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Affordable and Sustainable Transportation: Key Drivers and Policy Choices for a Megacity in India

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Abstract

The city of Bengaluru is one of the latest entrants to the list of 33 mega cities in the world. The transportation infrastructure of the city is expanding to accommodate the rapidly increasing population. As such, there is a need to reevaluate public transport policies to achieve the Sustainable Development Goal (SDG) target 11.2. In this study, we conducted a socio-economic survey of 1350 households belonging to the low and low-middle income categories in Bengaluru city to understand their travel behaviour and transportation mode choices in the event of changing transport infrastructure dynamics of the city. While two-wheelers are the dominant mode among employed working males in the age group of 18-45 years, buses are preferred for long-distance travel. Metro ridership is low even where metro stations are accessible at the start of the journey because low- and middle-income groups are unable to afford metro services. Additionally, we used Random Forest model to assess the contribution of each explanatory variable in mode choice determination. The results shows that travel cost followed by travel time and travel distance are the most important explanators in determining the mode choice for our sample population. Based on these findings, the authors have created two scenarios to assess the impact of metro fare rationalisation on metro ridership. This study quantifies the co-benefits of the proposed policy changes in terms of economic benefits to the operators and the avoidance of air pollution and CO_2 emissions.

Keywords

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Socio-economic survey; Random Forest; CO_2 emissions; Particulate Matter pollution; SDG target 11.2.

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1. Introduction

With growing urbanisation, there is a growing demand for transportation that affects travel patterns and mode choice (Zhang, 2016; Depersin and Barthelemy, 2018). However, automobile-centric transportation policies have put excessive pressure on existing road infrastructure, leading to congestion, reduced economic output, and increased greenhouse gas emissions and local air pollution (Verma and Ramanayya, 2014; Litman, 2017). Apart from economic losses due to traffic congestion, the current state of the transportation sector has led to increased greenhouse gas emissions and local air pollution (Colvile et al., 2001; Ortmeyer and Pillay, 2001). To address these issues, experts and practitioners advocate for a comprehensive approach that includes improving public mass transit, along with encouraging non-motorised modes of transport (Aswini, 2015; IEA, 2019).

Public transit plays a crucial role in achieving equity for economically and socially disadvantaged sections by increasing their economic and social opportunities and allowing them to access public services, education and employment opportunities (Allen 2008; CTS 2010). The important role played by the public transportation system in ensuring equity, sustainability, and liveability of a city has been acknowledged in the SDG 11.2 of the Sustainable Development Goals, which states:

By 2030, provide access to safe, affordable, accessible, and sustainable transport systems for all, improving road safety, notably by expanding public transport, with special attention to the needs of those in vulnerable situations, women, children, persons with disabilities and older persons.

However, Public transit systems in megacities are often inadequate and cannot meet the transportation needs of residents. This results in overcrowding on public transit systems, increased travel times, and reduced access to essential services (World Bank, 2019). Inadequate pedestrian and cycling infrastructure further discourage active modes of transportation, leading to increased reliance on private vehicles.

The Government of India recognises the need to improve the transportation system in the country, and has placed a focus on the development of mass rapid transit system as a key strategy, which is indicated in the following statement by Standing Committee of Parliament on Housing & Urban Affairs (MOHUA, 2022):

" Mass Rapid Transit Systems tend to reduce per capita vehicle ownership and usage and encourage more compact & walkable development pattern which provide developmental benefits to the society. Reduction in cost and time of travel lowers the cost of production of goods and services, which significantly improves the city's competitiveness. One of the significant contributions is a substantial reduction in per capita pollution emission, bringing down various chronic diseases, resulting in huge public health benefits."

This study focuses on a megacity in India, Bengaluru, which is the fastest-growing city in India (Holt, 2018). Rapid urbanisation and subsequent increase in disposable income among the urban population have led to a rise in the number of registered vehicles in the city, from 2.64 million in 2007-08 to 8.05 million in 2018-19 (MORTH, 2021). The rapid growth of vehicles on the road has led to endemic traffic congestion, and the economic losses due to congestion are estimated to be 5.92 billion USD per annum in Bengaluru alone (Chin et al., 2018). Further, the transportation sector in Bengaluru contributes 21.80 percent to the total

PM_{10} emissions and 36.55 percent to the total $PM_{2.5}$ emissions, thereby contributing significantly to negative health outcomes (Mangaraj et al., 2022).

The city of Bengaluru has only two modes of public transportation - bus and metro. The metro system started its operation in 2014. Currently, the operational network of the metro is 56.1 km which will increase to 175 km after the completion of Phases 2, 2A, and 2B, which are at various stages of construction. It is estimated that 175 km of metro transit will be functional by 2027-28. It is, therefore, essential that the travel behaviour of commuters is studied to arrive at an understanding of the gaps and requirements to enable effective utilisation of the city's public transport modes as they undergo phase-wise expansion. This study primarily focuses on investigating the commuting needs and behaviour of low- and medium-income households who are the largest users of public transport in India.

The key research questions answered in this study are as follows:

- What are the key factors which impact the transportation mode choice for low- and medium-income commuters in Bengaluru?
- What policy interventions are required to enhance the metro ridership to achieve SDG 11.2 in Bengaluru city?
- What are the economic and environmental benefits of the policy interventions recommended in this study?

Following this introduction, we review relevant literatures that explore various factors influencing commuters' mode choice decisions, especially in developing economies. Additionally, we also review the literatures which have examined the socio-economic and environmental impacts associated with the usage of urban rail transit. In Section 3, we present the data and methods employed in this study to answer the above research questions followed by a discussion of the key results of this study in section 4. Section 5 presents city wide scenarios under different policy frameworks followed by the conclusions and policy implications of this study summarised in Section 6.

2. Literature Review

While the study is for the city of Bangalore, the questions that we try to answer are relevant to other cities in India as well given the rapid rates of urbanisation and urban agglomeration that are taking place in the country. Similar issues have been studied for other regions, but many studies deal with questions of transportation in developed countries, where both the scale of existing transportation infrastructure and the levels of household incomes are significantly different. The paper tries to explore literature that is relevant to developing country contexts specifically. The themes covered in the literature review include 1) mode choice and its drivers, especially in low and low-middle-income households in developing economies, 2) need for sustainable mass transportation for cities, with the metro being an important element of this, and 3) elements of assessing the sustainability of mode choices in cities.

Studying mode choice is crucial to promote sustainable transportation as it helps in empirically identifying the critical variables which lead people to choose sustainable modes of transportation like public transit, cycling or walking. Such studies help in developing a better understanding of travel behaviours which can be used to develop relevant strategies and policies which will enable individuals to choose sustainable transport modes.

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Rahul and Verma (2013) studied the impact of various factors which influence the choice of non-motorised transport (NMT) modes for the city of Bengaluru. According to this study, the most important factors influencing the decision-makers to choose NMT modes are distance, safety, comfort, and availability of NMT infrastructure. Ashalatha et. al. (2013) studied the mode choice behaviour of individuals undertaking work-related trips for the city of Thiruvananthapuram, India. The variables used in the study are age, gender, income, vehicle ownership as well as variables related to the travel system like travel time and travel cost. The results suggest that the propensity to use car increases with age and income. Further, travel attributes like travel time and travel cost have a negative marginal impact on the propensity to use public transport. An increase in time and cost causes the commuters to switch from using public transport to private vehicles.

