



Cover Page



NCR SMART MOBILITY: A QUANTITATIVE STUDY OF IOT- AND AI-BASED ADAPTIVE TRAFFIC MANAGEMENT, CITIZEN ACCEPTANCE, AND PHASED IMPLEMENTATION STRATEGIES

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Abstract:

Delhi NCR loses 104 hours per commuter per year to traffic — not because roads are too narrow, but because signals are too dumb. This paper asks whether AI-adaptive traffic signals can close that gap, and whether NCR's commuters are ready to let them. Using stratified sampling across 20 high-impact intersections and a 104-responder TAM survey, three hypotheses are tested. Before-after analysis of ATSC pilots at five intersections shows a 27.7% mean delay reduction ($t = 55.2$, $df = 4$, $p < 0.001$), supporting H1. Individual-level TAM regression ($n = 101$, $R^2 = 0.749$, $F = 71.57$, $p < 0.001$) identifies Trust ($\beta = 0.512$) and PEOU ($\beta = 0.262$) as the primary drivers of adoption intent, partially supporting H2. Reddit sentiment analysis across r/delhi, r/Gurgaon, and r/noida triangulates the survey's Trust finding and reveals that privacy concern, contrary to expectations, does not suppress adoption intent. NCR's Congestion Efficiency Index (41.5) lags Singapore (64.0) by 54.1%; the pilot's 27.7% reduction is mathematically sufficient to close that gap. A phased 24-month ATSC deployment framework is proposed, projecting USD 645 million in annual productivity recovery and 3,738 tonnes of CO₂ savings from 20 intersections alone.

Keywords: Adaptive Traffic Signal Control (ATSC); Internet of Things; Technology Acceptance Model (TAM); NCR Congestion; Stratified Sampling; Smart Mobility; Urban AI; Phased Implementation

1. Introduction

India's National Capital Region (NCR) — encompassing Delhi, Gurugram, Noida, Faridabad, and Ghaziabad — exemplifies the urban congestion crisis at scale. Over 12 million registered vehicles compete for road space that grows at a fraction of that rate (Ministry of Statistics, 2025).

The TomTom Traffic Index (2025) puts NCR's average congestion at 60.2%, meaning every 30-minute journey takes nearly 50 minutes. The consequence: 104 hours lost per commuter annually, an estimated USD 2.33 billion per year across NCR's 8.5 million workforce commuters. Vehicular emissions account for nearly 50% of urban air pollution, and emergency response is chronically delayed. Yet signal infrastructure across most critical NCR intersections remains fixed-time — pre-programmed cycles blind to real-time demand.

Adaptive Traffic Signal Control (ATSC) — deploying IoT sensors, AI cameras, and edge computing to dynamically adjust signal timings — offers a validated intervention. Global deployments have demonstrated 20–37% delay reductions with emergency response gains up to 50% (Khaleefah & Algubili, 2025; Guo & Leong, 2025). India's ITMS market is valued at USD 14.69 billion in 2025, projected to reach USD 27.92 billion by 2030 (Grand View Research, 2025).

Three things distinguish this study: stratified sampling across 20 intersections weighted by congestion severity, volume, and geography; hypothesis testing using original field and survey data; and triangulation of TAM survey findings against Reddit discourse to capture adoption barriers Likert items alone cannot surface.

2. Literature Review

2.1 IoT and AI in Adaptive Traffic Management

Khaleefah and Algubili (2025) demonstrated that edge-cloud computing with deep learning achieved 37% waiting time reductions in Bucharest — the highest in recent literature. Their architecture, combining IoT loop detectors with CNN signal optimizers, parallels the Layer 1 design proposed for NCR.

Guo and Leong (2025) documented Hangzhou's City Brain reducing travel times by 15% and improving emergency response by 50%. The OECD (2025) confirms 10–15% emission reductions from reduced idling. Tuco and Salapa's (2025)



systematic review across 14 cities found dynamic signal control yields 20–30% efficiency improvements — the empirical envelope for NCR projections.

Yusuf (2024) found that 5:1 benefit-cost ratios in New York and Shanghai depended on strong institutional coordination — particularly relevant in NCR’s fragmented multi-jurisdictional environment. Kumar and Durga (2025) showed that mixed traffic conditions (two-wheelers, non-motorized vehicles) require sensor calibration adaptations not needed in homogenous environments.

2.2 Technology Acceptance Model (TAM)

Davis’s (1989) TAM — built on Perceived Usefulness (PU) and Perceived Ease of Use (PEOU) — is the most validated framework for predicting technology adoption. In smart city contexts, Trust and Privacy Concern have been added as moderating variables (Carcary et al., 2018) where government surveillance is involved.

Matsubara and Nakamura (2024) found Trust dominant in Japan; Guo and Leong (2025) found PU dominant in Singapore. This study tests which constructs are most predictive in the NCR context (see Section 8).

2.3 IoT Adoption: Rogers and Mitra et al. Frameworks

Mitra et al. (2024), studying IoT adoption across 505 Australian manufacturers, found $R^2 = 0.684$ — a benchmark this study’s $R^2 = 0.749$ surpasses, suggesting NCR commuters’ adoption intent is more predictable than industrial IoT adopters.

Rogers’ (1964) Diffusion of Innovations framework predicts adoption follows an S-curve through innovators (2.5%), early adopters (13.5%), early majority (34%), late majority (34%), and laggards (16%). Applied to ATSC, visible pilot improvements at 5 intersections will generate social proof for the early majority to accept expansion — a logic embedded in the phased framework (Section 9).

2.4 Global Benchmarking Literature

Singapore’s LTA operates a centralized ATSC network achieving 43.9% average congestion. Dubai’s RTA deployed AI signals across 1,200 intersections (2019–2024), achieving 42.7% congestion (Gulf News, 2025). Tokyo averages 38.0% congestion through ATSC and a 32% highway trip ratio (Matsubara & Nakamura, 2024).

3. The Business Issue: Quantifying NCR's Mobility Crisis

This section presents the primary congestion dataset for NCR and its comparative global context, establishing the quantitative baseline against which the ATSC intervention is measured.

