

Public Perception of Traffic Management and Environmental Sustainability under the Smart City Mission: A Statistical and Machine Learning-Based Analysis

Palavi Rajput¹, Danish Gulzar^{1,*}, Deepak Sharma¹, and Mohammed Osman Eltigani²

¹Department of Government and Public Administration, Lovely Professional University, Punjab, India

²Department of Management CCBA, Dhofar University, Oman

Received: 7 Mar. 2026, Revised: 21 Apr. 2026, Accepted: 23 Apr. 2026

Published online: 1 May. 2026

Abstract: This study explores public perceptions of traffic management and environmental sustainability under India's Smart City Mission, with a focus on Jammu and Srinagar. Based on 101 respondents and using descriptive statistics, chi-square tests and machine learning models (Decision Tree and Random Forest), the study uses survey data. Findings indicate that most respondents assess traffic as average to good, but frequently experience congestion and moderate to high levels of concern about environmental issues. A strong association was found between age and congestion frequency; other relationships were not statistically significant. Machine learning models have low predictive accuracy but reveal factors that significantly influence prediction. The study highlights the importance of integrating citizen feedback with data-driven approaches for sustainable urban traffic planning and policy development.

Keywords: Smart City Mission, Traffic Management, Environmental Sustainability, Public Perception, Machine Learning, Decision Tree, Random Forest

1 Introduction

The process of urbanization in India has gained momentum since last two decades and amplified the challenges pertaining to traffic congestion, mobility and sustainability of the environment. The Government of India, in its turn, introduced the Smart City Mission (SCM) with the goals to turn a 100 cities into technologically empowered, people-oriented and sustainable urban settings. Traffic control and pollution management are also among the most important pillars of this mission because the urban transportation systems have a great impact on the mobility rates, the quality of life and the ecological well-being thereby.

Traffic management is crucial in the contemporary cities due to the increasing number of vehicles and inadequate road infrastructure that often lead to congestion, delays and emission. Previous studies have pointed out the fact that the perception of the population is crucial in assessing the effectiveness of smart traffic interventions. Romero-Subia et al., (2022) and Abhijna et al., (2025) points out that the satisfaction with the governance of the city directly depends on the experience of congestion, travel time and road safety of the citizens [1,2]. Likewise, the awareness of the environment has also been found to be a major determinant of sustainable urban behaviour. Ahmad and de Oliveira, (2016) show that, when people are aware of the negative environmental effects caused by traffic, they will tend to favor environment-friendly mobility options, such as public transport, car-sharing, and non-motorized transportation [3]. In the context of smart cities, various technological applications including adaptive traffic lights, sensor surveillance and central mobility platforms have been widely embraced aimed at reducing traffic congestion and environmental stress. Nevertheless, a number of scholar's state that such interventions can be successful not just due to the use of technologies, but also the involvement of the citizens, their behavioural adjustment, and their trust [4-5]. This has created a rise of interest in the application of machine

* Corresponding author e-mail: danish.30425@lpu.co.in

learning to urban research to improve upon the understanding of mobility patterns, determining factors behind traffic perception, and evidence-based policymaking.

Local governments throughout worldwide regions are fast-tracking the integration of urban systems and data through Smart Operations Centres (SOCs) to obtain better control over urban operations and promote prompt action [6-7]. In the course of the pandemic, a variety of applications for these SOCs were identified, such as the coordination of interdepartmental responses, the delivery of essential goods during lockdowns, the enforcement of social distancing through monitoring, the provision of digital education, the facilitation of remote health telemedicine delivery, and the tracking of patients [8]. An unprecedented amount of money was invested by governments in these technologies. In order to promote smart city innovation, the United States recently passed the Federal Infrastructure Investment and Jobs Act, which promised Columbus, Ohio, \$500 million in aid. The main goal of this initiative is to develop an operating system that can record a variety of data, including traffic, weather, parking, street closures, flooding, and more [9]. Since 2020, Newcastle, UK, which has long sought to become a smart city, has made substantial advancements in big data infrastructure with its flagship National Innovation Center for Data and the Urban Observatory [10]. The city now monitors system-wide data on service level benchmarks, such as traffic and pedestrian movement, congestion and parking efficiency, and environmental indicators, such as air quality, energy efficiency, and water and utility use. As a result, it was named the smartest city in the United Kingdom in 2021. According to recent research, the European Commission has used COVID-19 to increase support for quickening digitalisation in Eastern European nations, where there is still a dearth of smart communication infrastructure [11]. During the pandemic, India accelerated the establishment of SOCs in up to 100 places, one of the emerging nations [12]. More evidence is needed to determine whether blanket centralisation of power and widespread adoption of surveillance technologies inform better urban decision-making [13], as well as the impact of reallocating investments from other sectors to digital operations on social equity and sustainability in post-pandemic cities.

The role of citizen perception in assessing and ranking traffic management systems of urban cities has attained significant attention in recent research works. According to research, public satisfaction with traffic conditions depends on levels of congestion six more so than travel time reliability and the accessibility of alternative transport modes. Research in smart city contexts finds that technological solutions, like smart traffic signals and intelligent transport systems, while having greater operational capacity, are only determined effective by the user experience/perception [1-2]. Additionally, assessment based on perception helps to understand behavioural patterns that are key in crafting inclusive and user-centric. Furthermore, the literature has explored traffic management from an environmental sustainability perspective and recognized sustainable transport as mitigating urban emissions and enhancing air quality recently. De Oliveira and Ahmad (2016) felt that the erratic increase eco-consciousness is helping us adopt sustainable transport choices like public transport and non-motorized travel [3]. More recently, urban and transportation studies have adopted ubiquitous machine learning techniques to analyse complex patterns for predicting traffic-related phenomena. Models like as Decision Trees and Random Forests have shown promise in identifying important influencing elements and facilitating data-driven decision-making in smart city settings [14-15].