Singh and Vasudevan (2018) studied the mode choice behaviour of school going students and the factors affecting the decision-making process among them for the city of Kanpur, India. The authors suggest that distance plays an important role in mode choice decision along with demographic variables like age, gender, household income and vehicle availability.

The role of urban rail transit in promoting sustainable development is an important topic that has been extensively studied. The role played by metro transit in ensuring mobility for marginalised, and economically vulnerable groups have been the subject of many studies (Sanchez et al., 2004; Giuliano, 2005). The opportunities to access affordable public transport enable such groups to expand their social, economic, and cultural opportunities. The goals of ensuring accessibility and affordability can be achieved by subsidising public transport services and expanding necessary infrastructure, which includes improved first and last-mile connectivity (Tiwari, 2002; Guzman and Oviedo, 2018).

The direct and indirect economic impact of urban rail transit on cities has been studied by various researchers. The study by Tao et al. (2022) revealed that it has a positive impact on the population, GDP, and employment opportunities, particularly in economically developed cities. Knowles and Ferbrache (2016) found that it increases accessibility, employment opportunities, and economic growth but may negatively impact housing affordability. The empirical investigations by Laura et al. (2019) identified the benefits of urban rail transit on high-skilled job sectors but concluded that it might not have a significant impact on job opportunities for low-wage workers. A few studies have explored the impact of rail transit on marginalised and economically vulnerable groups in society (Sanchez et al., 2004; Giuliano, 2005). These findings highlight the potential benefits of urban rail transit, as well as the need for policymakers to consider and address its potential negative impacts on housing affordability and equity.

Two studies conducted by Sharma et al. (2014) and Soni and Chandel (2018) examined the impact of metro rail systems in Delhi and Mumbai on emissions. Both studies found that the implementation of metro rail systems led to a reduction in on-site emissions of CO_2 and local pollutants. The shift in ridership to the metro was mainly from buses rather than private vehicles, which limited the full potential of CO_2 mitigation by enhancing public transit use. These findings underscore the importance of utilising sustainable energy sources to power metro systems and promoting a shift towards public transit from private vehicles to realise their full environmental benefits.

Overall, these studies demonstrate the potential of urban rail transit to promote sustainable development by supporting economic growth, increasing accessibility, and reducing environmental impacts. However, they also highlight the need for careful consideration of

potential negative impacts and the importance of ensuring that benefits are shared equitably among all the members of society.

With the social, economic, and environmental importance of metro transit empirically identified, researchers have studied and proposed various policy interventions required to enable a shift of ridership from other private modes of road-based motorised transport to the metro. Table 1 enumerates a representative list of such policy recommendations to induce a shift in ridership to the metro.

Table 1. Policy recommendations to increase metro ridership.

Target Mode of Passenger Transport	Policy recommendations	Source
Ridership shift from bus to metro	Restructuring the fare system to make it more affordable. Operator losses can be compensated through various funding instruments like the Green Climate Fund. An integrated fare system to provide common metro and bus fares. Formation of a unified transport authority to regulate the pricing of the metro and bus in the city and roll out the city's public transportation under one umbrella organisation.	Matas et al., (2020). Matas (2004). Sharaby and Shiftan (2012), National Metro Policy (2017)
Ridership shift from two-wheelers to the metro	Pricing instruments like congestion policy, increased road tax, and increased tax on two-wheelers. Imposing a cap on the number of two-wheelers owned by households etc.	Verma et al., (2015). Verma et al., (2021)
Ridership shift from four-wheelers to metro	Increased tax on four-wheelers, increased road tax, and higher parking charges. De-congestion policies like banning cars in certain designated zones.	Wang et al., (2014). Cipriani et al, (2019).
Ridership shift from auto (three-wheelers) to metro	Encourage shared autos, especially electric ones with higher occupancy and less emitting potential.	Bagul et al., (2021). Khan et al., (2022).

Finally, the Standing Committee of the Indian Parliament on Housing & Urban Affairs has reviewed the performance of all metro systems in India has *inter alia* stated that (MoHUA, 2022):

> *".... If metro rail projects are to be made as mass transportation medium in true sense and operate them on sustainable basis the commuters are to be weaned away from using private vehicles, a compelling proposition should be made available to them in terms of comfort, convenience, quality, affordability, and reliability, etc."*

3. Data and methods

3.1 Study area

The study area is the BBMP (Bruhat Bengaluru Mahanagara Palike) region of Bengaluru, which is the city's core zone, extending between 77.4°E to 77.8°E longitude and 12.8°N to 13.1°N latitude. The total area of the BBMP region is 710 km^2, with a population of 8.44 million and a working population of 3.69 million (Census, 2011). The population of the BBMP region crossed 11.3 million in 2018 and is projected to increase to 16.9 million by 2031 while the working population of 4.9 million in 2018 is projected to increase to 7.6 million by 2031 (RITES, 2019). The study area is shown in Figure 1.

As per the feasibility study for Bengaluru suburban rail corridors carried out by Government-owned South-Western Railway based in Bengaluru, 32 percent of the daily trips in the city are being undertaken by bus and metro services (RITES, 2019). Non-motorised transport modes (walking and cycling) constitute 26 percent of daily trips. The rest of the population commutes by private motorised modes (7 percent by car, 27 percent by two-wheeler and the remaining by autos and taxis).
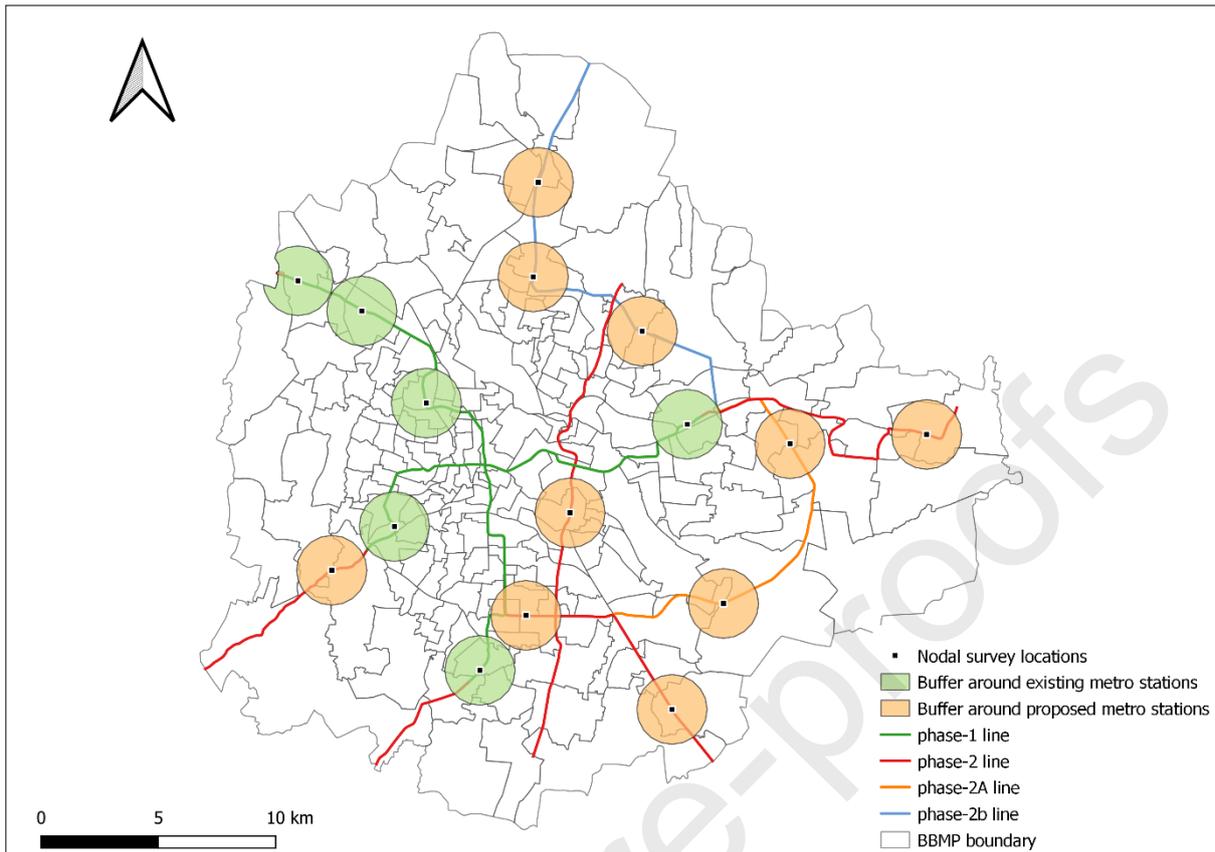
Figure 1. Map showing the nodal points of survey locations and the metro network (both existing and proposed).

