भारतीय प्रौद्योगिकी संस्थान खड़गपुर

INDIAN INSTITUTE OF TECHNOLOGY KHARAGPUR

MUST LAB

Multimodal Urban Sustainable Transportation Research Lab

Assessing the Impact of Air Pollution Exposure on Travel Behaviour

by

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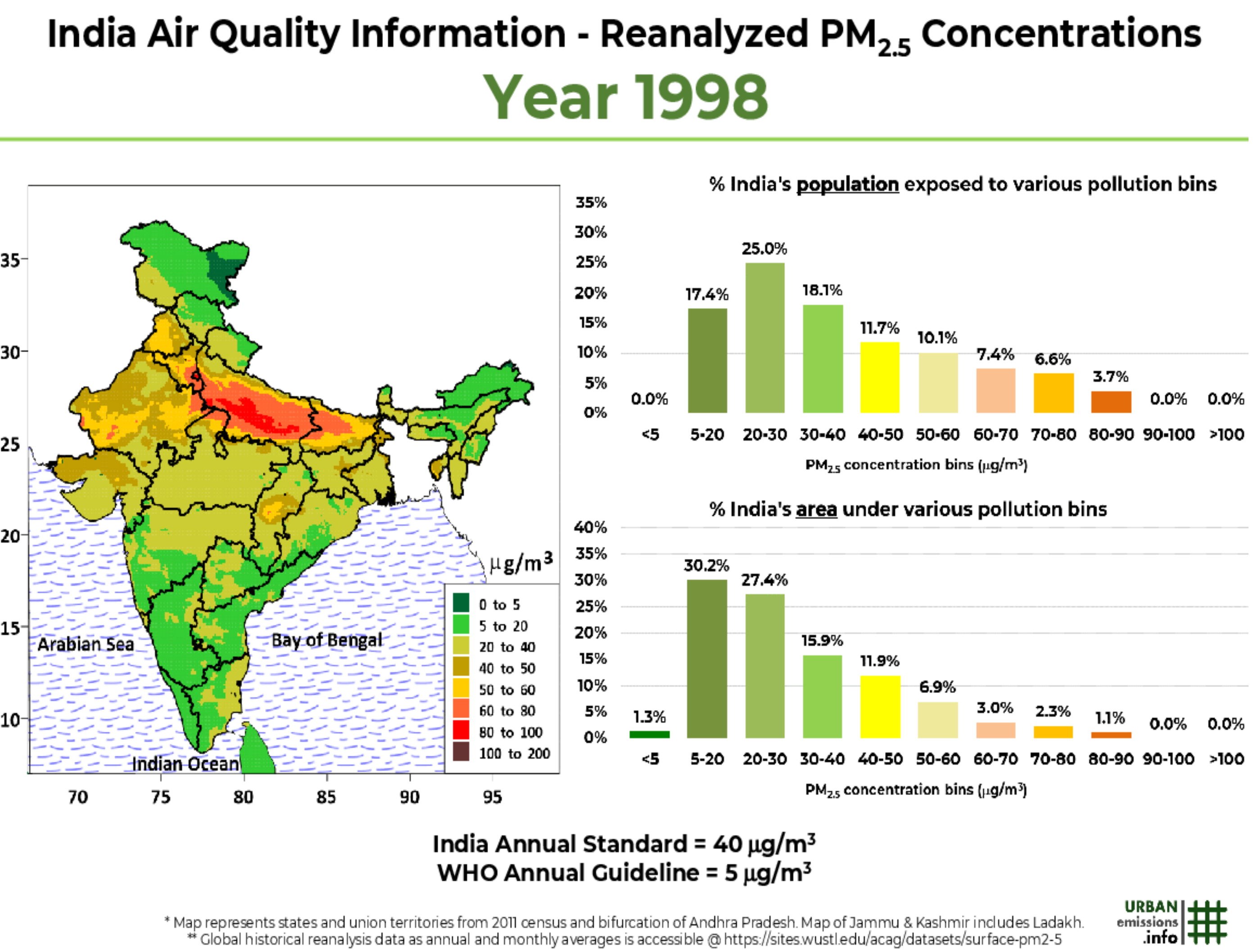
22th August

Background: The Invisible Crisis Globally



99%

99% of the world's population lived in areas that exceeded the WHO guideline for PM2.5 (WHO, 2023).

5 Years

Life Expectancy Reduced by 5 years (Greenstone and Fan,2020)

16 to 23 months

Air pollution collectively reduced life expectancy by 16 to 23 months in India (State Of Global Air/2019)

2nd

India is the second most polluted country in the World (Greenstone and Fan, 2020)

5th

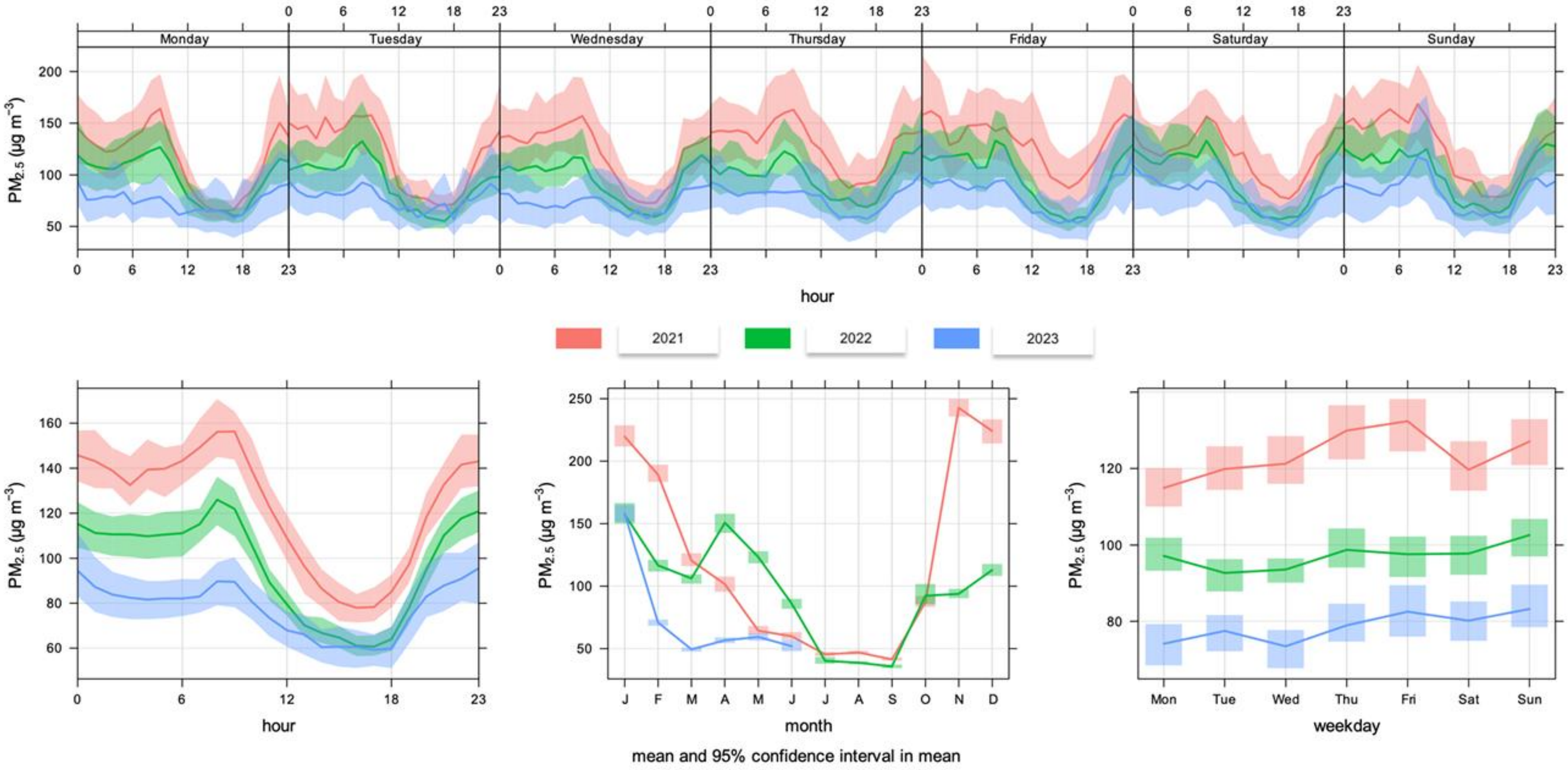
Air pollution is the fifth leading risk factor for mortality worldwide (State Of Global Air/2019).

1.7 Million

In India, 1.7 million deaths were due to air pollution in 2019 (The Lancet Planetary Health Study, 2021).

Background: The Invisible Crisis in INDIA

Diurnal $PM_{2.5}$ Trend in Kolkata



Air Pollution Exposure and Travel Behavior: Is There a Link?

YES, a Significant One.

- Travel is one of the activities where commuters are **most exposed** to air pollution in daily life (Singh et al. 2021).
- On average, **8%** of time spent in transport is responsible for **32.7%** of exposure (Dons et al. 2019) and more the time, more the exposure (*concentration * travel time*).

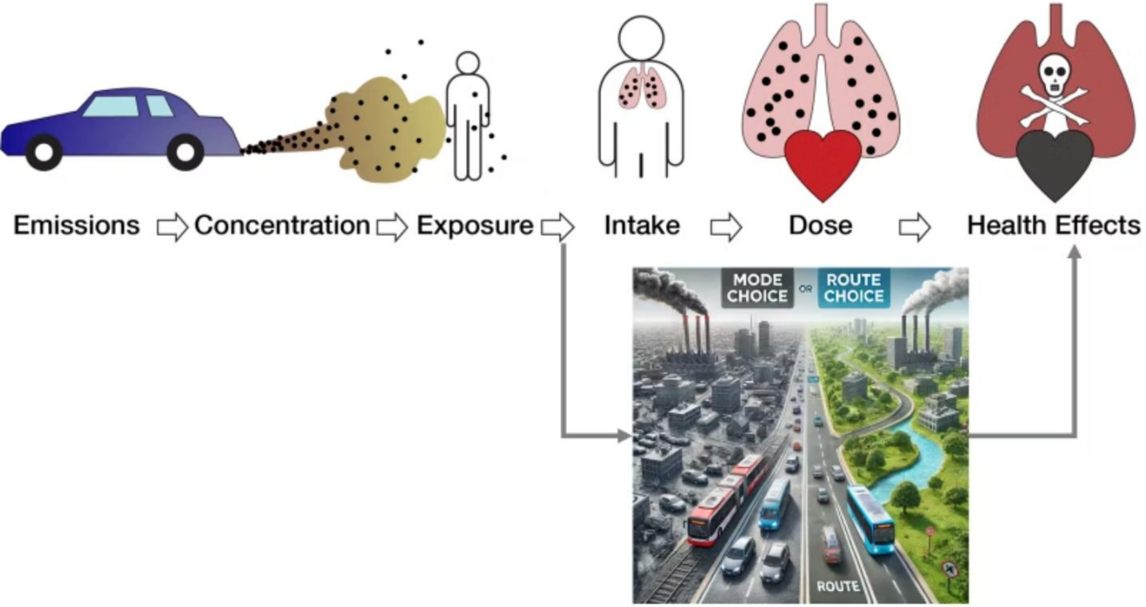
Empirical Evidence: Travel and Exposure

Author	Country	Exposure during activities
Beckx et al., 2009	Netherlands	**Highest exposure is estimated for in-transport**, followed by workplaces, shopping areas and home activities
Dons et al., 2012	Belgium	• Travelling (**6%** of 24 hours), the in-transport results in **21% of black carbon exposure.** • Concentrations levels in transport is found to be **2-5 times higher than home.**
Dons et al., 2019	Belgium, Spain and United Kingdom	**8%** time spent in transport is responsible for **32.7% of exposure**
Shekarrizfard et al., 2020	Toronto	For UFP and BC, the **mobility based exposure is 11.6% and 63.2%** higher than home based exposure.
Smith et al., 2016	London	People spend 94.7 to 97.9% of their time indoors and **2.1 to 5.3%** in **transit** and responsible for **30% exposure**.
Lu et al., 2019	Netherlands	**Travel contribution** to NO_2 exposure is between 8.0 and 18.8% and to outdoor PM10 is between **4.1 and 12.2%.**

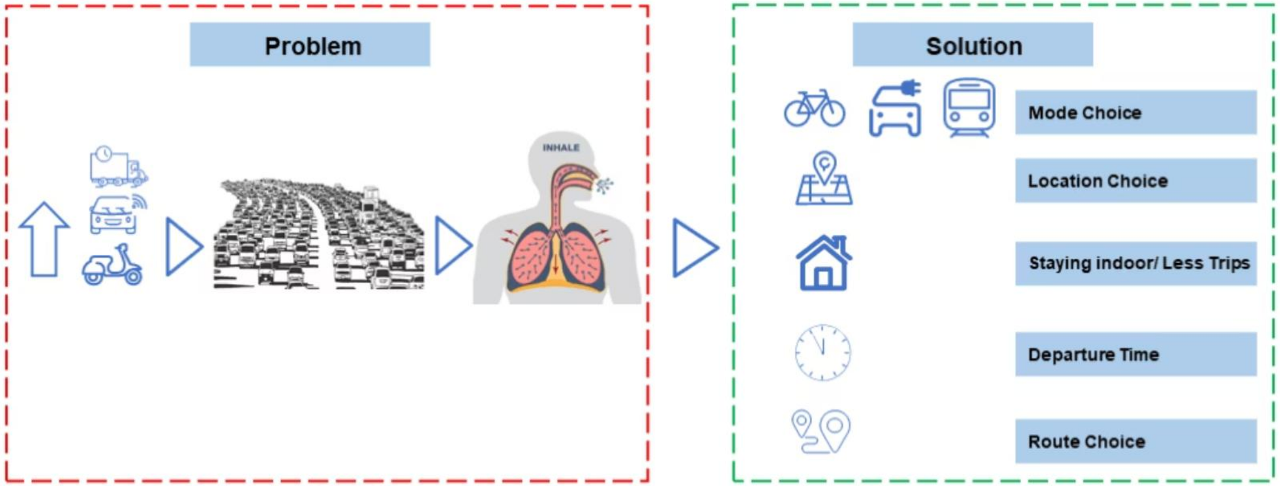
Inferences: Commuters experience significantly higher exposure to pollutants while outside home/indoors during travel.

Addressing the Challenge

The Problem



The Solution



Research Questions?

1. What are the key factors that influence individual exposure to air pollution during daily travel in urban settings?
2. How can a panel-based RP–SP survey be designed and implemented in the Indian urban context to capture seasonal variation (winter and summer) in travel behaviour?
3. How do travellers in Kolkata perceive and respond to air quality information in terms of route and mode choice decisions?
4. To what extent does travel behaviour vary across seasons (winter and summer) when air pollution levels differ significantly?
5. How can latent heterogeneity in awareness, attitudes, and protective actions be modelled to explain variations in behavioural responses?
6. In what ways can modelling insights be operationalised into decision-support tools (such as personalised routing applications and dashboards) to reduce exposure and support sustainable mobility?

Research Objectives & Framework

Objective 1
To establish the conceptual and methodological framework.

Systematic Literature Review
Identify key determinants of exposure

Develop Panel Survey Framework
Capture seasonal variation (Winter/Summer)

Design Stated Preference (SP) Experiment
- Define Attributes & Levels
- Generate D-Optimal Design
- Pre-test & Refine

Implement Digital Survey Platform

Objective 2
To empirically analyze econometric modeling...

Administer RP-SP Panel Survey
Kolkata (Winter & Summer)

Latent Class Cluster Analysis (LCCA)
Uncover traveller segments

Estimate Discrete Choice Models
(MNL, Mixed Logit, Joint RP-SP)

Extend to Panel-Data Models
Capture seasonal variation & state dependence

Objective 3
To operationalise findings into practical tools...

Develop Personalised DRUM App
Integrate preferences & real-time AQI

Build Interactive Air Quality Dashboard
Visualize exposure levels & risk patterns

Derive Policy Insights & Recommendations

Objective – 1

1. **To establish the conceptual and methodological framework for capturing travel behaviour under air pollution exposure**

1.1. Identify influencing factors through a systematic literature review to classify the key determinants of exposure during travel (mode, route, time-of-day, awareness, and protective actions).

1.2. Develop a panel survey framework to capture seasonal variation (winter and summer) in exposure and travel behaviour.

1.3. Design and implement a digital survey platform to administer RP and SP surveys efficiently while ensuring accessibility and data integrity.

1.4. Design of a stated preference (SP) of route and mode choice experiment:

- 1.4.1. Define relevant travel attributes (e.g., travel time, cost, waiting time, cleanliness, AQI levels) based on literature and pilot studies.
- 1.4.2. Specify attribute levels in line with empirical evidence and urban transport conditions.
- 1.4.3. Generate an efficient fractional factorial design (D-optimal) to construct choice sets that balance realism with statistical efficiency.
- 1.4.4. Pre-test and refine the experimental design to ensure clarity, realism, and respondent understanding.

Objective – 1.1:Factors identifications

1. Identify influencing factors through a systematic literature review to classify the key determinants of exposure during travel (mode, route, time-of-day, awareness, and protective actions).

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A review of air pollution exposure impacts on travel behaviour and way forward

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ARTICLE INFO

Keywords:
Air quality
Travel choices
Travel behaviour

ABSTRACT

Travel is an activity that everyone carries out in their daily life. While travelling, commuters are exposed to air pollution, which is likely to impact their mode, route, and/or departure time choice. Various review studies on vehicular emissions have been conducted in the past, but the aspects of its impact on resulting air quality and travel behaviour are sporadic and largely unorganized. In an effort to close this gap, this study carried out an extensive review of 63 studies to document the influence of air pollution on travel behaviour. The findings reveal that a majority of the research in this arena has been carried out in the USA and China, and the highest instances of behaviour change was observed when users shifted their routes to reduce exposure. The awareness about AQI and its real-time pre-trip information plays a vital role in lowering commuters' air pollution exposure. Finally, strategies such as congestion/emission pricing schemes, MaaS, etc. could provide a clean travel environment to all commuters by reducing their exposure during travel.

Objective – 1.1 (cont.)

