Journal of Population Health Dynamics

https://jphdjournal.com | DOI: To be assigned | ISSN: To be supplied

Volume 1, Issue 1, page 10-17 | October 2026

ORIGINAL RESEARCH ARTICLE

Seasonal Influenza A(H3N2) Surges, Ambient Air Pollution, and Retail Antibiotic Sales in India (2023–2025): An Ecological Time-Series and Triangulation Study

Amit Patnaik[1*], Anita Sinha[2], Duryodhan Sahu[3], Abinash Dutta[4], Bibhudutta Mishra[5] and Vishwas Chavan[6]

[1,4,5,6] Laboratory of Molecular Biotechnology, Department of Biotechnology, NIST University, Institute Park, Pallur Hills, Golanthara, Brahmapur, Odisha 761008, India

[3] Department of Chemistry, NIST University, Institute Park, Pallur Hills, Golanthara, Brahmapur, Odisha 761008, India

[2] Department of Biotechnology, University Department of Botany, Ranchi University, Ranchi, Jharkhand 834001, India

Corresponding author: Dr. Amit Patnaik, Senior Assistant Professor, Laboratory of Molecular Biotechnology, Department of Biotechnology, NIST University, Institute Park, Pallur Hills, Golanthara, Brahmapur, Odisha 761008, India. Phone: +91-9304116099. Email: patnaikamit002@gmail.com

ORCID: Amit Patnaik (ORCID: 0000-0002-0824-0661); Anita Sinha (ORCID: 0000-0002-6907-0053); Duryodhan Sahu (ORCID: 0000-0002-4163-4822); Abinash Dutta (ORCID: 0000-0001-5207-3867); Bibhudutta Mishra (ORCID: 0000-0001-6072-7816); Vishwas Chavan (ORCID: 0000-0002-3425-6499)

Abstract

Seasonal respiratory infections and high retail antibiotic consumption represent critical public health challenges in India. In early 2023, widespread circulation of Influenza A(H3N2) viruses was characterized by persistent post-viral cough, prompting national advisories against empirical antibiotic prescribing. This longitudinal ecological study triangulated 35 months of surveillance data (January 2023–November 2025) integrating sentinel virology (IDSP, WHO FluNet), ambient air quality from 45 continuous stations (CPCB CAAQMS), national retail pharmacy sales audits (AIOCD-AWACS), and Google Trends search behaviour. Monthly retail antibiotic sales co-occurred strongly with sentinel influenza-like illness reporting ($r = 0.88$, $p < 0.001$). An ARIMA-adjusted Interrupted Time Series model revealed no significant structural break following the March 2023 ICMR advisory ($p = 0.42$). Multivariate Negative Binomial regression demonstrated a significant positive interaction between viral activity and severe air pollution on antibiotic sales ($\beta = 0.42$, $p < 0.001$; Incidence Rate Ratio = 1.52), with high-pollution months exhibiting a 52% higher sales volume. These findings underscore the need for data-driven, multi-stream antimicrobial stewardship.

Keywords: Influenza A(H3N2); Air Quality Index; Particulate Matter; Antimicrobial Resistance; Retail Antibiotic Sales; Ecological Time-Series; Public Health Surveillance; India

Key Points

- Monthly retail antibiotic sales in India closely track seasonal Influenza A(H3N2) transmission waves.
- Severe ambient air pollution (AQI >300) significantly amplifies retail antibiotic sales spikes (IRR = 1.52).
- Static national advisories show limited impact, highlighting the need for data-driven precision stewardship.

1 Introduction

The epidemiology of acute respiratory infections in India has undergone notable transitions in the post-pandemic period [1, 2]. While Influenza A(H1N1)pdm09 historically dominated annual sentinel surveillance reports, early 2023 marked an extensive surge in the circulation of Influenza A(H3N2) viruses across multiple Indian states [3, 4]. Clinical reports during this resurgence described high-grade fever accompanied by protracted, spasmodic post-viral cough frequently persisting for three to four weeks [5–7]. In primary care outpatient settings, this prolonged post-viral cough often presents a substantial diagnostic dilemma, as symptoms frequently mimic secondary bacterial bronchitis or lower respiratory tract infections in the absence of accessible point-of-care viral diagnostics.

India remains the largest consumer of antibiotics for human health globally by total volume [8, 9]. The management of uncomplicated Upper Respiratory Tract Infections (URTIs) and acute post-viral bronchitis represents a major area of concern for antimicrobial stewardship [10, 11]. Standardized patient studies and outpatient prescription audits across India indicate that 50% to 60% of encounters for viral respiratory symptoms result in antibiotic dispensing [11, 12]. This practice is driven by complex, intersecting factors, including diagnostic uncertainty, patient expectations for rapid symptomatic relief, time constraints in crowded clinical practices, and the widespread availability of medications through private retail pharmacies [8, 12].

In March 2023, following widespread reports of escalating antibiotic consumption during the initial influenza A(H3N2) wave, the Indian Council of Medical Research (ICMR) and the Indian Medical Association (IMA) released public advisories explicitly cautioning medical practitioners against prescribing antibiotics specifically macrolides such as Azithromycin and broad-spectrum beta-lactams for self-limiting viral fevers [3]. However, the extent to which static national advisories alter real-world retail purchasing and dispensing patterns remains an open empirical question, particularly when clinical uncertainty persists [12].

