International Journal of Recent Development in Engineering and Technology
Website: www.ijrdet.com (ISSN 2347-6435 (Online) Volume 15, Issue 11, November 2026)

Urban Traffic Congestion and Public Transport Usage in Bengaluru: A Data-Driven Analysis of Area-Level Mobility, Capacity Stress, and Environmental Impact

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***Abstract*—This study analyzes urban traffic conditions in Bengaluru using a dataset of 8,936 daily observations recorded across 8 areas and 16 roads and intersections between 1 January 2022 and 9 August 2024. We examine traffic volume, average speed, travel time index, congestion level, road capacity utilization, incident reports, environmental impact, public transport usage, and pedestrian and cyclist counts. Mean daily traffic volume is 29,236 vehicles and mean speed is 39.4 km/h; 43.5% of all observations reach a congestion level of 100%, and 62.2% exceed 80%. Congestion is strongly spatial: Koramangala (mean congestion 94.0%) and M.G. Road (90.6%) are the most stressed areas, whereas Electronic City (54.5%) and Yeshwanthpur (62.4%) are the least. Congestion is closely tied to traffic volume ($r = 0.84$) and negatively tied to pedestrian and cyclist counts ($r = -0.74$), while environmental impact is a deterministic function of volume ($r = 1.00$). Weather and roadwork showed no statistically significant effect on congestion, and public transport usage (mean 45.1%) was statistically unrelated to congestion ($r = -0.003$, $p = 0.79$), a result we interpret with caution. To extend the baseline to 2025 and 2026, we benchmark these findings against published external indicators, which show continued deterioration: TomTom's congestion level for Bengaluru rose to 74.4% in 2025, road deaths reached 999, and registered vehicles passed 1.28 crore by June 2026. We establish baseline traffic KPIs, present six figures and nine tables describing the network, and outline recommendations on area-targeted demand management, junction capacity, public transport priority, and pedestrian infrastructure.**

***Index Terms*—Urban traffic congestion, Bengaluru, travel time index, road capacity utilization, public transport usage, environmental impact, data visualization, exploratory data analysis.**

I. Introduction

Bengaluru is one of India's fastest-growing metropolitan regions and a major technology hub, and it is widely associated with severe road congestion. Rapid growth in private vehicle ownership, concentrated employment corridors, and limited road space cause long and unpredictable travel times that affect commuters, businesses, and urban air quality.

Congestion also imposes costs that are rarely visible to individual drivers, including lost working hours, higher fuel consumption, elevated emissions, and a greater likelihood of crashes and incidents.

Data-driven analysis helps planners move from anecdotal impressions to measurable baselines. Indicators such as average speed, travel time index (TTI), and road capacity utilization describe how well a corridor serves its traffic, while incident reports, signal compliance, and environmental impact describe safety and sustainability outcomes. Understanding how these indicators vary across areas and conditions is a prerequisite for targeted interventions, because a measure that works on a lightly loaded suburban corridor may have little effect on a saturated central junction.

This study analyzes a traffic dataset covering eight Bengaluru areas (Indiranagar, M.G. Road, Koramangala, Jayanagar, Hebbal, Whitefield, Yeshwanthpur, and Electronic City). In accordance with the institution's data visualization framework, we investigate: (1) what the overall traffic and congestion profile of the city looks like; (2) how congestion, speed, and incidents differ across areas and roads; (3) which factors (traffic volume, weather, roadwork, public transport usage, pedestrian activity) are associated with congestion and environmental impact; (4) whether these patterns are stable over time; and (5) what practical interventions the evidence supports.

The main contributions of this paper are: a reproducible exploratory analysis of the dataset using standard statistical tools; a set of baseline KPIs for Bengaluru's road network; an area- and road-level ranking of congestion stress; a quantified description of how speed, incidents, and environmental impact change as volume rises; a candid assessment of which variables in the dataset carry usable signal and which do not; and a 2025–2026 extension that benchmarks the dataset findings against published congestion, vehicle, transit, and road-safety statistics.

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II. Related Work

Congestion has long been studied as an economic and engineering problem. Small and Verhoef [6] describe congestion as an externality: each additional vehicle slows others, but the driver bears only a fraction of that cost, which is the basis for pricing and demand-management policies. Downs [4] argues that peak-hour congestion is difficult to eliminate by adding capacity alone because travelers adjust their departure times, routes, and modes until the extra capacity is filled, a process he describes as triple convergence.

Empirical evidence supports this view. Duranton and Turner [5] found that vehicle-kilometers traveled in US cities increase roughly in proportion to road capacity, which implies that road building alone does not reduce congestion. Cervero and Kockelman [3] showed that built-environment characteristics, namely density, diversity, and design, influence how much people travel and which modes they choose, supporting land-use and street-design measures alongside traffic engineering.

Performance measurement is central to traffic management. The Highway Capacity Manual [7] defines level-of-service categories based on speed, density, and volume-to-capacity ratios, and the Urban Mobility Report series [2] popularized the travel time index as a comparable measure of congestion across cities.

Our dataset provides TTI, congestion level, and capacity utilization together with incident, environmental, and active-travel indicators, which allows a multi-dimensional view of congestion rather than a single speed metric. Open scientific Python tools [8]–[10] make such analyses reproducible and are used throughout this work.