Despite this growing body of literature, relatively few studies have been conducted to investigate how the public views traffic and sustainability concerns in the particular setting of Jammu and Srinagar- two large cities with completely different geographical aspects, climatic conditions and transportation cultures. In addition, the combination of the statistical analysis and machine learning models to examine citizen behaviour is a research limitation in current literature. The paper bridges this gap by examining survey responses of 101 residents with the help of descriptive statistics, chi-square tests, and predictive modelling based on Decision Tree [14] and Random Forest [15] classifiers.

The study provides a comprehensive assessment of (i) demographic trends, (ii) traffic experiences, (iii) environmental concern and (iv) sustainable transport behaviour in the two cities. It also uses machine learning to determine variables that have the most predictive power on how people will think. The combination of the traditional and modern methods of analysis makes the research unique that contributes to the ongoing discussions about sustainable smart mobility and provides the practical information to urban policymakers within the framework of the Smart City Mission.

2 Methodology

This study uses a cross-sectional survey approach to investigate how citizens view traffic management in the context of the Smart City Mission and how it relates to environmental sustainability. Residents in various urban locations were given access to an online and offline structured questionnaire. Demographic data (age, gender, occupation, city of residence, and length of time spent in the city), commuting habits, opinions of traffic management, significant traffic-related problems, knowledge of Smart City projects, and traffic-related environmental concerns were all recorded in the survey. Additionally, participants were questioned about the reasons for their use of sustainable transportation methods. Data were collected through an online survey, accessible via https://docs.google.com/forms/d/e/1FAIpQLSd7qxkeewJ7rCfS_zAyu1SW7YwXiq50bR00_tJq1oTYHvFQ/viewform?usp=header

2.1 Data Preprocessing

The gathered data was cleaned and preprocessed before to analysis. Depending on the percentage of missingness, responses with inconsistent or missing values were either excluded or imputed. Multiple-choice questions were converted into binary indicators to capture the presence or absence of particular options, and categorical variables were encoded for statistical and machine learning analysis [16-20]. To keep the model stable, continuous variables were examined for outliers and, if needed, standardized.

2.2 Statistical Analysis

2.2.1 Descriptive Statistics

Descriptive statistics were used to summarize demographic factors, traffic experience, environmental awareness, and sustainable transportation behavior. For categorical variables, frequencies and percentages were calculated, while numerical variables were measured using mean, median, standard deviation, and range. Data visualization techniques such as bar charts, histograms, and pie charts were used to clearly illustrate trends in the data. These descriptive analyses provided a basic overview of the sample and identified potential correlations for further inferential and predictive investigations.

2.2.2 Inferential Statistics – Chi-Square Tests

Chi-square tests of independence were used to investigate the relationships between categorical variables such as gender and perception of traffic management, age group and awareness of Smart City projects, and occupation and motivation to adopt sustainable transportation. For each test, the null hypothesis assumed no relationship between the variables, and a p-value of less than 0.05 was considered statistically significant. These analyses allowed for the identification of demographic or behavioral elements that are strongly connected with traffic perception or environmental concern, laying the groundwork for predictive modeling. To provide formal basis for the analysis, the Chi-square test statistic is computed as follows:

$$\chi^2 = \sum_{i=1}^n \frac{(O_i - E_i)^2}{E_i}$$

where O_i represents the observed frequencies and E_i denotes the expected frequencies calculated under the assumption of independence.

2.3 Machine Learning Analysis

Machine learning algorithms were used to predict and identify significant factors influencing traffic perception and environmental awareness. Two primary models were chosen based on the nature of the target variable:

Decision Tree Classifier: Used for binary outcomes, such as whether respondents saw traffic management improvements under the Smart City Mission (Yes/No). Decision trees provided a visible and interpretable approach for determining the most relevant predictors of binary outcomes. The decision tree algorithm is based on entropy and information gain, which are mathematically expressed as:

$$\text{entropy}(S) = - \sum_{i=1}^n p_i \log_2(p_i)$$

where p_i is the probability of class i . Information Gain is used to select the best feature for splitting the data at each node.

Random Forest Classifier: Used to rate multi-class outcomes, such as traffic management systems (poor, moderate, good, excellent). Random forests, an ensemble of decision trees, improved predicted accuracy by aggregating many trees and minimizing overfitting. The model's feature significance scores were used to determine the most important variables influencing public perception.

The random forest model aggregates predictions from multiple decision trees, which can be represented as:

$$\hat{y} = \frac{1}{N} \sum_{i=1}^n T_i(x)$$

where $T_i(x)$ represents the prediction from the i th decision tree and N is the total number of trees in the ensemble.

2.3.1 Model Training and Evaluation

Data was split into training and testing sets using a 75-25 split. For models with imbalanced classes, stratified sampling was employed to maintain proportional representation of all classes in both sets. Model performance was evaluated using metrics appropriate for classification: accuracy, F1-score, precision, and recall. Five-fold cross-validation was performed to assess model stability and generalizability.