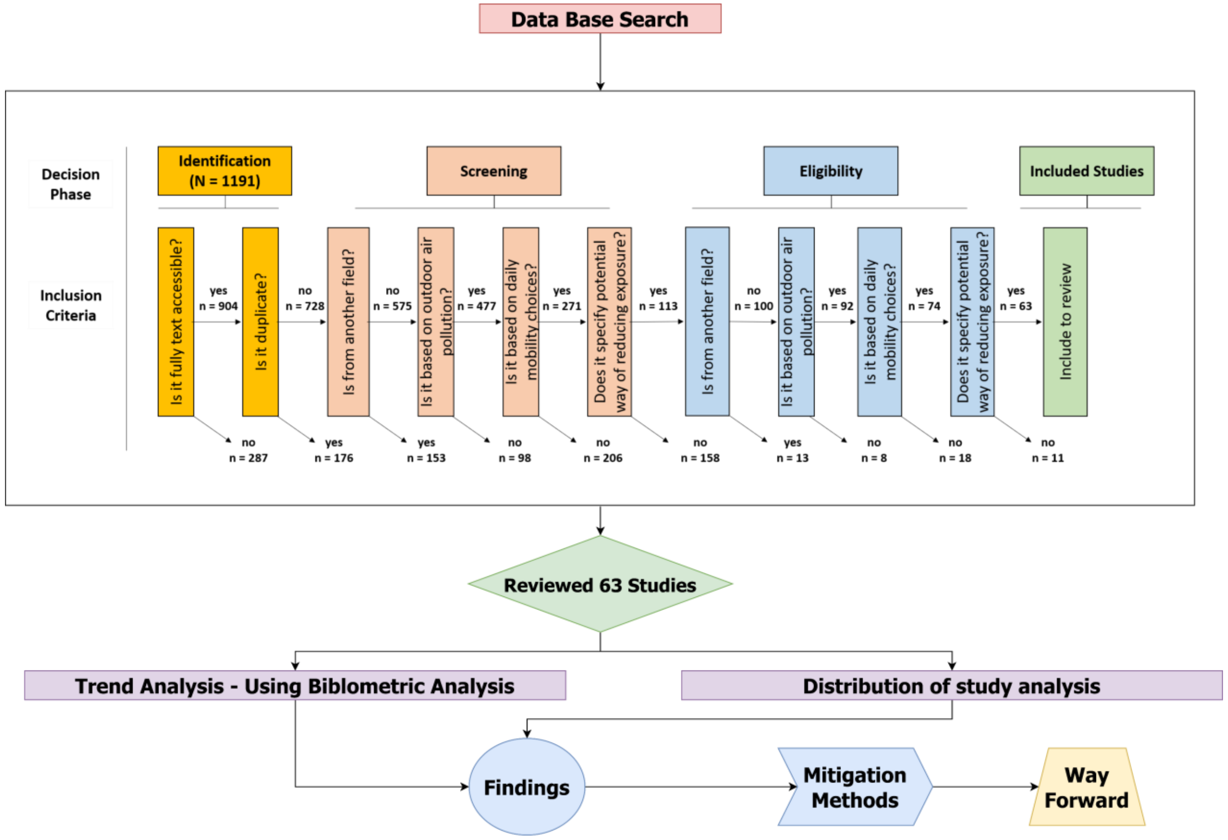
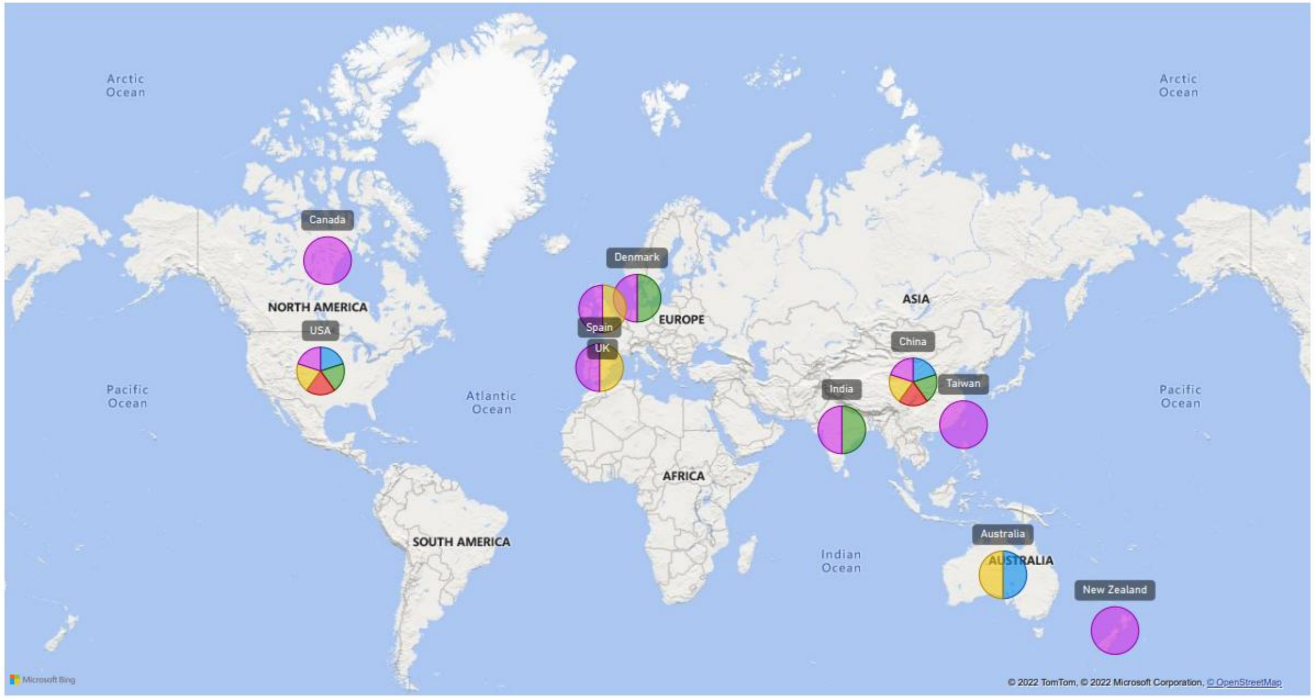


Fig: Systematic screening of literature. (Image Source: Author).



Avoidance choice • Departure time choice • Location choice • Mode choice • Route choice

majority of the research in this arena has been carried out in the **USA and China**

Objective – 1.1 (cont.)

Mode choice

Route choice

Maximum behavior change seen in route shifts

Avoidance choice

Departure time choice

Awareness about AQI and its real-time **pre-trip information** plays a vital role in lowering commuters' air pollution exposure.

Objective – 1.2 (Panel Data Framework)

What is Panel Data?

Longitudinal Tracking

Repeated measurements from the same respondents across multiple time points (waves).

Within-Person Change

Crucial for estimating individual changes, controlling for unobserved differences.

Controls for Unobserved Factors

By observing the same entities over time, panel data helps account for time-invariant unobserved characteristics, reducing bias in estimates.

Enables Policy Evaluation

Panel data allows for precise evaluation of policy interventions and program impacts by comparing outcomes before and after implementation for the same subjects.

Captures Dynamic Processes

It provides unique insights into how phenomena evolve, change, and interact over time, enabling the study of dynamic relationships and lagged effects.

Objective – 1.2 (Panel Data Framework)

Key Challenges in the Indian Urban Context

Respondent Recontact

High urban mobility, frequent SIM card changes, and informal addresses make recontacting the same person across waves extremely difficult.

Precise Geolocation Absence

Standard survey tools like Google Forms often lack the capability to capture accurate latitude/longitude coordinates at the exact interview location.

Brittle Matching Across Waves

Without reliable geotags and unique Panel IDs, linking data from the same respondent across different waves becomes highly error-prone and unreliable.

Operational Complexities

Managing multilingual scripts, ensuring data privacy and consent, and accommodating device variability in the field add layers of complexity.

Objective – 1.2 (Panel Data Framework)

Overcoming Challenges: Our Approach

Source Geolocation & Panel ID

- Capture **lat/long + timestamp + accuracy** with consent for every interview.
- Auto-generate and return a **unique Panel ID** to respondents post-submission (QR/SMS/email).

Geofenced Re-identification

- On revisit, match by **Panel ID** and/or **nearby lat/long** (within a defined buffer).

Instrument Invariance & Retention

- Lock wording/scales across waves; implement version control.

Real-time Quality Assurance

- Dashboards to flag outliers (duration, straightlining, duplicates) instantly.
- Track Winter/Summer progress and field team efficiency in real-time.

Impact of Air Pollution Exposure on Travel Behaviour

Did You Know?

Our exposure to air pollution is highest during travel—more than any other daily activity! 🚗 🚌 From sitting in traffic jams ⏳ to waiting at bus stops 🕒, commuting exposes you to harmful pollutants at levels far greater than indoors or other activities. 🌎 💡

About the Survey 📝

This survey explores how air quality impacts your travel decisions. Discover how air pollution exposure influences your choice of routes and modes, encouraging a shift towards greener options like public transit 🚍 🚇.

Your participation contributes to creating smarter, healthier urban mobility solutions for a sustainable future. 🌱

Start Survey

📧 For Queries or Assistance

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In-House Survey Platform

Designed for Panel Data Survey

Live Survey

Live Responses

GitHub

Code Repo: https://github.com/kapil2020/react-frontend-kgp
Survey link: https://survey-iitkgp.vercel.app/
Real-time response link: https://survey-iitkgp.vercel.app/responses

Platform Capabilities: Precision & Performance

Core Technology

- **Single-Page Form (SPA):** All questions on a dynamic page with conditional reveals, instant validation.
- **Tech Stack:** ReactJS (UI/logic), Tailwind CSS (responsive design), D3.js (real-time charts & maps).

Data Integrity & Security

- **Built-in GPS:** Consented lat/long, accuracy, and timestamp recorded with each submission.
- **Auto Panel ID:** Unique ID displayed and shareable via QR/SMS/email for Wave-2 re-identification.
- **Data Format:** Structured JSON payloads with schema versioning for reproducible pipelines.

Advanced Matching & Quality Control

- **Geofenced Re-match:** Locate prior respondents via Panel ID or proximity search (± buffer).
- **Quality Controls:** Duplicate detection, duration checks, device metadata, enumerator flags.

Real-time Insights

- **Real-time Analytics:** Interactive dashboards to filter by Winter/Summer waves, track completion/attrition, and flag anomalies.
- **Secure Export:** De-identified, analysis-ready long format for advanced panel modeling.

Panel Survey Methodology

01

Sampling & Onboarding

Define strata, recruit respondents, obtain consent, assign unique Panel IDs.

02

Wave 1: Winter Data Collection

Collect socio-demographic, health, AQI awareness, and travel diary data. Record lat/long at interview site and return Panel ID to respondent.

03

Wave 2: Summer Data Collection

Re-identify respondents via Panel ID or geofence. Replicate the instrument for comparability.

04

Linkage & Validation

Join Winter and Summer data using Panel ID + time/location stamps. Conduct consistency checks and de-identification.

Objective – 1.3 (Survey Tool)

Demonstrating Data Quality & Coverage

723

Winter Valid Observations

High-quality observations retained for analysis.

583

Summer Valid Observations

High-quality observations retained for analysis.

96.9%

Winter Effective Response Rate

Valid completed surveys from eligible cases.

78.2%

Summer Effective Response Rate

Valid completed surveys from eligible cases (N=746).

- **Accurate Matching:** Combination of **Panel ID** and **geofence** significantly minimizes mislinks across waves, ensuring high data integrity.
- **Measurement Consistency:** Identical wording and scales were maintained across seasons, ensuring strict comparability of responses.
- **Rigorous QC:** Comprehensive duration and logic checks, duplicate removal, and de-identification processes were applied to ensure data robustness.

Objective – 1.4 (Survey Design)

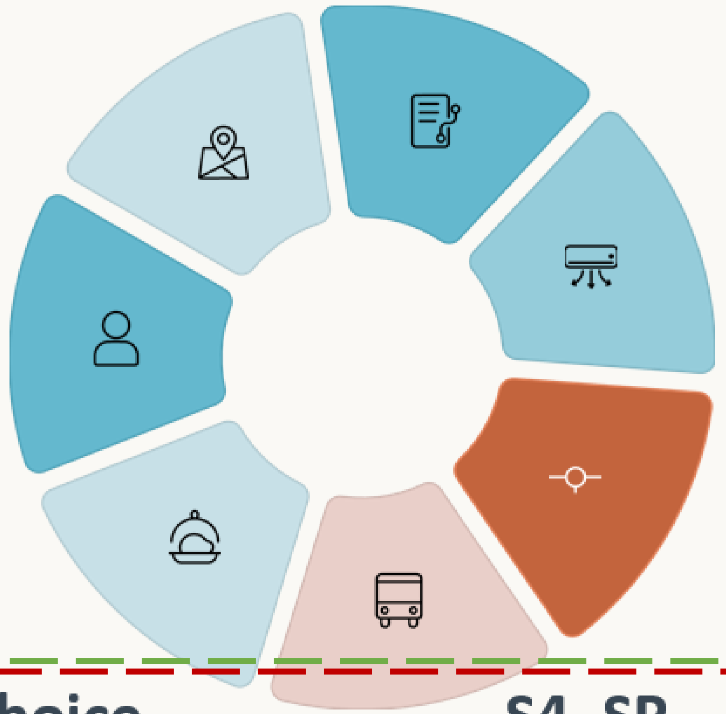
RP-Survey

S0. Pre-Survey (GPS)

Latitude/Longitude capture; optional landmark.

S1. Trip Information

Typical O–D, primary mode, frequency, purpose, distance.



S2. Air-Quality Awareness

Health awareness, perceived exposure, AQI knowledge, protective actions.

S6. Socio-Demographics

Gender, age, occupation, education, income, household, vehicles, license.

S3. Perceptions (Likert 1–5)

Awareness, PT preference, PV attitudes, route preference, tech info.

SP-Survey

S5. SP — Route Choice

Route A vs B; attributes: pre-trip AQI, route AQI, time, cost, green cover.

S4. SP — Mode Choice

Car / Bus / Metro / IPT; attributes: AQI, time, cost, wait, cleanliness.

Objective – 1.4 (Survey Design)

Mode Choice Survey

Section 4: Stated Preference Survey(Mode Choice) *

Choice 1: Select Your Preferred Travel Option *

Attributes	Car	Bus	Metro	IPT
A Q I	Poor(201-300) Poor (201-300)	Poor(201-300) Poor (201-300)	Moderate(101-200) Moderate (101-200)	Poor(201-300) Poor (201-300)
Travel Time	High: 50 min	Medium: 35 min	Low: 15 min	Medium: 20 min
Travel Cost	Low: 50 INR	High: 20 INR	Medium: 20 INR	High: 30 INR
Waiting Time	No waiting	Medium: 10 min	High: 10 min	Low: 2 min
Cleanliness	Moderate Cleanliness	Low Cleanliness	High Cleanliness	Low Cleanliness
Trip Purpose	Work/Business	Leisure/Personal	Work/Business	Work/Business
Select	Car	Bus	Metro	IPT

Route Choice Survey

Section 5: Route Preference Survey(Route Choice) *

Choice 1: Select Your Preferred Route *

Attributes	Route A	Route B
Pre-trip AQI available	Not Available	Not Available
Air Quality Level	Poor (201-300)	Good (0-50)
Travel Time	Low: 20 min	Medium: 30 min
Travel Cost	Low: 15 INR	Medium: 25 INR
Trip Purpose	Work/Business	Education
Delay	Significant Delay 26-50% additional time	Moderate Delay 11-25% additional time
Green Cover	Low Green Cover (urban/industrial areas)	Moderate
Select		

Objective – 2 – Data analysis; Latent class cluster analysis; mode choice

2. **To empirically analyse behavioural heterogeneity and seasonal dynamics**

   2.1. Administer the RP–SP panel survey in Kolkata across both winter and summer seasons.

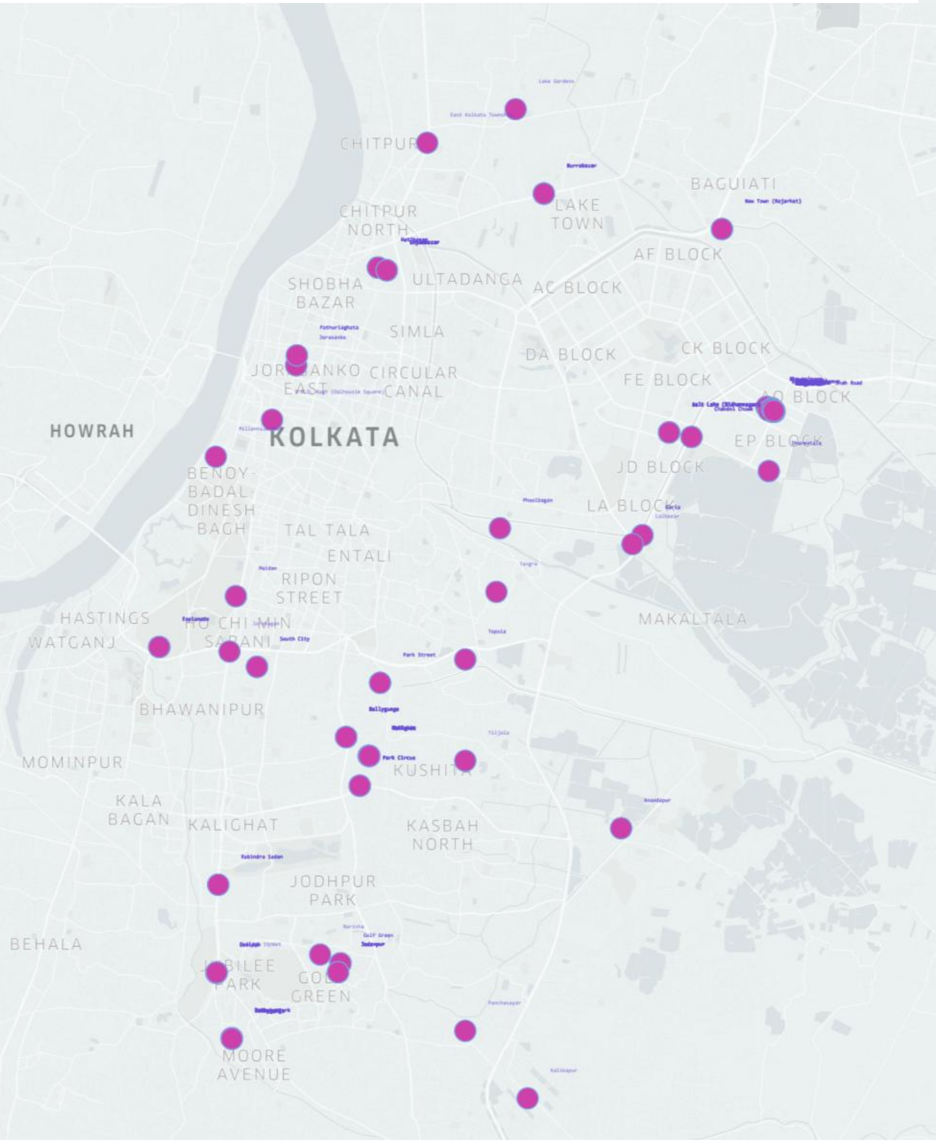
   2.2. Apply Latent Class Cluster Analysis (LCCA) to uncover segments of travellers based on awareness, attitudes, and protective actions.