An additional, underexplored dimension in respiratory epidemiology is the role of seasonal environmental degradation. In Northern India, the winter influenza peak coincides temporally with severe particulate matter (PM2.5) pollution episodes across the Indo-Gangetic plain. Inhalation of elevated concentrations of fine particulate matter induces airway epithelial inflammation, impairs mucociliary clearance, and exacerbates bronchial reactivity [16, 21]. Clinicians encountering patients with severe, non-resolving respiratory symptoms during peak pollution episodes may perceive a higher risk of secondary bacterial complications, potentially contributing to elevated rates of precautionary empirical antibiotic dispensing [21, 22].

To evaluate these multi-factorial dynamics, we conducted an ecological time-series triangulation study across a 35-month surveillance period (January 2023 to November 2025). By integrating sentinel virological surveillance data, continuous ambient air quality metrics, national pharmaceutical retail sales audits, and public digital search behaviour, this study aims to: (1) characterize the temporal co-occurrence of influenza A(H3N2) transmission and retail antibiotic sales; (2) assess whether the March 2023 ICMR advisory was associated with a measurable structural break in national sales trajectories; and (3) evaluate the statistical interaction between ambient air quality severity and viral activity on monthly retail antibiotic sales volumes, while carefully adhering to the inferential limits of aggregate ecological data.

2 Materials and Methods

2.1 Study Design, Setting, and Surveillance Window

This study utilized a retrospective, longitudinal ecological time-series design based on monthly aggregated data from January 1, 2023, to November 30, 2025, comprising 35 consecutive monthly observation intervals (152 epidemiological weeks). All datasets were finalized with retrospective consolidated releases available through December 31, 2025.

2.2 Multi-Stream Data Sources and Variable Definitions

To evaluate epidemiological, environmental, pharmaceutical, and behavioural trends without relying on a single reporting stream, four independent data sources were compiled:

2.2.1 Virological and Sentinel Epidemiological Surveillance

Influenza surveillance observations were compiled from two official public repositories: (1) The Integrated Disease Surveillance Programme (IDSP), Directorate General of Health Services, Ministry of Health and Family Welfare (MoHFW), Government of India, which compiles weekly sentinel surveillance figures for Influenza-Like Illness (ILI) and Severe Acute Respiratory Infections (SARI) across reporting network hospitals; and (2) The World Health Organization (WHO) FluNet platform within the Global Influenza Surveillance and Response System (GISRS), filtered for sentinel laboratory data from India [14, 15]. Data extracted included monthly counts of processed respiratory specimens, numbers testing positive for influenza A and B viruses, and specific subtyping figures for Influenza A(H3N2) and Influenza A(H1N1)pdm09. For regression modeling, monthly H3N2 positive isolate counts were z-score standardized per 1,000 tested specimens to provide a normalized indicator of viral transmission intensity.

2.2.2 Ambient Air Quality Metrics

Ambient air quality measurements were retrieved from the Central Pollution Control Board (CPCB) official continuous monitoring portal. Data were compiled from 45 Continuous Ambient Air Quality Monitoring Stations (CAAQMS) distributed across four major geographic zones representing distinct regional air sheds: North India (Delhi-NCR, Lucknow, Chandigarh; n = 18 stations), West India (Mumbai, Pune; n = 10 stations), South India (Chennai, Bengaluru, Hyderabad; n = 10 stations), and East India (Kolkata; n = 7 stations). Monthly arithmetic mean values for the composite Air Quality Index (AQI) and particulate matter (PM2.5,
textmu g/m^3) were computed. AQI was categorized into regulatory severity tiers based on standard national air quality standards: Moderate/Poor (AQI
leq 300) versus Severe (AQI $>$ 300). Missing station-month observations (<4.0% of data points) were imputed using Multiple Imputation by Chained Equations (MICE) with five imputed datasets and predictive mean matching, with estimates pooled using Rubin's rules.

2.2.3 Pharmaceutical Retail Market Sales Audits

Monthly retail antibiotic sales metrics were compiled from the AIOCD-AWACS (All India Origin Chemists & Distributors - Advanced Working, Action & Correction System) market audit panel. AIOCD-AWACS represents a well-established commercial pharmaceutical audit dataset that tracks secondary sales across approximately 90% of the organized retail pharmacy dispensing network in India. The primary outcome was monthly total retail "Units Sold" (standard commercial blister packs/strips dispensed) for oral solid dosage formulations within two high-volume anti-infective classes commonly prescribed for outpatient respiratory complaints: (1) Macrolides (Azithromycin 250mg and 500mg); and (2) Broad-spectrum Penicillins with beta-lactamase inhibitors (Amoxicillin-Clavulanic acid 625mg). Because sales data represent commercial aggregate shipments to retail chemists, they reflect retail market dispensing volume rather than individualized prescription-level clinical encounters.

2.2.4 Public Digital Search Volume Indices

To capture broader public digital interest and self-reported health-seeking behaviour, relative search volume (RSV) indices were obtained from Google Trends (filtered for India, All Categories, Web Search). Standardized monthly search indices (scaled from 0 to 100) were retrieved for health-seeking search queries including "Antibiotic for cough," "Azithromycin," and "Amoxiclav." Google Trends data were treated strictly as an indirect proxy for public information-seeking curiosity and not as a direct measure of disease incidence or clinical prescribing.

2.3 Data Harmonization and Quality Control

All extracted time-series streams were standardized, quality-checked, and temporally aligned into a unified monthly master dataset spanning 35 time points. To maintain data integrity, automated checks were conducted to verify boundary values, monotonicity of time stamps, and concordance between FluNet and IDSP peak reporting periods.