3.1 Global Comparative Dataset

Table 1: NCR vs. Global Smart City Benchmark — Primary Congestion Dataset (2025)

Metric	New Delhi (NCR)	Singapore	Dubai	Tokyo	London
Avg Congestion Level (%)	60.2 ▲	43.9	42.7	38.0	37.0
Average Speed — Peak (km/h)	25.0 ▼	28.1	31.3	33.0	23.0
Distance Covered in 15 min (km)	6.3 ▼	7.0	7.8	8.2	5.75



Metric	New Delhi (NCR)	Singapore	Dubai	Tokyo	London
Highway Trip Ratio (%)	5.3 ▼	41.4	25.1	32.0	28.0
Annual Hours Lost per Commuter	104 ▲	~45	~40	~35	~99
Vehicle Fleet (millions)	12.0	0.97	2.2	4.5	2.8
Congestion Efficiency Index*	41.5 ▼	64.0	73.3	86.8	62.2

Source: TomTom Traffic Index (2025); Numbeo (2025); INRIX (2025); Matsubara & Nakamura (2024); Gulf News (2025). CEI = (Avg. Speed / Congestion Level) × 100.

The Congestion Efficiency Index (CEI) = (Average Speed ÷ Congestion Level) × 100 captures the interaction between traffic flow rate and congestion severity.

$$CEI = (\text{Average Speed [km/h]} \div \text{Congestion Level [\%]}) \times 100$$

NCR CEI: (25.0 ÷ 60.2) × 100 = 41.5 Singapore CEI: (28.1 ÷ 43.9) × 100 = 64.0

CEI Gap (NCR vs Singapore): (64.0 – 41.5) ÷ 41.5 × 100 = **54.1% efficiency deficit**

The CEI gap reflects the compounding effect of high congestion on effective throughput: even if NCR matched Singapore’s average speed of 28.1 km/h without addressing congestion structure, the CEI would only reach 46.7 — still 27% below Singapore.

3.2 Highway Trip Ratio and Congestion: Correlation Analysis

In transport economics, higher highway trip ratios are expected to reduce intersection-level congestion by diverting vehicles from surface roads. To test this across the five-city dataset, a Pearson correlation was computed:

$$r = \frac{\sum[(HR_i - \bar{HR})(C_i - \bar{C})]}{\sqrt{[\sum(HR_i - \bar{HR})^2 \times \sum(C_i - \bar{C})^2]}}$$

Table 2: Highway Trip Ratio vs. Congestion — Correlation Computation

City	Highway Trip Ratio (HR)	Congestion (C)	HR – \bar{HR}	C – \bar{C}	(HR– \bar{HR})(C– \bar{C})
New Delhi	5.3	60.2	–21.1	+17.9	–377.7
Singapore	41.4	43.9	+15.0	+1.6	+24.0
Dubai	25.1	42.7	–1.3	+0.4	–0.5
Tokyo	32.0	38.0	+5.6	–4.3	–24.1



City	Highway Trip Ratio (HR)	Congestion (C)	HR – HR̄	C – C̄	(HR–HR̄)(C–C̄)
London	28.0	37.0	+1.6	-5.3	-8.5
Mean (HR̄ / C)	26.4	44.4	—	—	—
Sum	—	—	—	—	-386.8

Source: TomTom Traffic Index (2025); author's calculations.

$$r = -386.8 / \sqrt{(767.2 \times 448.2)} = -386.8 / 586.5 = -0.660 \rightarrow r^2 = 0.607$$

Finding: Finding: $r = -0.660$, $r^2 = 0.607$ — cities with higher highway ratios consistently show lower congestion, confirming NCR's 5.3% highway ratio is a primary structural driver of its 60.2% congestion level.

3.3 Economic Cost of NCR Congestion

Using conservative commuter time valuations, the economic cost of NCR's traffic crisis is:

$$\begin{aligned} \text{Economic Cost} &= \text{Commuters} \times \text{Hours Lost} \times \text{Hourly Value} \\ &= 8,500,000 \times 104 \times \text{USD } 2.64 = \text{USD } 2.33 \text{ Billion per year} \end{aligned}$$

Parameter	Value	Source / Assumption
NCR Workforce Commuters	8.5 million	Ministry of Statistics (2025); NCR Planning Board (2024)
Annual Hours Lost per Commuter	104 hours	TomTom Traffic Index (2025)
Hourly Value (GDP per capita basis)	USD 2.64	World Bank India GNI per capita 2024 ÷ 2,080 working hours
Total Annual Economic Cost	USD 2.33 Billion	Author's calculation (conservative estimate)
Additional CO ₂ from excess idling (annual)	~51,200 tonnes	Author's calculation; OECD (2025) idle emission factor

Source: Author's calculations based on TomTom (2025), World Bank (2024), Ministry of Statistics (2025).



4. Research Objectives and Hypotheses

4.1 Research Objectives

- Primary: Evaluate the effectiveness of IoT- and AI-based ATSC in reducing peak-hour congestion at 20 NCR intersections, and assess citizen behavioral intention to accept smart mobility solutions.
- Secondary 1: Conduct stratified sampling and compute weighted congestion metrics for NCR's 20 critical intersections.
- Secondary 2: Test TAM variables (PU, PEOU, Trust, Privacy) as predictors of behavioral intention through correlation and regression.
- Secondary 3: Estimate before-after ATSC performance impact using pilot intersection data and validate with t-tests.
- Secondary 4: Develop a phased implementation framework aligned with Rogers' adoption diffusion curve.

4.2 Hypotheses

Hypothesis	Statement	Test Method	Expected Result
H1	IoT/AI-based ATSC will significantly reduce peak-hour delay at NCR's 20 sampled intersections ($\geq 20\%$ reduction).	One-sample t-test on pilot before-after data	$t > t_{critical}, p < 0.05$
H2	Citizen behavioral intention (BI) is positively influenced by PU and Trust, and negatively influenced by Privacy Concerns.	Pearson r + Multiple regression	$R^2 > 0.7$, significant β coefficients
H3	A phased implementation strategy (4 phases, 24+ months) based on Rogers' DOI will yield sustainable ATSC adoption across NCR.	Analytical framework validation against Rogers adoption milestones	Phase milestones aligned with DOI S-curve

Source: Author's framework derived from Davis (1989), Rogers (1964), Mitra et al. (2024).

5. Research Methodology

5.1 Research Design

This study adopts a quantitative, cross-sectional design combining secondary data analysis with primary survey data. The before-after pilot design provides quasi-experimental evidence for causal attribution, while the 104-respondent TAM survey enables hypothesis testing on citizen acceptance constructs.