III. Data And Methods

A. Dataset

The analysis uses the Bengaluru Traffic Dataset provided with this project [1], consisting of 8,936 records and 16 attributes with no missing values and no duplicate rows. Each record corresponds to one road or intersection on one date, spanning 952 distinct dates from 1 January 2022 to 9 August 2024 (3,424 records in 2022, 3,413 in 2023, and 2,099 in 2024). The data cover 8 areas and 16 roads and intersections, such as 100 Feet Road, CMH Road, Sarjapur Road, Silk Board Junction, Hebbal Flyover, and Marathahalli Bridge. Records per area range from 552 (Electronic City) to 1,720 (Indiranagar), so sampling is uneven and area averages are weighted accordingly.

B. Variables

The attributes fall into four groups: traffic flow and performance, safety and compliance, environment and mobility context, and external conditions. Table I lists them with their observed ranges.

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TABLE I
DESCRIPTION OF DATASET VARIABLES

Variable	Observed Range / Values	Interpretation
Traffic Volume	4,233 – 72,039	Vehicle count recorded for the road on the date
Average Speed	20.0 – 89.8 km/h	Mean vehicle speed on the road
Travel Time Index	1.00 – 1.50	Ratio of actual to free-flow travel time (capped at 1.50)
Congestion Level	5.2 – 100.0 %	Share of capacity-related congestion (capped at 100)
Road Capacity Utilization	18.7 – 100.0 %	Use of available road capacity (capped at 100)
Incident Reports	0 – 10	Number of reported incidents
Environmental Impact	58.5 – 194.1	Index of emission-related impact
Public Transport Usage	10.0 – 80.0 %	Share of travel using public transport
Traffic Signal Compliance	60.0 – 100.0 %	Share of road users obeying signals
Parking Usage	50.0 – 100.0 %	Occupancy of parking supply
Pedestrian and Cyclist Count	66 – 243	Number of pedestrians and cyclists counted
Weather Conditions	5 categories	Clear, Overcast, Fog, Rain, Windy
Roadwork and Construction	Yes / No	Roadwork present in 9.9% of records

C. Preprocessing and Validation

The data were checked for missing values, duplicates, and implausible entries. No values were missing and no rows were duplicated; every date–road combination is unique. Speed, volume, and the percentage variables fall within plausible ranges. Three variables are bounded: congestion level and road capacity utilization at 100%, and the travel time index at 1.50. These ceilings are reached frequently (in 43.5% of records for congestion level, 73.7% for capacity utilization, and 58.5% for the travel time index), so they are treated as censored measures rather than outliers, and no observations were removed.

D. Analytical Approach and KPIs

Analysis was carried out in Python using pandas [8] and SciPy [10] for aggregation and statistical testing, with matplotlib [9] for visualization. We computed descriptive statistics, area- and road-level aggregates, quartile-based comparisons, Pearson correlation coefficients, one-way ANOVA and Kruskal–Wallis tests across weather conditions, and a two-sample t-test for roadwork.

Five primary Key Performance Indicators (KPIs) were established: Mean Traffic Volume, Mean Average Speed (km/h), Mean Congestion Level (%), Saturation Share (% of observations with congestion level at 100%), and Mean Public Transport Usage (%). Statistical significance is assessed at the 5% level.

E. External Indicators for 2025–2026

The dataset ends on 9 August 2024 and contains no records for 2025 or 2026, so these years cannot be analyzed at record level with the methods above. To extend the study, we collected published annual indicators from public sources as of 2 November 2026: congestion level, peak-hour time lost, and rush-hour speed from the TomTom Traffic Index [11]–[13]; road accidents and fatalities from Bengaluru Traffic Police statistics [14]; vehicle registrations from Karnataka Transport Department data [15]–[17]; and Namma Metro ridership from BMRCL figures [18]–[21]. These indicators are city-level, differ in definition from the dataset variables, and are used descriptively to test whether the dataset's conclusions still hold, not pooled with the dataset records.

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IV. Results

A. Overall Traffic Profile

Across all 8,936 observations, the mean traffic volume is 29,236 vehicles (median 27,600) and the mean average speed is 39.4 km/h. The mean congestion level is 80.8% and the median is 92.4%, showing that conditions are heavily skewed toward saturation: 43.5% of observations record a congestion level of 100% and 62.2% record 80% or above.

The travel time index averages 1.38 and reaches its recorded maximum of 1.50 in 58.5% of observations, while mean road capacity utilization is 92.0%. Only 9.6% of records show an average speed below 25 km/h, which indicates that the network is more often slow and crowded than completely gridlocked. Table II summarizes the primary KPIs.

TABLE II
HEADLINE TRAFFIC KPIS FOR BENGALURU

Dashboard KPI / Metric	Value	Baseline Context (Bengaluru Dataset, N=8,936)
Observations Analyzed	8,936	8 areas, 16 roads/intersections, 952 dates
Mean Traffic Volume	29,236	Median 27,600; maximum 72,039
Mean Average Speed	39.4 km/h	Minimum 20.0; maximum 89.8 km/h
Mean Congestion Level	80.8%	Median 92.4%; 43.5% of records at 100%
Mean Travel Time Index	1.38	Recorded maximum 1.50 in 58.5% of records
Mean Road Capacity Utilization	92.0%	Median 100.0%
Mean Incident Reports	1.57	Maximum 10 incidents per record
Mean Public Transport Usage	45.1%	Range 10.0% to 80.0%
Mean Signal Compliance	79.9%	Range 60.0% to 100.0%

B. Area-Level Congestion

Congestion differs sharply by area. Koramangala is the most stressed area, with mean traffic volume of 40,832, mean speed of 36.1 km/h, mean congestion of 94.0%, and a saturated congestion level (100%) in 75.5% of its observations.