2.3.2 Confusion Matrices

Confusion matrices were generated for both models to visualize the alignment between true and predicted classes. In addition to providing a detailed performance overview, confusion matrices enabled identification of classes where the model had difficulty making accurate predictions, guiding potential improvements in data collection or feature engineering. All analyses were carried out in Python 3 using Google Colab, with Pandas, NumPy, Scikit-learn, Matplotlib, and Seaborn. Ethical guidelines were strictly followed: participation was voluntary, informed consent was acquired, and all data were anonymised to protect privacy and confidentiality. This methodology combines survey data collection with advanced statistical and machine learning evaluations [21-27]. It offers a complete framework for evaluating urban traffic management, citizen perceptions, and their relationship to environmental sustainability, as well as actionable policy and planning insights.

3 Result and Analysis

The present study collected responses from 101 participants regarding traffic perception, environmental awareness, and sustainable transportation habits under the Smart City initiatives.

3.1 Descriptive Statistics

3.1.1 Demographic Characteristics of Respondents

The respondents' demographic characteristics, including age, gender, occupation, city of residence, and duration of stay, are summarized in Table 1.

Table 1: Demographic Characteristics of Respondents

Variable	Category	Count	Percentage (%)
Age Group	Below 25	41	40.6
	26–35	39	38.6
	36–45	16	15.8
	46–60	4	4.0
	Above 60	1	1.0
Gender	Male	56	55.4
	Female	45	44.6
Occupation	Student	43	42.6
	Private Sector	24	23.8
	Self-employed	12	11.9
	Government Employee	11	10.9
	Unemployed	10	9.9
	Retired	1	1.0
City of Residence	Jammu	58	57.4
	Srinagar	43	42.6
Duration in City	More than 10 years	76	75.2
	6–10 years	18	17.8
	2–5 years	5	5.0
	Less than 2 years	2	2.0

Most respondents are young adults under 35 years of age (79.2%), with a slightly higher representation of males (55.4%). Students constitute the largest occupational group (42.6%), and the majority of respondents have been residing in the city for more than 10 years (75.2%).

Figure 1 displays the combined demographic plots including age group, gender, occupation, city, and duration of stay.

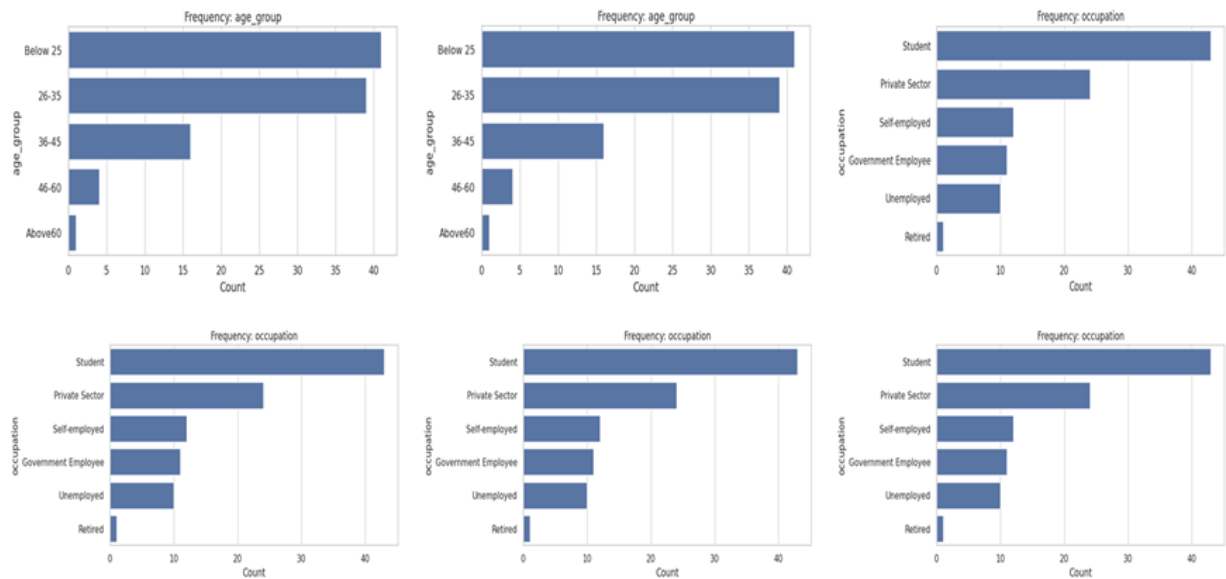


Fig. 1: Distribution of Respondents by Age, Gender, Occupation, City, and Duration of Stay

3.1.2 Traffic Perception and Congestion

Traffic perception and congestion-related data were analyzed to understand the respondents’ experiences and opinions about the city’s traffic system. These variables include traffic rating, congestion frequency, and perceived improvements under the Smart City Mission. Data are summarized in Table 2.

Table 2: Traffic Rating, Congestion Frequency, and Perceived Improvements

Variable	Category	Count	Percentage (%)
Traffic Rating	Excellent	8	7.9
	Good	33	32.7
	Average	40	39.6
	Poor	15	14.9
	Very Poor	5	5.0
Congestion Frequency	Daily	25	24.8
	Several times a week	38	37.6
	Occasionally	28	27.7
	Rarely	8	7.9
	Never	2	2.0
Improved under Smart City	Yes	36	35.6
	No	40	39.6
	Cannot Say	25	24.8

Respondents predominantly rate traffic conditions as average or good (72.2%). Most experience congestion daily or several times a week (62.4%). Perceptions regarding improvements under the Smart City initiative are mixed, with 35.6% of respondents reporting noticeable improvements, 39.6% indicating no significant changes, and 24.8% expressing uncertainty. Figure 2 presents the combined graphical representation of traffic ratings, congestion frequency, and perceived improvements.