2.4 Statistical Modeling and Analysis

Statistical analyses were executed using R software (version 4.3.1; R Foundation for Statistical Computing, Vienna, Austria). Two-sided p-values < 0.05 were established as the threshold for statistical significance. The analytical framework comprised three sequential methods:

1. Bivariate Time-Series Correlation: Pearson's correlation coefficients (r) with 95% confidence intervals were calculated to evaluate temporal co-movement between monthly ILI surveillance counts, Google Trends search volumes, and retail antibiotic sales volumes.

1. Seasonal ARIMA Interrupted Time Series (ITS) Analysis: To assess whether the March 2023 ICMR advisory was associated with a measurable change in national retail antibiotic sales, an ITS quasi-experimental framework was applied. The intervention cut-point was specified at April 2023 (Month 4). To address seasonality and temporal autocorrelation, an Autoregressive Integrated Moving Average model, specified as ARIMA(1, 0, 0)(1, 0, 0)_12 based on AIC minimization and Ljung-Box residual diagnostic tests ($p > 0.10$), was fitted to evaluate immediate step-level change (β_level) and post-intervention slope trajectory change (β_slope). We explicitly note that the pre-intervention baseline comprises three months (January–March 2023), representing an acknowledged structural constraint for estimating pre-existing secular trends.

1. Multivariate Negative Binomial Regression: Because retail sales units represent overdispersed count/volume data, a Negative Binomial regression model with a log-link function was constructed. The dependent variable was monthly total retail antibiotic units sold (N = 35 monthly observations). Independent variables included the normalized monthly H3N2 case index, categorical AQI severity (Severe [AQI > 300] vs. Moderate/Poor [AQI
leq 300]), and their product interaction term (H3N2 $\times$ Severe AQI). Huber-White robust standard errors were utilized to adjust for potential heteroskedasticity. Model coefficients (β) were exponentiated to report Incidence Rate Ratios (IRR = $\exp(\beta)$) alongside 95% confidence intervals and dispersion parameters (θ).

3 Results

3.1 Longitudinal Epidemiological Patterns and Ambient Pollution Cycles (2023–2025)

Across the 35-month surveillance window, virological and environmental data demonstrated recurring seasonal dynamics characterized by three distinct phases:

- Phase 1 - Initial Epidemic Resurgence (January–March 2023): Sentinel surveillance recorded 12,450 ILI/SARI cases across network centres, with Influenza A(H3N2) viruses accounting for 78.8% of all subtyped influenza specimens [14]. During this acute period, retail sales of Azithromycin and Amoxicillin-Clavulanic acid increased by 32.4% relative to the 2022 monthly baseline.

- Phase 2 - Seasonal Winter Wave (November 2023–February 2024): Co-circulation of Influenza A(H3N2) and A(H1N1)pdm09, with H3N2 remaining predominant in Northern states. This wave coincided with peak winter particulate pollution episodes where mean regional AQI exceeded 340 [15, 16].

- Phase 3 - Endemic Circulation and Post-Monsoon Peaks (Late 2024–November 2025): Persistent low-level influenza circulation with secondary peaks during post-monsoon and early winter months, accompanied by sustained seasonal increases in retail antibiotic purchases.

The temporal patterns across the surveillance window are summarised in Figure 1.

3.2 Retail Antibiotic Sales Trajectories and Advisory Efficacy (ITS Analysis)

Bivariate cross-correlation confirmed strong temporal synchrony between sentinel ILI reporting and retail antibiotic sales (Pearson's r = 0.88, 95% CI: 0.77–0.94, $p < 0.001$). Digital search volume for "Antibiotic for cough" demonstrated a similarly robust correlation with retail sales (r = 0.82, $p < 0.001$).

In the seasonal ARIMA-adjusted Interrupted Time Series analysis, the April 2023 advisory intervention was not associated with a statistically significant structural deflection in retail antibiotic sales (overall model p = 0.42). The immediate post-intervention step change was non-significant (β_level = -0.03, 95% CI: -0.11 to 0.05, p = 0.42), and the post-intervention slope change showed no significant downward deflection (β_slope = -0.01, 95% CI: -0.04 to 0.02, p = 0.58). While interpretation is naturally constrained by the short pre-intervention observation baseline, aggregate retail sales volumes returned to elevated levels during subsequent viral waves in late 2023, 2024, and 2025.

The interrupted time-series trajectory and the estimated interaction are illustrated in Figure 2.