M.G. Road and Indiranagar follow closely. At the other extreme, Electronic City averages only 16,347 vehicles and 54.5% congestion, with saturation in just 3.1% of observations. Table III details the comparison and Fig. 1 visualizes the ranking.

International Journal of Recent Development in Engineering and Technology
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TABLE III
TRAFFIC CONDITIONS ACROSS BENGALURU AREAS (SORTED BY CONGESTION)

Area	Records	Mean Volume	Mean Speed (km/h)	Mean Congestion (%)	Mean TTI	Saturated (100%) Share
Koramangala	1,364	40,832	36.1	94.0	1.47	75.5%
M.G. Road	1,501	35,300	37.5	90.6	1.44	63.3%
Indiranagar	1,720	32,284	38.6	87.6	1.40	58.3%
Hebbal	950	26,533	40.2	80.1	1.37	38.0%
Jayanagar	1,173	24,601	39.8	77.0	1.36	27.6%
Whitefield	942	21,295	42.1	69.1	1.29	15.5%
Yeshwanthpur	734	18,932	43.5	62.4	1.26	7.2%
Electronic City	552	16,347	43.7	54.5	1.23	3.1%

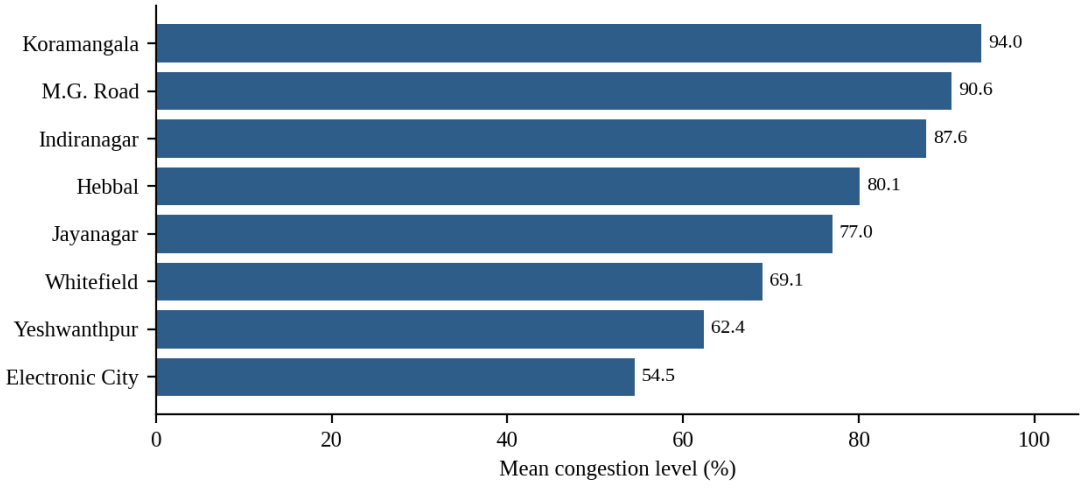


Fig. 1. Mean congestion level by area.

Incident rates follow the same ordering: M.G. Road (1.86), Koramangala (1.85), and Indiranagar (1.78) record the most incidents per observation, while Electronic City (0.78) and Yeshwanthpur (1.08) record the fewest. Conversely, pedestrian and cyclist counts are highest in the least congested areas (Electronic City 143.5, Yeshwanthpur 131.4) and lowest in Koramangala (104.6).

C. Road- and Intersection-Level Patterns

Table IV lists all 16 monitored locations. Road-level differences within an area are small: the two Koramangala locations (Sony World Junction and Sarjapur Road) average 94.1% and 93.8% congestion, and the two Electronic City locations (Hosur Road and Silk Board Junction) average 55.2% and 53.7%.

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The spread between the most and least congested location (Sony World Junction versus Silk Board Junction) is 40.4 percentage points, whereas the spread within any single area never exceeds 3.9 points.

Congestion is therefore driven mainly by area-level demand rather than by features unique to individual junctions.

TABLE IV
CONGESTION BY ROAD AND INTERSECTION

Area	Road / Intersection	Records	Mean Volume	Mean Speed (km/h)	Mean Congestion (%)
Koramangala	Sony World Junction	684	41,471	36.0	94.1
Koramangala	Sarjapur Road	680	40,190	36.1	93.8
M.G. Road	Anil Kumble Circle	759	35,252	37.4	90.8
M.G. Road	Trinity Circle	742	35,350	37.7	90.4
Indiranagar	CMH Road	860	32,612	38.9	88.2
Indiranagar	100 Feet Road	860	31,957	38.4	87.1
Hebbal	Hebbal Flyover	474	26,795	40.3	80.7
Hebbal	Ballari Road	476	26,273	40.0	79.5
Jayanagar	South End Circle	593	24,704	39.4	77.3
Jayanagar	Jayanagar 4th Block	580	24,496	40.1	76.7
Whitefield	ITPL Main Road	450	21,866	42.0	71.1
Whitefield	Marathahalli Bridge	492	20,773	42.3	67.2
Yeshwanthpur	Yeshwanthpur Circle	373	19,277	43.0	63.7
Yeshwanthpur	Tumkur Road	361	18,575	43.9	60.9
Electronic City	Hosur Road	277	16,557	44.0	55.2
Electronic City	Silk Board Junction	275	16,135	43.3	53.7

D. Traffic Volume, Speed, and Environmental Impact

Traffic volume is the dominant correlate of congestion ($r = 0.84$, Fig. 2).