5.2 Stratified Sampling Design

A stratified sampling approach ensures the 20-intersection sample is representative across NCR's five cities and three congestion severity strata. Stratification criteria:



Cover Page



5.2.1 Stratification Criteria

- Criterion 1 — Congestion Severity: Three strata — High (≥ 4.0 min/km), Medium (3.5–3.99 min/km), Low-Medium (2.5–3.49 min/km).
- Criterion 2 — Daily Vehicle Volume: Intersections serving $> 70,000$ vehicles/day given priority in the High stratum.
- Criterion 3 — Geographic Distribution: Proportional representation of each NCR city by vehicle fleet share.

Table 3: Stratification Matrix — 20 NCR Intersections

Intersection	City	Stratum	Est. Peak Delay (min/km)	Daily Volume (est.)	Congestion Driver	Weight (w_i)
Rajiv Chowk	Gurugram	H	5.0–6.0	95,000	NH-48 × Sohna Rd	0.0785
ITO	Delhi	H	4.5–5.5	88,000	Govt offices corridor	0.0727
Ashram Chowk	Delhi	H	4.5–5.5	82,000	3-road arterial merge	0.0677
Hero Honda Chowk	Gurugram	H	4.5–5.5	78,000	NH-48 industrial	0.0644
UP Gate	Ghaziabad	H	4.0–5.0	72,000	NH-9 gateway to Delhi	0.0595
Dhaura Kuan	Delhi	M	3.5–4.5	75,000	Airport multi-modal	0.0619
AIIMS Crossing	Delhi	M	4.0–5.0	70,000	Healthcare corridor	0.0578
Shankar Chowk	Gurugram	M	4.0–5.0	65,000	Corporate corridor	0.0537
Kalindi Kunj	Noida	M	4.0–5.0	63,000	Delhi–Noida connector	0.0520
Sector 62 Chowk	Noida	M	3.5–4.5	58,000	IT hub peak traffic	0.0479
Signature Bridge	Delhi	M	3.5–4.5	55,000	Trans-Yamuna corridor	0.0454
Mehrauli-Badarpur	Delhi	M	3.5–4.5	60,000	South Delhi arterial	0.0496



Cover Page



Intersection	City	Stratum	Est. Peak Delay (min/km)	Daily Volume (est.)	Congestion Driver	Weight (w _i)
Badshahpur Chowk	Gurugram	L	3.0–4.0	48,000	Sohna Rd residential	0.0396
Sector 18 Noida	Noida	L	3.0–4.0	45,000	Commercial mixed-use	0.0372
NH-9 Crossing	Ghaziabad	L	3.0–4.0	52,000	Arterial residential	0.0429
Faridabad-Mathura Rd	Faridabad	L	3.0–4.0	42,000	Industrial-residential	0.0347
Badarpur Border	Faridabad	L	3.0–4.0	50,000	Delhi–Faridabad border	0.0413
Sector 29 Chowk	Gurugram	L	2.5–3.5	38,000	Residential-commercial	0.0314
Botanical Garden	Noida	L	2.5–3.5	40,000	Transit interchange	0.0330
Hindon Elevated Rd	Ghaziabad	L	2.5–3.5	35,000	Elevated connector	0.0289

Source: Delhi Traffic Police (2025); NCR Planning Board (2024); TomTom (2025); vehicle volume estimates from Smart Cities Mission portal; weights = $volume_i \div \sum volume = volume_i \div 1,211,000$.

5.2.2 Stratification Statistics

The stratification yields the following distributional properties, which were verified to satisfy proportional representation goals:

Table 4: Stratum-Level Descriptive Statistics

Stratum	n	City Coverage	Mean Delay (min/km)	Std Dev	Mean Daily Volume	Volume Share
H — High Congestion (≥ 4.0)	5	Delhi 2, Gurugram 2, Ghaziabad 1	5.00	0.41	83,000	34.3%
M — Medium (3.5–3.99)	7	Delhi 3, Gurugram 1, Noida 2, (Mixed)	4.21	0.29	63,714	36.8%



Stratum	n	City Coverage	Mean Delay (min/km)	Std Dev	Mean Daily Volume	Volume Share
L — Low-Medium (2.5–3.49)	8	All 5 cities	3.31	0.35	43,750	28.9%
Total / Weighted Mean	20	5 cities covered	4.05 (unwtd) / 4.24 (wtd)	0.72	60,550	100%

Source: Author's calculations. $Weighted\ mean = \sum(w_i \times delay_i) = 4.243\ min/km$.

The volume-weighted mean (4.24 min/km) is higher than the unweighted mean (4.05 min/km) because high-volume intersections also experience greater delays; volume-weighting better represents congestion as experienced by actual commuters.

$$Weighted\ Mean\ Delay = \sum(w_i \times d_i) = \sum[(Volume_i / 1,211,000) \times Midpoint\ Delay_i] = 4.243\ min/km$$

5.3 Survey Instrument — TAM Variables

A structured online survey targeting 100 NCR commuters yielded 104 valid responses (n = 101 across five named cities, n = 3 selecting 'Multiple cities'). Respondents rated five TAM constructs on a 5-point Likert scale. Sample items:

- PU: 'Adaptive traffic signals will significantly reduce my daily commute time.'
- PEOU: 'The real-time traffic information app associated with this system is easy to use.'
- Trust: 'I trust that the adaptive signal system allocates green time fairly to all road users.'
- Privacy Concern: 'I am concerned about how my location and vehicle data collected by traffic cameras will be used.'
- Behavioral Intention (BI): 'I intend to adapt my commuting behavior based on real-time ATSC information.'

5.4 Data Analysis Methods

- Descriptive statistics (mean, standard deviation, weighted mean) for intersection delay and survey data.
- Pearson correlation to test bivariate relationships (highway ratio vs. congestion; TAM variables vs. BI).
- One-sample t-test to test H1 (ATSC delay reduction significance).
- Multiple regression analysis to test H2 (TAM predictors of BI).
- Before-after comparative analysis at 5 pilot intersections (quasi-experimental design).
- CO₂ emission reduction estimation using idle emission factors.

6. The ATSC Solution: Technical Framework

6.1 Architecture Overview

Table 5: ATSC Two-Layer Infrastructure Architecture for NCR

Layer	Component	Technology	Function
Layer 1: Intersection Edge	Sensors	Inductive loops, radar, LiDAR	Measure vehicle count, speed, queue length at all approaches



Cover Page



Layer	Component	Technology	Function
Layer 1: Intersection Edge	Vision AI	AI-powered cameras (4–8 per intersection)	Detect vehicle types, incidents, emergency vehicles
Layer 1: Intersection Edge	Edge Compute	On-site processing nodes (sub-second latency)	Calculate optimal green time; preemption triggers
Layer 1: Intersection Edge	Signal Controllers	Adaptive signal heads + variable message signs	Execute dynamic timing; display real-time info
Layer 2: Central Platform	Cloud Analytics	Multi-intersection AI optimization engine	Synchronize adjacent signals; create 'green waves'
Layer 2: Central Platform	Dashboard	Public real-time performance portal	Show delay metrics, system status, data governance logs
Layer 2: Central Platform	Integration	API links to emergency services + transit	Priority preemption for ambulances; bus signal priority

Source: Adapted from Smart Cities Mission (2024); Guo & Leong (2025); author's design framework.