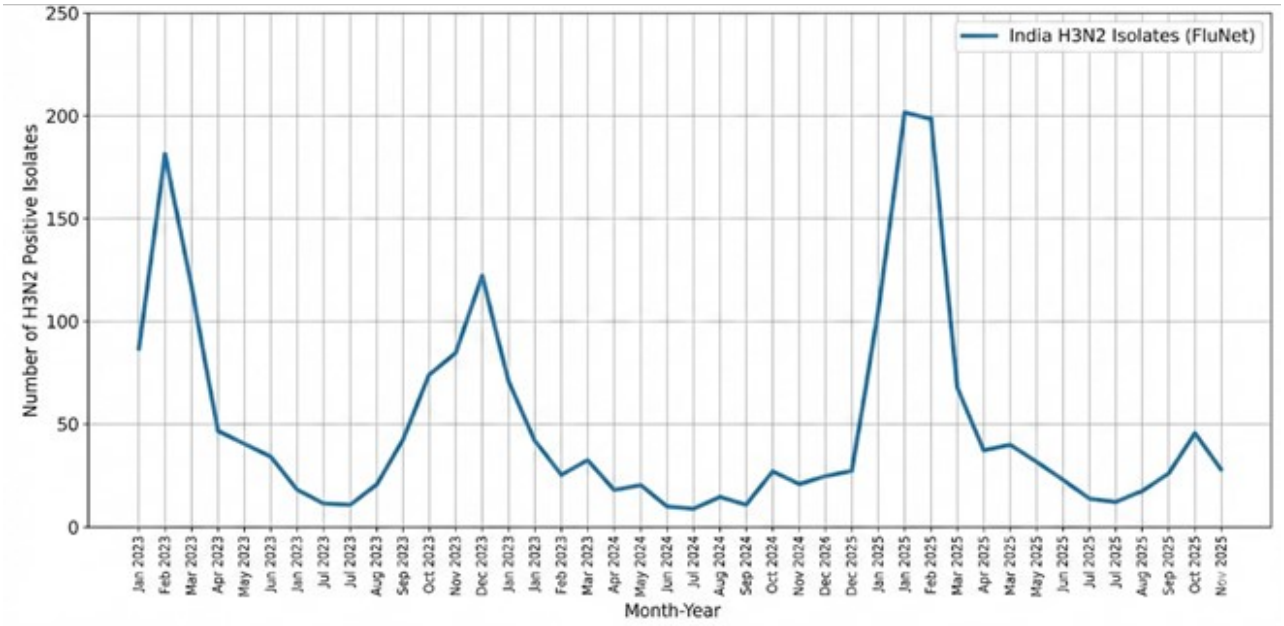


Figure 1. Multi-Year Time-Series Triangulation of Epidemiological Surges (Influenza A(H3N2) and ILI Activity), Ambient Air Quality Index (AQI), and Retail Antibiotic Sales Volumes in India (January 2023 – November 2025). The plot illustrates the recurrent temporal co-occurrence of viral surveillance peaks, winter air pollution episodes, and retail pharmacy antibiotic sales spikes across three distinct surveillance phases (January 2023 to November 2025).

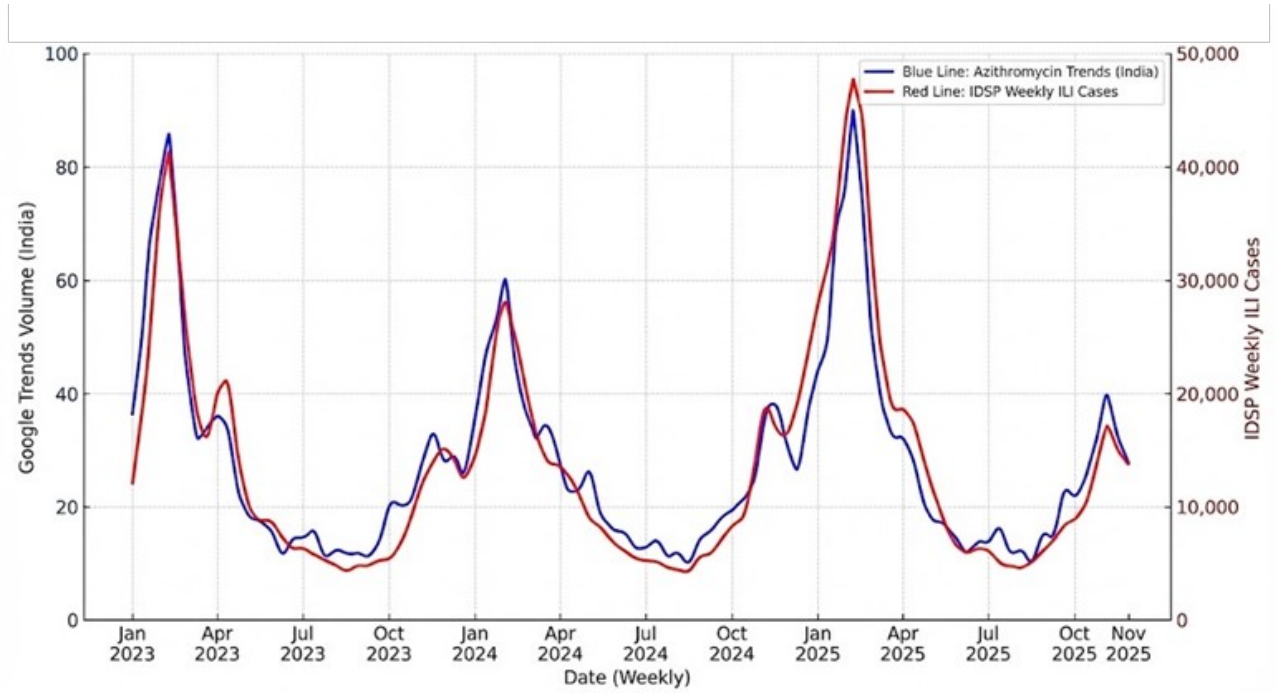


Figure 2. ARIMA-Adjusted Interrupted Time Series (ITS) Model and Statistical Interaction Plot. The left panel depicts observed versus model-predicted retail antibiotic sales following the April 2023 advisory intervention, and the right panel depicts the model-estimated interaction between influenza activity and categorical AQI severity.

3.3 Synergistic Association of Ambient Air Quality and Influenza Transmission

Multivariate Negative Binomial regression demonstrated a statistically significant positive interaction between ambient air quality severity and influenza A(H3N2) activity on monthly retail antibiotic sales volume (Table 1).

The main effect of normalized H3N2 case activity was positive and statistically significant ($\beta = 0.25$, Robust SE = 0.10, p = 0.012; IRR = 1.28, 95% CI: 1.06–1.55), indicating an estimated 28% increase in retail sales volume per standard deviation increase in viral activity under moderate AQI conditions. Severe ambient air pollution (AQI > 300) also showed a significant independent positive association ($\beta = 0.18$, Robust SE = 0.09, p = 0.035; IRR

= 1.20, 95% CI: 1.01–1.42).