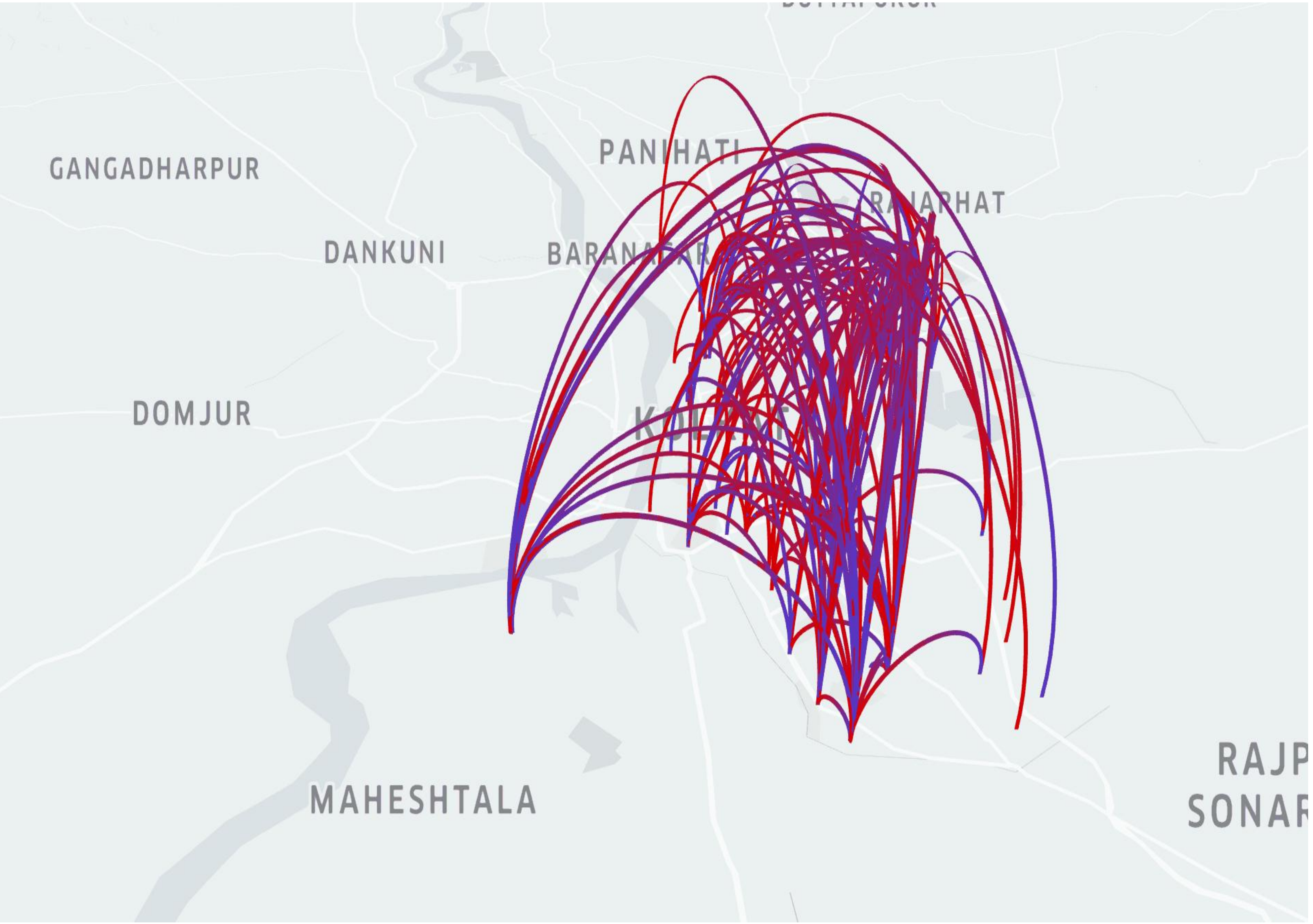
   2.3. Estimate discrete choice models (MNL, Mixed Logit, and joint RP–SP) to examine the impact of air pollution exposure on mode and route choice.

   2.4. Extend the analysis to panel-data models to capture seasonal variation and state dependence between winter and summer travel behaviour.

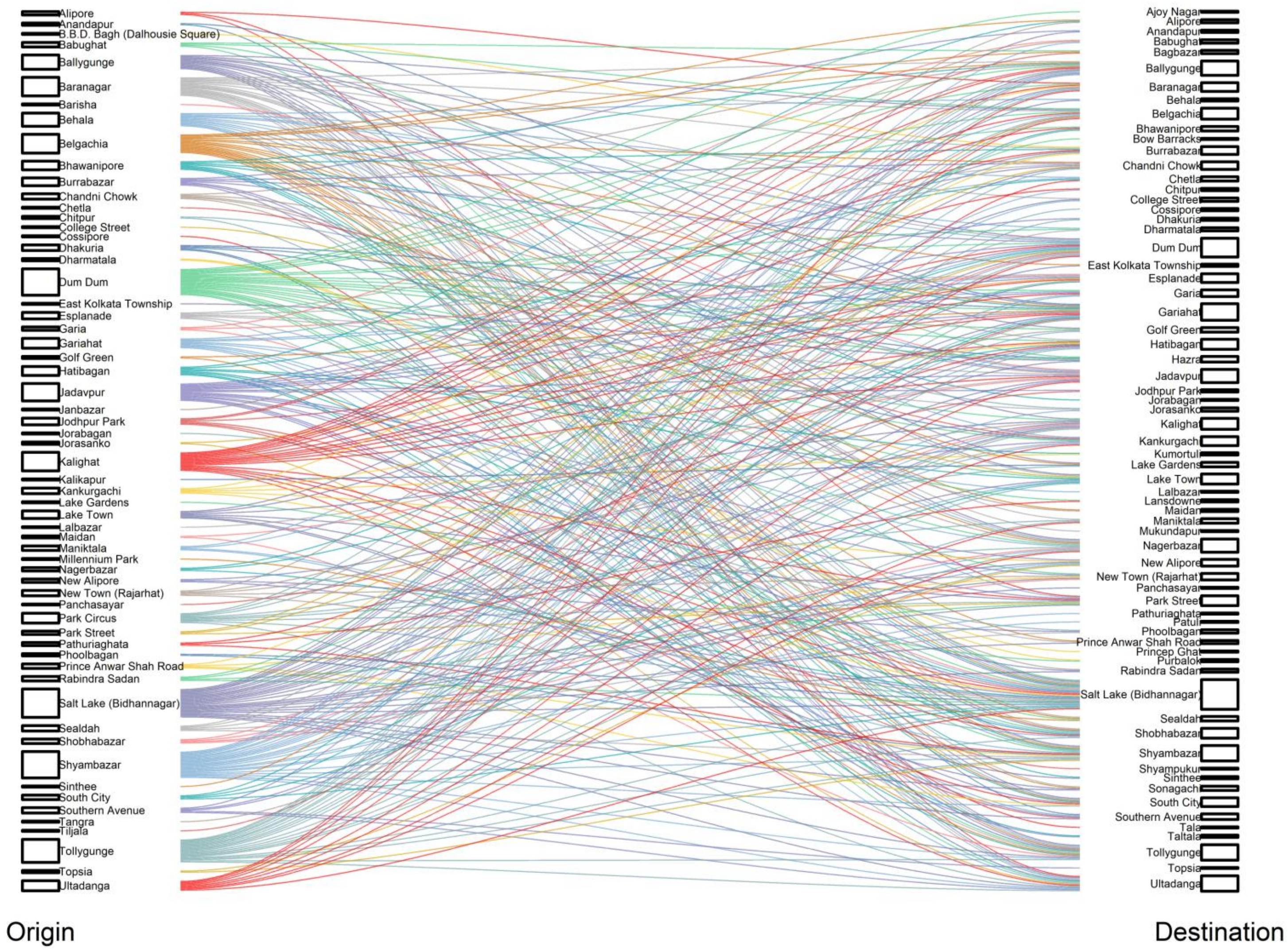
Meena, K.K., and A.K. Goswami (2026). *"Not all travellers think alike: Segmenting travel behaviour under air pollution exposure using a hybrid latent class and discrete choice approach."* Submitted to the **Transportation Research Board (TRB) 2026** Annual Meeting, Washington, DC

Objective – 2 – Data analysis; Latent class cluster analysis; mode choice

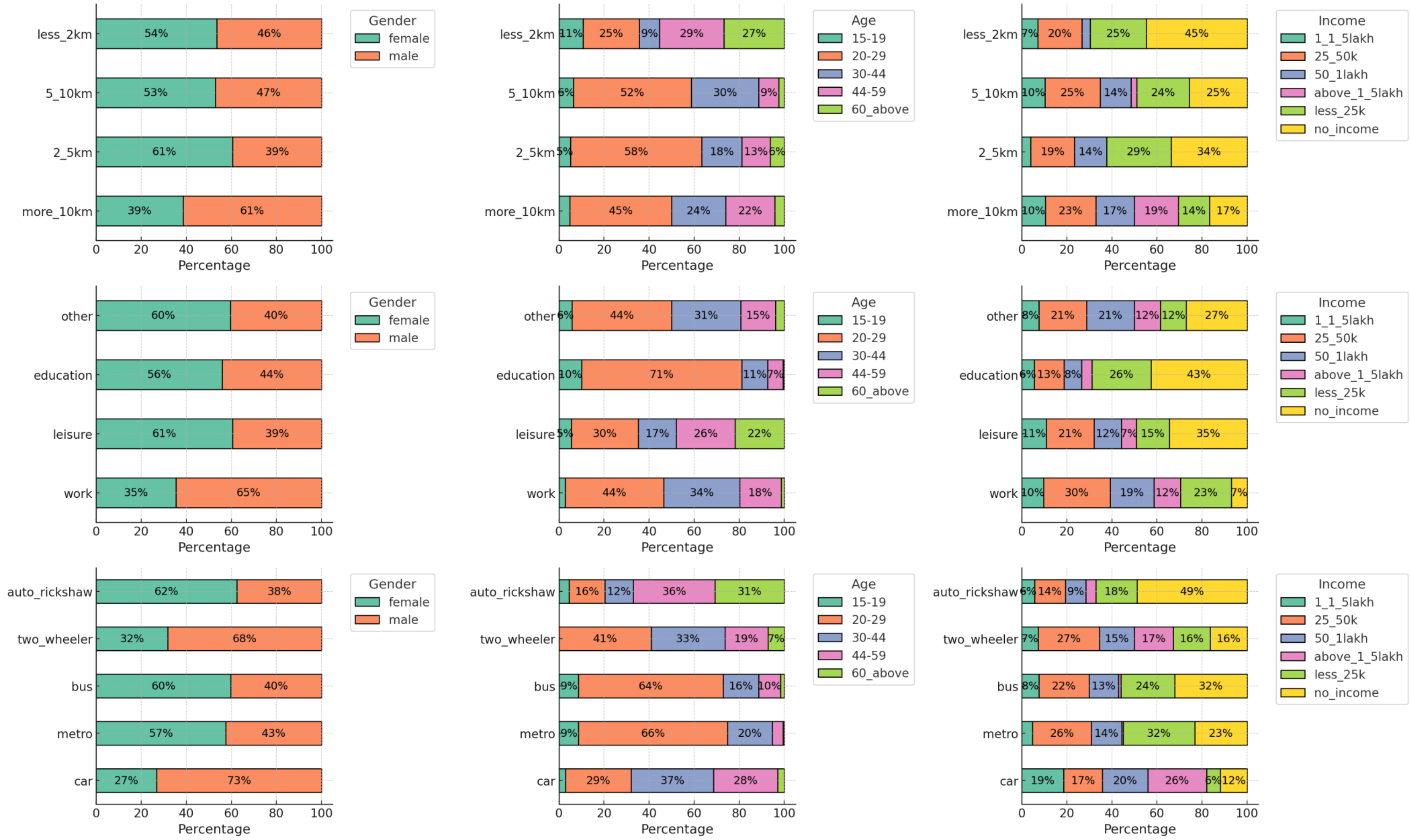




Objective – 2 – Data analysis; Latent class cluster analysis; mode choice



Objective – 2 – Data analysis; Latent class cluster analysis; mode choice



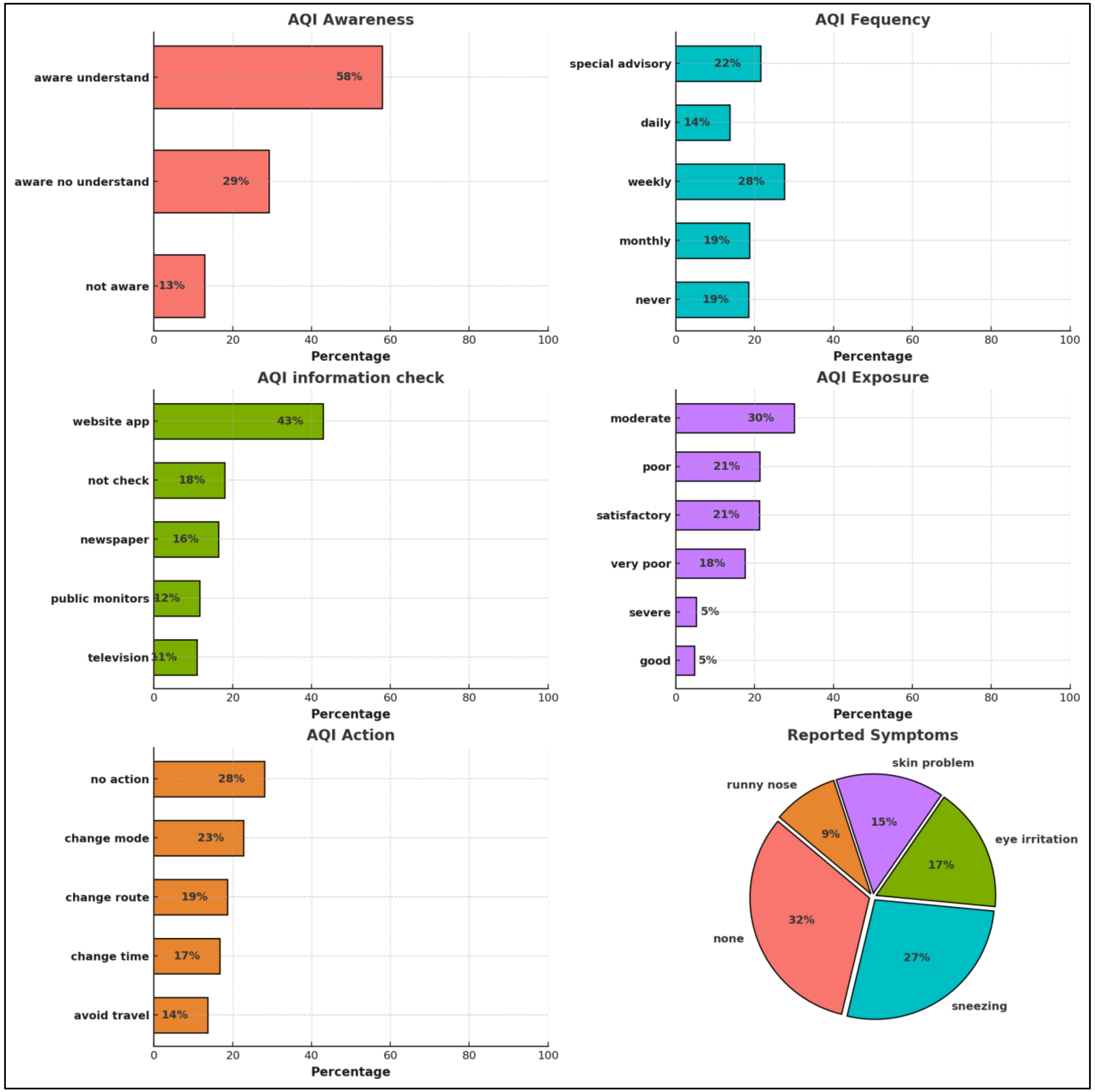
Short Trips (<5 km):
- Female majority
- Bus / Metro / Auto
- More low-income / no-income

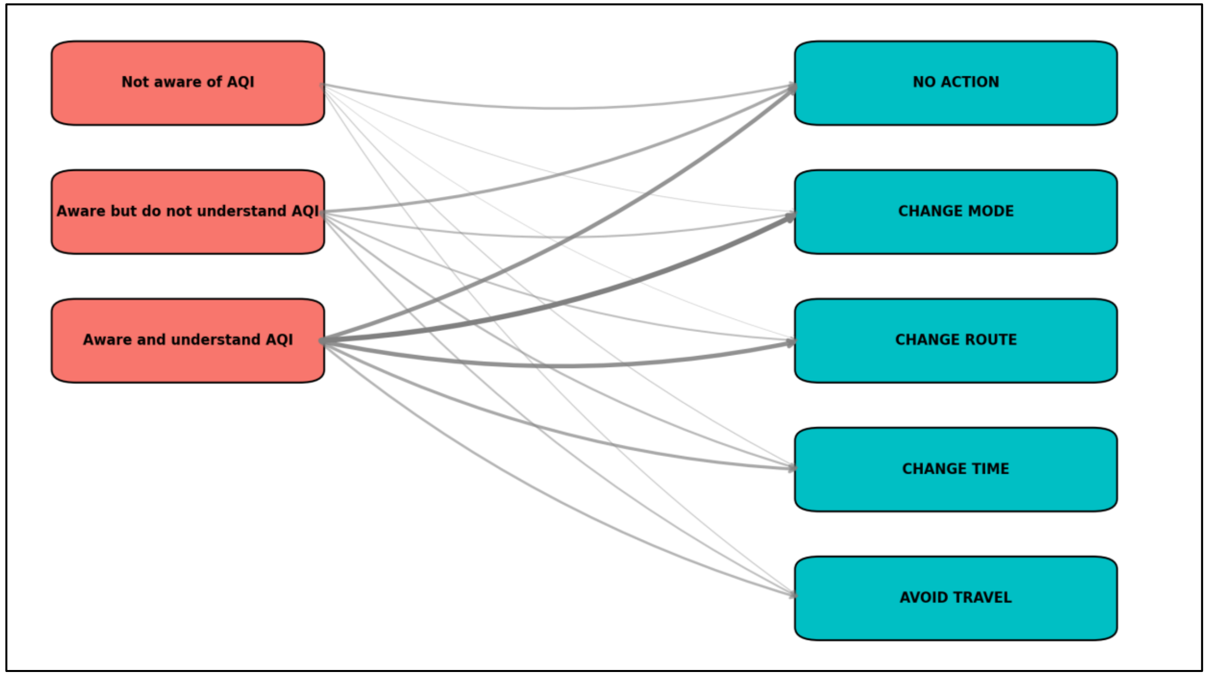
Long Trips (>10 km):
- Male majority
- Car / Two-Wheeler
- Higher-income