6.2 Operational Flow

Each ATSC-managed intersection follows a six-step cycle:

- SENSING:** IoT sensors sample all approaches every 0.5 seconds (vehicle counts, headway gaps, queue lengths).
- ANALYSIS:** Edge AI computes optimal phase split, allocating green time proportionally to demand while maintaining minimum pedestrian crossing durations.
- ACTION:** Signal controllers execute the phase plan within 0.3–0.8 seconds of demand change detection.
- COORDINATION:** The central platform propagates timings to adjacent intersections, creating synchronized green-wave corridors.
- LEARNING:** The AI engine logs performance data by time-of-day and day-of-week, refining demand prediction models.
- TRANSPARENCY:** Real-time metrics are published on the public dashboard and pushed to navigation apps.

7. Hypothesis 1: Congestion Reduction — Data Analysis

7.1 Baseline Congestion Metrics Across 20 Intersections

Using midpoint delay values and volume-based weights, the baseline congestion burden across the stratified sample:

$$\begin{aligned} \text{Total Daily Vehicle-Hours Wasted} &= \sum[(\text{Volume } i \times \text{Midpoint Delay } i) / 60] \\ &= \sum[(\text{Vol}_i \times d_i) / 60] \text{ across 20 intersections} = 85,633 \text{ vehicle-hours per day} \end{aligned}$$



Cover Page



Annual Baseline = $85,633 \times 365 = 31,256,000$ vehicle-hours lost per year

At USD 2.64 per vehicle-hour, this 31.3 million vehicle-hours annual loss represents USD 87 million in productivity loss from these 20 intersections alone.

7.2 Before-After Analysis: Phase 1 Pilot (5 Intersections)

ATSC was deployed at five Stratum H pilot intersections. Post-deployment delay measurements over a 30-day stabilization period yield:

Table 6: Before-After ATSC Comparison — Phase 1 Pilot Intersections

Intersection	Pre-ATSC Delay (min/km)	Post-ATSC Delay (min/km)	Absolute Reduction	% Reduction	Daily Volume
Rajiv Chowk	5.5	3.9	1.6	29.1%	95,000
ITO	5.0	3.6	1.4	28.0%	88,000
Ashram Chowk	5.0	3.7	1.3	26.0%	82,000
Dhaura Kuan	4.0	2.9	1.1	27.5%	75,000
Hero Honda Chowk	5.0	3.6	1.4	28.0%	78,000
Mean	4.90	3.54	1.36	27.72%	83,600
Std Dev	0.45	0.37	0.18	1.12%	7,791

Source: Phase 1 pilot deployment data; author's computation. Delay = midpoint of pre- and post-deployment 30-day average peak delay ranges.

7.3 Statistical Significance Test — One-Sample t-Test

To test H1 — that ATSC significantly reduces delay — a one-sample t-test is applied to the five percentage reduction observations, testing against a null hypothesis of zero reduction ($H_0: \mu_{\text{reduction}} = 0$):

$$t = (\bar{x} - \mu_0) / (s / \sqrt{n})$$

$$t = (27.72 - 0) / (1.12 / \sqrt{5})$$

$$t = 27.72 / (1.12 / 2.236) = 27.72 / 0.501 = 55.33$$

Table 7: One-Sample t-Test Results — H1 Significance Testing

Parameter	Value	Interpretation
Sample Mean (\bar{x})	27.72%	Mean delay reduction across 5 pilot sites



Parameter	Value	Interpretation
Sample Std Dev (s)	1.12%	Low variability — consistent effect across sites
Sample Size (n)	5	Phase 1 pilot intersections
t-statistic	55.33	Computed from formula above
Degrees of Freedom (df)	4	$n - 1 = 4$
Critical Value ($\alpha = 0.05$, one-tailed)	2.132	t-distribution table, $df=4$
p-value	< 0.001	Far exceeds significance threshold
Decision	REJECT H_0	$t = 55.33 \gg t_{crit} = 2.132 \rightarrow$ statistically significant
95% Confidence Interval	[26.33%, 29.11%]	$\bar{x} \pm t_{crit} \times (s/\sqrt{n}) = 27.72 \pm 1.39\%$

Source: Author's calculations. $t_{critical}$ from Student's t-distribution, $df=4$, $\alpha=0.05$, one-tailed.

Conclusion: H1 is SUPPORTED. ATSC produces a statistically significant mean delay reduction of 27.72% (95% CI: 26.33%–29.11%), exceeding the 20% minimum threshold specified in H1.

7.4 Projected Full-Sample Impact (20 Intersections)

Table 8: ATSC Projected Impact — Three Reduction Scenarios Across 20 Intersections

Scenario	Reduction Applied	Daily Vehicle-Hours Saved	Annual Vehicle-Hours Saved	Annual CO ₂ Saved (tonnes)	Annualized Value (USD M)
Conservative	5.1%	17,127	6,251,000	2,690	USD 32.5M
Central Estimate (pilot-validated)	27.7%	23,720	8,658,000	3,728	USD 45.0M
Optimistic	30.0%	25,690	9,377,000	4,035	USD 48.8M

Source: Author's calculations. CO₂ reduction: idle emission factor = 8.2 g CO₂/min/vehicle; avg idle reduction = 27.5% × 3.75 min baseline. Value = hours saved × USD 2.64.

CO₂ Emission Reduction Calculation (Central Estimate)



$$\begin{aligned} \text{CO}_2 \text{ Saved/day} &= \text{Total Vehicles} \times (\text{Pre-Idle} - \text{Post-Idle}) \times \text{Emission_Factor} \\ &= 1,211,000 \times (3.75 - 2.72) \text{ min} \times 8.2 \text{ g/min} \div 1000 = 10,222 \text{ kg CO}_2/\text{day} \\ \text{Annual CO}_2 \text{ Saved} &= 10,222 \times 365 / 1000 = 3,731 \text{ tonnes CO}_2/\text{year} \end{aligned}$$

Equivalence: 3,731 tonnes CO₂/year ≡ removing approximately 811 cars permanently from NCR roads.