The relationship is not linear: binned means rise steeply between roughly 10,000 and 30,000 vehicles and then flatten at the 100% ceiling. To show how conditions change as volume grows, Table V groups observations into volume quartiles.

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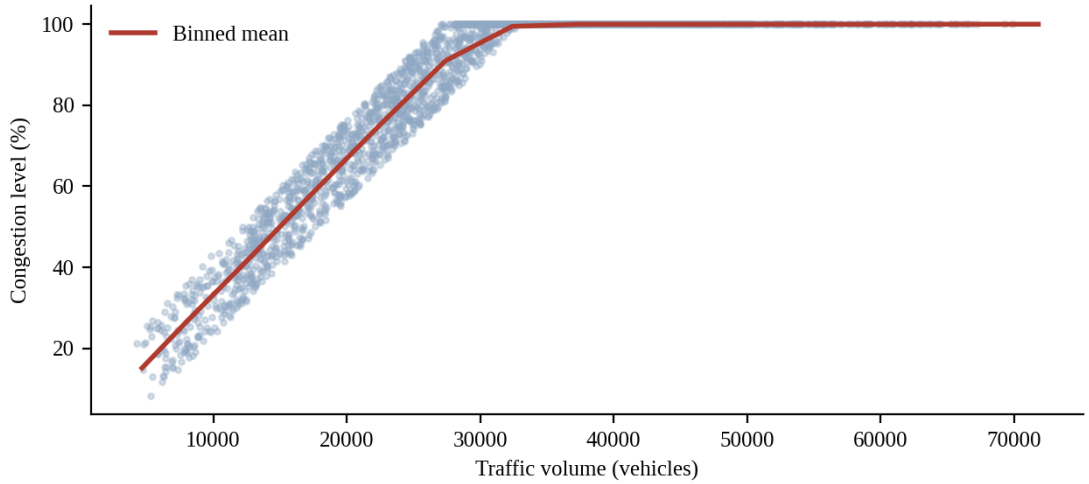


Fig. 2. Congestion level versus traffic volume (random sample of 2,500 records) with binned mean.

TABLE V
TRAFFIC CONDITIONS BY TRAFFIC VOLUME QUARTILE

Volume Quartile	Volume Range	Mean Speed (km/h)	Mean Congestion (%)	Mean Incidents	Env. Impact (mean)	Ped./Cyc. (mean)
Q1 (lowest)	4,233–19,404	44.9	45.5	0.5	77.3	158.4
Q2	19,416–27,591	41.6	79.4	1.7	97.5	100.1
Q3	27,609–38,057	35.9	98.3	2.0	115.1	99.8
Q4 (highest)	38,063–72,039	35.4	100.0	2.0	143.9	99.8

Moving from the lowest to the highest volume quartile raises mean congestion from 45.5% to 100% and environmental impact by 86% (77.3 to 143.9), while mean speed falls only from 44.9 to 35.4 km/h (Fig. 3). Incident reports quadruple from 0.5 to 2.0 per record between the first and third quartile and do not rise further.

Congestion effectively saturates from the third quartile onward, after which additional volume mainly lengthens queues rather than changing the recorded congestion level. Environmental impact is perfectly correlated with traffic volume ($r = 1.00$), so it behaves as a direct function of vehicle count in this dataset.

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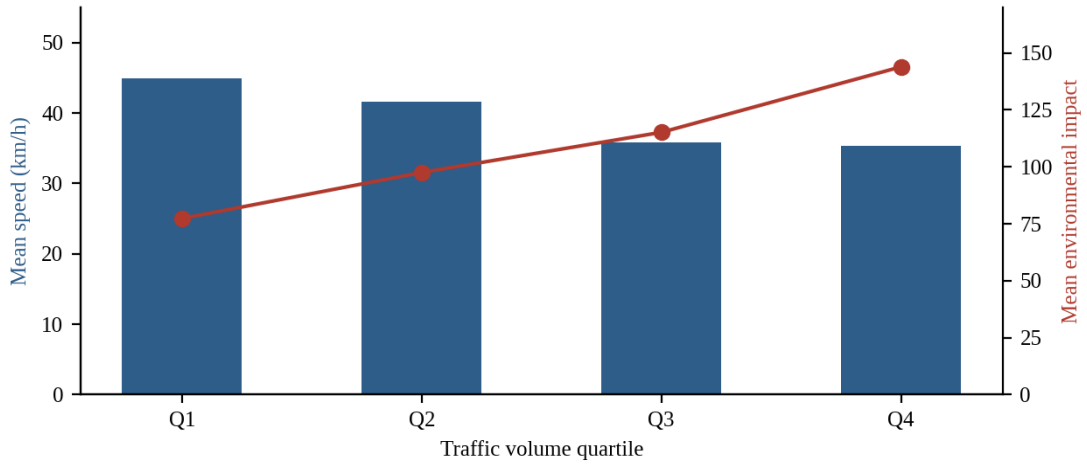


Fig. 3. Mean speed (bars) and environmental impact (line) by traffic volume quartile.