This study primarily focuses on the travel behaviour of households within a 1500-meter radius of six of the existing metro stations of Phase 1 of the Bengaluru metro and ten of the metro stations that are under construction as part of the ongoing Phases 2, 2A, and 2B of the Bengaluru metro network as shown in Figure 1.

Phase 1 of the Bengaluru metro is divided into green and purple lines, which cover the North-South and East-West ends of the city, respectively. During the socio-economic and mobility survey of 1350 households conducted for this study, the respondents were asked about their daily trip-making attributes prior to the detection of the first case of COVID-19 in Bengaluru in March 2020.

Before 2020, the green line of the metro had 24 stations, and the purple line had 16 stations. The total route length of Phase-1 was 42.3 km. Phase 2 of the Bengaluru metro has a route length of 72 km with 67 stations, and Phases 2A and 2B are additions to Phase 2 of the project. Once completed, the Bengaluru metro services will cover a total route length of 175 km by the year 2025 (ADB, 2023).

3.2 Primary Survey

The primary purpose of our study is to explore the possibilities of metro usage and its role in a large sustainable transportation transition for the city; hence we design our sampling

Define study area as

strategy based on current and upcoming metro lines and stations. Figure 2 shows the schematics of the sample selection technique employed in this paper.

| Wards where metro stations are present. | | Wards where metro stations are not present. |

Figure 2. Plan for sample selection

 Our sample is limited to the BBMP area which has 198 wards within its jurisdiction. As wards are the smallest administrative areas, we used ward-level attributes to quantify the sample for our study. We employed a stratified proportionate sampling method to first select the 69 wards where metro stations are already operational or under construction. From within this list of 69 wards, we select sixteen wards which have the highest number of households. A sample set of households proportionate to the total number of households in the ward was selected from each ward. Of these sixteen wards, six wards have existing (Phase-1) metro stations, and ten wards will have metro stations once Phases 2, 2A, and 2B are completed. The other question is one of addressing affordability as a key to ensuring sustainable transportation in cities in developing countries. Therefore, our target respondents were low and low-middle-income households who could be either present or potential metro users. We conducted a reconnaissance in a buffer zone with a radius of 1500 meters around each of the sixteen metro stations (operational or under construction) selected to choose the low and low-middle-income households for our survey. The reason for adopting this sampling technique is that there are no readily available travel survey datasets for the city of Bengaluru. Purely random sampling technique without baseline data is impossible to conduct, and hence, we had to employ proportionate random sampling technique to select the 1350 households to be surveyed using a detailed survey questionnaire (uploaded as Table A2 in the appendix section

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of this paper). We used Cochran's sampling method to check whether the sample size derived meets the sample size requirement (Israel, 1992).

Primary data collection was done through face-to-face interviews. Data on the socio-economic and demographic characteristics, and travel-related attributes of the modes used for commuting by the respondents, including the spatial and temporal aspects of their daily commutes, was collected. A Likert scale-based rating was also part of the questionnaire to inquire about commuters' perception of the specific mode of travel. A team of eight to ten surveyors with proficiency in the local language were trained and deployed to conduct the survey. The survey was conducted between July and September 2021 and covered 5073 individuals in 1350 households.

Since travel time (and travel distances) based on commuters' perception can vary daily, we collected information on precise locations of the trip destinations, which were geo-coded to extract the latitude and longitude of the destination points. As the trip originates at the place of residence of the household itself, we calculated the travel distance between the origin and the destination using GIS. Additionally, there are a range of reasons for mode choice, all of which cannot be hard coded in the questionnaire itself. These emerge during discussions with the respondent. Respondents are also often reticent about disclosing income and expenditure information. Data for these variables were collected only as a range. Acknowledging these limitations, we conducted an exploratory data analysis, and the primary survey data was used as an input in the Random Forest Model to ascertain the key drivers of mode choice. A detailed discussion of the random forest method is given in section 3.3.
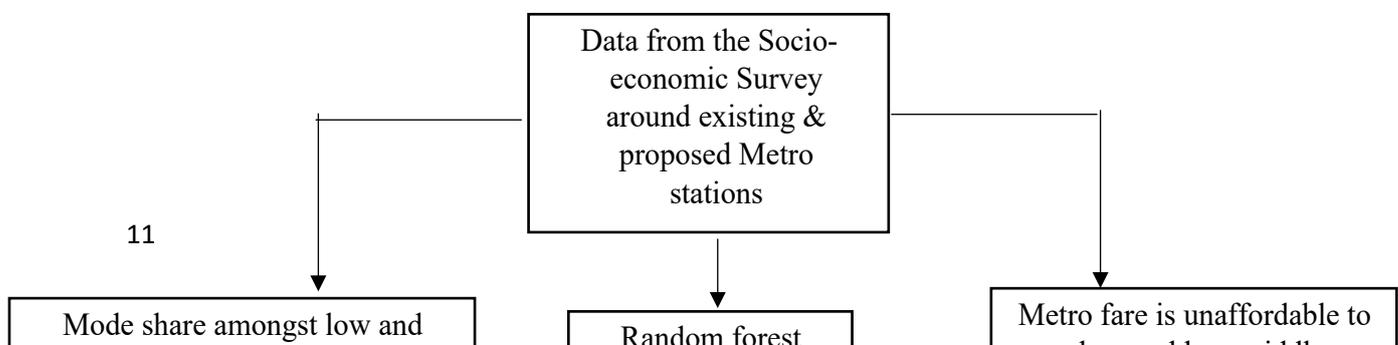
3.3 Random Forest model

The random forest is an ensemble machine-learning algorithm which uses bootstrapping and random feature selection to make predictions. Ensembling technique is used to combine multiple machine learning algorithms to make predictions which is accurate than a single machine learning algorithm. Random forest uses bootstrapping to ensemble decision trees, which is the base model for this algorithm, wherein each tree is created from different training samples which are randomly selected from the training dataset with replacement. As sampling is done with replacement, some observations might appear more than once, and others might not be chosen at all. Such left out observations in the bootstrap sample is called out-of-bag (OOB) observations (Brieman, 2001). A single decision tree is prone to high variance/ overfitting. Bootstrap aggregation is used to reduce the variance of a classification algorithm as it combines the results of multiple machine learning models and predicts using a method called majority voting. Randomness is incorporated to decrease/ remove the possible correlations between the subtrees and is implemented either by a) random sampling of observations from the training data set which is then used to train base tree models b) random sampling of a set of explanatory variables to split each node.