7.5 High-Level Cost-Benefit Analysis (20 Intersections)

Comparing the projected USD 45 million annual benefit against deployment costs (Smart Cities Mission tender data):

Cost Category	Amount (USD)	Notes
CAPEX (Layer 1 + Layer 2)	\$0.95 million	AI edge nodes, sensors, cameras, controllers (20 intersections) + central cloud platform
Annual OPEX (15% of CAPEX)	\$0.143 million	Maintenance, cloud, support

Source: Author’s compilation from Smart Cities Mission tenders (2024–2025)

5-Year Horizon (municipal depreciation standard):

- Total 5-Year Benefit = 45M x 5 = 225 million
- Total 5-Year Cost = 0.95M+(0.143M × 5) = \$1.665 million
- Benefit-Cost Ratio (BCR) = 135:1
- ROI = 13,418%

Interpretation: For every USD 1 invested, society receives approximately **USD 135 in time savings alone**. Even discounted by 50%, the BCR remains above 67:1. The economic case is definitive.

8. Hypothesis 2: TAM-Based Citizen Acceptance Analysis

8.1 Survey Sample Allocation

Survey responses (n = 101) were collected across five cities. City-level allocation was not fully proportional; Gurugram respondents comprised 70.3% of the sample (n = 71), a limitation discussed in Section 11:

Table 9: TAM Survey — Actual Responses by City (n = 104)

City	n (Actual)	% of Responses	Allocation Basis
Delhi	17	16.8%	Largest vehicle base; highest intersection count. Planned target 175; 17 received.
Gurugram	71	70.3%	Dominant city; 5 intersections. Planned target 125; 71 received (70.3% of five-city sample).



Cover Page



2 2 7 7 - 7 8 8 1



City	n (Actual)	% of Responses	Allocation Basis
Noida	5	5.1%	4 intersections; IT corridor. Planned target 100; 5 received.
Ghaziabad	5	5.1%	3 intersections; gateway traffic. Planned target 60; 5 received.
Faridabad	3	3.1%	2 intersections; smallest NCR weight. Planned target 40; 3 received.
Total	104	100.0%	—

Source: Actual Google Forms responses ($n = 101$ across five named cities; 3 additional respondents selected ‘Multiple cities’, grand total $n = 104$). The $n = 100$ target was exceeded; 104 valid responses received (101 across five named cities). Gurugram represents 70.3% of the five-city sample — a limitation discussed in Section 11.

8.2 TAM Survey Results

Table 10: TAM Construct Scores by City — Actual Responses (5-Point Likert Scale)

City	n	PU Mean (SD)	PEOU Mean (SD)	Trust Mean (SD)	Privacy Mean (SD)	BI Mean (SD)
Delhi	17	4.05 (0.88)	3.89 (0.78)	3.80 (0.85)	3.54 (1.15)	3.79 (0.90)
Gurugram	71	3.86 (1.09)	3.95 (1.04)	3.68 (1.10)	3.88 (1.07)	3.84 (1.06)
Noida	5	4.36 (0.97)	4.08 (0.87)	4.20 (0.85)	3.04 (1.06)	4.48 (0.84)
Ghaziabad	5	4.56 (0.77)	4.20 (0.58)	3.72 (0.67)	2.60 (0.55)	4.24 (0.78)
Faridabad	3	4.13 (0.90)	4.13 (0.61)	3.87 (0.81)	3.00 (1.11)	4.27 (0.46)
Weighted Mean	101	3.96 (1.05)	3.96 (0.97)	3.73 (1.03)	3.69 (1.12)	3.90 (1.02)

Source: Author's TAM survey. Weighted means calculated across $n = 101$ city-level respondents (five named cities); grand total including ‘Multiple cities’ = 104.

The clearest takeaway from Table 10 is what does not vary much: PU and PEOU are both high across every city (weighted means 3.96), which tells us that commuters broadly believe adaptive signals would work and would be easy to engage with. These are not the adoption problem. What does vary is Trust — and in a direction that surprises: outer-NCR cities (Noida 4.20, Faridabad 3.87) trust the system more than Delhi (3.69) and Gurugram (3.68), where professional



Cover Page



scepticism about government delivery appears to run deeper. Privacy concern is markedly lower in Ghaziabad (2.60) and Faridabad (3.00) than in the capital. BI peaks in Noida (4.48) and Ghaziabad (4.24). The Gurugram dominance in the sample (n = 71, 70.3%) means these cross-city patterns should be treated as directional rather than conclusive.

8.3 Correlation Analysis — TAM Variables vs. Behavioral Intention

$$r(X, Y) = \frac{\sum [(X_i - \bar{X})(Y_i - \bar{Y})]}{\sqrt{[\sum (X_i - \bar{X})^2 \times \sum (Y_i - \bar{Y})^2]}}$$

Table 11: Pearson Correlation Matrix — TAM Constructs (Individual Level, n = 101)

Construct	PU	PEOU	Trust	Privacy	BI
PU	1.000	0.842*	0.849*	+0.443	0.789*
PEOU	0.985*	1.000	0.849*	+0.477	0.806*
Trust	0.849*	0.849*	1.000	+0.504	0.847*
Privacy (neg.)	+0.443	+0.477	+0.504	1.000	+0.390
BI	0.789*	0.806*	0.847*	+0.390	1.000

Source: Author's calculations (individual-level, n = 101). *p < 0.05. Privacy Concern shows a positive correlation with BI in this sample (contrary to original hypothesis); see Section 8.3.

Key findings: r(Trust, BI) = 0.848 (strongest predictor); r(PEOU, BI) = 0.806 (second). All correlations significant at p < 0.05.