E. Correlation Structure

Fig. 4 shows the correlation matrix of the main numeric variables. Congestion is positively associated with volume (r = 0.84), road capacity utilization (r = 0.87), and travel time index (r = 0.75), and moderately with incident reports (r = 0.42). Average speed is moderately and negatively correlated with volume (r = −0.34) and congestion (r = −0.36).

Pedestrian and cyclist counts are strongly negatively correlated with capacity utilization (r = −0.87) and congestion (r = −0.74), which suggests that active-travel activity is highest on lightly loaded days and locations. In contrast, public transport usage has a correlation of essentially zero with every other variable.

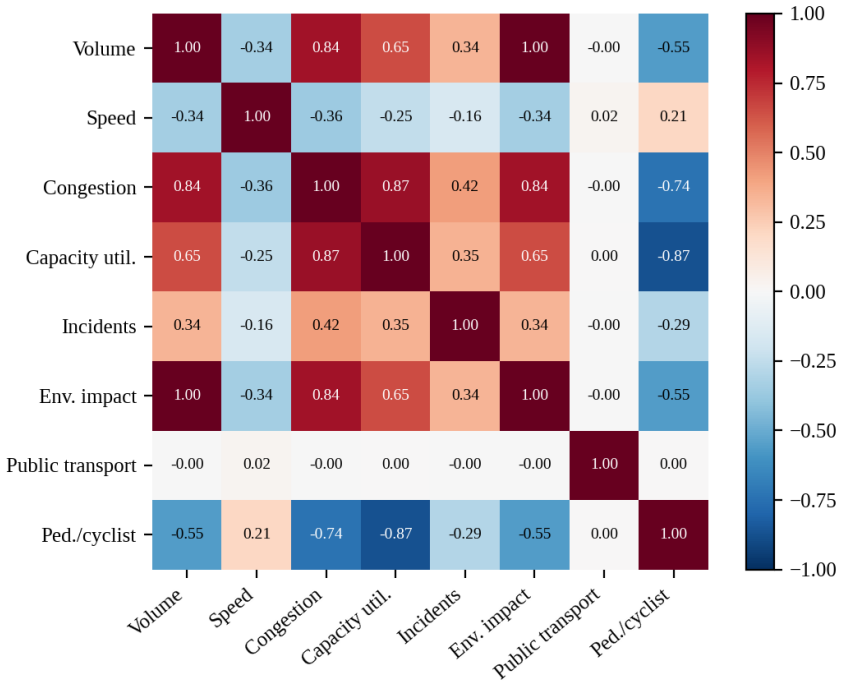


Fig. 4. Pearson correlation matrix of key traffic variables.

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F. Weather and Roadwork

Contextual factors showed little effect (Table VI). Mean congestion ranges only from 80.3% (Overcast) to 82.4% (Windy) across the five weather conditions, and the differences are not statistically significant (ANOVA $p = 0.44$; Kruskal–Wallis $p = 0.34$). Observations with roadwork (mean congestion 80.8%) were virtually identical to those without (80.8%; t-test $p = 0.96$), and roadwork records show slightly fewer incidents (1.52 versus 1.58).

TABLE VI
TRAFFIC CONDITIONS BY WEATHER AND ROADWORK

Condition	Records	Mean Volume	Mean Speed (km/h)	Mean Congestion (%)	Mean Incidents
Clear	5,426	29,167	39.5	80.7	1.56
Overcast	1,296	29,053	39.4	80.3	1.58
Fog	959	29,183	39.5	81.6	1.62
Rain	827	29,559	39.3	80.5	1.55
Windy	428	30,163	39.5	82.4	1.59
Roadwork: No	8,054	29,195	39.5	80.8	1.58
Roadwork: Yes	882	29,614	39.0	80.8	1.52

G. Temporal Stability

Conditions are remarkably stable over the observation window (Table VII, Fig. 5). Annual mean congestion is 81.1% in 2022, 80.4% in 2023, and 81.1% in 2024, with mean volume between 29,016 and 29,456 and mean speed between 39.4 and 39.5 km/h. Quarterly mean congestion varies only between 79.2% and 81.9%, with no sustained upward or downward trend.

Day-of-week means are also flat (mean congestion 80.3% to 81.4%), so the data do not show a distinct weekday–weekend pattern. External indicators for 2025 and 2026 (Section IV-I) show that this stability within the dataset has not been followed by improvement on the ground.