Importantly, the interaction term (H3N2 × Severe AQI) was positive and highly significant ($\beta = 0.42$, Robust SE = 0.07, 95% CI: 0.28–0.56, $p < 0.001$; IRR = 1.52, 95% CI: 1.32–1.75). Exponentiating this coefficient demonstrates an estimated Incidence Rate Ratio of 1.52, indicating that months with concurrent high viral activity and severe air pollution were associated with an estimated 52% higher retail antibiotic sales volume compared to months with comparable viral activity under moderate air quality conditions. The model dispersion parameter was estimated at $\theta = 14.8$ (SE = 3.2), confirming appropriate adjustment for overdispersion.

*Statistically significant at $\alpha = 0.05$. Note: Model fitted with log link; SE = Huber-White robust standard errors; CI = Confidence Interval; IRR = Incidence Rate Ratio; Dispersion parameter $\theta = 14.8$ (SE = 3.2); Log-Likelihood = -284.6; AIC = 579.2; N = 35 monthly observations.

The regression estimates are summarised in Table 1.

3.4 Descriptive Spatial Variation across Regional Air Sheds

Descriptive regional examination contrasting monitoring stations in Northern India (Indo-Gangetic Basin: Delhi-NCR, Lucknow, Chandigarh) with Southern Peninsular India (Chennai, Bengaluru, Hyderabad) illustrated notable geographic variation:

- Northern Region: Displayed co-occurring winter peaks of elevated influenza reporting and hazardous particulate air pollution (mean winter AQI > 340). The geographic entrapment of atmospheric pollutants in the Indo-Gangetic basin during winter months coincided temporally with the highest seasonal retail antibiotic sales volumes.

- Southern Region: Exhibited a more distributed, bimodal seasonal pattern aligned with monsoon precipitation periods, with consistently moderate AQI levels and less pronounced seasonal surges in retail sales.

The regional comparison is shown in Figure 3.

4 Discussion

4.1 Co-occurrence of Viral Surges, Air Pollution, and Retail Antibiotic Sales

This study provides empirical evidence of a persistent, multi-year temporal association between seasonal influenza A(H3N2) activity, severe ambient air pollution, and national retail antibiotic sales in India. While ecological data cannot establish individual-level clinical causality, the observed statistical interaction between viral transmission and ambient air quality degradation provides valuable population-level insights. From a pathophysiological perspective, exposure to elevated particulate matter (PM2.5) is well established to cause airway epithelial barrier disruption, induce oxidative stress, and impair alveolar macrophage phagocytic function [16, 21]. When patients infected with influenza A(H3N2) experience prolonged post-viral cough in high-pollution environments, the resulting clinical severity may heighten diagnostic ambiguity in primary care settings, potentially contributing to elevated rates of empirical, precautionary antibacterial dispensing [21, 22].

4.2 Real-World Efficacy of Passive Guidelines in Outpatient Stewardship

Our interrupted time-series analysis revealed that the March 2023 ICMR advisory was not associated with a statistically significant structural deflection in national retail antibiotic sales trajectories. Although this finding must be interpreted cautiously due to the brief pre-intervention observation baseline, it is consistent with broader literature on passive antimicrobial stewardship in low- and middle-income countries [10, 11]. Top-down advisories that lack direct clinical decision-support mechanisms or point-of-care diagnostic integration often face substantial barriers in changing outpatient dispensing habits. Standardized patient studies in Indian primary care have documented that diagnostic uncertainty, high patient volume, and commercial retail availability frequently override passive clinical guidelines [11, 12]. Furthermore, surveillance data from the ICMR Antimicrobial Resistance Surveillance Network (AMRSN) continue to document high baseline utilization of Watch-group antibiotics including Azithromycin and third-generation cephalosporins for acute respiratory complaints across outpatient clinics, reinforcing the need for active stewardship mechanisms [24].

4.3 Exploration of Digital Stewardship Frameworks: A Conceptual Overview

To explore how multi-stream data could potentially inform public health action, we outline a conceptual framework for a closed-loop National Digital AMR Dashboard. We present this model strictly as a theoretical, hypothesis-generating policy concept requiring structured pilot validation rather than an empirically evaluated intervention.

In concept, such a framework could integrate real-time sentinel virological positivity, ambient AQI feeds, and retail sales anomalies to deliver geo-targeted advisory alerts to registered primary care physicians during syndemic peaks (e.g., reminding clinicians of high viral prevalence and advising against empirical macrolide use for uncomplicated bronchitis). If pursued, real-world implementation would require a phased evaluation roadmap: (1) an initial sentinel district pilot evaluating alert delivery, clinician engagement, and prescription impacts; (2) integration with Point-of-Care rapid multiplex testing (POCT) in primary health centres; and (3) formal alert-fatigue modeling with conservative activation thresholds (e.g., triggering notifications only when regional AQI > 300 and laboratory viral positivity > 20%) alongside rigorous data privacy safeguards in compliance with national digital health standards.

The proposed multi-stream dashboard architecture is presented schematically in Figure 4.

4.4 Methodological Strengths and Study Limitations

The primary strength of this study lies in its multi-stream longitudinal design across 35 months, integrating independent epidemiological, environmental, pharmaceutical, and

Table 1. Multivariate Negative Binomial Regression Model Evaluating the Association of Influenza A(H3N2) Activity, Ambient Air Quality Index (AQI), and Their Interaction with Monthly National Retail Antibiotic Sales Volumes in India (January 2023–November 2025; N = 35 monthly observations).