Unlike other machine learning algorithms which acts as black box, Random Forest provides interpretability of the results using a measure called feature importance. The relative importance of explanatory variables which contribute to the model is calculated using Gini impurity index. Every time a node split is done on a variable, Gini impurity index decreases as Gini impurity for the two descendant nodes is less than the parent node. The average decrease of Gini impurity index over all trees in the forest provides the importance measure for a particular variable.

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Random forest algorithm has been used to explain mode choice determination. Ermagun et al. (2014) analysed travel mode choice using Random Forest and Nested Logit model. The authors used explanatory variables like socio-economic attributes, built environment variables and psychological variables in their models to analyse and predict travel mode choice. The results showed that the Random forest model significantly outperformed the nested logit model in prediction accuracy. Cheng et al.(2019) used socio-demographic attributes, trip information and built environment variables to analyse and predict mode choice using machine learning models like Random forest, AdaBoost, and SVM and econometric models like the Multinomial logit model (MNL). Random Forest reported the highest prediction accuracy and computational efficiency among all the models.

In this paper, we have used the random forest model to determine the major factors which influence mode choice decisions among low and low-middle-income households. Informed by the results of the model, we further evaluate the economic and environmental impact of the reduced metro fares preceded by the implementation of other policy interventions indicated in Table 1 and the recommendations of the Standing Committee of Parliament regarding the social benefits of metro services (MoHUA, 2022). A discussion of this overall methodological structure is shown in Figure 3.

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Data from the Socio-economic Survey around existing & proposed Metro stations

| Mode share amongst low and | | Random forest | | Metro fare is unaffordable to |

Figure 3. Schematics of the methodological interactions

4. Results and Discussion

4.1 Demographic characteristics of the survey respondents

Four hundred and thirty-six households were surveyed around existing metro stations, while 914 households were surveyed from areas around the proposed metro stations. The average household size of the population surveyed for both locations is approximately 4.2. The average working and dependent members in each sampled household around the existing metro stations are 1.8 and 2.5, respectively, while the corresponding figures in the areas around the proposed metro stations are 1.9 and 2.4, respectively. Males constitute 51 percent, and females constitute 49 percent of the sample population. The dominant age group of individuals in the sample belongs to the 18-45 years range, followed by individuals older than

45 years. The share of individuals with an age less than 18 years is lowest in the sample. Households with a monthly income of less than Rs.10,000 constitute 81 percent of the total sample, while households with monthly incomes ranging between Rs.10,000 to Rs.30,000 constitute 18 percent of the entire sample. Households with monthly incomes greater than Rs.30,000 account for only 1 percent of the entire sample. The median household income of the population in the sample is Rs 7805 per month. It is evident, therefore, that most households in the sample belong to low and low-middle-income categories as defined by the Consumer Pyramids Household Survey (CPHS) data conducted by the Centre for Monitoring Indian Economy (CMIE) (Sharma, 2022).

The occupation type has been classified into seven different occupation categories, namely "Salaried, "Wage-earners," Self-employed, "Full-time houseworker," "Unemployed," "Retired," and "Students." Salaried individuals constitute about 28 percent of the surveyed population, followed by students (~24 percent). As far as the distribution of incomes with respect to occupation is concerned, the salaried class constitutes a significant proportion among all the three income categories, followed by wage earners. None of the respondents in the "wage-earning" category had a monthly income greater than Rs.30,000. Only 20 percent of the respondents were graduates, while 15 percent have completed their secondary school education.

4.2 Travel-related characteristics

We surveyed a total of 5073 individuals across 1350 households. Of these 5073 individuals, 4550 are regular commuters (approximately 89.6 percent). The share of different travel modes used by regular commuters around the existing and future metro stations is shown in Figure 4.
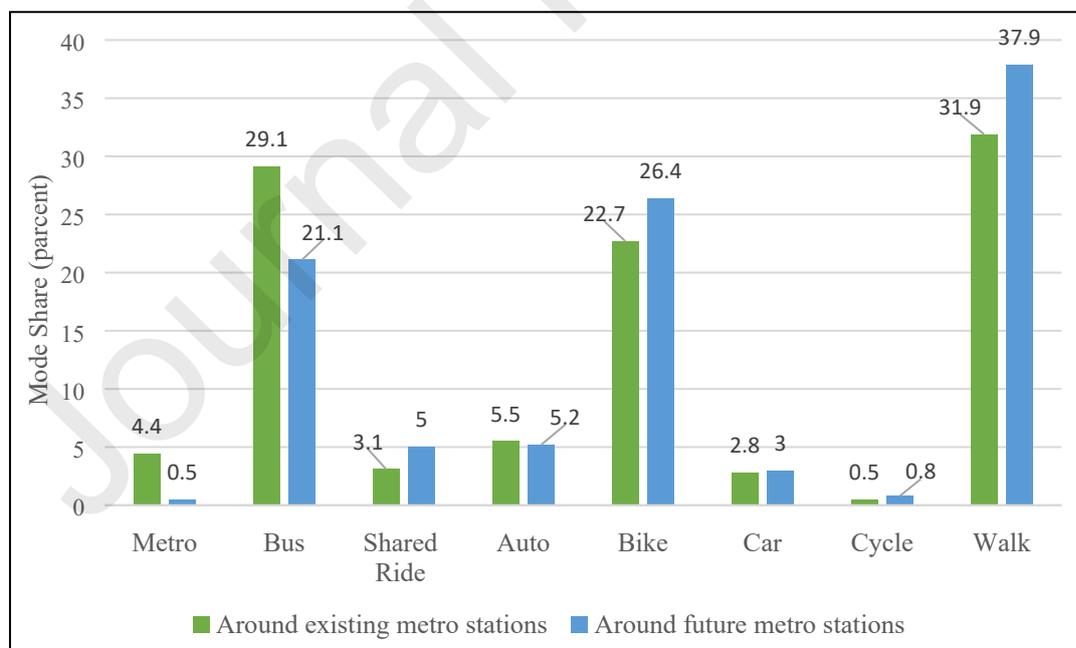
Figure 4.

Modal share for the sampled population (4550 individuals)

The share of metro users for individual sites studied ranges from 1.7 percent to 10 percent. Although the survey respondents living around the existing metro stations live within an accessible range from the metro stations, their mode choice reveals other pertinent factors

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besides accessibility in determining mode choice. The mode choice of the 1350 households (4550 individuals) surveyed with respect to gender, age, educational qualification, occupation type, and vehicle ownership is shown in the Table A1 of the Appendix.

The survey results show that among respondents with a graduate degree, at least 32 percent use two-wheelers for commuting. On the other hand, among respondents with less than ten years of schooling, 40 percent do not use any motorised mode for commuting. Further, the more vulnerable section in the sample population, including non-earning members of households and the elderly, predominantly use non-motorised options (mostly walking) to meet their daily commuting needs. Around 47% of the respondents, either unemployed, retired, or students, use non-motorised modes for their daily commute. This finding aligns with previous studies' results (Uteng and T.P.,2011; Jain and Tiwari, 2019; Jain and Tiwari, 2020). Their studies found a pattern between travel mode choice among marginalised sections like low-income individuals, workers, and women, who depend on non-motorised modes for short-distance travel and public transport modes for long-distance travel to meet their active travel requirements.