TABLE VII
ANNUAL TRAFFIC INDICATORS

Year	Records	Mean Volume	Mean Speed (km/h)	Mean Congestion (%)	Env. Impact	Public Transport (%)
2022	3,424	29,456	39.4	81.1	108.9	45.0
2023	3,413	29,016	39.5	80.4	108.0	45.5
2024 (to 9 Aug)	2,099	29,235	39.4	81.1	108.5	44.6
2025†	n/a	n/a	n/a	74.4†	n/a	n/a
2026 (to 30 Sep)†	n/a	n/a	n/a	n/a	n/a	n/a

†Not computed from the dataset, which ends on 9 August 2024. The 2025 congestion value is TomTom's annual congestion level for Bengaluru [11], measured as extra travel time against free flow, and is shown for context only (72.7% for 2024 on the same basis). TomTom's 2026 edition is not yet released; n/a: not available.

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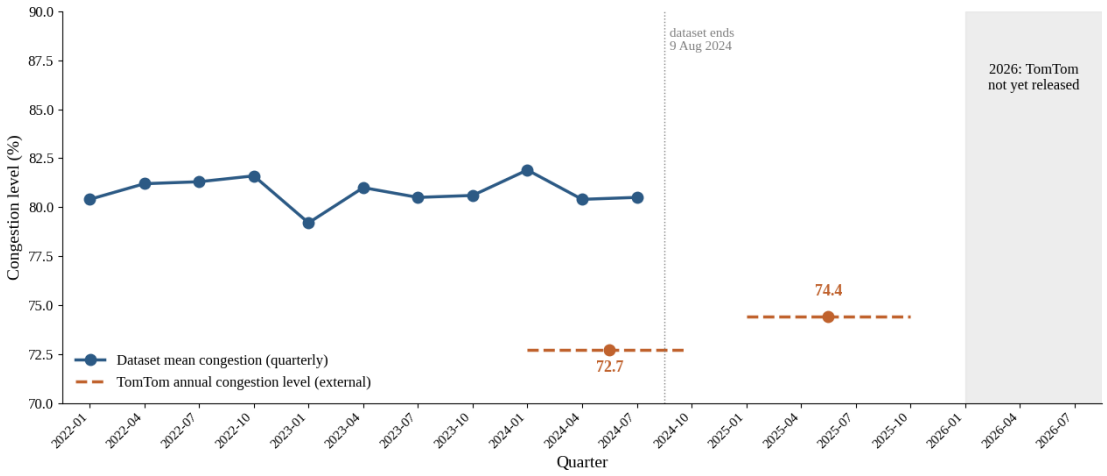


Fig. 5. Quarterly mean congestion level, 2022–2024 (dataset), with TomTom annual congestion level for 2024–2025 (external).

H. Public Transport, Parking, and Signal Compliance

Public transport usage averages 45.1% and varies only from 44.0% to 46.1% across areas. It has essentially no linear relationship with congestion ($r = -0.003$, $p = 0.79$), speed ($r = 0.02$), or volume ($r = 0.00$). Dividing observations into public transport usage quartiles produced mean congestion between 80.2% and 81.7% with no trend. Parking usage (mean 75.2%) and signal compliance (mean 79.9%) are likewise nearly uncorrelated with congestion ($r = -0.03$ and $r = 0.00$) and are almost identical across areas (parking 74.5% to 75.8%; compliance 79.6% to 80.2%).

I. Extension to 2025 and 2026

External indicators suggest that conditions in 2025 and 2026 were not better than those in the dataset period (Table VIII). TomTom reports that Bengaluru's average congestion level rose from 72.7% in 2024 to 74.4% in 2025, that peak-hour time lost rose from about 155 to 168 hours per driver, and that rush-hour speed fell to 13.9 km/h, about 1 km/h slower than in 2024; a 10 km trip took 36 min 9 s, which was 2 min 4 s longer than a year earlier [11]. Bengaluru moved from third to second most congested city in the world, and the worst day of 2025 (17 May) averaged 101% congestion [11]. These series measure extra travel time against free flow, whereas the dataset records capped daily congestion levels that were already at 100% in 43.5% of observations, so a further rise in delay would be largely invisible in the dataset's own scale.

TABLE VIII
EXTERNAL BENCHMARKS FOR BENGALURU, 2022–2026

Year	TomTom Congestion (%)	Peak-Hour Time Lost (h)	Road Accidents	Road Deaths	Deaths per 100 Accidents
2022	n/a	129	3,822	772	20.2
2023	63.0	132	4,974	915	18.4
2024	72.7*	155*	4,769	894	18.7
2025	74.4	168	5,459	999	18.3
2026 (to 30 Sep)	—†	—†	4,702	836	17.8

Sources: TomTom Traffic Index [11]–[13]; Bengaluru Traffic Police statistics [14]. Deaths per 100 accidents is derived. n/a: not retrieved. *2024 as restated in the 2025 TomTom edition, which uses metro-wide coverage; the 2024 edition originally reported 117 hours, and the 2022–2023 values use the earlier city-centre method, so TomTom values are not strictly comparable across the series break. †TomTom's 2026 edition is not yet available.

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Road safety shows the same direction (Fig. 6). Traffic police data report 3,822 accidents and 772 deaths in 2022, 4,974 and 915 in 2023, 4,769 and 894 in 2024, and 5,459 and 999 in 2025, a 53% increase in deaths since 2021 [14]. In the first nine months of 2026 alone, Bengaluru recorded 4,702 accidents, including 808 fatal ones, with 836 deaths and 4,111 injuries [14]; after nine months, this already equals 86% of the 2025 accident total and 84% of its death toll. Deaths per 100 accidents have drifted down from 20.2 in 2022 to 17.8 in 2026, so the rise reflects more crashes rather than more severe ones. Officials note that the expansion of police limits contributes to part of the recorded increase [14].