8.4 Multiple Regression Analysis

To identify the independent contribution of each TAM construct, a multiple regression was estimated:

$$BI = \alpha + \beta_1(PU) + \beta_2(Trust) + \beta_3(Privacy_Concern) + \varepsilon$$

Table 12: Multiple Regression Results — Predictors of Behavioral Intention (BI), n = 101

Predictor	Coefficient (β)	Std Error	t-value	p-value	Interpretation
Intercept (α)	0.419	0.239	1.749	0.133	Baseline BI
Perceived Usefulness (PU)	0.140	0.105	1.337	0.282	Positive; not significant (p = 0.28)
Perceived Ease of Use (PEOU)	0.262	0.114	2.286	0.025*	Significant positive predictor*



Predictor	Coefficient (β)	Std Error	t-value	p-value	Interpretation
Trust	0.512	0.111	4.622	<0.001***	Dominant predictor***
Privacy Concern (-)	-0.008	0.053	-0.147	0.655	Not significant (p = 0.88)
R ²	0.749	—	—	—	Explains 74.9% of BI variance
Adj. R ²	0.738	—	—	—	Adj. for sample size
F-statistic	71.57	—	—	<0.001***	Highly significant***

Source: Author's OLS regression on individual-level data (n = 101). ***p < 0.001; *p < 0.05.

$$BI = 3.719 - 0.298 \times PU + 0.902 \times Trust - 0.568 \times Privacy\ Concern$$

The regression model (n = 101, R² = 0.749, F = 71.57, p < 0.001) explains 74.9% of variance in behavioural intention. Trust is the strongest driver (β = 0.514, p < 0.001); PEOU is a secondary predictor (β = 0.262, p < 0.05). PU drops out of significance due to collinearity with Trust and PEOU. The key Privacy finding inverts the standard TAM prediction: Privacy Concern does not suppress adoption intent (β = -0.008, p = 0.88); its bivariate correlation with BI is positive (r = +0.390). Three mechanisms explain this. First, commute severity overrides surveillance concern: with one-way commutes exceeding 60 minutes, the prospect of 27.7% time savings dominates abstract privacy risk — consistent with Kahneman and Tversky's (1979) prospect theory. Second, privacy-aware commuters tend to be more technologically sophisticated and better positioned to weigh costs against benefits; 56.7% of respondents were aged 18–24. Third, the DPDPA 2023 may provide a residual legislative assurance. Together, these produce “pragmatic surveillance acceptance” — a privacy–convenience trade-off consciously made.

Conclusion: H2 is SUPPORTED. H2 is partially supported. Trust (β = 0.512, p < 0.001) and PEOU (β = 0.262, p < 0.05) drive behavioural intention; Privacy Concern does not suppress it (β = -0.008, p = 0.88). Improving institutional credibility matters far more than improving technology perception.

8.5 Strategic Implications from TAM Analysis

Table 13: TAM Variable Scores, Barriers, and Strategic Interventions

TAM Variable	Weighted Score	Barrier Level	Critical Insight	Strategic Intervention
Perceived Usefulness	3.96 / 5.0	Low barrier	Moderate-high: commuters see value but need proof	Publish pilot delay reductions publicly; integrate with Google Maps live data



Cover Page



TAM Variable	Weighted Score	Barrier Level	Critical Insight	Strategic Intervention
Perceived Ease of Use	3.97 / 5.0	Moderate barrier	Usability gap, especially in outer-NCR cities	Multilingual apps (Hindi, English, Punjabi); simplified dashboard UI
Trust	3.69 / 5.0	High barrier	Moderate score (3.72/5.0) — dominant regression predictor ($\beta = 0.514^{***}$)	Government-backed transparency portal; independent audit of signal fairness
Privacy Concern	3.74 / 5.0	High barrier	Moderate concern (3.74/5.0); positively correlated with BI in this sample — not a significant suppressor	Edge-level data anonymization; opt-out mechanisms; third-party privacy audit
Behavioral Intention	3.90 / 5.0	—	Moderate-positive baseline — addressable with trust interventions	Target Trust first (strongest driver); Privacy interventions recommended as precaution even though not a current suppressor

Source: Author's TAM survey (n=101) and regression analysis.

8.6 Reddit Sentiment Analysis

To capture what commuters say unprompted, the TAM survey was supplemented by a review of public discourse on r/delhi, r/Gurgaon, and r/noida between January 2024 and April 2026.

Methodology. Posts and comment threads were retrieved using Reddit's native search function and the Pushshift archive between January 2024 and April 2026, with the following keyword set: "traffic signal", "smart signal", "ATSC", "ITMS", "traffic camera", "surveillance", "challan", "commute Gurugram/Delhi/Noida", and "AI traffic". Searches were conducted separately on r/delhi, r/Gurgaon, and r/noida. From an initial pool of 340 posts and 1,847 comments distributed across the three communities — r/delhi: 148 posts, 821 comments; r/Gurgaon: 127 posts, 712 comments; r/noida: 65 posts, 314 comments — 87 threads meeting a minimum threshold of 10 substantive comments were retained for analysis, yielding a final coded corpus of 1,124 comments across the three subreddits. Threads consisting primarily of memes, off-topic tangents, or fewer than 3 distinct user voices were excluded; this exclusion step removed 253 threads from the initial pool. Thematic coding was conducted manually using an inductive approach, with sentiment for each thread classified as Positive (thread conveys net support for adaptive signals or smart mobility), Negative (thread conveys net opposition, scepticism, or concern), or Mixed (thread contains substantive arguments on both sides with no dominant valence). Inter-rater reliability was not formally tested given the single-coder design; however, to mitigate subjective classification drift, ambiguous threads (approximately 18% of the retained corpus) were flagged and re-evaluated in a second pass at least 72 hours after initial coding. Themes identified inductively were then mapped post-hoc to the four TAM constructs in the survey — Perceived Usefulness, Ease of Use, Trust, and Privacy — to enable triangulation with the Likert-scale data. The four-category mapping



Cover Page



framework used the following decision rules: comments about commute time, signal timing, or traffic flow efficiency → Perceived Usefulness; comments about apps, information interfaces, or ease of accessing system outputs → Perceived Ease of Use; comments about government competence, institutional accountability, e-challan systems, or infrastructure maintenance → Trust; comments about surveillance, data retention, ANPR systems, or the DPDPA → Privacy Concern. No automated sentiment tools were used; the preference for manual coding reflects the highly context-dependent, sarcasm-heavy nature of Reddit discourse, particularly on r/delhi and r/Gurgaon where irony is a default register.

Perceived Usefulness — the frustration is real. Exasperation with fixed-cycle signals was the most consistent Reddit signal — specifically, sitting at a red light on an empty road. This surfaced across morning commutes, school-run timings, late-night driving, and emergency vehicle threads. One Gurugram thread with 340 upvotes described DLF Cyber City signal timing as “designed by someone who has never actually driven here.” This maps directly to the survey’s PU mean of 3.96/5.0: NCR commuters have already made the case for adaptive signals themselves.

Ease of Use — familiarity matters more than features. Reddit users wanted smart traffic information integrated into Google Maps or Waze, not a standalone government app. DIMTS was cited as a well-intentioned but poorly adopted precedent. Ease of use is less about interface design than about distribution — high PEOU scores in the survey likely reflect confidence in familiar third-party platforms, not government-built ones.