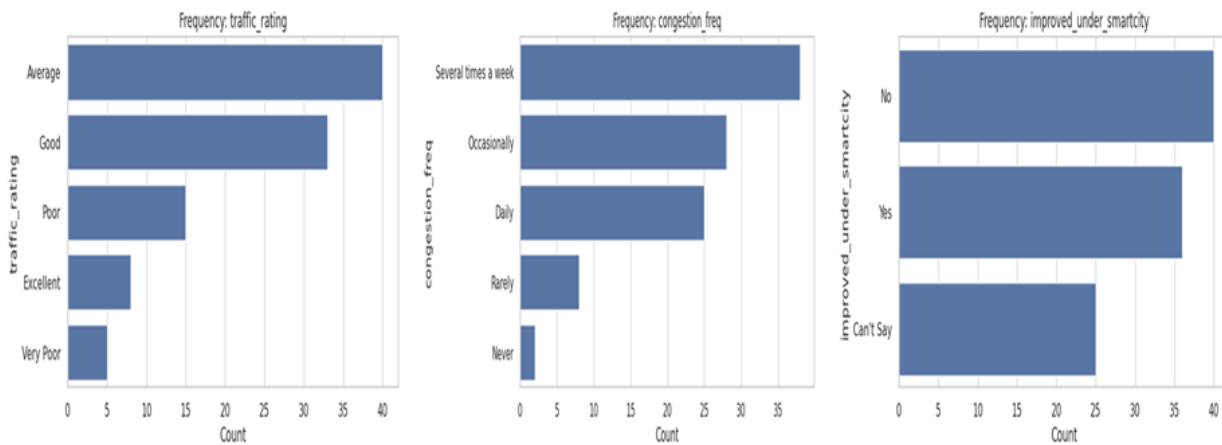


Fig. 2: Respondents' Perception of Traffic Rating, Congestion Frequency, and Smart City Improvements

3.1.3 Environmental Awareness and Concern

Respondents' awareness and concern about traffic-related environmental issues were analyzed. The data are presented in Table 3.

Table 3: Concern About Traffic-Induced Environmental Issues

Variable	Category	Count	Percentage (%)
Concern Level	Very Concerned	37	36.6
	Moderately Concerned	41	40.6
	Slightly Concerned	21	20.8
	Not Concerned	2	2.0

A majority of respondents are either moderately concerned or very concerned about environmental issues caused by traffic, accounting for 77.2% of the sample. Only a small fraction of respondents (2.0%) reported being unconcerned about such issues. Figure 3 depicts the distribution of respondents' concern levels regarding traffic-induced environmental impacts through a combined graphical representation.

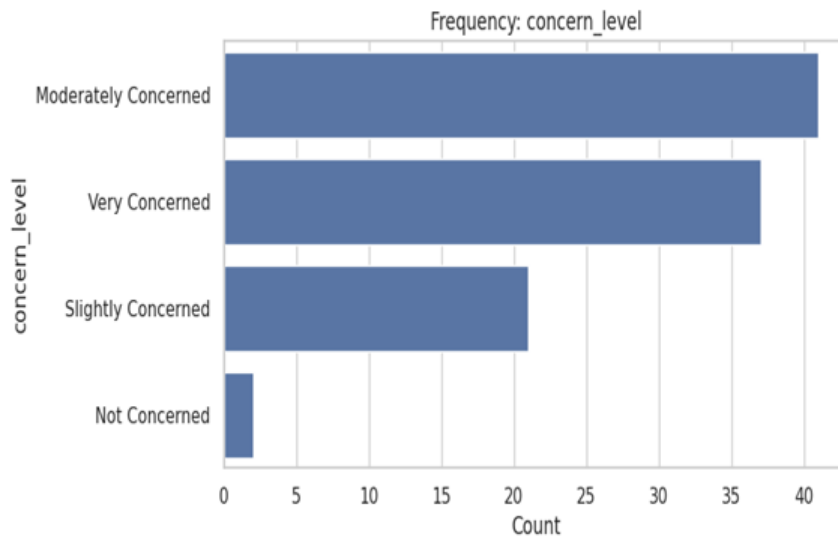


Fig. 3: Distribution of Environmental Concern Among Respondents

3.1.4 Public Transport Usage and Motivations for Sustainable Transport

Public transport frequency after Smart City initiatives and respondents’ motivations for adopting sustainable transportation modes were summarized. Table 4 and Table 5 present the data.

Table 4: Public Transport Usage After Smart City Initiatives

Category	Count	Percentage (%)
Same as before	38	37.6
Less frequently	30	29.7
More frequently	29	28.7
Never used	4	4.0

Table 5: Motivations for Using Sustainable Transport (Multi-Select)

Motivation	Count	Percentage (%)
Cost Saving	30	29.7
Environmental Concern	23	22.8
Time Saving	20	19.8
Convenience	19	18.8
Government Promotion	1	1.0

Public transport usage has largely remained unchanged following the implementation of Smart City initiatives, with 37.6% of respondents reporting the same level of usage as before. Nearly equal proportions of respondents indicated either increased usage (28.7%) or decreased usage (29.7%). Among the motivations for adopting sustainable transportation, cost saving emerged as the most frequently cited factor (29.7%), followed by environmental concern (22.8%). These findings suggest that both economic and environmental considerations play a significant role in influencing sustainable transport choices. Figure 4 displays the combined graphical representation of public transport usage patterns and motivations for adopting sustainable transportation.