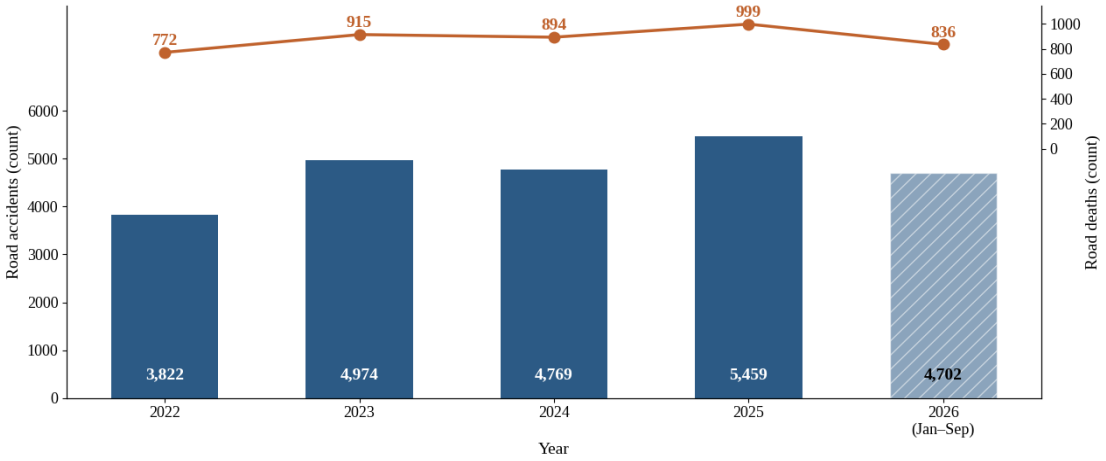


Fig. 6. Road accidents (bars) and road deaths (line) in Bengaluru, 2022–2026 (2026: January–September).

Vehicle growth and transit growth both continued. Bengaluru added 7.22 lakh vehicles in 2024–25 [16] and about 7.9 lakh in 2025–26 [17], and reached 1.28 crore registered vehicles on 30 June 2026, including 87 lakh two-wheelers and 25.2 lakh private cars [15]. The highest monthly total on record was 86,014 registrations in October 2025, following GST rationalisation [15]. Namma Metro carried an average of 7.58 lakh passengers per day in 2024–25 [18]; the Yellow Line opened in August 2025, daily ridership passed one million for the first time on 11 August 2025, the April 2026 average reached 9.16 lakh [20], and the record rose to 11.19 lakh on 10 August 2026 [19]. Even so, daily metro ridership of around 10 lakh remains well below the earlier projection of about 30 lakh for the operational corridors, partly because of first- and last-mile gaps [21].

V. Discussion

A. Spatial Concentration of Congestion

The results reveal a pronounced spatial disparity. Core commercial and residential areas (Koramangala, M.G. Road, and Indiranagar) operate at or near capacity in most observations, with mean capacity utilization above 95%, whereas peripheral or newer corridors such as Electronic City and Yeshwanthpur retain meaningful spare capacity (76.3% and 82.4%).

Because road-level differences within an area are small, interventions are likely to be most effective when planned at the area or corridor level rather than for isolated junctions.

B. Saturation and Limited Network Resilience

The saturation of congestion beyond roughly 30,000 vehicles per record implies that the road network has little buffer: small increases in demand during already busy periods lead to full congestion, higher incident counts, and sharply higher emissions. This is consistent with the capacity-based reasoning behind level-of-service definitions [7] and with the view that added capacity is quickly consumed by induced demand [4], [5]. For the three busiest areas, supply-side expansion alone is therefore unlikely to restore free-flow conditions.

C. Environmental and Active-Travel Implications

Environmental impact rises in direct proportion to volume, so demand reduction would deliver an environmental benefit as well as a travel-time benefit. The strong inverse relation between congestion and pedestrian and cyclist counts also indicates that congested areas are less hospitable to active travel, which may create a feedback loop that pushes short trips back onto motor vehicles. This is in line with evidence that street design and density influence travel behavior [3].

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Website: www.ijrdet.com (ISSN 2347-6435 (Online) Volume 15, Issue 11, November 2026)

D. Interpreting the Public Transport Result

The finding that public transport usage is unrelated to congestion should be treated carefully. In practice, higher transit use is expected to relieve congestion, and the near-zero correlations with every other variable, together with a uniform spread of values between 10% and 80%, suggest that this field may not be an observed measurement or may not be aligned with the roads where it is recorded. Likewise, the absence of weather, roadwork, parking, and signal-compliance effects is surprising and may reflect how these fields were recorded rather than a true absence of impact. We therefore report these results as dataset findings, not as causal conclusions about Bengaluru's transit system.

E. Implications for Practice

Taken together, the strongest and most reliable signals in the data are volume, capacity utilization, and area. Planners with limited resources should focus on the few areas that account for most saturation, and should treat volume reduction, through pricing, parking policy, and mode shift, as the main lever. The flat temporal profile also suggests that the congestion problem is persistent rather than seasonal, which favors permanent structural measures over short-term event-based management.