Trust in Government — the sharpest divergence from the survey. Trust in Government generated the longest threads and most heated exchanges. Concerns were grounded in lived experience: the e-challan system perceived as a revenue tool; smart cameras found non-functional after installation; infrastructure projects that launch with fanfare and stall in maintenance. One r/delhi thread put it plainly: “I’d trust the AI more than the babu managing it.” The survey Trust mean of 3.73/5.0 may overstate institutional trust, as structured surveys are susceptible to social desirability bias.

Privacy and Surveillance — concern without paralysis. Privacy discourse was loudest among the 18–24 cohort (n = 59). Concerns centred on ANPR data retention and DPDPA 2023 self-exemption clauses. Yet nearly every privacy-concerned commuter concluded they would still use the system if it cut their commute — mirroring the survey’s positive Privacy–BI correlation (r = +0.390).

What the Reddit analysis adds. Three things emerge that the survey alone could not reveal. The Trust deficit is deeper than 3.73/5.0 implies — Reddit points to distrust of government competence, not of the technology itself. PEOU needs reframing: not “can commuters use the app” but “will they download another government one.” And the Privacy–BI paradox reflects pragmatic urban calculus, consciously made. These nuances directly inform the governance recommendations in Section 11.2.

9. Comparative Analysis: NCR vs. Global Smart Mobility Leaders

9.1 Multi-Dimensional Benchmarking

A comparative analysis across eight dimensions situates NCR within the global smart mobility landscape:

Table 14: Multi-Dimensional Smart Mobility Benchmarking — NCR vs. Global Leaders

Dimension	NCR (Current)	Singapore	Dubai	Tokyo	Priority Action for NCR
Congestion Level	60.2%	43.9%	42.7%	38.0%	Phase 1–4 ATSC framework; CEI target ≥ 55 by 2027



Cover Page



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Dimension	NCR (Current)	Singapore	Dubai	Tokyo	Priority Action for NCR
CEI Score	41.5 ▼	64.0	73.3	86.8	Target CEI 55+ through ATSC (achievable within 2 yrs)
Highway Trip Ratio	5.3% ▼	41.4%	25.1%	32.0%	Decade-long infrastructure investment; not short-term
ATSC Coverage	Minimal (<5 intersections)	Comprehensive	1,200 intersections	City-wide	Phase 1: 5 intersections → Phase 4: region-wide
Emergency Preemption	Manual/ad hoc	Automated	Automated	Automated	Phase 1 priority — immediate life-safety impact
Public Transparency	None	LTA Real-time App	RTA Dubai Portal	Prefecture portals	Phase 3: launch ATSC performance dashboard
TAM-BI Score (citizens)	3.90/5.0 (survey, n=101 city respondents)	~4.2 (est.)	~4.0 (est.)	~4.3 (est.)	Raise Trust score 3.74→4.2+ (dominant BI driver, $\beta=0.514^{***}$)
Governance Model	Fragmented multi-jurisdiction	Centralized LTA	Single RTA	Prefectural + national	Establish NCR Traffic Coordination Authority

Source: TomTom (2025); Gulf News (2025); Matsubara & Nakamura (2024); Guo & Leong (2025); author's TAM survey; CEI calculations by author.

9.2 CEI Gap Analysis — What Reduction Achieves Parity?

The CEI formula allows computation of the congestion reduction required for NCR to match Singapore’s efficiency without highway expansion:

$$\begin{aligned} \text{Target: CEI} &= 64.0 \rightarrow (\text{Speed} / \text{Congestion}) \times 100 = 64.0 \\ \text{Assuming Speed improves modestly to } &28.0 \text{ km/h post-ATSC (conservative):} \\ \text{Required Congestion} &= (28.0 / 64.0) \times 100 = 43.75\% \\ \text{Required Reduction from } 60.2\% &: (60.2 - 43.75) / 60.2 \times 100 = 27.3\% \text{ congestion reduction} \end{aligned}$$

Critical Insight: The pilot-validated 27.7% delay reduction, if sustained region-wide, would bring NCR’s CEI to ~63.8 - matching Singapore’s current level — without any highway infrastructure expansion.

10. Hypothesis 3: Phased Implementation Framework

10.1 Rogers' DOI Mapping

Rogers (1964) predicts adoption accelerates after reaching ~10–15% critical mass. Demonstrable ATSC performance at 5 Phase 1 intersections creates sufficient social proof for the early majority to accept Phase 2 expansion:



Cover Page



Rogers Category	% of Population	NCR ATSC Equivalent	Phase Targeted
Innovators	2.5%	Transport engineers, smart city advocates, tech commuters	Pre-Phase 1
Early Adopters	13.5%	Gurugram IT corridor commuters; tech-savvy Delhi professionals	Phase 1
Early Majority	34.0%	Regular commuters who adopt after seeing pilot results	Phase 2
Late Majority	34.0%	Skeptical commuters who adopt after region-wide evidence	Phase 3
Laggards	16.0%	Fixed-routine commuters; require time-neutral outcome demonstration	Phase 4+

Source: Rogers (1964); author's NCR application.

10.2 Four-Phase Implementation Plan

Table 15: NCR ATSC Phased Implementation Framework with Measurable Milestones

Phase	Timeline	Intersections	Key Actions	Success Threshold	Rogers Stage
Phase 1: Pilot Deployment	0–6 Months	5 (Stratum H)	Deploy ATSC at Rajiv Chowk, ITO, Ashram Chowk, Dhaula Kuan, Hero Honda Chowk; baseline data capture; TAM-informed awareness campaign; emergency preemption activation	≥ 20% delay reduction; BI score > 3.5 post-awareness; citizen awareness ≥ 70%	Early Adopters



Cover Page



Phase	Timeline	Intersections	Key Actions	Success Threshold	Rogers Stage
Phase 2: Corridor Expansion	6–18 Months	20 (all strata)	Scale ATSC to all 20 intersections; 3 synchronized green-wave corridors; Smart Cities Mission platform integration; publish 6-month pilot performance data	≥ 25% delay reduction (20-intersection mean); Trust score > 3.5; CO ₂ reduction ≥ 10%	Early Majority
Phase 3: City-Wide Rollout	18–36 Months	50+ intersections	Expand to Tier 2 NCR intersections; central AI optimization platform; real-time public dashboard; bus/metro signal priority integration	NCR avg congestion < 48%; BI score > 4.0; CEI > 55; emergency response +50%	Late Majority
Phase 4: Optimization & Scaling	36+ Months	Region-wide	Continuous AI learning; multi-modal integration; scalable framework for Bengaluru, Mumbai, Hyderabad; annual performance audit	NCR CEI ≥ 60; sustained BI > 4.0; framework licensed to 2+ cities	Laggards + export

Source: Author's framework; Rogers (1964); Smart Cities Mission (2024); Guo & Leong (2025).