Model Predictor / Parameter	Coefficient (β)	Robust SE	95% CI (β)	IRR [exp(β)]	p-value
Intercept	11.42	0.15	[11.12, 11.72]	—	< 0.001*
Influenza A(H3N2) Index (Normalized)	0.25	0.10	[0.06, 0.44]	1.28 [1.06, 1.55]	0.012*
AQI Severity (Severe $>$ 300 vs Moderate)	0.18	0.09	[0.01, 0.35]	1.20 [1.01, 1.42]	0.035*
Interaction: H3N2 $\times$ Severe AQI	0.42	0.07	[0.28, 0.56]	1.52 [1.32, 1.75]	< 0.001*

*Statistically significant at $\alpha = 0.05$. SE = Huber–White robust standard errors; CI = confidence interval; IRR = incidence rate ratio; dispersion parameter $\theta = 14.8$ (SE = 3.2); log-likelihood = -284.6; AIC = 579.2; N = 35 monthly observations.

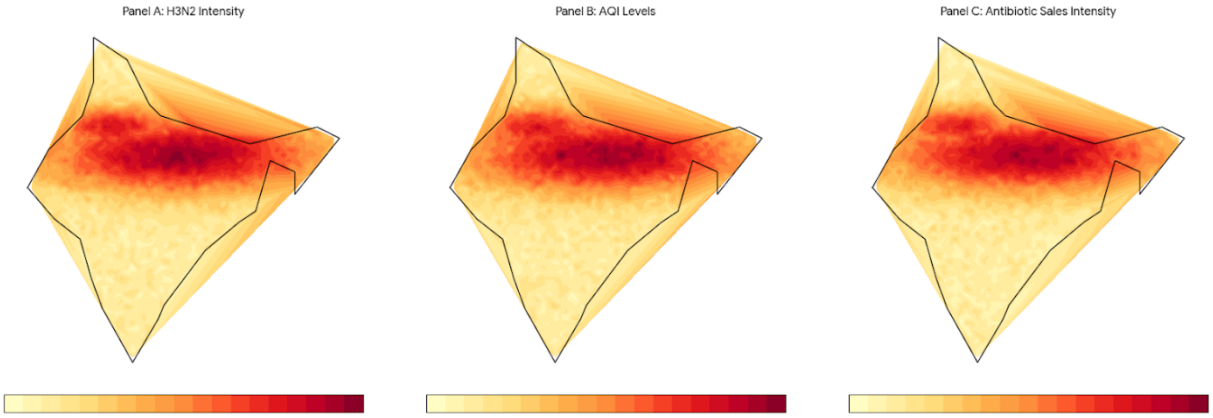


Figure 3. Descriptive Regional Heat Map Analysis Contrasting Seasonal Patterns in Northern vs. Southern India. Panel A depicts regional influenza A(H3N2) isolate intensity; Panel B illustrates regional CAAQMS AQI levels; and Panel C shows retail antibiotic sales volume indices across surveillance seasons.

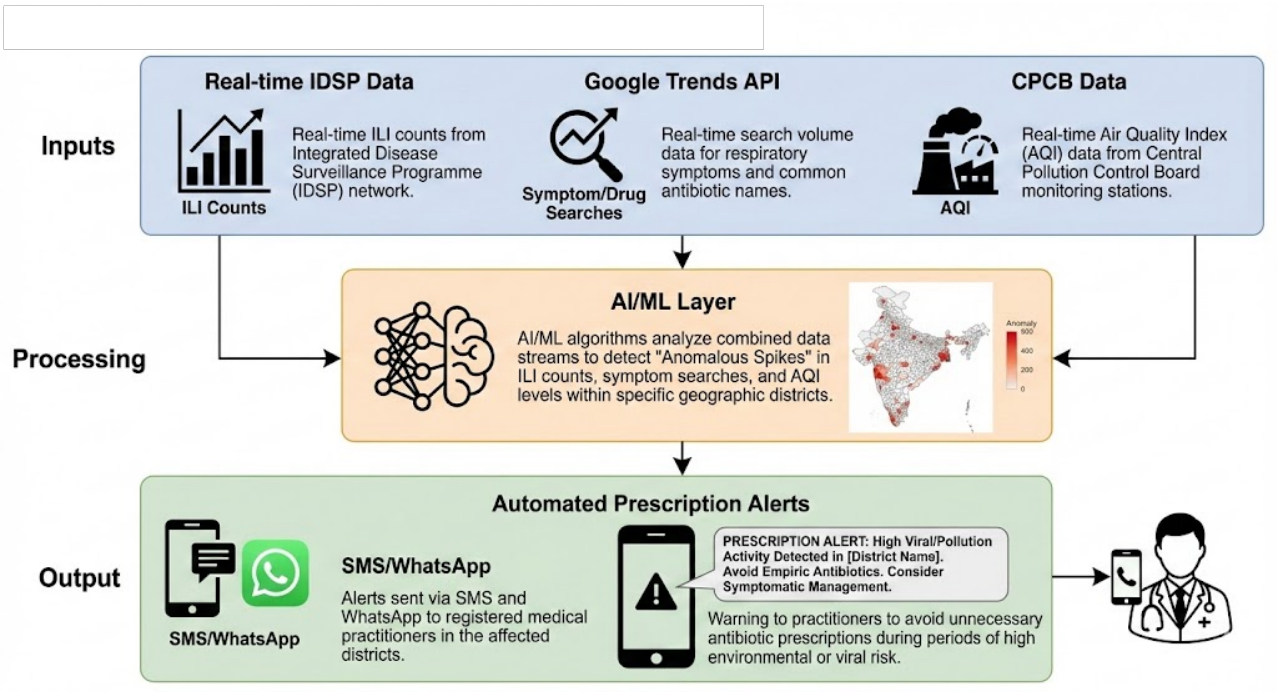


Figure 4. Conceptual Overview of a Multi-Stream Surveillance and Clinical Alert Framework. The schematic illustrates an exploratory architecture integrating sentinel virology (IDSP/FluNet), ambient air quality (CPCB), and retail sales trends, coupled with automated alert thresholds for outpatient antimicrobial stewardship.