F. Persistence into 2025–2026

The external indicators support the dataset's central message that congestion in Bengaluru is persistent and structural rather than seasonal. Because dataset congestion is capped at 100%, further growth in demand appears as longer delays and more crashes, which is what the TomTom time-lost series and the police accident series show, consistent with the limited network buffer discussed in Section V-B. Vehicle registrations of roughly 7.9 lakh in 2025–26 are being added faster than road space, and the rise in metro ridership from 7.58 lakh to 9.16 lakh per day has not been accompanied by lower congestion. Metro ridership has grown by about 21% over this period while the dataset's public transport usage field stays near 45%, which reinforces the caution in Section V-D that this field may not be an observed measurement.

VI. Limitations

This study has several limitations. First, congestion level and road capacity utilization are capped at 100%, and the travel time index is capped at 1.50, so the most severe conditions are censored and true delays on saturated roads are underestimated.

Second, the dataset contains one record per road per date and has no time-of-day information, so morning and evening peak behavior cannot be separated from daily averages. Third, the dataset covers only 8 areas and 16 locations and has uneven sampling (552 to 1,720 records per area), and 2024 is a partial year ending 9 August.

Fourth, the public transport usage, weather, roadwork, parking, and signal-compliance fields show almost no relationship with traffic outcomes, which limits what can be concluded about their influence; their collection method is not documented in the data. Fifth, the dataset does not include road length, number of lanes, or geographic coordinates, so volume-to-capacity ratios and spatial effects cannot be computed independently. Sixth, the 2025–2026 extension relies on published secondary sources rather than the dataset: the indicators are city-level, differ in definition and coverage from the dataset variables, include a TomTom method change in the 2025 edition, cover only January to September for 2026 road safety, and omit TomTom's 2026 edition, which is not yet released, so the extension is descriptive and does not allow Tables II–VII to be re-estimated. Finally, the analysis is correlational and does not establish causal effects of any intervention.

VII. Recommendations

Based on the evidence, we propose five actionable interventions for city authorities and transport planners:

1) Area-Targeted Congestion Management: Prioritize Koramangala, M.G. Road, and Indiranagar, where 58% to 76% of observations are fully saturated, for measures such as congestion pricing studies, parking management, and restricted peak-hour freight movement. Pricing aligns individual costs with the congestion each vehicle imposes on others [6].

2) Adaptive Signal and Junction Upgrades: Deploy adaptive signal control at high-volume junctions (Sony World Junction, Sarjapur Road, Anil Kumble Circle, Trinity Circle), and improve signal compliance, which averages only 79.9%, through enforcement and clearer junction design.

3) Public Transport Priority Corridors: Introduce bus priority lanes and frequent feeder services in the most congested areas to shift trips away from private vehicles, and collect reliable ridership data so that transit impact on congestion can be measured properly. Namma Metro ridership has risen to an average of 9.16 lakh passengers per day by April 2026, yet registrations of private vehicles continue to grow in parallel, so feeder services and first- and last-mile links remain a priority.

International Journal of Recent Development in Engineering and Technology
Website: www.ijrdet.com (ISSN 2347-6435 (Online) Volume 15, Issue 11, November 2026)

4) Safe Pedestrian and Cycling Infrastructure: Provide protected footpaths and cycle lanes in high-volume areas, where pedestrian and cyclist activity is lowest, to encourage short trips on foot or by bicycle and support the compact, walkable design that reduces travel demand [3].

5) Better Data Collection: Record time-of-day traffic data, uncensored delay measures, road geometry, and validated transit ridership so that future analyses can distinguish peak effects and evaluate interventions rigorously.

Table IX groups these measures by implementation horizon.

TABLE IX
SUGGESTED IMPLEMENTATION ROADMAP

Horizon	Measures	Target Indicator
Short term (0–1 year)	Adaptive signals at top junctions; signal-compliance enforcement; improved data collection	Signal compliance, incidents per record
Medium term (1–3 years)	Bus priority lanes; parking management; protected walking and cycling routes	Mean speed, public transport share
Long term (3+ years)	Congestion pricing in saturated areas; transit-oriented land-use planning	Saturated share, environmental impact

VIII. Conclusion

Bengaluru's road network operates close to saturation: 43.5% of recorded observations are at 100% congestion and mean speed is only 39.4 km/h. Published indicators for 2025 and 2026 point in the same direction: TomTom's congestion level for Bengaluru rose to 74.4% in 2025, road deaths reached 999, and the registered fleet passed 1.28 crore by June 2026, so the dataset baseline is unlikely to have improved. Congestion is concentrated in a few high-demand areas, scales strongly with traffic volume, and carries an environmental cost that rises in direct proportion to vehicle count. Area-level demand management, junction and signal improvements, public transport priority, and safer walking and cycling infrastructure are therefore the most evidence-supported directions, supported by improved data collection that captures peak-hour conditions and transit ridership.

Future work should refresh this analysis once TomTom's 2026 edition and full-year 2026 police statistics are released, and should combine this dataset with time-of-day sensor or GPS data, road geometry, and verified public transport ridership to build predictive congestion models and to evaluate interventions with before-and-after designs. The KPI baselines established here provide a repeatable framework for monitoring future progress.

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