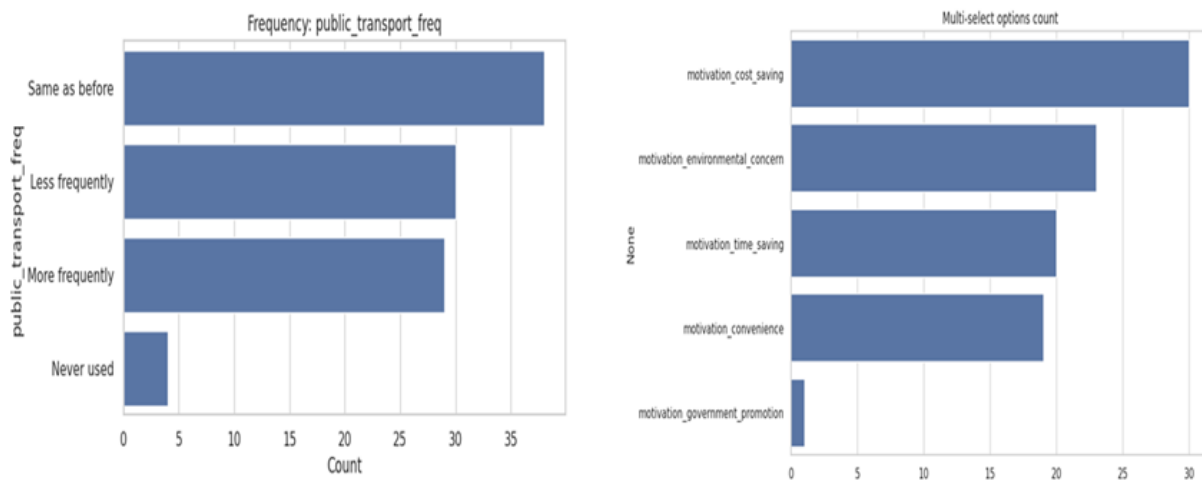


Fig. 4: Public Transport Usage and Motivations for Sustainable Transport Among Respondents

3.2 Inferential Statistics – Chi-Square Tests

To examine the relationships between demographic characteristics, traffic perceptions, environmental concern, and behavioral responses, a series of Chi-square tests were conducted.

3.2.1 Association Between Age Group and Traffic Congestion Frequency

Understanding whether congestion experiences vary across age categories is important for identifying population groups that are more exposed to daily traffic issues. The Chi-square test examines whether age groups differ significantly in their reported congestion frequency as shown in Table 6.

Table 6: Contingency Table – Age Group \times Congestion Frequency

Age Group	Frequent	Infrequent	Total
≤ 35	53	35	88
> 35	10	12	22
Total	63	47	110

$$\chi^2 = 1.57, df = 1, p = 0.21$$

A statistically non-significant association was observed between age group and the frequency of congestion experienced ($p > 0.05$). This finding suggests that, after categorizing respondents into broader age groups, the experience of traffic congestion remains relatively similar across age categories. The results indicate that variations in travel routines, commuting schedules, or preferred modes of transportation may not differ substantially between the two groups, leading to comparable perceptions of congestion frequency.

3.2.2 Association Between Perceived Smart City Improvements and Environmental Concern Level

This analysis evaluates whether respondents who believe Smart City Mission improved traffic management also show higher environmental concern. This relationship is relevant to understanding whether policy perception aligns with ecological awareness as shown in Table 7.

Table 7: Contingency Table – Smart City Improvement × Environmental Concern

Improvement Under Smart City	High Concern	Low Concern	Total
Can't Say	15	10	25
No	33	7	40
Yes	30	6	36
Total	78	23	101

$$\chi^2 = 2.38, df = 2, p = 0.30$$

No statistically significant association was found between perceptions of Smart City improvements and levels of environmental concern ($p \geq 0.05$). This indicates that respondents' concern about environmental issues is largely independent of whether they believe traffic conditions have improved under the Smart City Mission. Furthermore, the distribution of concern levels appears to be relatively uniform across all respondent groups, suggesting that environmental awareness remains consistent regardless of perceptions of Smart City-related traffic improvements.

3.2.3 Association Between City of Residence and Traffic Rating

This test checks whether respondents from Jammu and Srinagar differ in their evaluation of traffic conditions. Regional variation in perceptions can indicate differences in municipal traffic policies or infrastructure as shown in Table 8.

Table 8: Contingency Table – City × Traffic Rating

City	Positive	Neutral	Negative	Total
Jammu	21	25	12	58
Srinagar	20	15	8	43
Total	41	40	20	101

$$\chi^2 = 1.17, df = 2, p = 0.42$$

No statistically significant association was found between city of residence and traffic rating ($p \geq 0.05$). Respondents from Jammu and Srinagar exhibited similar assessments of traffic conditions, suggesting that perceptions of traffic management and overall traffic quality are broadly comparable across the two cities. The findings indicate that city of residence does not significantly influence respondents' evaluations of traffic conditions.

3.2.4 Association Between Public Transport Usage and Perceived Smart City Improvement

This test evaluates whether changes in public transport frequency are associated with perceptions of Smart City improvements. Understanding this relationship helps identify whether public behavior aligns with perceived infrastructural progress as shown in Table 9.