digital behavioural data streams. Nonetheless, several important methodological limitations must be acknowledged:

- Ecological Fallacy: The analysis relies entirely on aggregate population-level data. Consequently, individual-level prescribing practices, patient adherence, or clinical appropriateness cannot be inferred. We cannot directly verify what proportion of retail antibiotic packs sold was consumed specifically for viral influenza versus legitimate secondary bacterial

infections.

- Market Coverage and Urban Bias: While AIOCD-AWACS covers approximately 90% of the organized retail pharmacy sector, it underrepresents the informal and unorganized pharmacy sector in rural India. Similarly, CPCB CAAQMS stations are situated predominantly in urban and peri-urban centres, introducing a potential metropolitan exposure bias.

- Co-Circulating Pathogens and Residual Confounding: Sentinel data did not capture complete surveillance metrics for other co-circulating respiratory viruses (such as RSV, human rhinovirus, adenovirus, and SARS-CoV-2 sublineages), which may independently contribute to winter respiratory illness and healthcare attendance. Furthermore, unmeasured factors such as regional doctor-to-population ratios, private sector market share, over-the-counter dispensing practices, and state-level enforcement of Schedule H/H1 pharmacy regulations represent potential residual confounders.

- Pre-Intervention Baseline Duration: The interrupted time-series analysis was constrained by a three-month pre-intervention baseline (January–March 2023), limiting statistical power to characterize secular pre-existing trends independently of the acute 2023 surge.

5 Conclusions

Monthly retail antibiotic sales in India display a consistent seasonal co-occurrence with viral influenza A(H3N2) transmission, with sales volumes substantially heightened during months of severe ambient air pollution. Non-binding national advisories were not associated with a measurable structural break in retail sales trajectories. While these aggregate ecological associations cannot establish individual clinical prescribing decisions, they demonstrate the utility of multi-stream epidemiological and environmental surveillance in characterizing antimicrobial demand. Future public health strategies should evaluate active, data-driven stewardship approaches coupled with affordable point-of-care diagnostics to reduce unnecessary antibiotic utilization during seasonal respiratory epidemics.

Declarations

Declaration of Generative AI and AI-assisted technologies in the writing process: During the preparation of this work the authors used generative AI and AI-assisted technologies (specifically large language models) solely for grammatical refinement, language polishing, and manuscript formatting. After using this tool/service, the authors reviewed and edited the content as needed and take full responsibility for the content of the published article. All underlying scientific concepts, study design, data collection, statistical analyses, interpretations, and final text were authored, verified, and approved by the human authors.

Funding: This research received no specific grant or external financial support from any funding agency in the public, commercial, or not-for-profit sectors.

Conflict of interest: The authors declare that they have no financial or commercial conflicts of interest or personal relationships that could have appeared to influence the work reported in this paper.

Ethical approval: Not applicable. This study exclusively analyzed secondary, aggregated, fully anonymized ecological datasets available in the public domain or through commercial research audits. No individual human participants, identifiable personal health records, or animal models were directly involved, and institutional ethics review exemption applies.

Consent to participate: Not applicable. The study did not involve individual human participants or clinical trials.

Consent for publication: Not applicable. The manuscript contains no individual person's identifiable data, images, or details in any form.

Availability of data and material: All epidemiological, environmental, and search volume datasets analyzed in this study are openly accessible via their respective official portals: Integrated Disease Surveillance Programme (IDSP; https://idsp.mohfw.gov.in), WHO FluNet (https://www.who.int/tools/flunet), Central Pollution Control Board (CPCB; https://app.cpcbccr.com/ccr/), and Google Trends (https://trends.google.com). Pharmaceutical retail sales metrics from AIOCD-AWACS represent commercial market audit datasets utilized under academic research access provisions. Harmonized aggregate time-series datasets are available from the corresponding author upon reasonable academic request.

Authors' contributions: All authors made substantial contributions to the conception, design, and execution of this work. Conceptualization: Amit Patnaik, Vishwas Chavan; Methodology and Formal Analysis: Amit Patnaik, Anita Sinha, Duryodhan Sahu, Abinash Dutta; Data Curation: Amit Patnaik, Anita Sinha, Duryodhan Sahu; Software and Coding: Amit Patnaik, Bibhudutta Mishra; Writing – Original Draft: Amit Patnaik, Abinash Dutta; Writing – Review & Editing: Vishwas Chavan, Bibhudutta Mishra, Anita Sinha, Duryodhan Sahu; Supervision and Project Administration: Amit Patnaik, Vishwas Chavan. All authors read and approved the final submitted manuscript.

Acknowledgment: The authors express their sincere gratitude to the surveillance and technical teams at the Integrated Disease Surveillance Programme (IDSP), the Ministry of Health and Family Welfare (MoHFW), the World Health Organization (WHO) Global Influenza Surveillance and Response System (GISRS), the Central Pollution Control Board (CPCB), and Google Trends for maintaining publicly accessible data platforms that support public health and epidemiological research.