4.3. Mode choice vs distance

Further, we examined the role of travel distance in influencing mode choice among the sampled population. For this purpose, we discretised the travel distance into six bands (less than 2 km, 2-5 km, 5-12 km, 12-21 km, 21-32 km, and greater than 32 km) based on the distance slabs fixed by the Government-owned metro operator for metro fares in Bengaluru. The percentage share of various modes used by commuters in each distance category is summarised in Table 2 (existing metro stations) and Table 3 (future metro stations).

Table 2. Share of respondents living around existing metro stations using various transport modes with respect to distance travelled (values are in percentages)

| Distance (kilometres)	Metro	Bus	Shared Ride	Auto	Two-wheeler	Car	Cycle	Walking
Less than 2	0.0	0.7	0.7	1.7	8.5	0.2	0.5	87.7
2-5	1.7	21.6	4.6	12.4	29.3	2.6	0.9	27.0
5-12	6.1	50.1	2.7	6.6	30.2	4.2	0.0	0.0
12-21	14.1	49.0	3.4	1.0	28.2	3.4	1.0	0.0
21-32	7.8	54.7	7.8	1.6	18.8	9.4	0.0	0.0
Greater than 32	0.0	61.5	23.1	0.0	7.7	7.7	0.0	0.0

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Table 3. Share of respondents living around future metro stations using various transport modes with respect to distance travelled (values are in percentages)

Distance (kilometres)	Metro	Bus	Shared Ride	Auto	Two-wheeler	Car	Cycle	Walking
Less than 2	0.0	0.9	1.3	2.2	9.8	0.7	0.7	84.4
2-5	0.0	17.3	6.8	11.4	34.5	2.5	1.5	26.0
5-12	0.7	37.8	8.7	5.6	40.6	5.3	0.7	0.6
12-21	2.0	51.0	5.8	2.3	33.5	5.2	0.0	0.0
21-32	2.0	51.0	6.9	1.0	30.4	8.8	0.0	0.0
Greater than 32	0.0	56.0	0.0	8.0	28.0	8.0	0.0	0.0

Tables 2 and 3 indicate a similar mode share trend for both the sample site locations. People tend to use non-motorised modes like walking for shorter distances, while buses are preferred for medium to long-distance travel. The usage of two-wheelers remains consistent across all distance categories, indicating that individuals in the sample set find it the most useful mode of transport regardless of the distance travelled. Joshi (2014) conducted a study on the mobility practices of the urban poor in Ahmedabad, which revealed that most of them either walked or cycled. Nonetheless, Joshi found that many young people among the poor aspired to own two-wheelers as they provided them with more opportunities to access job opportunities. This trend of aspiration for two-wheelers is not unique to Ahmedabad but is also observed in other developing cities, as reported by Shirgaokar in 2012 and Mahendra et al. in 2015.

*4.4 Reasons for not choosing metro and willingness to shift*

Respondents living near the metro stations were asked the reason for not using the metro as their mode of commute, and a Likert scale-based rating was used to register their reasons. Figure 5 summarises the analysis of the determinants cited by the respondents for not using the metro services during their daily commute.
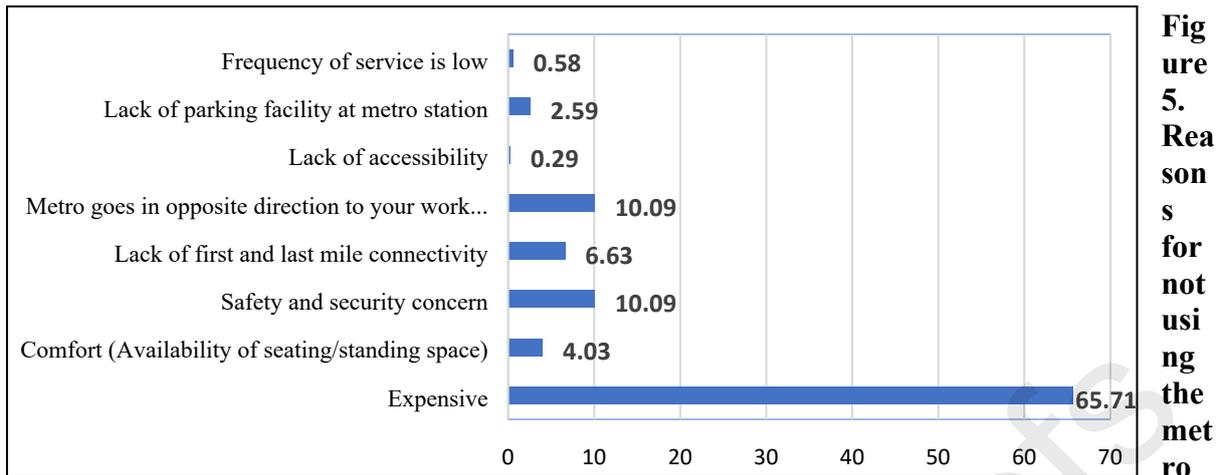
Figure 5. Reasons for not using the metro (where metro stations are accessible)

As shown in Figure 5, 66% of the households surveyed believe that the metro is too expensive and do not use it despite living close to metro stations currently. Other significant reasons for not using metro services despite their accessibility are also shown in Figure 4. Similarly, individuals who are not living near the metro stations today were asked whether they will use the metro services when the metro comes to their neighbourhood, to which 80% of the surveyed individuals responded positively. Figure 6 presents the willingness of respondents (living in wards where the metro is not currently present) to shift to the metro once it becomes accessible to them.
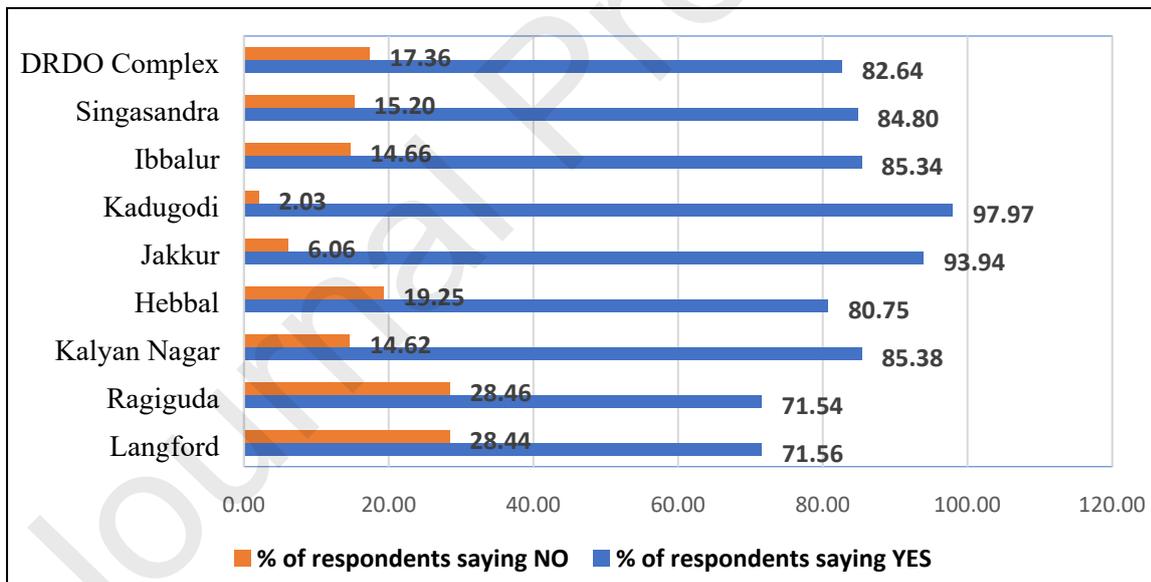
Figure 6. Willingness of people to use the metro once it is made accessible.