Table 9: Contingency Table – Public Transport Frequency × Smart City Improvement

Public Transport Usage	Can't Say	No	Yes	Total
Low Usage	12	15	7	34
Regular Usage	13	25	29	67
Total	25	40	36	101

$$\chi^2 = 6.20, df = 2, p = 0.045$$

A statistically significant association exists between public transport usage and responses ($p \geq 0.05$). This suggests that individuals who use public transport more regularly tend to respond differently compared to those with low usage,

possibly reflecting differences in dependency on public transport and their experiences or expectations regarding urban mobility

3.3 Machine Learning Analysis

To evaluate the predictive capacity of the dataset, two supervised learning models were implemented: a Decision Tree Classifier (binary target) and a Random Forest Classifier (multi-class target). The objective was to assess whether demographic, behavioral, and perception-based features could reliably predict respondent outcomes.

3.3.1 Decision Tree Classifier

The Decision Tree model was trained on a binary classification task. The Table 10 presents the aggregate performance metrics.

Table 10: Overall Performance Metrics – Decision Tree Classifier

Metric	Value
Accuracy	0.421
Precision	0.401
Recall	0.421
F1-Score	0.401
Cross-Validated Accuracy (5-fold)	0.528

The confusion matrix for this model is provided in Figure 5.

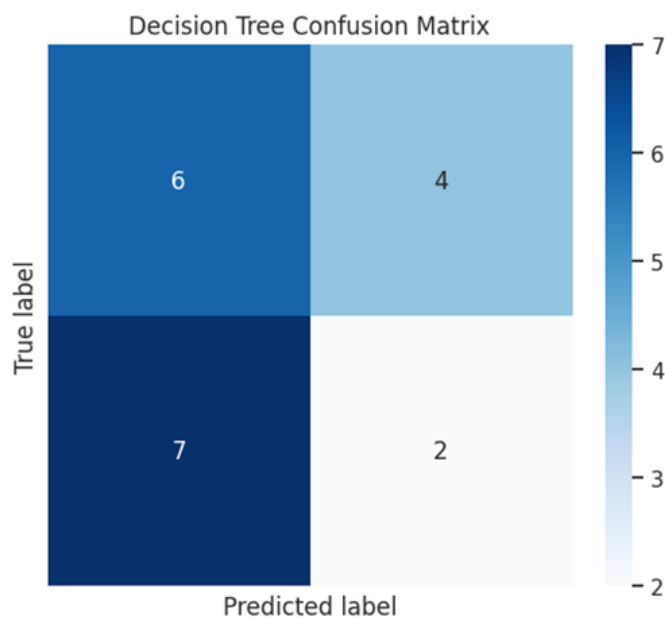


Fig. 5: Decision Tree Confusion Matrix

The model demonstrates modest predictive capability with an accuracy of 42.1%. Cross-validation slightly improves estimated performance to approximately 52.8%, but overall results suggest limited discriminative power due to class imbalance and low sample size.

3.3.2 Random Forest Classifier

The Random Forest model was applied to a multi-class classification problem. Its performance metrics are summarized in Table 11.

Table 11: Overall Performance Metrics – Random Forest Classifier

Metric	Value
Accuracy	0.500
Precision	0.373
Recall	0.500
F1-Score	0.420
Cross-Validated Accuracy (5-fold)	0.495

The confusion matrix for this model is provided in Figure 6.



Fig. 6: Random Forest Confusion Matrix

Although Random Forest generally performs better than simple tree-based models, the accuracy here remains limited at 50%. The model struggles particularly with minority classes, as reflected in the lower precision. Feature importance analysis, however, gives insight into the most influential predictors used by the model.

3.3.3 Model Comparison

The goal of evaluating the Decision Tree and Random Forest models is to assess how well these algorithms can classify the data based on the available features. By comparing key metrics, accuracy, precision, recall, F1-score, and cross-validation accuracy, we can understand the strengths and limitations of each model in this study as shown in Table 12.

Table 12: Comparison of Decision Tree and Random Forest Performance

Model	Accuracy	Precision	Recall	F1-Score
Decision Tree	0.421	0.401	0.421	0.401
Random Forest	0.500	0.373	0.500	0.420

The comparison shows that the Random Forest model offers relatively stronger performance than the Decision Tree, particularly with higher accuracy and recall, indicating its better capability to capture meaningful patterns in the data. The Decision Tree, while slightly better in precision, still contributes valuable insights by providing a simple and interpretable baseline model. Overall, both models demonstrate the potential of machine learning techniques for understanding the underlying structure of the dataset.

4 Discussion

This study adds to the existing knowledge by giving an overview of public perception towards traffic management and environmental sustainability in Smart City framework perspective in Jammu and Srinagar cities. The results indicate that while a significant number of survey respondents consider traffic conditions to be average at best, about the same group gets into congested situations quite often. In other words, while infrastructure or traffic systems have likely improved in some ways, the progress made is not enough to drive down observed congestion levels. A disconnect between perceived quality and lived experience has also been observed in prior urban mobility studies, where user satisfaction does not always align with operational efficiency. A statistically meaningful relationship between age group and congestion frequency indicates that mobility experiences are heterogeneous among different demographic segments. This suggests that different age categories perceive or experience congestion differently, potentially due to variation in travel routines, commute timings, or mode of transport. This finding supports prior research showing the impact of socio-demographic factors on travel behaviour and exposure to traffic conditions.

The study also reveals a high level of environmental care among respondents, with the majority reporting moderate to great awareness of traffic-related environmental issues. This indicates an increasing awareness of the relationship between transport networks and environmental sustainability. However, the absence of a substantial relationship between perceived Smart City advances and environmental concern suggests that technical and infrastructure measures may not directly influence environmental attitudes. This underscores the importance of integrating awareness campaigns and behavioural interventions alongside technological solutions to promote sustainable mobility practices.