Work Trips:
- Male
- Car / Two-Wheeler

Education & Leisure Trips:
- Female
- Bus / Metro / Auto

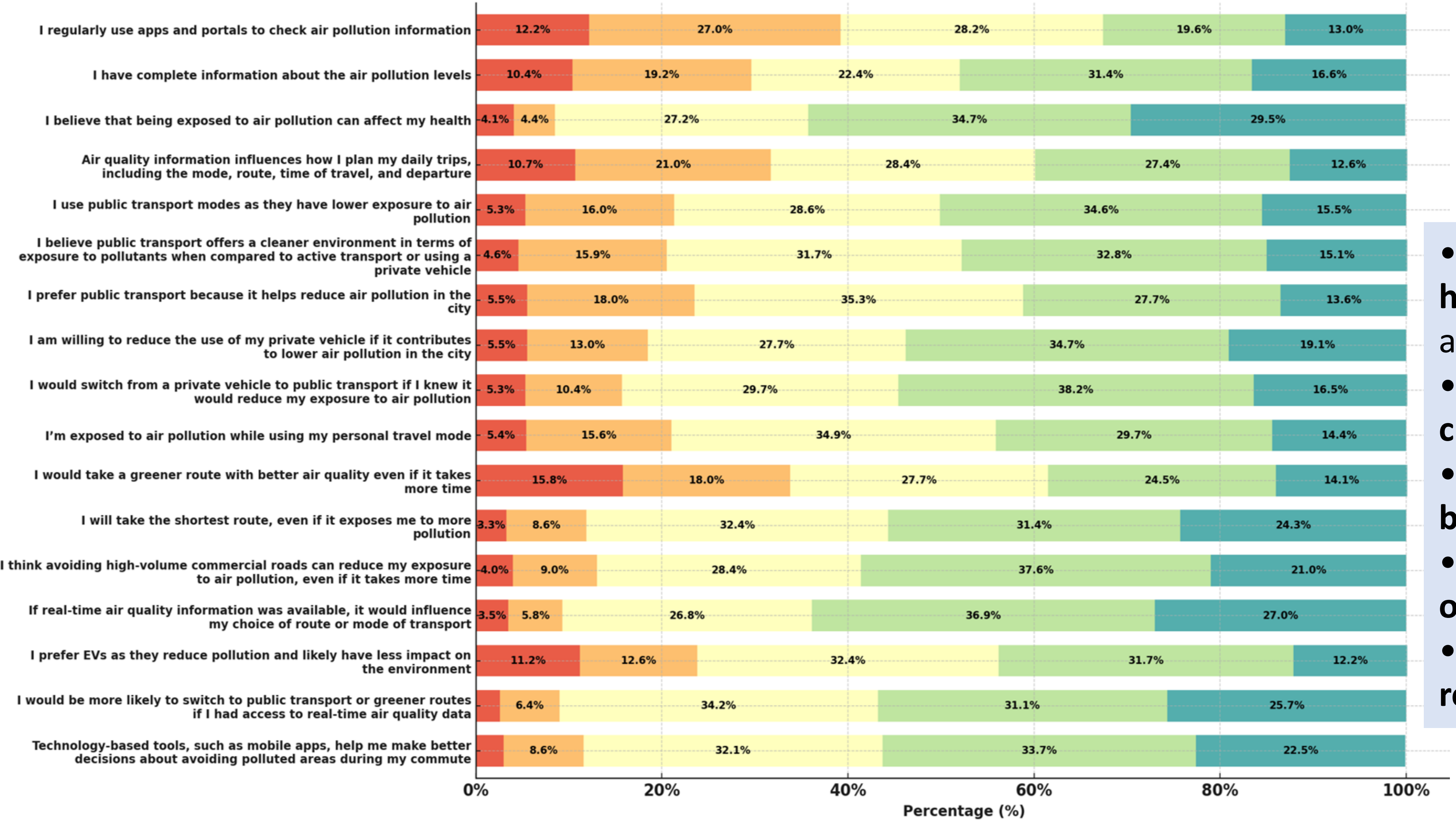
Objective – 2 – Data analysis; Latent class cluster analysis; mode choice





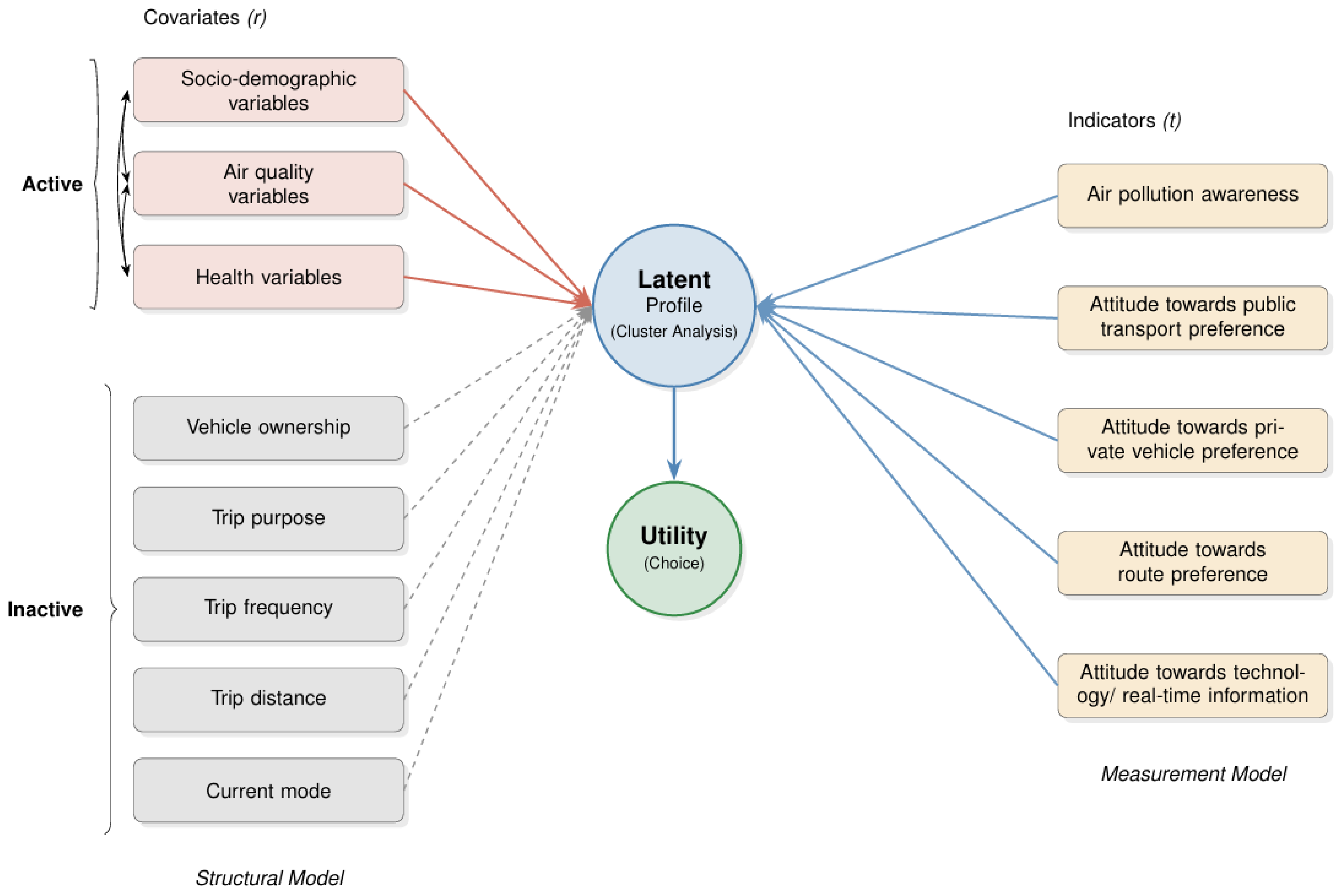
- ⚠ **Awareness–Action Gap:** While **58% understand AQI**, almost **1 in 3 still take no protective action**.
- **Digital Dependence:** AQI checks are dominated by **apps/websites (43%)**, far more than traditional sources (TV/newspaper <20%).
- **Reactive, not proactive:** People check AQI **weekly (28%) or only during advisories (22%)**, showing limited daily engagement.
- **Behavioral adaptation is selective:** Mode shift (23%) is the top protective action, while **avoiding travel (14%) is least preferred**.
- **Health Impact: 32% report no symptoms;** common issues = sneezing (27%) & eye irritation (17%).

Objective – 2 – Data analysis; Latent class cluster analysis; mode choice

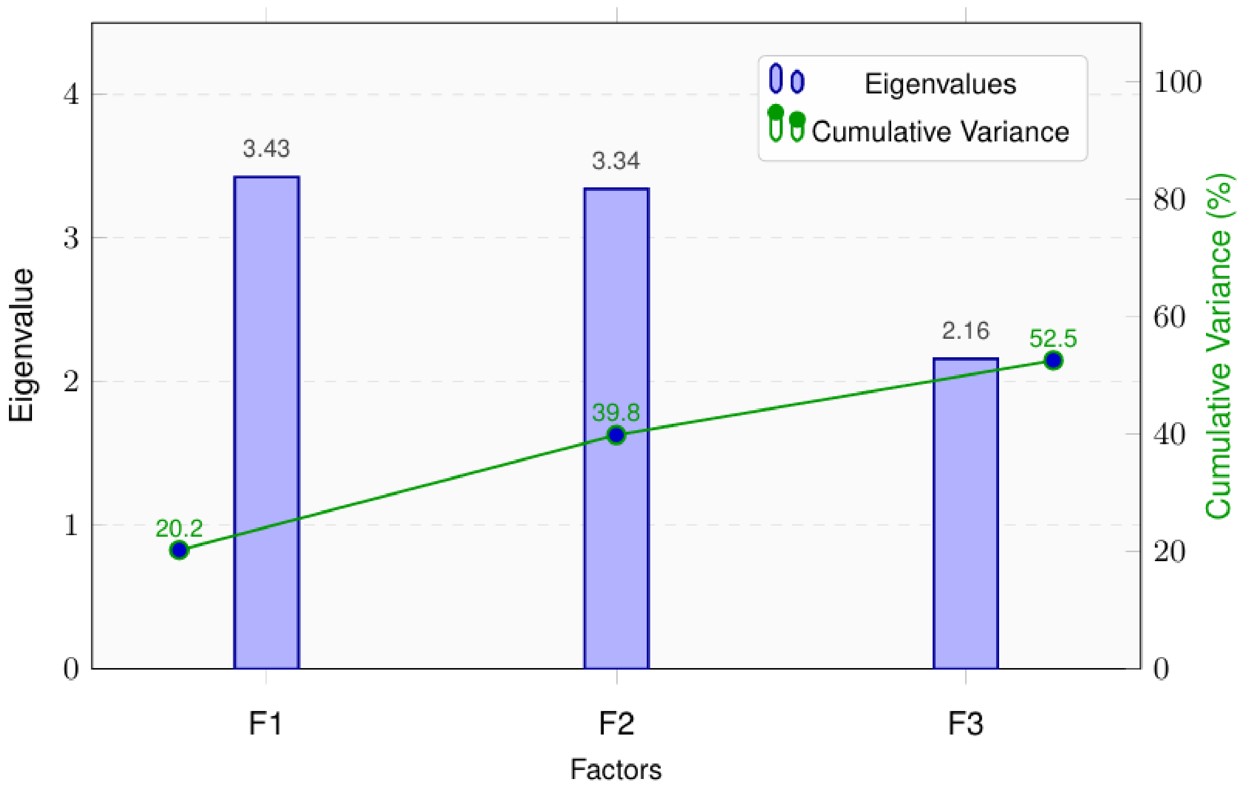


- **92% agree air pollution harms health** → strong awareness.
- **80%+ see PT as cleaner & city-friendly.**
- **Real-time AQI/apps (83%) = biggest behavior trigger.**
- **2 in 3 prefer cleaner routes over faster ones.**
- **Car users know risks but resist change** → behavior gap.

Objective – 2 – Data analysis; Latent class cluster analysis; mode choice



Objective – 2 – Data analysis; Latent class cluster analysis; mode choice

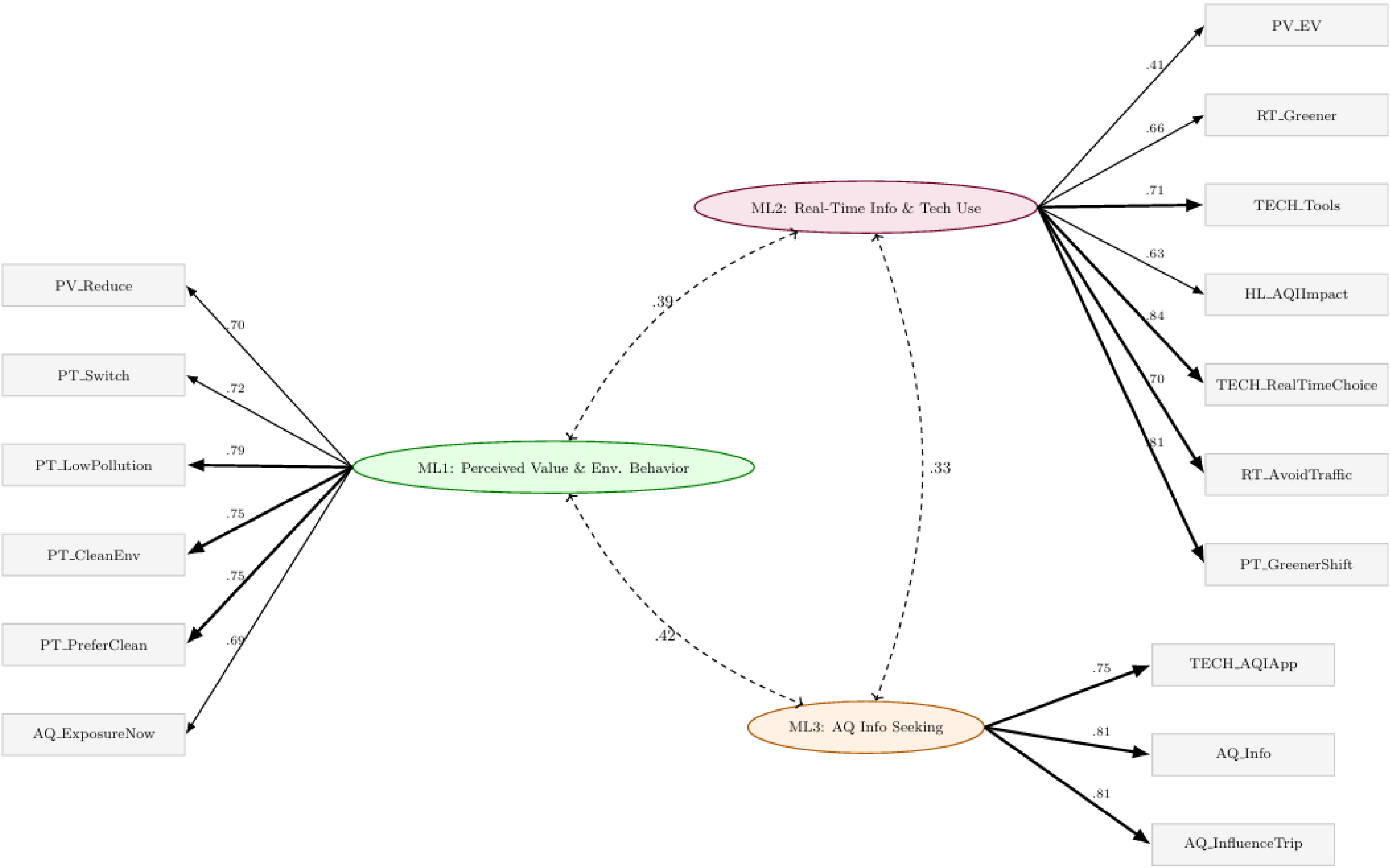


Variable	ML1	ML2	ML3
PV_Reduce	**0.673**		
PT_Switch	**0.725**		
PT_LowPollution	**0.768**		
PT_CleanEnv	**0.698**		
PT_PreferClean	**0.709**		
AQ_ExposureNow	**0.671**		
RT_Greener		**0.638**	
TECH_Tools		**0.682**	
HL_AQIImpact		**0.611**	
TECH_RealTimeChoice		**0.841**	
RT_AvoidTraffic		**0.670**	
PT_GreenerShift		**0.811**	
TECH_AQIApp			**0.713**
AQ_Info			**0.837**
AQ_InfluenceTrip			**0.733**
Eigenvalue	3.43	3.34	2.16
Variance Explained (%)	20.2	19.7	12.7
Cumulative Variance (%)	20.2	39.8	52.5

KMO (Overall): 0.87 *Bartlett's Test*: $\chi^2(136) = 5745.18$, $p < .001$
Cronbach's Alpha (Standardized): 0.88

ML1	Perceived Value & Env. Behavior
ML2	Real-Time Info & Tech Use
ML3	AQI Info Seeking