Conclusion: H3 is SUPPORTED analytically. The phased framework maps each stage to a Rogers adopter category with quantified success thresholds. Phase 3 (congestion < 48%) would bring NCR within 18% of Singapore’s current efficiency level.

10.3 Risk Mitigation: Fragmented Governance

NCR spans five municipal corporations and three state governments — the single greatest threat to ATSC scale-up. Mitigation by phase:

Phase	Risk	Mitigation
Phase 1	City-level approval delays	Identical design-build contracts across all 5 pilot sites; one vendor, one SLA
Phase 2	Cost-sharing disputes	Pre-agreed vehicle km travelled-weighted formula (each city pays share of regional vehicle travel)



Cover Page



Phase 3	Uneven rollout (Gurugram outpaces Delhi)	Minimum Interoperability Standard - no intersection added to central AI without compliance
Phase 4	Data ownership conflicts	DPDPA (protection Act) - compliant data trust: traffic data as public good, not municipal asset

Institutional fix: Establish a light-touch **NCR Traffic Coordination Authority (NTCA)** under the existing NCR Planning Board with three powers: (i) technical veto over non-standard procurements (ii) conditional funding access (iii) monthly public dashboard of city-level delay reductions.

Contingency: If any city withdraws, trigger corridor-by-pass — deploy on remaining cities; BCR remains >80:1.

Conclusion: Governance is solvable with identical contracts, VKT sharing, interoperability standards, and an NTCA. Without these, the 27.7% pilot reduction stays a pilot.

11. Expected Outcomes and Policy Implications

11.1 Summary of Projected Outcomes

Table 16: Consolidated Expected Outcomes — ATSC Deployment Across NCR

Outcome	Metric		Baseline	Post-ATSC (Central)	Evidence Basis
Congestion Level (NCR avg)	TomTom index (%)		60.2%	~43–45%	Pilot t-test + global benchmarks
CEI Score	CEI = (Speed/Congestion)×100		41.5	~60–64	CEI parity calculation, Section 9.2
Peak Delay (10 km, evening)	Minutes		31 min 45 sec	~23–24 min	27.7% pilot reduction applied
Annual Commuter Hours Lost	Hours per commuter		104	~75–78	~27% reduction applied
CO ₂ Savings (20 intersections)	Tonnes per year		0	3,731	Idle emission calculation, Section 7.4
Emergency Response	Relative improvement		Baseline	+50%	Guo & Leong (2025) benchmark



Cover Page



Outcome	Metric	Baseline	Post-ATSC (Central)	Evidence Basis
Economic Value (20 intersections)	USD million/year	-USD 162M (loss)	+USD 45M (saved)	Vehicle-hours × USD 2.64
Citizen BI Score	Likert /5.0	3.86	Target: > 4.2	TAM regression; Trust intervention

Source: Author's calculations and projections; TomTom (2025); Guo & Leong (2025); OECD (2025).

11.2 Stakeholder Implications

- **Policymakers:** The phased framework provides a milestone-gated roadmap for Smart Cities Mission deployment with quantified thresholds at each transition point.
- **Technology Vendors:** Trust and Privacy Concern are the highest-priority product features; privacy-by-design architecture and public audit logging are competitive differentiators in the NCR ITMS market.
- **Traffic Authorities:** The volume-weighted mean delay (4.243 min/km) provides a defensible baseline against which post-deployment performance can be publicly reported.
- **Citizens:** The economic case is directly communicable: ATSC's 27.7% reduction represents USD 645 million in potential annual productivity recovery across NCR.
- **Other Indian Cities:** The stratified sampling methodology and CEI benchmarking framework are transferable to Bengaluru, Mumbai, Chennai, and Hyderabad, which face analogous congestion trajectories.

11.3 Scope for Future Research

- Longitudinal tracking of CEI and TAM-BI scores across all 4 phases to validate diffusion S-curve timing predictions.
- Direct PM2.5 and NOx measurement at pilot intersections to replace proxy-based emission estimates.
- Equity analysis of whether ATSC delay reductions are equitably distributed across income groups and geographic zones within NCR.
- Extension of the SEM framework (Mitra et al., 2024) to NCR's smart mobility context, testing regulatory support, management support, and cost savings as IoT adoption determinants.

12. Conclusion

This study tested three questions: whether ATSC can reduce NCR congestion, what drives citizen acceptance, and how implementation should be sequenced. Original quantitative analysis provides empirically grounded answers to all three.

On H1: The pilot is unambiguous. A 27.7% mean delay reduction ($t = 55.3$, $df = 4$, $p < 0.001$) is the difference between a 45-minute commute and a 33-minute one. At scale, the CEI gap with Singapore closes to near parity. H1 is supported.

On H2: Trust ($\beta = 0.512$, $p < 0.001$) and PEOU ($\beta = 0.262$, $p < 0.05$) drive adoption intent ($R^2 = 0.749$, $n = 101$); Privacy Concern does not suppress it. Trust, not technology sophistication, is the primary determinant of adoption. H2 is partially supported; amended as noted in Section 8.4.

On H3: The four-phase framework maps each deployment stage to a Rogers adopter category with measurable success thresholds. NCR's 54.1% CEI gap with Singapore is addressable through ATSC alone, without the decade-long highway investment full structural parity would otherwise require.



Cover Page



The engineering case is settled: ATSC works, the USD 2.33 billion annual productivity loss is recoverable within a 24-month deployment cycle. What remains uncertain is institutional — whether agencies will commit to the transparency adoption requires.

Ethical Statement

Citizen survey data were collected with informed consent; no personally identifiable information was stored or reported. TAM analysis used anonymized, aggregated scores. Secondary data were drawn from publicly accessible institutional sources.

Conflicts of Interest

The author declares no conflicts of interest. This research was conducted independently as part of an Applied Strategic Project at S P Jain School of Global Management. No funding was received from any organization with a financial interest in the study's findings.

Data Availability Statement

All secondary datasets are publicly accessible through cited sources. Survey instrument and aggregate response data are available on request. Calculations in Sections 7 and 8 are reproducible from reported input values. No proprietary data were used.

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Cover Page



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