Based on these results, we conclude that affordability and accessibility are the two main reasons for such low metro ridership among the survey respondents.

4.5. Average income vs average expenditure on travel

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We found that the average monthly household income of commuters using the metro was Rs 13,544 ($169), while the average monthly cost for commuting was Rs 1,152 ($14.4). On the other hand, the average monthly household income of bus users among the respondents was Rs 6,104 ($76), while their average monthly travel cost was Rs 378 ($4.7). This indicates that the average monthly cost incurred by metro users is three times higher than for bus users. If the individuals using the bus start commuting by the metro, their average travel expenditure would constitute about 19% of their average monthly income. This is prohibitively expensive for this section of commuters.

Travel cost incurred by those using two-wheelers for daily commute is lower than the bus and metro for travel distances less than 12 km. This is also one of the major reasons for the widespread use of two-wheelers in Bengaluru. However, the cost of commuting using two-wheelers is higher than that of bus and metro services when the travel distance exceeds 12 km. Even so, many commuters travelling farther than 12 km still use two-wheelers. This may be due to the inadequate first and last-mile access for the current metro stations.

The mode share analysis shows that two-wheelers and buses are the predominant motorised modes used by the sample population. Even though a sizeable proportion of the population lives within an accessible metro system, they do not currently use the metro to commute. A significant proportion of the respondents cited cost as the main factor for not using the metro. Therefore, it is essential to look at the impact of an affordable metro system on ridership, the operator's cost, and the environmental benefits of such a ridership shift. Increased ridership can lead to higher revenue and make the metro services financially viable.

4.6 Determinants of mode choice using Random Forest model

The Random Forest model is developed for 4359 individuals in the dataset with eight mode choices. The travel mode choices used in this model are Metro, Bus, Shared ride, Auto, Bike, Car, Cycle and Walk.

The variables used in the random forest model are:

1) Travel-related characteristics like travel time, travel distance and travel cost.
2) Socio-economic attributes like age, household income, occupation type, educational qualification, nature of trips, etc. The occupational category in the model includes individuals who are salaried, self-employed, daily wage workers and non-working members. Similarly, the educational qualification comprises individuals with degrees equivalent to graduate degrees and more, individuals who have done schooling till high school/intermediate, and individuals who have done schooling till primary school education. The nature of trips in the model includes trips made for work-related purposes, leisure-related purposes, educational purposes and trips made for household chores.
3) Built environment attributes like population and employment density.

The dataset was divided into two parts: 70% of the data was randomly selected to train the model, and 30% of the data was selected to test the generalizability and transferability of the model. The dataset was normalised using min-max normalisation[1](Sethi et al., 2023). As such, all the independent variables are in the range of 0 to 1.

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[1]min-max normalisation is a data normalisation technique and is calculated by following expression.

Hyperparameters (λ) are a set of external parameters which control the learning process of the machine learning algorithm and must be tuned for the algorithm to achieve optimal accuracy. In the case of Random forest, hyperparameters are the number of trees in the forest (n) and the maximum depth of each tree i such that $i \in 1,2,...n.$ The hyperparameters are tuned using five-fold cross-validation. The accuracy of the model is estimated by the F1-score[2], which is a harmonic mean of precision and recall. F1-score ranges between 0 and 1, where 0 can be interpreted as the worst score and 1 can be interpreted as the best score (Sethi et al., 2023).

The best F1 score for training accuracy is 0.61, which is obtained at the optimal hyperparameters of ($n = 100, Max(d_i) = 10$), and the best F1 score for testing accuracy is 0.4.

The contribution of each variable in determining mode choice was calculated using Mean Decrease in Accuracy (MDA), which is designed to compute feature importance on permuted out-of-bag (OOB) samples. Table 4 presents the comparison of each variable in determining mode choice among the sample respondents.

Table 4. Comparison of variable importance by Random Forest

Travel cost	45.29%
Travel distance	15.58%
Travel time	11.97%
Household two-wheeler ownership	6.62%
Age of respondents	3.32%
Household Income	3.27%
Education	2.92%

$x_{norm} = \dfrac{x - x_{min}}{x_{max} - x_{min}}$

$x_{norm} = normalised\ variable,\ x_{max} = maximum\ value\ of\ variable\ and\ x_{min}$
$= minimum\ value\ of\ the\ variable$

[2] $F1\ score = \dfrac{2 \times (precision \times recall)}{precision + recall}\ where, precision = \dfrac{True\ positive}{True\ positive\ +\ False\ Positive}$ and $recall = \dfrac{True\ positive}{True\ positive\ +\ False\ Negative}$

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Occupation	2.72%
Main travel purpose	2.63%
Household four-wheeler ownership	1.96%
Employment density of destination ward	1.14%
Population density of origin ward	1.04%
Metro availability	0.83%
Gender	0.72%

Our results show that the travel cost, travel distance, and travel time, in that order, are the important decision variables that drive the decision-making behaviour of individuals with respect to mode choice. In fact, travel cost proves to be the overwhelming driver of mode choice for the low-middle- and low-income households covered in our survey.

5. Scenarios for city-wide ridership

One of the key objectives of the RITES (2019) study commissioned by South-Western Railway was to establish the feasibility of electrified public transport to reduce energy usage and local emissions associated with road transport in Bengaluru. In this study, RITES (2019) have projected ridership of 3 million for the Bengaluru metro out of a total ridership of 16 million for all motorised modes by the year 2031. Since the projected share of 18 percent for metro services in the total ridership in 2031 is much higher than the current metro ridership of 7 percent, there is a need to identify policies and enablers to increase the ridership of metro services to 18 %.

Our research shows that over 80% of the people surveyed who live within a 1.5 km radius of the metro stations that are under construction have expressed their eagerness to use the metro once it becomes operational. However, about 67% of the people surveyed who live within a 1.5 km radius of the existing metro stations feel that the fares are too high for them to afford. To increase the usage of the metro, it would be beneficial to make the fares for the bus and metro equivalent so that a commuter is indifferent to the use of either of these modes as far as travel cost is concerned.

 Further, the state government of Karnataka has created a unified land use and transport authority called Bengaluru metropolitan land transport authority (BMLTA) in October 2022 interalia to plan and coordinate public transport services in the Bengaluru metropolitan area.

The BMLTA is empowered to coordinate between transport agencies (including bus and metro services) and will be able to ensure the rationalisation of routes and fares of the city bus services as well as the fares of the metro services leading to potential implications for metro ridership (Rao and Kumar, 2022).