Objective – 2 – Data analysis; Latent class cluster analysis; mode choice



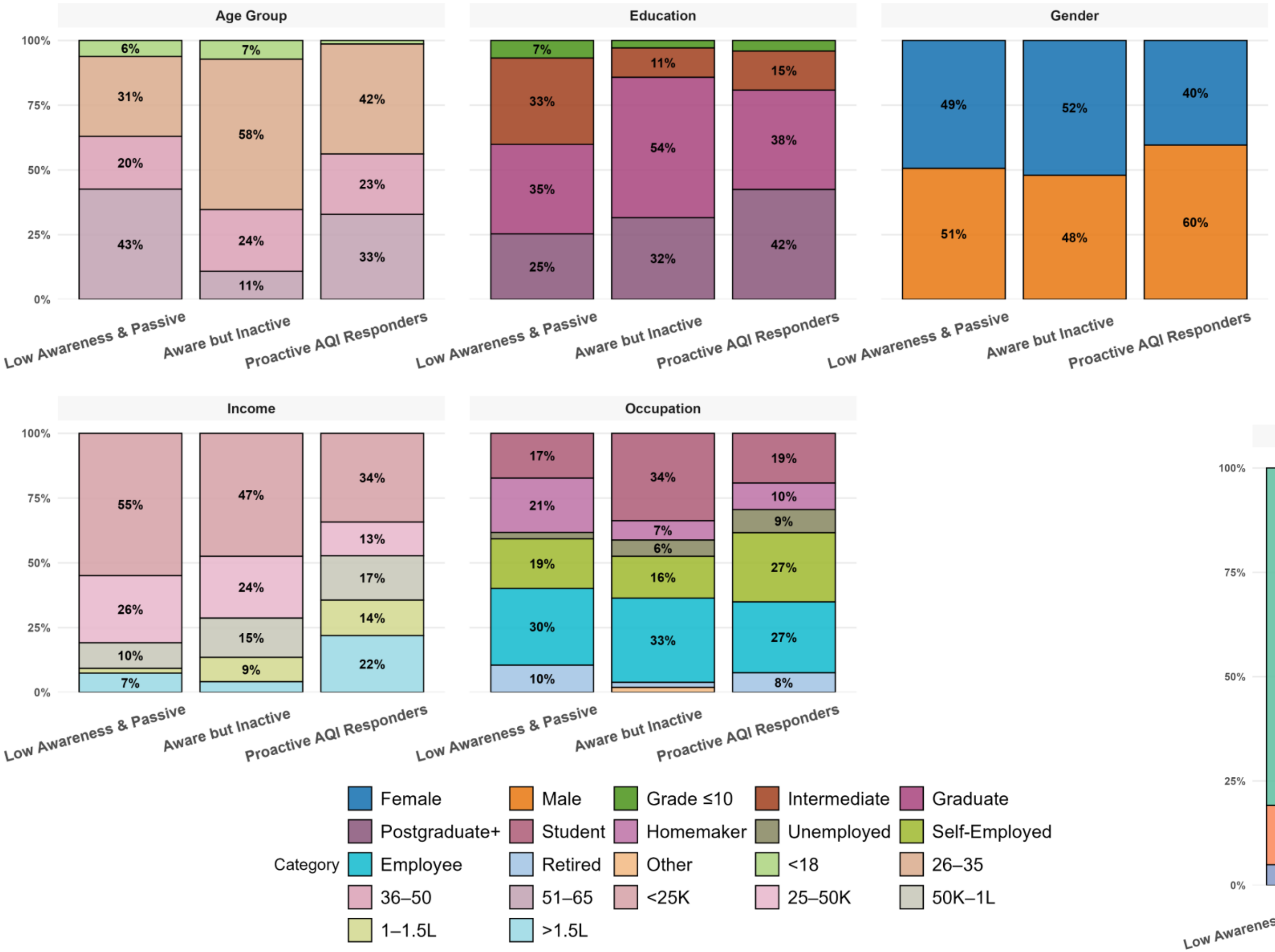
Objective – 2 – Data analysis; Latent class cluster analysis; mode choice

TABLE 4: Model Fit Indices for Latent Class Cluster Models

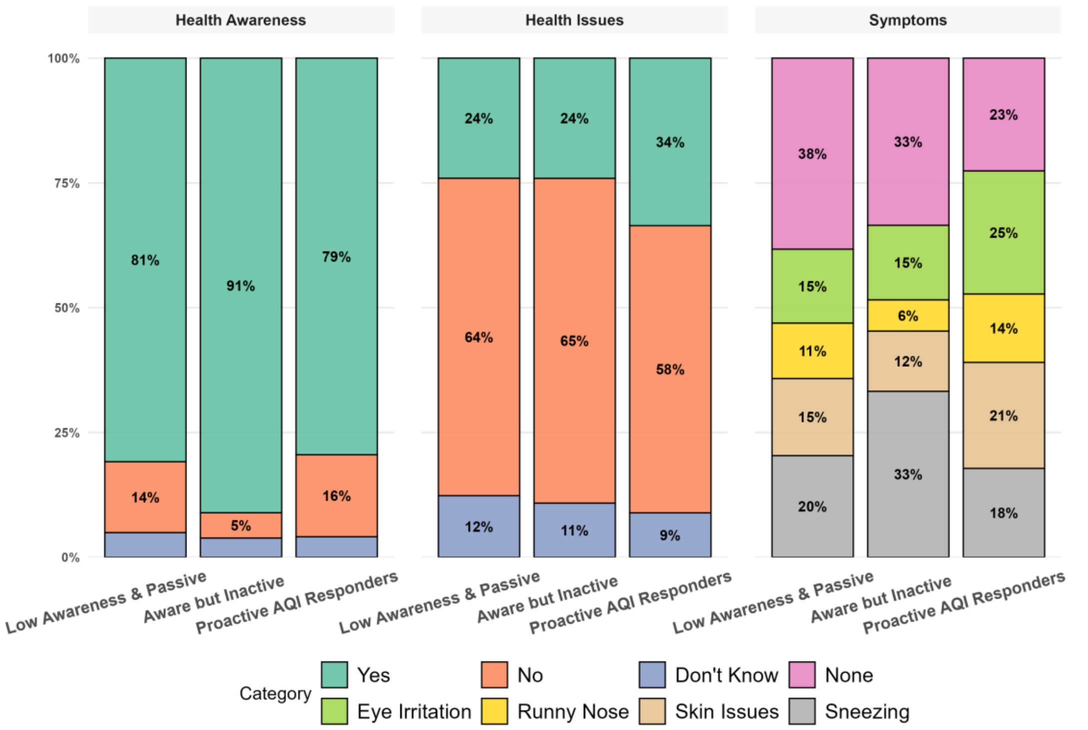
Model	Classes	LogLik	AIC	BIC	G^2	Class Proportions
2-class	2	-1825.45	3676.90	3736.49	73.98	40%, 60%
3-class	**3**	**-1804.94**	**3649.89**	**3741.55**	**32.96**	**24%, 57%, 19%**
4-class	4	-1796.88	3647.76	3771.52	16.84	20%, 19%, 16%, 45%
5-class	5	-1789.30	3646.59	3802.43	1.67	13%, 15%, 7%, 10%, 54%
6-class	6	-1788.51	3659.01	3846.93	0.09	13%, 33%, 10%, 6%, 34%, 4%
7-class	7	-1788.46	3672.92	3892.93	<0.01	15%, 17%, 9%, 9%, 19%, 5%, 26%
8-class	8	-1788.46	3686.92	3939.01	<0.01	11%, 17%, 5%, 13%, 19%, 22%, 6%, 6%
9-class	9	-1788.46	3700.92	3985.09	<0.01	9%, 9%, 17%, 27%, 2%, 5%, 10%, 6%, 14%
10-class	10	-1788.46	3714.92	4031.18	<0.01	4%, 7%, 24%, 12%, 12%, 7%, 9%, 12%, 3%, 11%

Latent Attitudinal Variables	Low Awareness & Passive	Aware but Inactive	Proactive AQI Responders
Cluster Size (%)	24%	57%	19%
General AQI Awareness	2.75	3.58	4.23
Private Vehicle Attitudes	3.33	3.29	3.51
Public Transport Attitudes	3.45	3.36	3.68
Route Preferences	3.15	3.36	3.96
Technology & Real-Time Tools	2.85	3.31	4.11

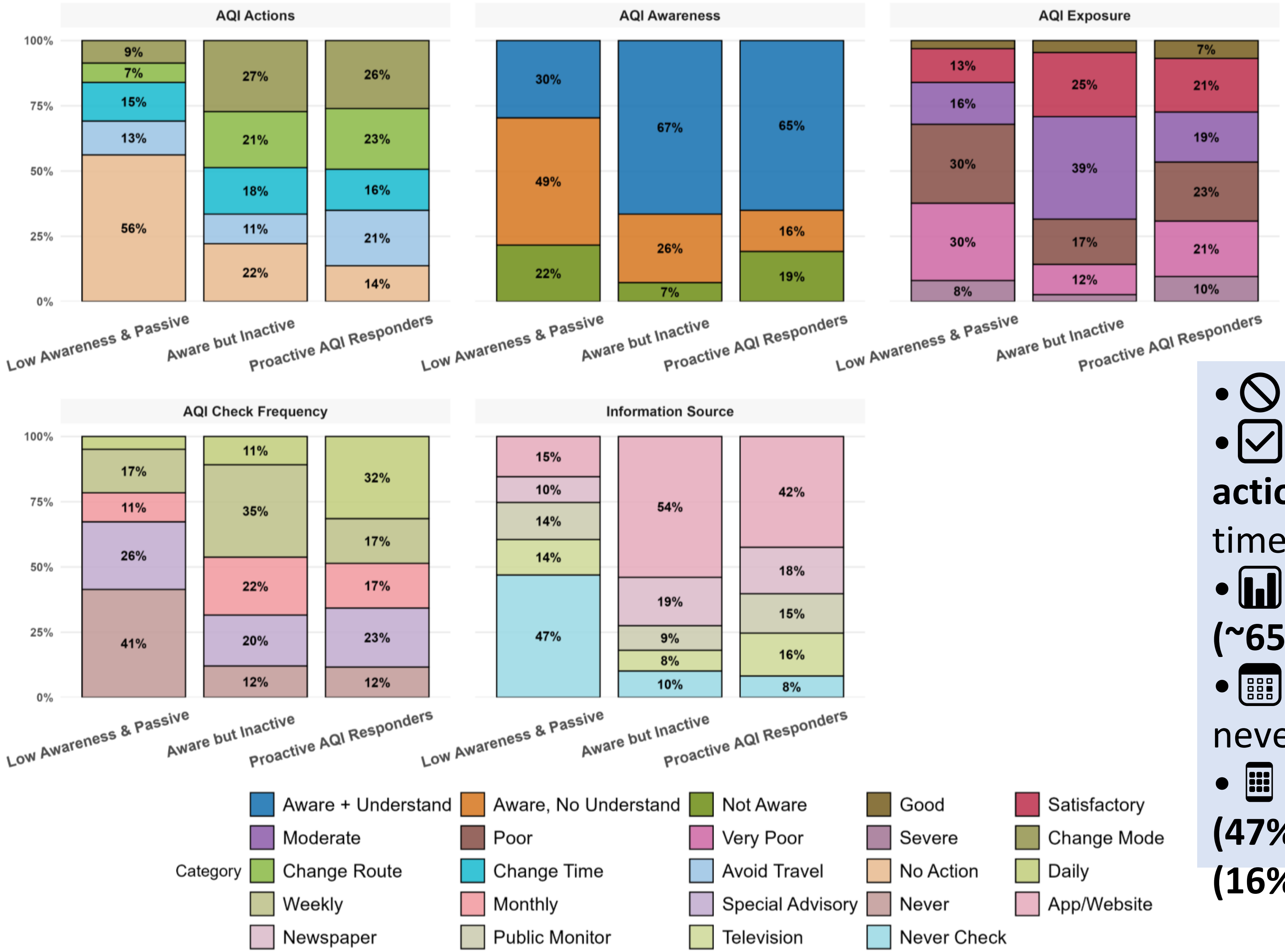
Objective – 2 – Data analysis; Latent class cluster analysis; mode choice



- **Proactive AQI responders skew younger (26–35: 42%)**, while passive groups are older (36–50: 43%).
- **Higher education drives action** — graduates & postgrads dominate proactive group (42%+).
- **Men (60%) are more proactive**, while women lean toward passive/aware-but-inactive.
- **Higher-income (>1L) households (22%) are more proactive**, while low-income (<25K: 55%) remain passive.
- **Employees & self-employed (54%) lead proactive action**, vs. homemakers/retired clustered in passive groups.

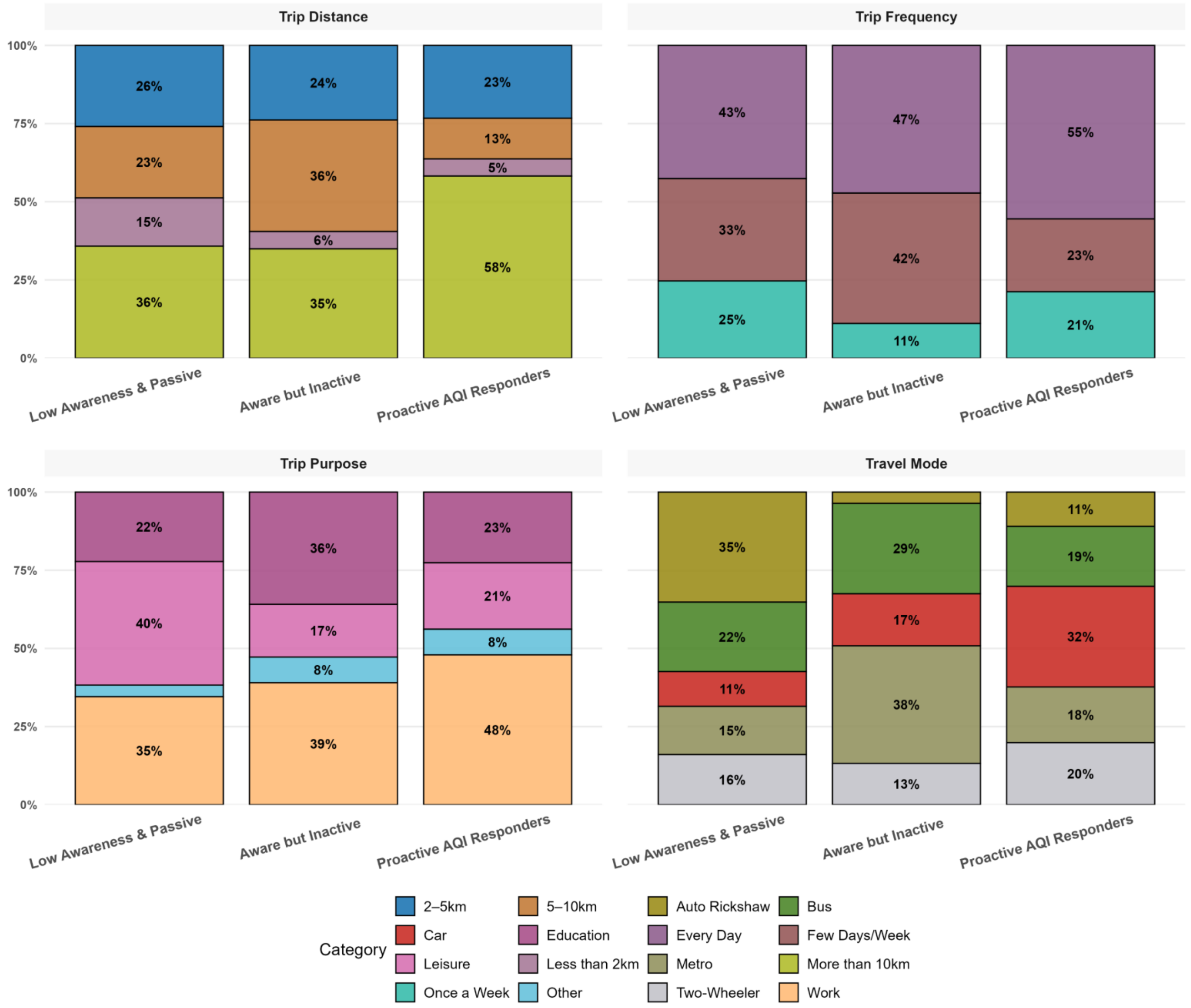


Objective – 2 – Data analysis; Latent class cluster analysis; mode choice



- 56% of passive = no action.
- **Proactive responders diversify actions:** change mode (27%), route (23%), time (21%), avoid travel (14%).
- **Awareness high in active groups (~65–67%).**
- **Check frequency differs:** passive = never/daily; proactive = weekly.
- **Passive = rely heavily on apps (47%), proactive = apps (42%) + monitors (16%).**

Objective – 2 – Data analysis; Latent class cluster analysis; mode choice



- 📏 **Proactive responders take longer trips** — 58% travel >10 km vs. only 35–36% in passive groups.
- 📅 **Higher travel intensity** — 55% of proactive responders travel *every day*, while passives are more weekly/few days.
- 🎓 💼 **Work dominates proactive trips (48%)**, while passive groups have more leisure/education trips (40–36%).
- 🚌 **Proactive = more Car (32%) & Metro (20%) users**, while passives lean Auto/Bus.
- 🔄 **Storyline:** Proactive groups = **longer, more frequent, work-based commutes, relying on private + metro modes**, while passive groups = **shorter, leisure/education trips with bus/auto**.

Objective – 2 – Data analysis; Latent class cluster analysis; mode choice

Variable Name	Variable Description	Travel Mode			
		Auto Rickshaw	Bus	Car	Two Wheeler
Air Quality Information / Awareness					
website_app	Uses AQI websites or apps	-1.635 (0.696)*	–	-1.823 (0.720)*	-1.925 (0.683)**
newspaper	Reads newspaper for AQI info	–	-1.560 (0.578)***	–	-2.454 (0.733)***
television	Watches TV for AQI info	–	-1.729 (0.650)**	-2.370 (0.880)**	–
public_monitors	Refers to AQI public displays	–	–	–	-2.715 (0.791)***
change_mode	Has changed mode due to AQI	–	-0.921 (0.358)*	–	–
aware_understand	Aware and understands AQI	–	–	2.793 (0.907)**	-3.087 (0.818)***
daily	Checks AQI daily	–	1.740 (0.593)**	–	–
satisfactory	Finds AQI exposure satisfactory	-2.694 (1.080)**	–	–	–
Health					
eye_irritation	Experiences eye irritation	–	–	–	1.777 (0.490)***
Latent Class					
aware_inactive	Aware but does not take action	-1.790 (0.645)**	–	-1.562 (0.516)**	-1.098 (0.442)*
Socio-demographic					
female	Female respondent	–	–	–	-1.003 (0.341)**
no_income	Monthly income: None	–	–	-5.538 (1.420)**	-4.200 (1.297)***
income_below_25k	Monthly income ¡ Rs. 25,000	–	–	-6.110 (1.422)***	-4.936 (1.306)***
income_25k_50k	Monthly income Rs. 25k–50k	-5.780 (1.758)**	–	-5.677 (1.373)***	-4.705 (1.296)***
income_50k_1L	Monthly income Rs. 50k–1L	-4.945 (1.652)**	–	-5.076 (1.372)***	-4.893 (1.311)***
income_1L_1.5L	Monthly income Rs. 1L–1.5L	-4.223 (1.725)*	–	-3.925 (1.424)**	-4.888 (1.390)***
grade_10_below	Education: Grade 10 or below	–	-3.406 (1.238)**	–	–
intermediate	Education: Intermediate level	–	–	-2.129 (0.833)*	–
graduate	Education: Graduate degree	–	-0.951 (0.298)**	–	–
Trip Attributes					
purpose_work	Trip purpose: Work	-2.483 (1.027)*	–	-1.812 (0.689)**	-1.742 (0.699)*
purpose_education	Trip purpose: Education	-2.429 (0.965)*	–	-3.100 (0.765)***	-1.893 (0.697)**
dist_lt_2km	Distance ¡ 2 km	3.918 (0.937)***	–	–	–
dist_2_5km	Distance 2–5 km	3.898 (0.760)***	–	–	–
dist_5_10km	Distance 5–10 km	–	1.131 (0.314)***	1.287 (0.420)**	–
Intercept					
intercept	Constant term	9.936 (2.722)***	1.355 (2.530)	6.376 (2.505)*	9.019 (2.295)***

Note: β coefficients with standard errors in parentheses; * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$.