How to cite this paper

Patnaik A, Sinha A, Sahu D, Dutta A, Mishra B, Chavan V. Seasonal influenza A(H3N2) surges, ambient air pollution, and retail antibiotic sales in India (2023–2025): an ecological time-series and triangulation study. *Journal of Population Health Dynamic* . 2026;1(1):10·17.

References

[1] Boppana H, et al. The Recent H3N2 Viral Outbreak in India, 2023: Is It Worrying? Health Sci Rep 2023; 6(10): e1417. doi: 10.1002/hsr2.1417.

[2] Chadha MS, et al. Dynamics of Influenza Seasonality at Sub-Regional Levels in India and Implications for Vaccination Timing. PLoS One 2015; 10(5): e0124122. doi: 10.1371/journal.pone.0124122.

[3] Ministry of Health and Family Welfare (MoHFW). Update on Seasonal Influenza 2023 / ICMR Advisory on Judicious Antibiotic Use. New Delhi: Government of India; 2023.

[4] Baldo V, et al. The New Pandemic Influenza A/(H1N1)pdm09 Virus: A Historical Perspective. J Prev Med Hyg 2016; 57(1): E19–E22.

[5] Corrin B, Nicholson AG. Infectious Diseases of the Respiratory Tract. In: Pathology of the Lungs. 3rd ed. London: Churchill Livingstone / Elsevier; 2011: 153–214. doi: 10.1016/B978-0-7020-3369-8.00007-8.

[6] Biselli R, et al. A Historical Review of Military Medical Strategies Against Influenza and Respiratory Pandemics. Biomedicines 2022; 10(9): 2050. doi: 10.3390/biomedicines10092050.

[7] Dicpinigaitis PV. Cough: An Unmet Clinical Need. Br J Pharmacol 2011; 163(1): 116–124. doi: 10.1111/j.1476-5381.2010.01198.x.

[8] Laxminarayan R, Chaudhury RR. Antibiotic Resistance in India: Drivers and Opportunities for Action. PLoS Med 2016; 13(3): e1001974. doi: 10.1371/journal.pmed.1001974.

[9] Farooqui HH, et al. Community Level Antibiotic Utilization in India: An Analysis of Private Sector Dispensing Data. PLoS One 2018; 13(10): e0204805. doi: 10.1371/journal.pone.0204805.

[10] Gandra S, et al. Antimicrobial Resistance Surveillance in Low- and Middle-Income Countries: Progress and Challenges in Implementation. Clin Microbiol Rev 2020; 33(4): e00048-19. doi: 10.1128/CMR.00048-19.

[11] Walia K, et al. Antimicrobial Stewardship Programme (AMSP) Practices in India: ICMR Experience and National Action Plan. Indian J Med Res 2015; 142(2): 130–138. doi: 10.4103/0971-5916.164228.

[12] Sulis G, et al. Antibiotic Prescription Practices in Primary Care across India: A Standardized Patient Study. PLoS Med 2020; 17(11): e1003139. doi: 10.1371/journal.pmed.1003139.

[13] Ginsberg J, et al. Detecting Influenza Epidemics Using Search Engine Query Data. Nature 2009; 457(7232): 1012–1014. doi: 10.1038/nature07634.

[14] Koul PA, et al. Differences in Influenza Seasonality by Latitude, Northern India. Emerg Infect Dis 2014; 20(10): 1746–1749. doi: 10.3201/eid2010.140431.

[15] Potdar V, et al. Influenza A(H3N2) Virus Circulation and Genomic Characterization in India during 2023. J Med Virol 2023; 95(8): e29012. doi: 10.1002/jmv.29012.

[16] Balakrishnan K, et al. The Impact of Air Pollution on Deaths, Disease Burden, and Life Expectancy across the States of India: The Global Burden of Disease Study 2017. Lancet Planet Health 2019; 3(1): e26–e39. doi: 10.1016/S2542-5196(18)30261-4.

[17] Van Boeckel TP, et al. Global Antibiotic Consumption 2000 to 2010: An Analysis of National Pharmaceutical Sales Data. Lancet Infect Dis 2014; 14(8): 742–750. doi: 10.1016/S1473-3099(14)70780-7.

[18] Atal S, et al. Continued Use of Azithromycin for Mild COVID-19 in India: A Real-World Prescription Audit. J Family Med Prim Care 2021; 10(12): 4341–4346. doi: 10.4103/jfmpc.jfmpc_848_21.

[19] Ghosh S, et al. Antimicrobial Resistance Threats in the Emerging COVID-19 Pandemic. J Infect Public Health 2021; 14(4): 555–560. doi: 10.1016/j.jiph.2021.02.003.

[20] Mijac V, et al. Trends in Macrolide Resistance in Respiratory Tract Pathogens: A Global Perspective. Epidemiol Infect 2015; 143(3): 648–656. doi: 10.1017/S095026881400122X.

[21] Barker AK, et al. Social Determinants of Antibiotic Misuse: A Qualitative Study of Primary Care Physicians in India. BMC Public Health 2017; 17(1): 333. doi: 10.1186/s12889-017-4261-x.

[22] Kotwani A, et al. Antibiotic-Prescribing Practices in Primary, Secondary and Tertiary Care in New Delhi, India. Value in Health 2012; 15(4): S116–S119. doi: 10.1016/j.jval.2011.11.008.

[23] McGettigan P, et al. Access, Watch, and Reserve Antibiotics in India: Challenges for National Policy Implementation. Lancet Glob Health 2017; 5(11): e1075–e1084. doi: 10.1016/S2214-109X(17)30365-0.

[24] Indian Council of Medical Research (ICMR). Antimicrobial Resistance Surveillance Network (AMRSN) Annual Report 2023. New Delhi: ICMR; 2024.