The following section utilises the "what-if" scenario method to compare the current mode share trend with the projected mode share trend. Two scenarios for 2031 have been created: "Business as Usual (BAU)" and "Affordable Metro Service (AMS)." For both scenarios, ridership, revenue, and emissions have been estimated. In the AMS scenario, the assumption is made that bus and metro fares are equalised for distance slabs greater than 5 km, as people tend to use non-motorised modes for distances less than 5 km in the study area. Additionally, it is assumed that the Bengaluru metropolitan land transport authority (BMLTA) will coordinate between bus and metro services to reduce route duplication, enhance bus feeder services to metro stations, and maximise utilisation of the metro network.

5.1. Business as Usual (BAU) Scenario

We developed a scenario called Business-as-Usual (BAU) by assuming that the mode share of motorised modes, including public transport (metro and bus), intermediate public transport (auto), and private transport (two-wheeler and car), would remain the same as the current mode share. We also assumed that phase 2, 2A, and 2B of the metro system would be operational and the demand for metro services would be uniform across the BBMP region. Additionally, the current fare differential between metro and bus services, which makes metro fares significantly higher than bus fares for all distance ranges, was assumed to hold true for this scenario.

To estimate the ridership for each mode in 2031 under the Business as Usual (BAU) scenario, we utilised the current distance-wise mode share of motorized transportation modes and multiplied it by the total projected demand for 2031, which was provided as 16 million by RITES (2019). Our analysis indicates that the daily ridership of the metro in 2031 would reach 1.3 million, a significantly lower figure than the projection of 3 million in the draft Detailed Project Report (DPR) by RITES (2019). Consequently, a sizeable gap of 1.7 million daily metro ridership exists under the BAU scenario when compared to the ridership projections in the aforementioned DPR.

5.2. Affordable Metro Service (AMS) scenario

We created an affordable metro scenario to address the gap in ridership between BAU and the projected ridership of three million. This scenario assumes that reducing the metro fare will encourage people to shift from other motorised modes, as cost was identified as the main factor deterring metro use by 67% of respondents. Hence, we construct an affordable metro scenario assuming that the fare of metro is same as that of bus for a distance greater than 5 km. Since the shift from each individual mode to the metro is not known, we assume that the shift will happen proportionately to the mode share for each distance band. Therefore, the shift of 1.7 million riders to the metro will happen (in that order) from buses, two-wheelers, autos, and cars. As the mode share of bus is highest for the distance band of 5-12 km, the highest shift will be realised in this distance band for the bus mode. Table 6 presents the breakup of the shift in ridership from other motorised modes to the metro.

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Table 5. Breakup of motorised ridership by mode & distance range in 2031 under the BAU scenario (values are in thousands)

Distance range	Metro	Bus	Auto	Two-wheeler	Car
Less than 2	0	60	147	688	17
2-5	124	1502	905	1950	153
5-12	516	4086	568	2352	289
12-21	599	2023	42	1109	119
21-32	103	701	21	229	102
Greater than 32	0	160	0	19	17
Total	1342	8532	1683	6348	698

Table 6. Number of trips projected to shift from other motorised modes to the metro after policy interventions.

Distance range (km)	Ridership shift to the metro from (in thousands)				Total ridership shift within each distance band (in thousands)
	Bus	Auto	Two-wheelers	Car	
5-12	572	80	329	41	1022
12-21	283	6	155	17	461
21-32	98	3	32	14	148

Greater than 32	22	0	3	2	27
Total ridership shift from each mode to the metro	976	88	519	74	1658

As a result of the shift in ridership from other motorised modes to the metro, the mode share of the metro in 2031 increases from 7 percent (BAU scenario) to 17 percent of all motorised trips in the AMS scenario (Figure 7).
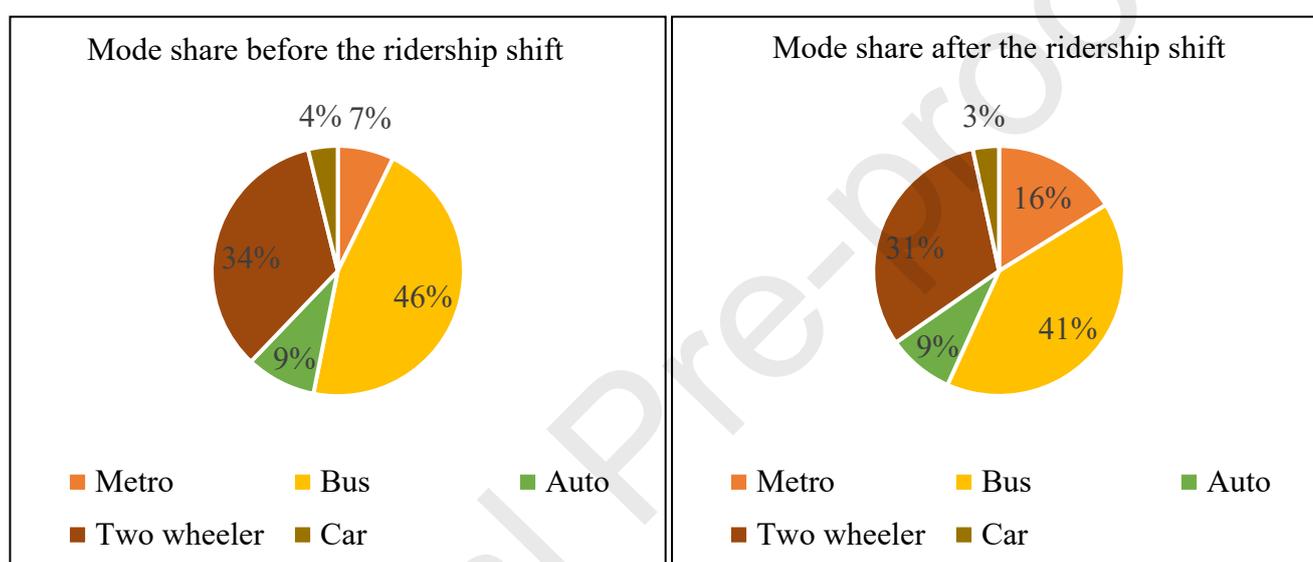
Figure 7. Mode share before and after the ridership shift (BAU versus AMS scenarios)

The average daily ridership of metro in the AMS scenario (3 million as shown in Table 7) is the sum of the ridership shift from each mode to the metro (1.66 million as shown in Table 6) and the metro ridership in the BAU scenario (1.34 million as shown in Table 7). We evaluated the change in revenue for the metro operator under the AMS scenario. The ridership for the metro and the fare-box revenue estimated for both BAU and AMS scenarios are given in Table 7.

Table 7. Projected revenues at current and discounted fares for metro services in 2031

Distance Range (km)	Metro ridership in the BAU Scenario	Metro Ridership in the AMS Scenario	Revenue at current fare for BAU Scenario	Revenue at the subsidised fare for AMS Scenario

	Number of trips in thousands		Values are in 000s Rs (000s USD)	
Less than 2	0	0	0	0
2-5	124	124	1858 (23.2)	1239 (15.5)
5-12	516	1538	10325 (129.1)	26912 (336.4)
12-21	599	1060	17965 (224.6)	23850 (298.1)
21-32	103	251	4130 (51.6)	6270 (78.4)
Greater than 32	0	27	0	756 (9.5)
Total	**1342**	**3000**	**34279 (428.5)**	**59027 (737.8)**

As a result of the ridership shift from other motorised modes to the metro, the metro ridership and the fare box revenue of the metro operator increases from Rs.34 million ($0.425 million) to Rs.59 million ($0.738 million) per day due to increased ticket sales. The net revenue gain in the AMS scenario compared to the BAU scenario is estimated to be approximately Rs 25 million ($0.31 million) per day. In the next section, we evaluated the emission avoided due to the ridership shift from motorised modes to the metro.