Model fit: $-2LL = 1303.37$; LR $\chi^2 = 954.66$; McFadden's $R^2 = 0.42$.

Objective – 3

3. **To operationalise findings into practical tools and policy recommendations**

   3.1. Develop a personalised Dynamic Route Planning for Urban Mobility (DRUM) application integrating individual preferences with real-time air quality information.

   3.2. Build an interactive Air Quality Dashboard to visualise and communicate exposure levels and risk patterns to the public.

   3.3. Derive policy insights and recommend strategies to reduce inequities in travel exposure while maintaining accessibility and efficiency in urban mobility planning.

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Research Article

Transportation Research Record
1–21

DOI: 10.1177/03611981251331011
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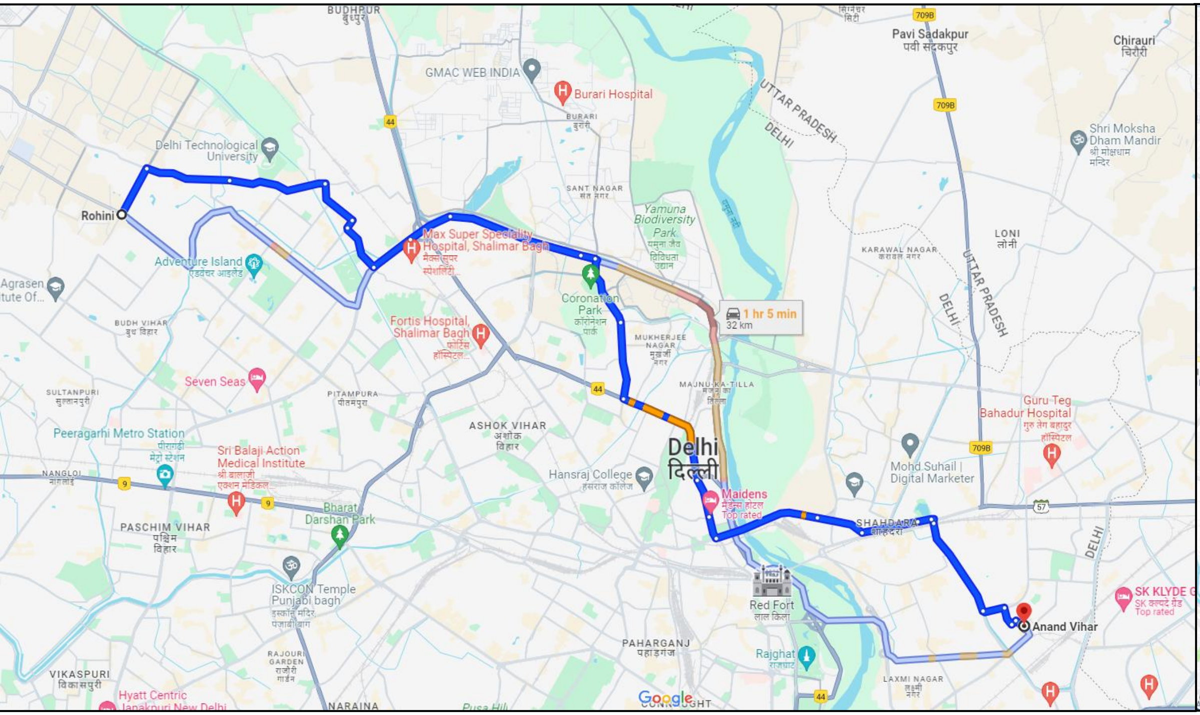
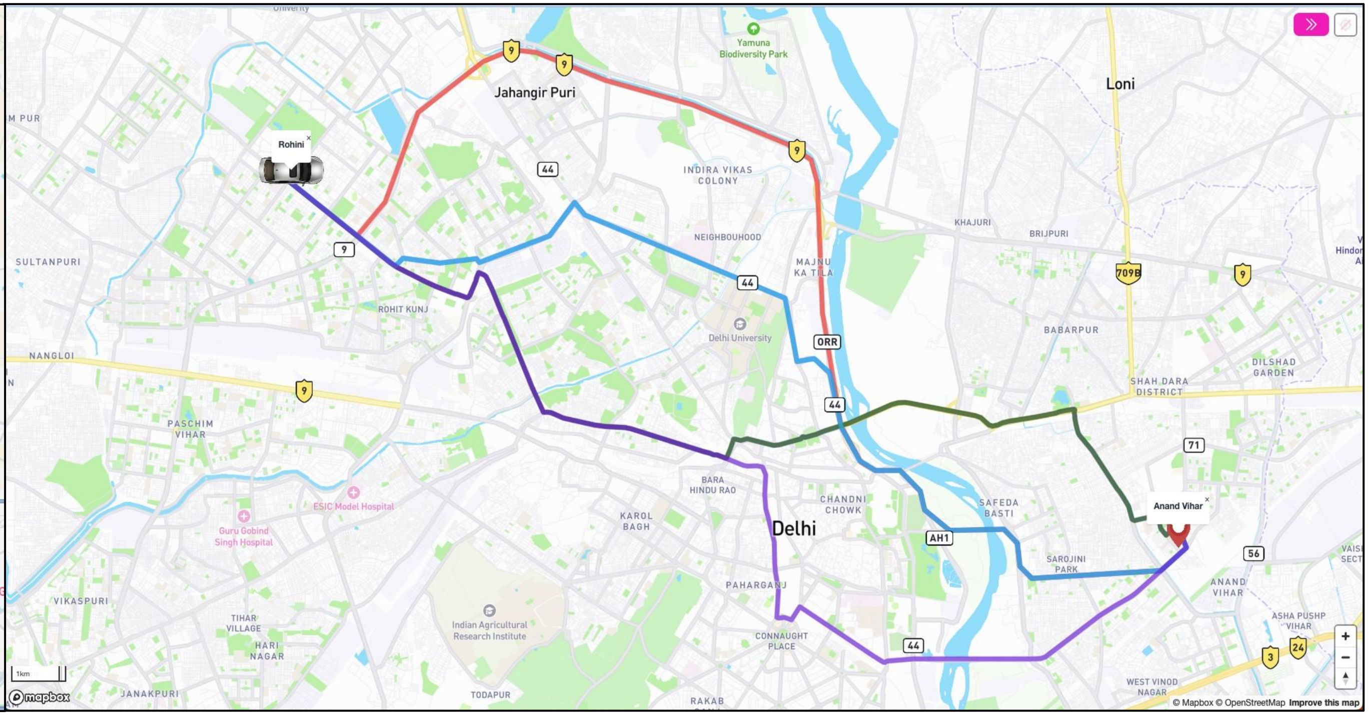
Dynamic Route Planning for Urban Green Mobility: Development of a Web Application Offering Sustainable Route Options to Commuters

Kapil Kumar Meena[1], Aditya Kumar Singh[2], and Arkopal Kishore Goswami[1]

Objective of the Study





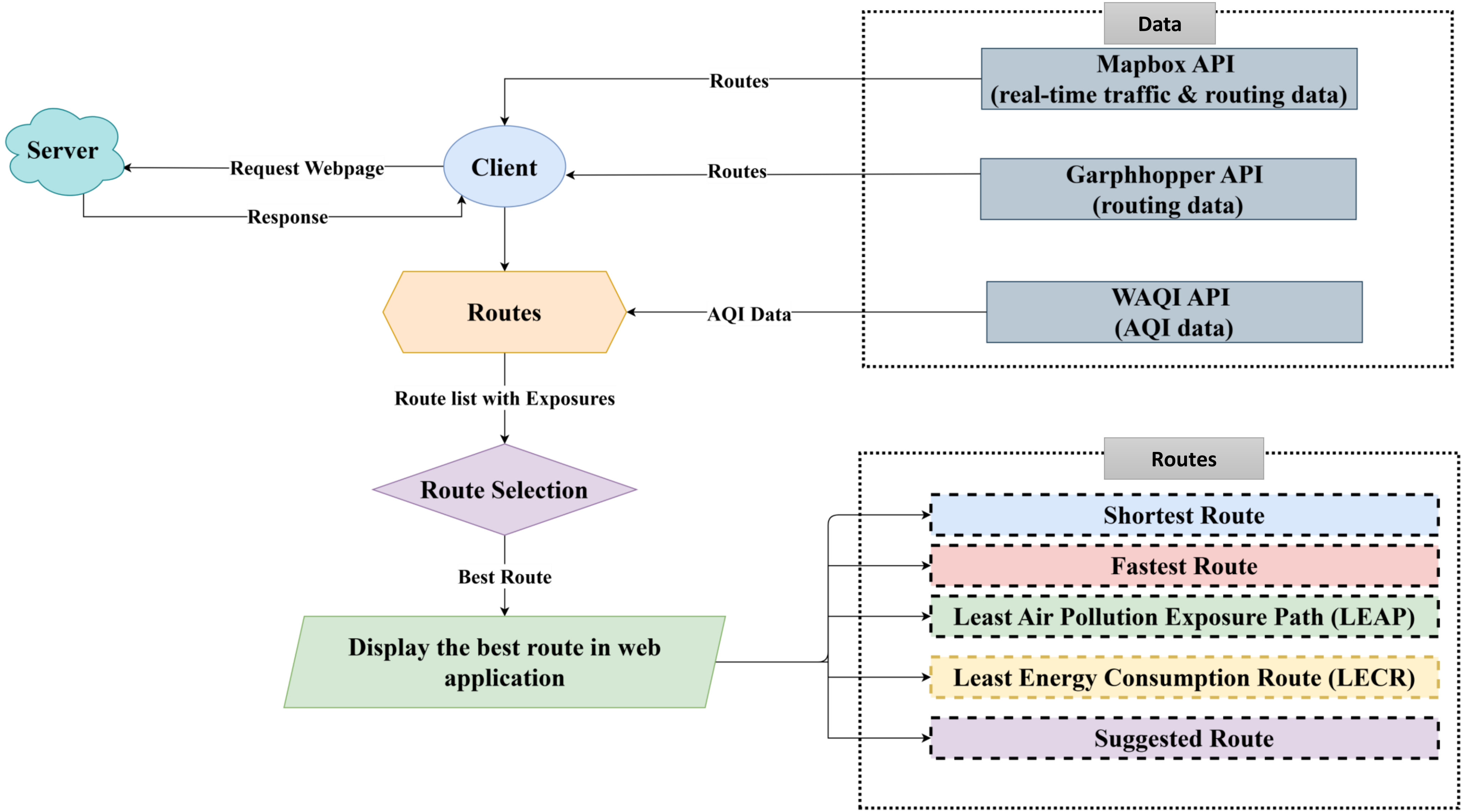
Google Map, that show

- **Shortest route,**
- **Fastest route**

DRUM (current application), that show:

- **Shortest route,**
- **Fastest route,**
- **Least air pollution route (LEAP),**
- **Least energy consumption route (LECR),**
- **Suggested route**

Methodology



Algorithms

Algorithm 1 Get Fastest Route

```
procedure GETFASTESTROUTE (routes, mode)
    geojson ← {type: 'Feature', properties: {}, geometry:
    { type: 'LineString', coordinates: '', }}
    console.log({routes})
    routes.sort((a, b) → a.time − b.time)
    if mode.includes('traffic') then
        geojson.geometry.coordinates ← routes[0].geometry.coordinates
    else
        geojson.geometry.coordinates ← routes[0].points.coordinates
    end if
    return {geojson, routes}
end procedure
```

$$T^* = \min_{i\in\{1,2,,n\}} T_i$$

$$\mathscr{I}_f = \left\{ i \in \{1, 2, \ldots, n\} \mid T_i = T^* \right\}$$

Algorithm 2 Get Shortest Route

```
procedure GETSHORTESTROUTE (routes, mode)
    geojson ← {type: 'Feature', properties: {}, geometry:
    { type: 'LineString', coordinates: '', }}
    console.log({routes})
    routes.sort((a, b) → a.distance − b.distance)
    if mode.includes('traffic') then
        geojson.geometry.coordinates ← routes[0].geometry.coordinates
    else
        geojson.geometry.coordinates ← routes[0].points.coordinates
    end if
    return {geojson, routes}
end procedure
```

To find the shortest-distance route D^*:

$$D^* = \min_{i\in\{1,2,,n\}} D_i.$$

To define the set of routes with minimal distances:

$$\mathscr{I}_s = \left\{ i \in \{1, 2, \ldots, n\} \mid D_i = D^* \right\}.$$

Algorithms

Algorithm 3 Get LEAP Route

```
procedure GETLEAPROUTE (routes, mode)
    geojson ← {type: 'Feature', properties: {}, geometry: { type:
    'LineString', coordinates: '', }}
    console.log({routes})
    routes.sort((a, b) → a.time − b.time)
    if mode.includes('traffic') then
        routes[0] ← (routes[0])
        geojson.geometry.coordinates ← routes[0].geometry.coordinates
    else
        geojson.geometry.coordinates ← routes[0].points.coordinates
    end if
    return {geojson, routes}
end procedure
```

$$r_{\mathrm{LEAP}} = \min_{r \in R} E(r)$$

where the $E(r)$ is the cumulative pollutant exposure for route r, as given by:

$$E(r) = \sum_{s \in S(r)} \text{Exposure}(s) = \sum_{s \in S(r)} C(s) \cdot T(s)$$

Algorithm 4 Get LECR Route

```
procedure
ROUTE(source, destination, tempMode)
    mass ← getMassfromMode(tempMode)
    routes ← fetch(graphhopperRoutingApiUrl)
    geojson ← { type: 'Feature', properties: {}, geometry: { type: 'LineString', coordinates: '', }, }
    for i ← 0, routes.length − 1 do
        routes[i].totalEnergy ← 0
        segments ← routes[i].instructions
        for j ← 0, segments.length − 1 do
            startIndex ← segments[j].interval[0]
            endIndex ← segments[j].interval[1]
            heightGain ← routes[i].points.coordinates[endIndex][2] − routes[i].points.coordinates[startIndex][2]
            distance ← segments[j].distance
            time ← segments[j].time
            if time == 0 and distance == 0 then
                continue
            end if
            averageVelocity ← distance/time
            totalPotentialEnergy ← mass*9.8*heightGain
            totalKineticEnergy ← 0.5*mass*averageVelocity*averageVelocity
            routes[i].totalEnergy ← routes[i].totalEnergy + totalPotentialEnergy + totalKineticEnergy
        end for
    end for
    ROUTES.SORT((a, b) → a.totalEnergy − b.totalEnergy)
    geojson.geometry.coordinates ← routes[0].points.coordinates
    return {geojson, routes }
end procedure
```

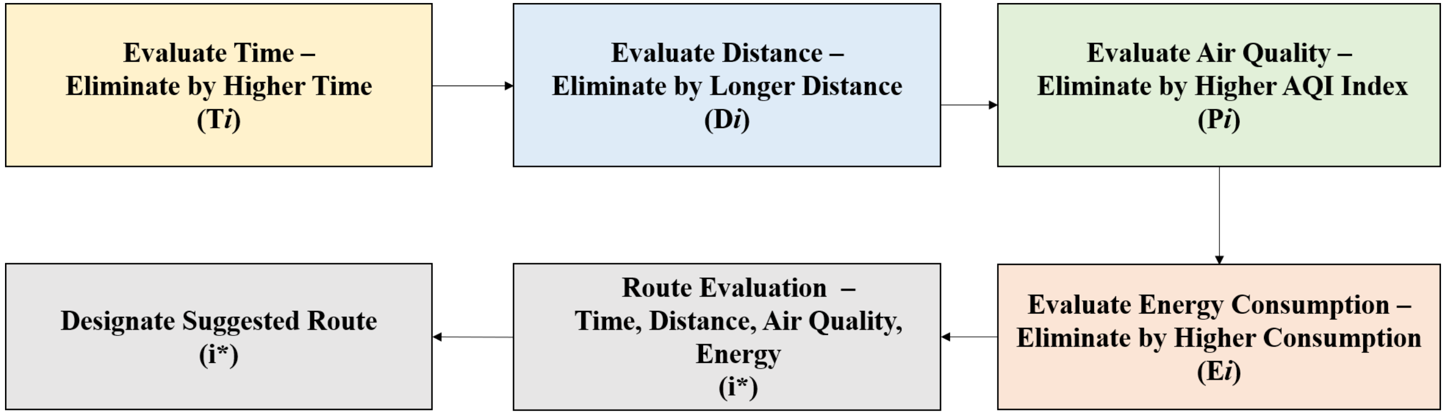
$$E_{\mathrm{LECR}}(r) = \sum_{s \in S(r)} \left(\frac{1}{2} \mathrm{mV}(s)^2 + m \cdot g \cdot h(s) \right)$$

$$V(s) = \frac{\text{Distance (s)}}{\text{Time (s)}}$$

Algorithms

Algorithm 5 Get Suggested Route

```
procedure GETSUGGESTEDROUTE(source, destination)
    routes ← fetch(graphhopperRoutingApiUrl)
    for i ← 0 to routes.length - 1 do
        routes[i].totalEnergy ← calculateRouteEnergy(routes[i])
        routes[i].totalExposure ←
        calculateRouteExposureMapbox(routes[i])
    end for
    routes.sort((a, b) → a.time - b.time)
    routes.pop(routes.length - 1)
    routes.sort((a, b) → a.distance - b.distance)
    routes.pop(routes.length - 1)
    routes.sort((a, b) → a.totalExposure - b.totalExposure)
    routes.pop(routes.length - 1)
    routes.sort((a, b) → a.totalEnergy - b.totalEnergy)
    geojson ← {type: 'Feature', properties: {}, geometry: {type:
    'LineString', coordinates: routes[0].geometry.coordinates}}
    return {geojson, routes}
end procedure
```