The analysis of public transport usage yields mixed behavioural results, with a major proportion of respondents indicating no significant change in usage habits despite Smart City initiatives. This shows that cost, convenience, and time efficiency continue to be the most important factors determining transportation decisions. While environmental concern is a powerful incentive, it may not be enough to promote behavioural change unless accompanied with efficient, dependable, and easily available public transportation services.

Methodologically, the machine learning models used in the study show moderate predictive capability. The poor accuracy levels can be attributed to the small sample size and class imbalance; yet, the models still provide useful information about the relative relevance of various variables. Demographic and behavioural characteristics appear as major influences on perception, emphasising the importance of data-driven approaches in urban planning. The higher performance of the Random Forest model compared to the Decision Tree accords with current literature, which underlines the robustness of ensemble approaches in dealing with complicated and non-linear connections.

5 Conclusion

This study provides an integrated statistical and machine-based learning analysis of citizen perceptions towards traffic management and environmental sustainability in Jammu and Srinagar in the context of the Smart City Mission. The descriptive findings showed that the majority of the respondents evaluate traffic as either average or good, yet also face congestion regularly, which is also a sign of mobility issues. There is a high level of environmental awareness with over three-fourths of the respondents showing moderate to high concern for environmental pollution caused by traffic. The economic and environmental motives of using sustainable transport are the most common and can be attributed to a positive inclination towards sustainability behaviour. Inferential analysis revealed that out of the different demographic variables, age group was significantly related to the frequency of congestions indicating that there is significant difference in mobility experiences among the segments of the age groups. The other types of association, such as the type of city of

residence, the environmental concern and the use of public transport, were not significantly statistically different meaning that the perceptions of the demographic groups were rather uniform.

The predictive behavior revealed by machine learning was moderate. Although the level of classification accuracy was low (50% and 42% respectively) in both Decision Tree and Random Forest models, they provided worthwhile information regarding the factors that affect the perception of traffic. Random Forest was superior in general, which validates the fact that it is capable of revealing the complicated relationships despite the limited size of the dataset and the imbalance between classes. The outcome of the feature importance using the demographic variables and pattern of behaviour further emphasized the applicability of the demographic variables and behavioural pattern in influencing the perception of the people.

At large, the study has pinpointed that the Smart Cities interventions have generated ambivalent social attitudes and a significant part of the population will not be able to explicitly define the positive impact on traffic conditions [28-29]. Furthermore, a high degree of environmental concern and consistent use of the public transport signifies the willingness of the population to be actively involved in the sustainability projects provided that the efficient urban planning and development of infrastructure should be ensured.

In the above background, the results highlight the necessity of:

- o More specific traffic control policies
- o Improved communication of Smart City initiative to the citizens
- o Expand the growth of sustainable mobility modes
- o Deeper integration of data-driven decision making in urban governance landscape

Therefore, by incorporating the public perception, statistical evidence and machine learning forecasts, the given study provides a multi-layered approach for improving the traffic planning and environmental policy within the smart cities.

References

- [1] Romero-Subia, J. F., Jimber-del Rio, J. A., Ochoa-Rico, M. S., and Vergara-Romero, A. (2022). "Analysis of Citizen Satisfaction in Municipal Services." *Economies*, 10(9), 225.
- [2] Abhijna, M., Rao, K. K., and Perumal, V. (2025). "How New Metro Lines Shape a Sustainable Future: A Before-After Study of Travel Behavior, Perceptions, and Emissions in Mumbai Metropolitan Region, India." *Sustainable Cities and Society*, 127, 106431.
- [3] Ahmad, S., and de Oliveira, J. A. P. (2016). "Determinants of Urban Mobility in India: Lessons for Promoting Sustainable and Inclusive Urban Transportation in Developing Countries." *Transport Policy*, 50, 106–114.
- [4] Dash, A. (2024). "Smart Mobility in Smart Cities: Transforming the Experiences of Citizens into the Future of Smart Cities." *Transforming Government: People, Process and Policy*, 18(2), 287–302.
- [5] Bastos, D., Fernández-Caballero, A., Pereira, A., and Rocha, N. P. (2022). "Smart City Applications to Promote Citizen Participation in City Management and Governance: A Systematic Review." In *Informatics*, Vol. 9, No. 4, p. 89. MDPI.
- [6] Praharaaj, S. (2020). "Development Challenges for Big Data Command and Control Centres for Smart Cities in India." In Z. Alwan and S. M. Jones (Eds.), *Data-Driven Multivalence in the Built Environment* (pp. 75–90). Cham: Springer.
- [7] Kesar, P., and Ache, P. M. (2024). "Past, Present and Future of the Smart City in India: An Institutional Perspective." *Cities*, 146, 104775.
- [8] Loewenson, R., Colvin, C. J., Szabzon, F., Das, S., Khanna, R., Coelho, V. S. P., Gansane, Z., Yao, S., Asibu, W. D., Rome, N., and Nolan, E. (2021). "Beyond Command and Control: A Rapid Review of Meaningful Community-Engaged Responses to COVID-19." *Global Public Health*, 16(8–9), 1439–1456.
- [9] Cocks, M., and Johnson, N. (2021). "Smart City Technologies in the USA: Smart Grid and Transportation Initiatives in Columbus, Ohio." In *Smart Cities for Technological and Social Innovation* (pp. 217–245). London: Academic Press.
- [10] James, P., Das, R., Jalosinska, A., and Smith, L. (2020). "Smart Cities and a Data-Driven Response to COVID-19." *Dialogues in Human Geography*, 10(2), 255–259.
- [11] Creel, J., Holzner, M., Saraceno, F., Watt, A., and Wittwer, J. (2020). "How to Spend It: A Proposal for a European COVID-19 Recovery Programme." *Policy Notes and Reports*, No. 38.
- [12] Renukappa, S., Suresh, S., Shetty, N., Gandhi, L., Abdalla, W., Yabbati, N., and Hiremath, R. (2024). "The Role of Smart Cities in Managing the COVID-19 Outbreak in India." *Smart and Sustainable Built Environment*.
- [13] Reardon, L., Marsden, G., Campbell, M., Gupta, S., and Verma, A. (2024). "Analysing Multilevel Governance Dynamics in India: Exercising Hierarchy Through the Smart Cities Mission." *Territory, Politics, Governance*, 12(8), 1217–1235.
- [14] Teng, F., Mao, Y., Li, Y., Qian, S., and Nanekaran, Y. A. (2024). "Comparative Models of Support-Vector Machine, Multilayer Perceptron, and Decision Tree Predication Approaches for Landslide Susceptibility Analysis." *Open Geosciences*, 16(1), 20220642.
- [15] Bo, Q., Lv, P., Wang, Z., Wang, Q., and Li, Z. (2024). "Predication of the Post Mining Land Use Based on Random Forest and DBSCAN." *PLoS One*, 19(1), e0287079.
- [16] Khan, M. S., Dar, A. A., Okechukwu, C. P., Hisam, M. W., Azad, I., Smerat, A., and Farooque, M. M. J. (2026). "Food Price Prediction in Nigeria: A Comparative Analysis of Linear Regression and Machine Learning Models to Analyze Subsector Price Interdependencies." *Research on World Agricultural Economy*, 745–772.

