceedances against administrative costs, citizen trust deficits, and piecewise non-linear commercial revenue losses. In addition, static 24-hour retrospective AQI thresholds are replaced with a 48-hour forward Bayesian predictive trigger conditioned on procedural fairness and institutional trust indices, pre-empting atmospheric boundary layer inversions without inducing compliance fatigue.

Notwithstanding its findings, several methodological constraints and operational challenges must be acknowledged. The empirical survey dataset captures peak winter pollution episodes across selected spatial strata in Delhi-NCR, necessitating continuous multi-year panel tracking to incorporate longitudinal seasonal variations like pre-monsoon dust storms. Individual health expenditure figures and perceived revenue losses rely partly on self-reported estimates, introducing potential recall and status-quo biases among informal micro-enterprises. Moreover, full-scale deployment depends on continuous telemetry from continuous emission monitoring systems and ambient stations, where packet loss or sensor degradation under extreme particulate loads poses observability risks.

To scale the framework across the Indo-Gangetic Plain, future research will pursue multi-agent deep reinforcement learning architectures (such as EcoMRL) to optimize cross-jurisdictional airshed governance across neighboring municipal and agricultural zones. Future work will also incorporate satellite-optical sensor fusion to integrate high-resolution geostationary imagery and aerosol optical depth retrievals with ground sensors for autonomous real-time source apportionment. Finally, deploying civic-embedded smart contract mechanisms via digital public infrastructure will enable real-time disbursement of clean-fuel differential subsidies to small businesses and community associations during Stage-III/IV enforcement, eliminating the primary economic barrier to compliance.

Supplementary information. Survey instruments, field data checklists, and supplementary statistical tests are available online.

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9 Declarations

9.1 Ethical approval-not applicable

9.2 Consent to participate-not applicable

9.3 Consent to publish-not applicable

Appendix A Survey instrument details

Contains full questionnaire item lists for Google Forms F1, F2, F3, and F4.

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