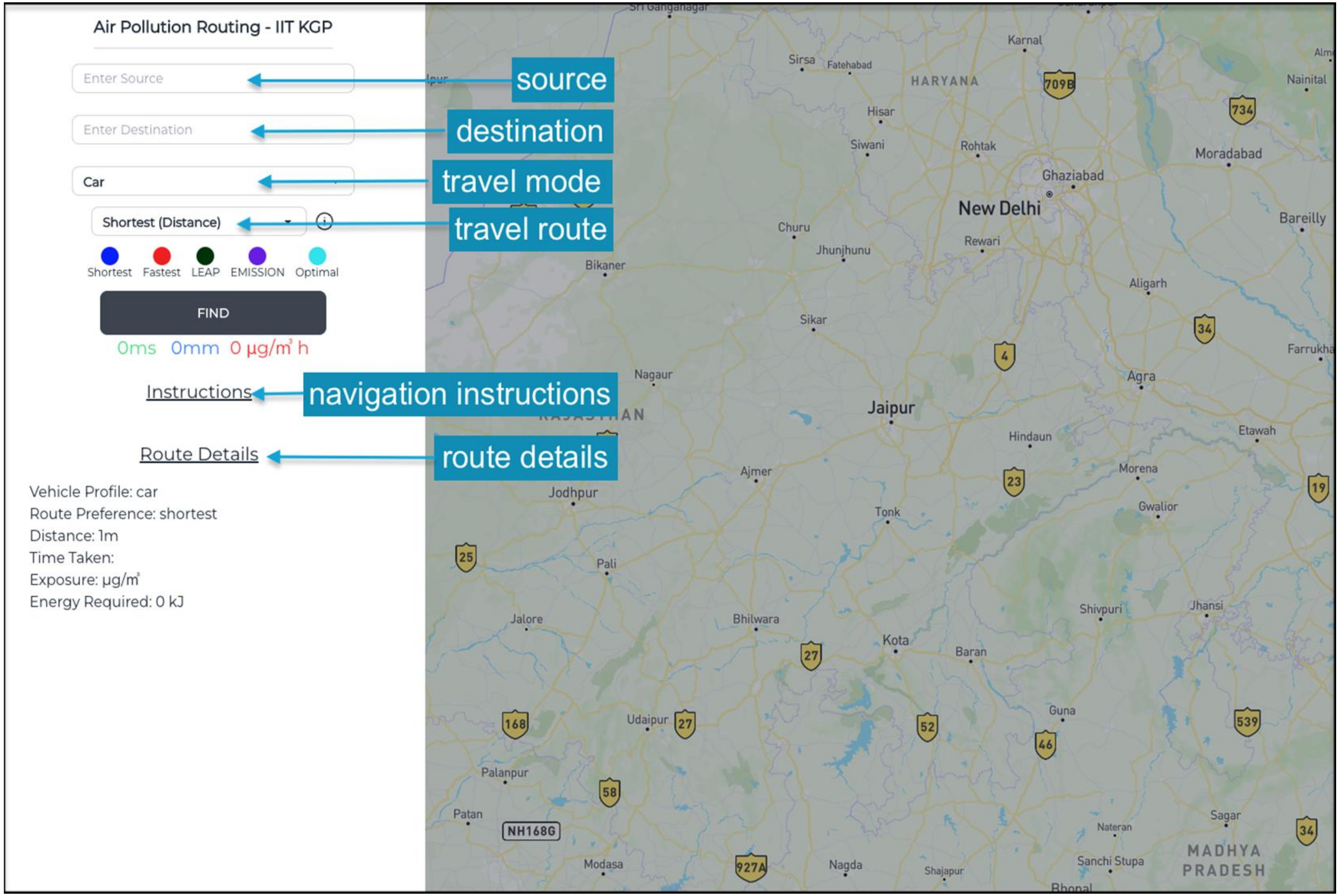


$$F(i) = T_i + \varepsilon D_i + \varepsilon^2 P_i + \varepsilon^3 E_i, \text{ for } i = 1, 2, \ldots, n.$$

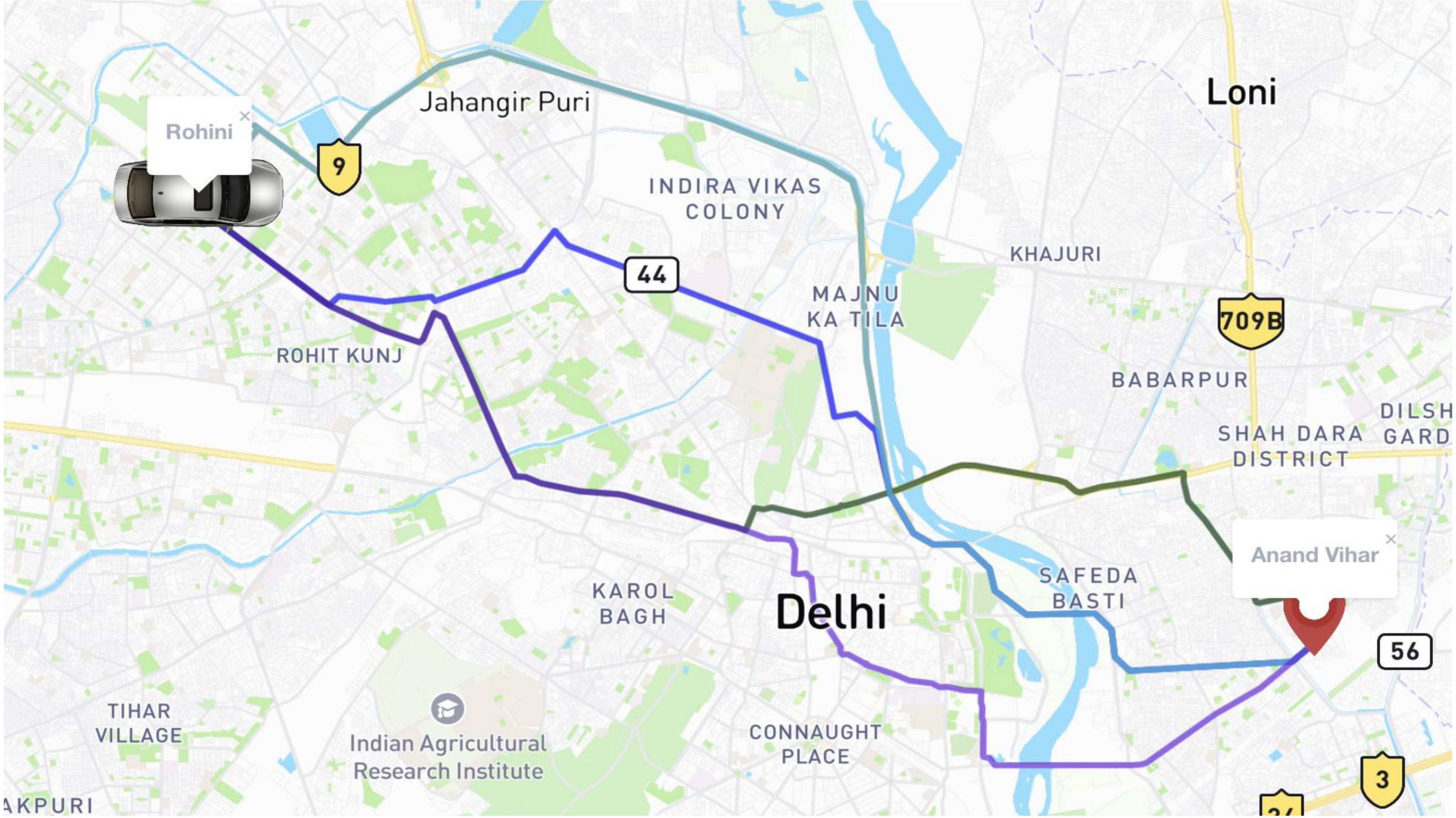
The suggested route i^* is then found by minimizing $F(i)$:

$$i^* = \arg \min_{i \in \{1,2,,n\}} F(i).$$

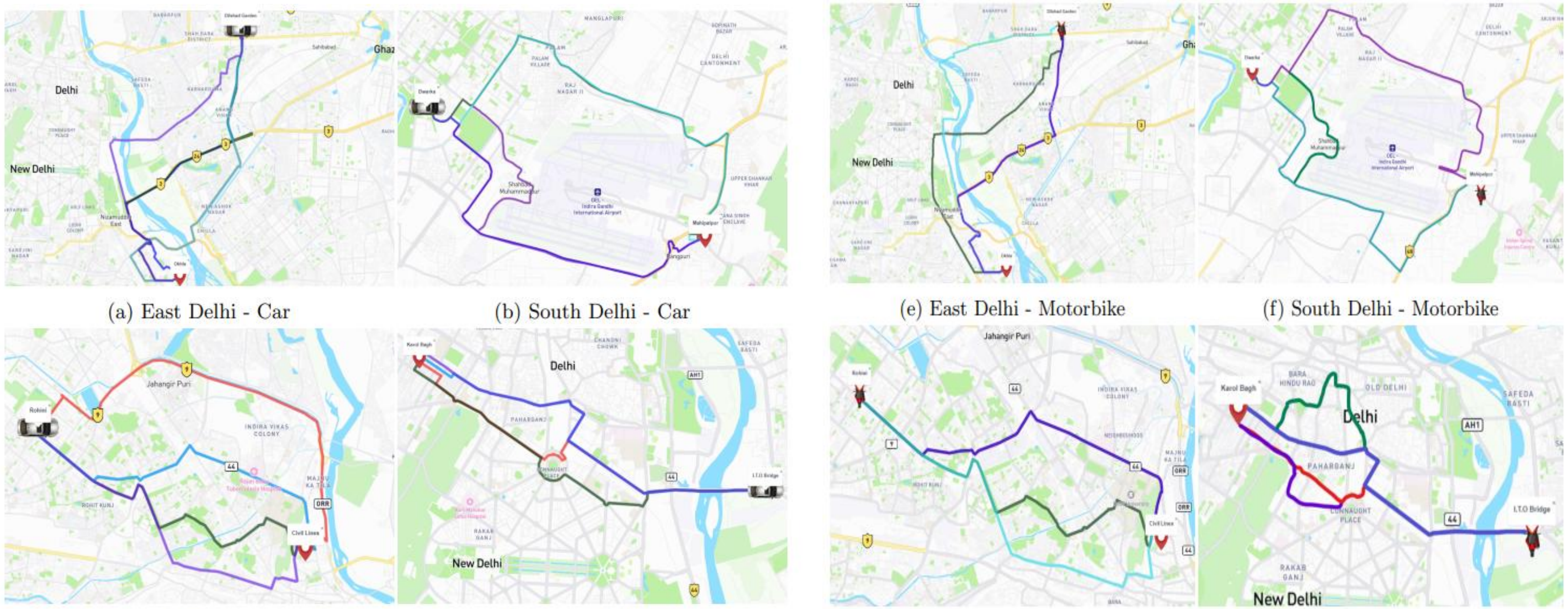
Framework of Application



Demo of Application



Results



(a) East Delhi - Car
(b) South Delhi - Car
(c) North Delhi - Car
(d) Central Delhi - Car
(e) East Delhi - Motorbike
(f) South Delhi - Motorbike
(g) North Delhi - Motorbike
(h) Central Delhi - Motorbike

Alternatives	East Delhi		South Delhi		North Delhi		Central Delhi	
	Car	2W	Car	2W	Car	2W	Car	2W
LEAP Vs. Fastest Route (Travel Time)	+24%	+36%	+54%	+7%	+35%	+8%	+42%	+16%
LEAP Vs. Fastest Route (Exposure)	-33%	-25%	-21%	-26%	-29%	-12%	-53%	-20%
LECR Vs. Fastest Route (Energy Saved)	27%	10%	29%	0%	11%	3%	9%	4%

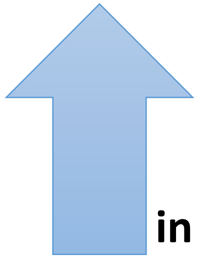
Sensitivity Analysis

A) Car

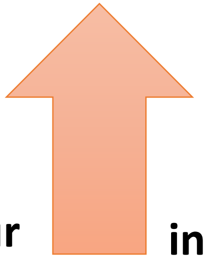
Traffic conditions	East Delhi		South Delhi		North Delhi		Central Delhi	
	Change in time %	Change in energy %	Change in time %	Change in energy %	Change in time %	Change in energy %	Change in time %	Change in energy %
Low Peak (8 Am)	11.63	23.14	22.50	22.61	12.00	27.19	13.04	17.80
Moderate Peak (9 Am)	23.26	41.39	46.75	46.53	24.00	41.79	26.09	34.43
High Peak (10 Am)	37.21	74.74	72.90	70.08	36.00	59.50	43.48	69.04

B) Two Wheeler

Traffic conditions	East Delhi		South Delhi		North Delhi		Central Delhi	
	Change in time %	Change in energy %	Change in time %	Change in energy %	Change in time %	Change in energy %	Change in time %	Change in energy %
Low Peak (8 Am)	12.20	8.97	22.22	10.94	21.43	8.33	35.29	6.94
Moderate Peak (9 Am)	26.83	20.51	37.04	23.44	39.29	18.06	64.71	19.44
High Peak (10 Am)	41.46	38.46	59.26	34.38	60.71	26.39	94.12	29.17



in Peak Hour



in Energy Consumption

East Delhi

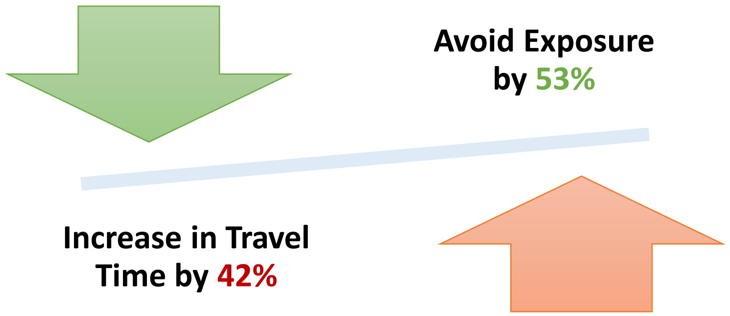
North Delhi

South Delhi

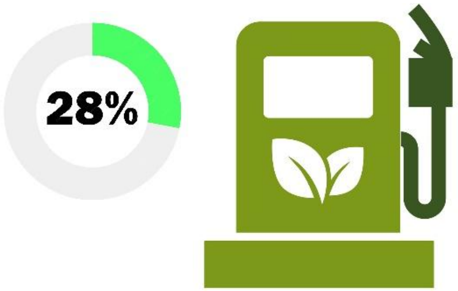
North Delhi

Summary

- ✓ By using LEAP route in Central Delhi, user could,

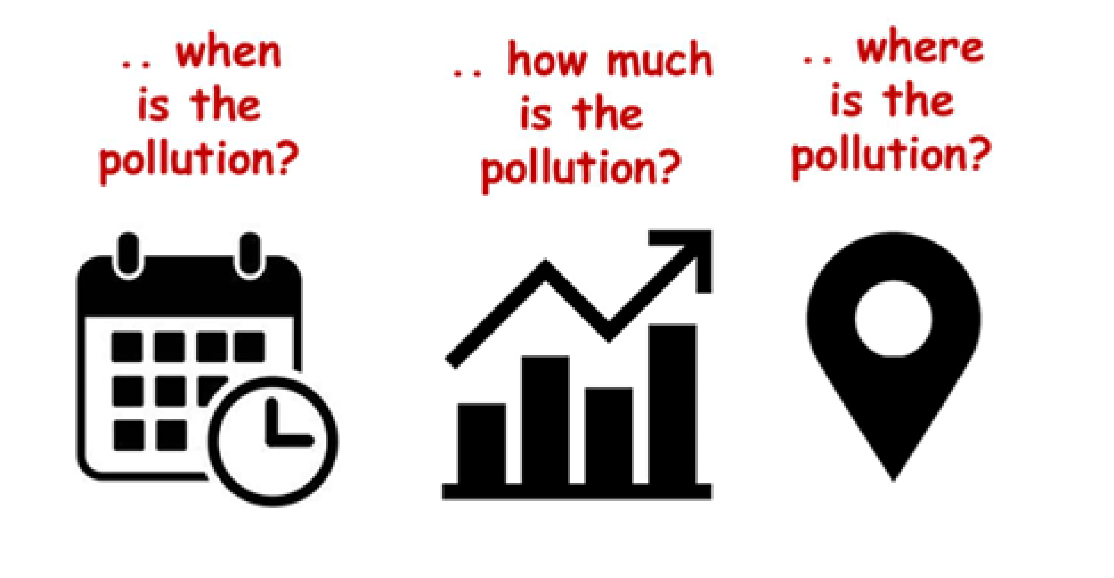


- ✓ By using LECR route user can save energy up to



in South Delhi

A Multi-Modal Analytics System for Real-Time Air Quality Monitoring, Diagnostics, and Prediction



A Multi-Modal Analytics System for Real-Time Air Quality Monitoring, Diagnostics, and Prediction

Objectives:

1. To Design a Robust Data Pipeline:

To ingest, process, and unify heterogeneous data sources, including live feeds, historical archives, and geospatial data, into a single, analysis-ready dataset.