- [17] Dar, A. A., Jahan, S. A., Khan, M. S., Azad, I., Khan, M. A. I., and Smerat, A. (2026). "Forecasting Crime Rates Using Time Series Models: A Comparative Analysis of ARIMAX, Prophet, and BSTS." *International Journal of Safety & Security Engineering*, 16(4), 871.
- [18] Jain, A., Dar, A. A., Khan, M. S., Hisam, M. W., Azad, I., Farooque, M. J., and Smerat, A. (2026). "Revolutionizing Forecasting: Leveraging Hybrid and Ensemble AI Models in Insurance Analytics." *Array*, 30, 100964.
- [19] Dar, A. A., Jahan, S. A., Khan, M. S., Azad, I., Farooque, M. M. J., Sindhuja, S., and Abidha, A. K. (2026). "Algorithmic Bias in Automated Decision-Making: A Statistical Study with Legal and Regulatory Implications." *Digital Technologies Research and Applications*, 1–14.
- [20] Jain, A., Basheeruddin, M., Dar, A. A., Qausain, S., Abidha, A. K., and Sheikh, T. A. (2025). "AI-Driven Insights into Disability Insurance Trends, Claim Duration, and Policy Shifts for Future-Ready Healthcare Planning." In *2025 3rd DMIHER International Conference on Artificial Intelligence in Healthcare, Education and Industry (IDICAIHEI)* (pp. 1–6). IEEE.
- [21] Okechukwu, C. P., Basheeruddin, M., Dar, A. A., Qausain, S., Sindhuja, S., and Obulezi, O. J. (2025). "Predictive Modelling of ART Patient Status Using Machine Learning: A Comparative Study of Classification Algorithms." In *2025 3rd DMIHER International Conference on Artificial Intelligence in Healthcare, Education and Industry (IDICAIHEI)* (pp. 1–8). IEEE.
- [22] Dar, A. A., Sanyal, S., Khan, K., Khan, M. S., Smerat, A., and Arora, V. (2025). "Forecasting Retail Sales in the Indian Market: Integrating Time-Series and Machine Learning Approaches." *Ingenierie des Systemes d'Information*, 30(11), 3029.
- [23] PM H, K. M., and Azad, I. (2026). "Bridging Accuracy and Interpretability: Comparative Insights from Interpretable and Black-Box Models for CO₂ Emission Forecasting." *Clean Energy Science and Technology*, 4(1), 530.
- [24] Dar, A. A., and Lone, W. Z. (Eds.). (2026). *Integrative Approaches to Quality, Data Analysis, and Interdisciplinary Research*. CRC Press.
- [25] Hisam, M. W., Khan, K., Khan, M. S., Arora, V., and Ahmad, A. (2026). "GDP Forecasting for Policy: Evaluating ARIMA, Exponential Smoothing, and XGBoost Models for Fiscal, Monetary, and Welfare Planning."
- [26] Dar, A. A., and Shaik, A. J. (2025). "Spatiotemporal Clustering and Multivariate Forecasting of Air Quality Index Across Indian Cities Using Machine Learning and Deep Learning Models." *Franklin Open*, 100435.
- [27] Shrouf, H., Shwede, F., Alzoubi, H. M., Aburub, F., and Joghee, S. (2026). "Integrating Machine Learning Algorithms and Business Intelligence: Enhancing Decision-Making in Food and Beverage Manufacturing Sector."
- [28] Shwede, F., Ahmad, A. Y. A., Almheiri, S., Mago, B., and Alawadi, R. (2025). "AI-Based Building Energy Management in Smart Cities." In *2025 International Conference on Business Intelligence for Technology Innovation (ICBITI)* (pp. 1–7). IEEE.
- [29] Shwede, F., Ali, S. M., Alqudah, M. K., and Radwan, E. (2025). "Intelligent Street Lighting System for Smart Cities." In *2025 International Conference on Business Intelligence for Technology Innovation (ICBITI)* (pp. 1–7). IEEE.