2. To Implement a Multi-Modal Analytics Engine:

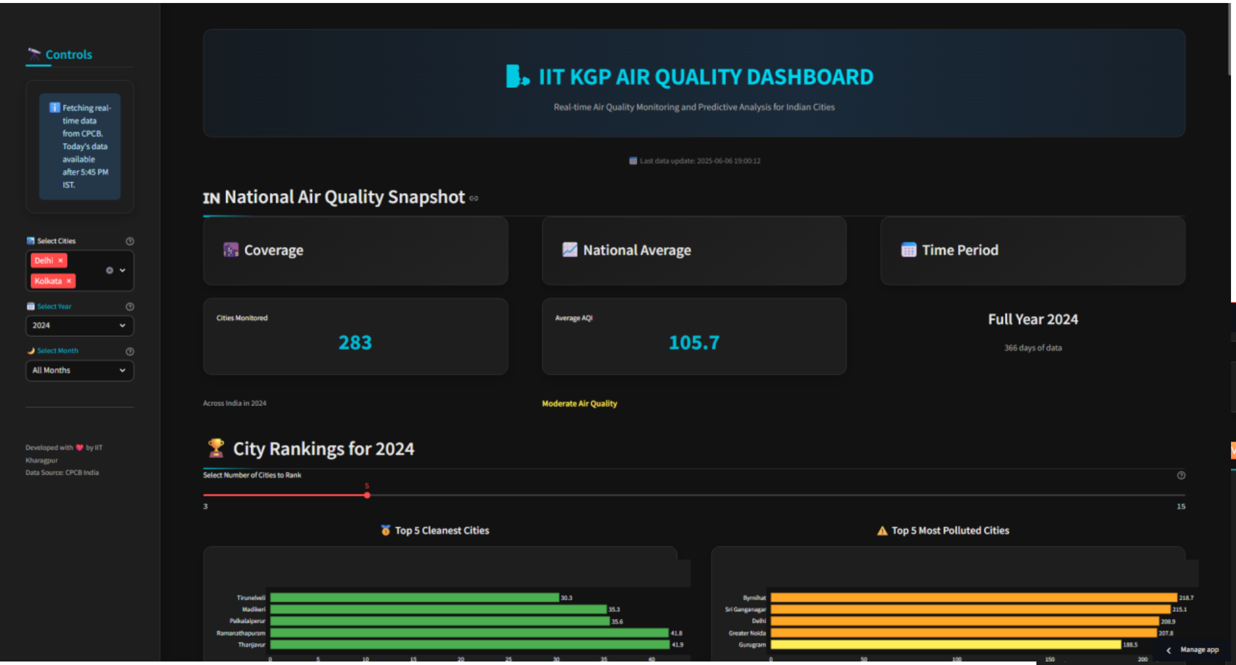
To move beyond simple monitoring by developing an engine capable of performing:

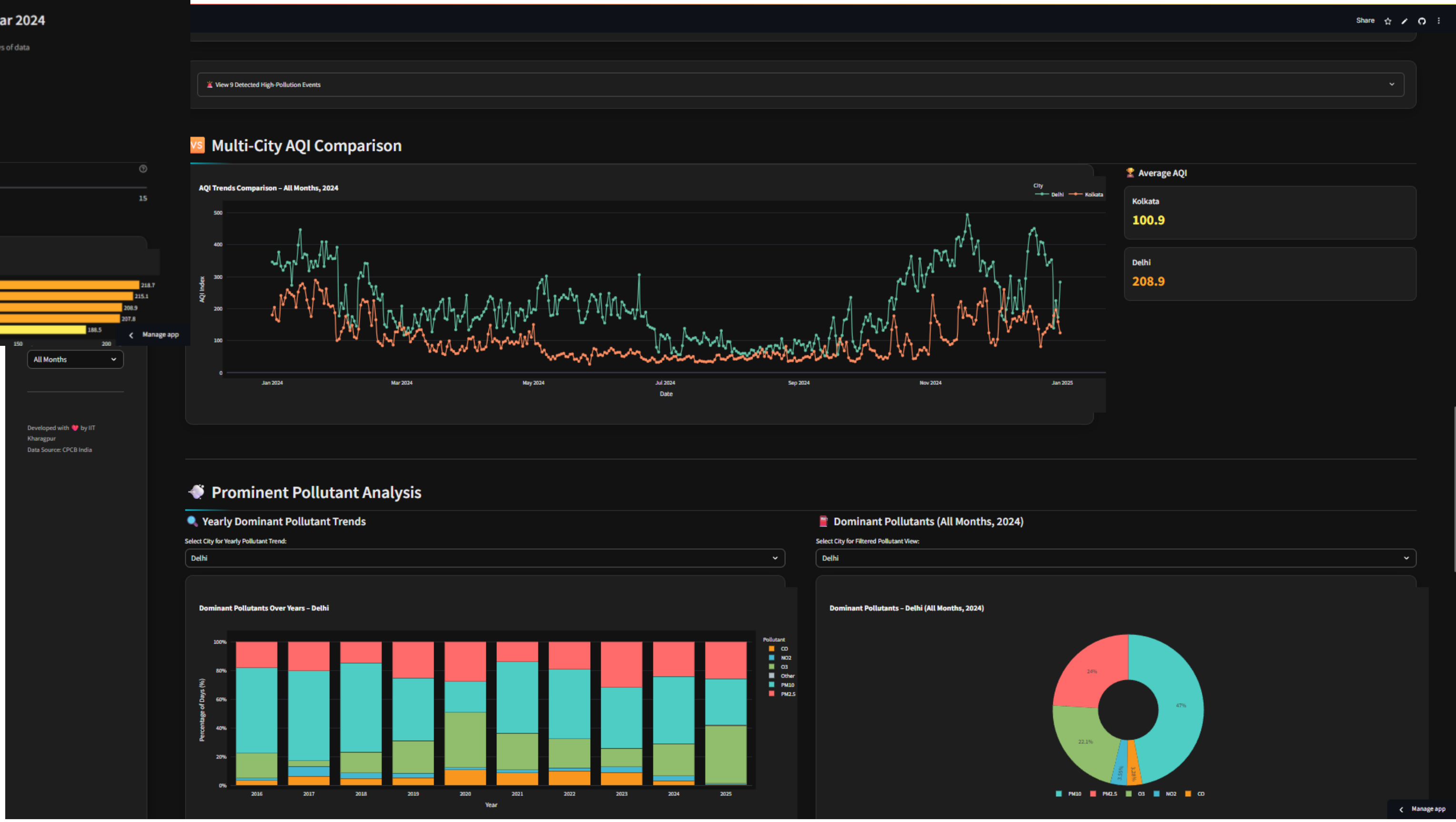
- **Descriptive Analytics** to understand current and historical trends.
- **Diagnostic Analytics** to automatically identify anomalies and their potential causes.
- **Predictive Analytics** to forecast future air quality conditions.

3. To Develop an Interactive and User-Centric Dashboard:

To present complex data and analytical insights through an intuitive visual interface, empowering researchers, policymakers, and analysts to make data-driven decisions.

A Multi-Modal Analytics System for Real-Time Air Quality Monitoring, Diagnostics, and Prediction





Algorithm 1: Integrated Urban Air Quality Analysis & Visualization System

Input: $\mathcal{H} = \{(t_i, c_i, y_i, p_i)\}_{i=1}^{N}$: historical AQI data,
$\mathcal{G} = \{(c_j, \phi_j, \lambda_j)\}_{j=1}^{M}$: city geolocations,
$\mathcal{P} = (\mathcal{C}^*, T^*, \mathcal{M}^*)$: user parameters
Output: $\mathcal{A}$: anomaly dates, $\{\hat{y}_{c,K+h}\}$: 15-day forecasts, $\mathcal{V}$: visualization suite

Preprocessing:
- Remove invalid records: $\mathcal{H} \leftarrow \{y_i > 0\}$;
- Impute missing pollutants: $p_i \leftarrow p_i$ or "Other";
- Extract temporal features: $\mathbf{x}_i = [\text{year}(t_i), \text{month}(t_i), \text{weekday}(t_i)]$;
- Geospatial join: $\mathcal{D} \leftarrow \mathcal{H} \bowtie_c \mathcal{G}$;
- Drop records beyond May 2025

Filtering:
- $\mathcal{D}_f \leftarrow \{(t_i, c_i, y_i) \in \mathcal{D} \mid c_i \in \mathcal{C}^*, t_i \in T^*\}$

Aggregation:
- $\bar{y}(t) \leftarrow \frac{1}{|\mathcal{C}_t|} \sum_{i \in \mathcal{C}_t} y_i$ where $\mathcal{C}_t = \{i : t_i = t\}$

Anomaly Detection:
- **for** $t = t_{31}$ **to** t_{end} **do**
  - $\mu(t) \leftarrow \frac{1}{30} \sum_{k=1}^{30} \bar{y}(t-k)$;
  - $\sigma(t) \leftarrow \sqrt{\frac{1}{30} \sum_{k=1}^{30} (\bar{y}(t-k) - \mu(t))^2}$;
  - **if** $\bar{y}(t) > \mu(t) + 2\sigma(t)$ **then**
    - $\mathcal{A} \leftarrow \mathcal{A} \cup \{t\}$;

Forecasting:
- **foreach** $c \in \mathcal{C}^*$ **do**
  - Extract sorted series $\{(t_{(k)}, y_{(k)})\}_{k=1}^{K}$;
  - $u_k \leftarrow (t_{(k)} - t_{(1)})_{\text{days}}$;
  - $\beta \leftarrow \arg\min \sum_{k=1}^{K} \left(y_{(k)} - \beta_0 - \beta_1 u_k - \beta_2 u_k^2\right)^2$;
  - **for** $h \leftarrow 1$ **to** 15 **do**
    - $\hat{y}_{c,K+h} \leftarrow \beta_0 + \beta_1(u_K + h) + \beta_2(u_K + h)^2$;

Health Mapping:
- Define $\mathcal{H}(y)$ mapping AQI to (category,risk) as in Table ??

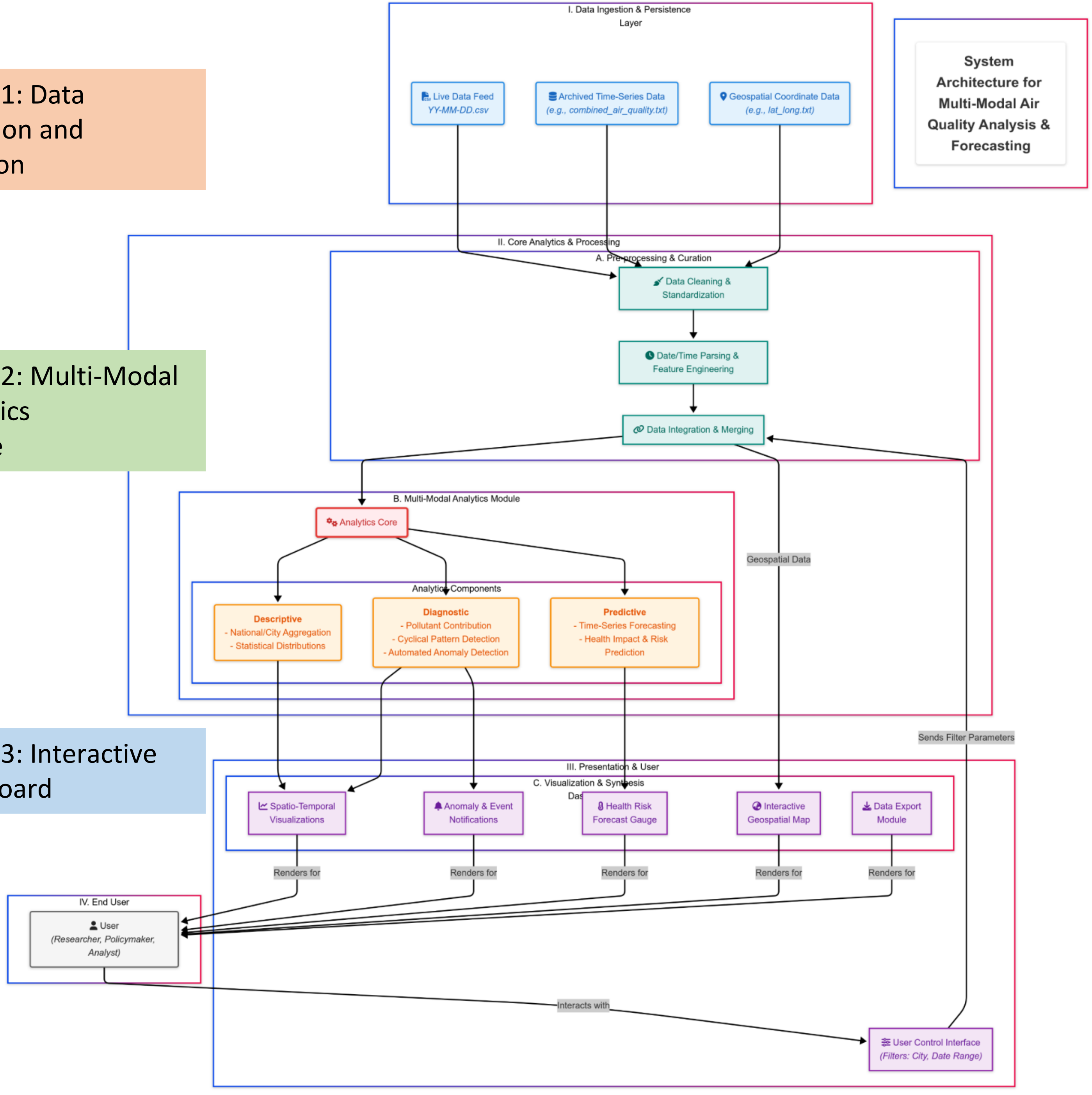
Spatio-Temporal Comparison:
- **if** $|\mathcal{C}^*| \geq 2$ **then**
  - Plot $\{y^{(c)}(t)\}_{c \in \mathcal{C}^*}$
- Plot city series vs national average

Visualization:
- $\mathcal{V}_{\text{cal}} = \textsc{CalendarHeatmap}(\bar{y}, \mathcal{H}(\bar{y}))$;
- $\mathcal{V}_{\text{ts}} = \textsc{AnnotatedSeries}(\bar{y}, \mathcal{A})$;
- $\mathcal{V}_{\text{fc}} = \textsc{ForecastPlot}(\{y_{(k)}\}, \{\hat{y}\})$;
- $\mathcal{V}_{\text{map}} = \textsc{GeospatialMap}(\mathbb{E}_c[y^{(c)}], \mathcal{G})$;
- $\mathcal{V} = \{\mathcal{V}_{\text{cal}}, \mathcal{V}_{\text{ts}}, \mathcal{V}_{\text{fc}}, \mathcal{V}_{\text{map}}\}$

Phase 1: Data Ingestion and Curation

Phase 2: Multi-Modal Analytics Engine

Phase 3: Interactive Dashboard



Publications

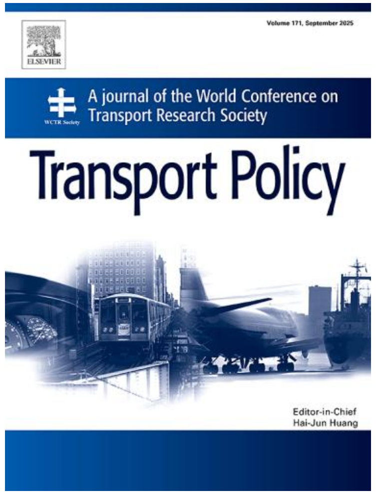
Journal Articles

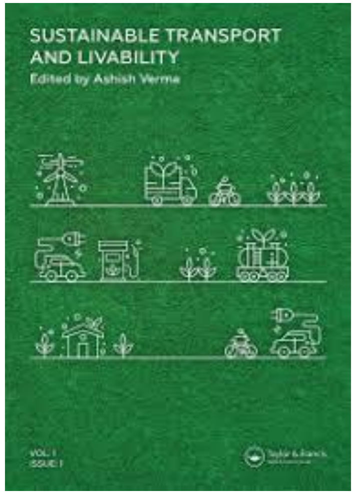
•**J1.** Meena, K. K., A. K. Singh, and A. K. Goswami (2025). "Dynamic route planning for urban green mobility: Development of a web application offering sustainable route options to commuters." ***Transportation Research Record***. doi:10.1177/0361198125133011.

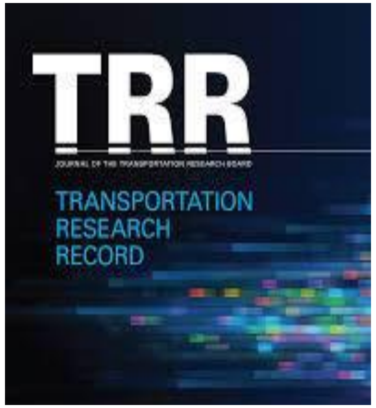
•**J2.** Manoj, B. S., K. K. Meena, and A. K. Goswami (2025). "A prioritization framework to identify key attributes of transit-oriented development (TOD) using a multi-criteria decision-making approach: An Indian context." ***Sustainable Transport and Livability***. doi:10.1080/29941849.2025.2516475.

•**J3.** Manoj, B. S., K. K. Meena, H. Panchal, G. S. Sharma, and A. K. Goswami (2025). "An integrated choice latent variable (ICLV) model to assess the willingness to bicycle for the first mile: A case of Mumbai suburban rail." ***International Journal of Sustainable Transportation*** (under second revision).

•**J4.** Meena, K. K., and A. K. Goswami (2024). "A review of air pollution exposure impacts on travel behaviour and way forward." ***Transport Policy***. doi:10.1016/j.tranpol.2024.05.024.







Publications

C1. Meena, K. K., and A. K. Goswami (2026). "Not all travellers think alike: Segmenting travel behaviour under air pollution exposure using a hybrid latent class and discrete choice approach." Submitted to the *Transportation Research Board (TRB) 2026 Annual Meeting*, Washington, DC (Submitted).

C2. Singh, A., K. K. Meena, G. Sharma, A. K. Goswami, and S. Mishra (2026). "Developing an integrated walkability score using image-based feature extraction and user preferences." Submitted to the *Transportation Research Board (TRB) 2026 Annual Meeting*, Washington, DC (Submitted).

C3. Manoj, B. S., K. K. Meena, and A. K. Goswami (2025). "A prioritization framework to identify key attributes of transit-oriented development (TOD) using a multi-criteria decision-making approach: An Indian context." Presented at the *1st World Symposium on Sustainable Transport and Livability (WSSTL-2025)*, IISc Bengaluru, India.

C4. Sumbhate, A., K. K. Meena, and A. K. Goswami (2025). "Assessing the air pollution exposure to school children in different modes of transport while commuting to school: A case of Kharagpur, India." In *Proceedings of EASTS* (Accepted).

C5. Kodukulla, R., K. K. Meena, G. Sharma, and A. K. Goswami (2025). "Accessibility assessment of urban public transit to key facilities through spatial analysis – A case study of Delhi." In *TIPCE*, IIT Roorkee (Accepted).

C6. Dasgupta, S., K. Meena, D. Majumdar, and A. Goswami (2025). "Air pollution exposure among Kolkata's auto-rickshaw drivers: PM variability, health risks, and predictive modeling." In *Energies, AEEE India* (Accepted).

C7. Sumbhate, A., M. Kapil, and A. K. Goswami (2024). "Breathable modes to school: Assessing the air pollution exposure of travel choices for school children in urban environments." Presented at the *52nd Urban Affairs Association (UAA) Annual Meeting*, Nashville, Tennessee, USA.

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$$e + M = c$$

Emission　Meteorology　Concentration

M is not in our hands, but **e** is.
Lower **e** will lead to lower **c.**