5.3. Avoided emissions: A comparison of the BAU and AMS Scenarios

We also estimate the amount of CO_2 and emissions of pollutants that can be avoided because of a shift in ridership shift from road-based motorised modes to the metro rail transit system. We use Equation 1 (Sahu et al., 2014) to estimate the emissions.

$$E_{ij} = N_j \times D_{ij} \times Ef_{ij} \qquad\qquad 1$$

Where, E_{ij} = emission of pollutant or gas i by vehicle type j

N_j = number of trips by vehicle category j

Ef_{ij} = Emission factor for pollutant or gas i by vehicle type j

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Emission levels are calculated for both the lower and upper bounds of the distance slabs. The emission factors used to calculate CO_2 emissions are taken from Harsha et al. (2018), and the emission factors for local air pollutants are from Mangaraj et al. (2022). The average occupancy of vehicles for the city of Bengaluru is from RITES (2019). The projected avoidance of CO_2 emissions and particulate matter (PM) pollution due to the ridership shift between the BAU and AMS scenarios are shown in Figures 8 and 9, respectively. The annual emissions avoided due to the ridership shift are 1.1 Gg of NO_x, 6.02 Gg of VOC, 2.82 Gg of CO, 0.13 Gg of PM, 0.04 Gg of SO_2, and 499 Gg of CO_2.
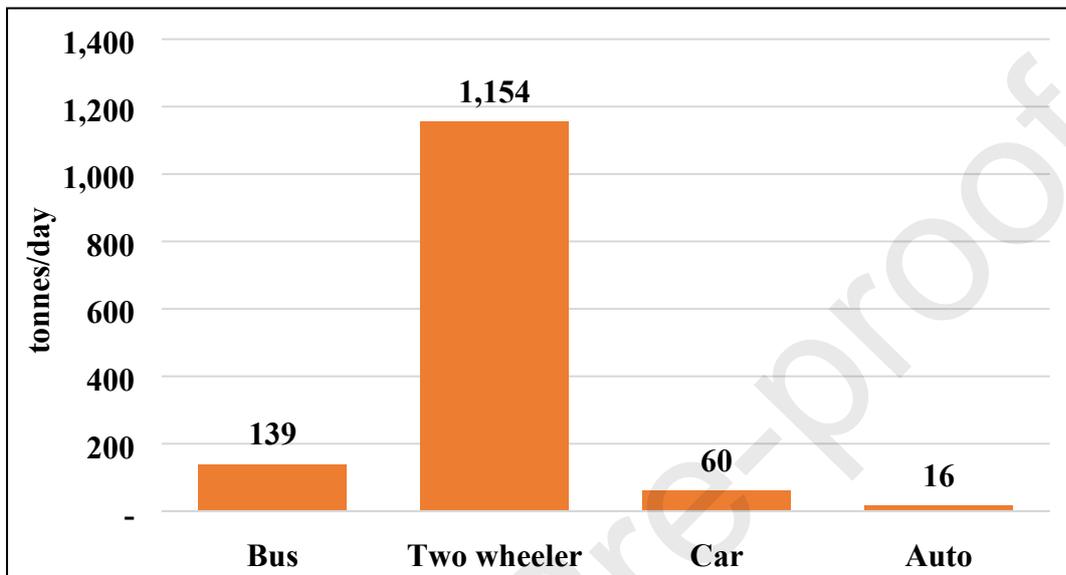
Figure 8. Avoidance in CO_2 emission (tons per day) in the AMS Scenario as compared to the BAU scenario.
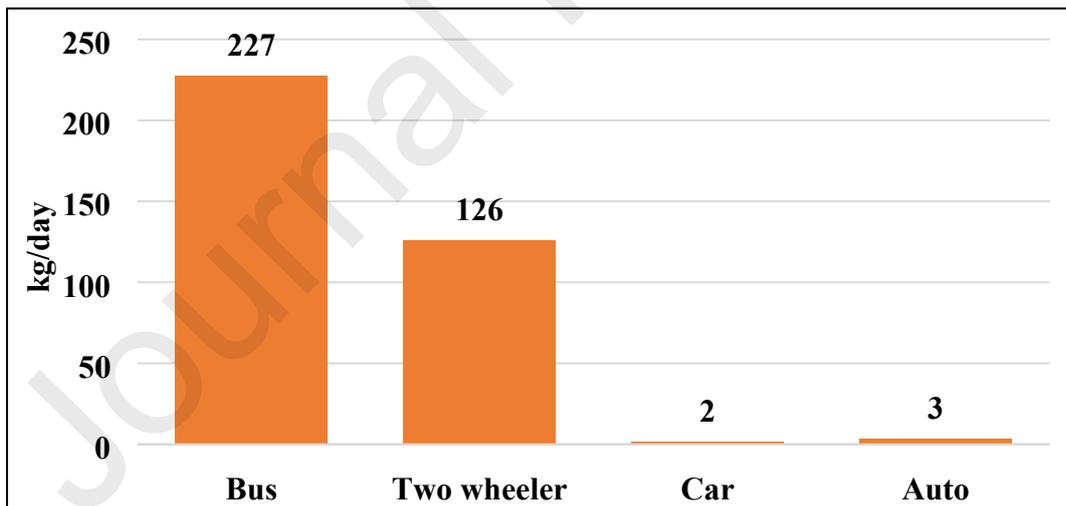

Figure 9. Avoidance of PM emission (kg/day) in the AMS Scenario as compared to the BAU scenario.

6. Policy recommendation and conclusion

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Ewing and Cervero (2010) examined the effect of the built environment on transit use, and their study suggested that people living near transit stops tend to use transit more than people living far. However, in this research, we found that people living near transit stops are rarely choosing metro transit for their active travel needs. The variable which predominantly impacts mode choice decisions among the population belonging to low and low-middle-income sections of society is the travel cost. The average expenditure on travel by metro is approximately three times the average expenditure on travel by bus. This makes the low-income population captive bus users who have only one choice when it comes to long-distance travel. Therefore, our policy recommendations which are derived from the combined insights of survey result analysis and random forest model, suggest fare rationalisation of metro services would make them affordable for captive bus users. The societal benefit of decreased metro fares is well understood, and our survey results are also indicative of the same. Along with the consumer's economic benefits, we have estimated the environmental benefit as well as the operator's economic benefit because of an increase in metro ridership as a result of the reduction in metro fares. Our study shows that even a nominal shift from other motorised modes of transport to the metro facilitated by a range of policies, including subsidised metro fares and convenient first and last-mile connectivity, can have a significant impact in terms of avoiding CO_2 emissions and particulate matter pollution. Despite the reduced fares, the overall increase in ridership can, in fact, result in an increase in metro revenue due to an increase in total ridership. Additional scenarios can be constructed to assess the range of benefits that can be obtained based on the scale of the shift and the trade-offs in terms of loss of revenue from other sources. One important scenario which can be tested is the impact of change in land-use mix on demand for metro usage. Given the rapid growth in the cities' transportation needs and the increase in demand across modes of transport, the two scenarios included in this study capture the potential benefits of policies to incentivise a higher utilisation of the metro network. The CO_2 emissions avoided due to ridership shift to the metro from other modes of motorised transport in Bengaluru are estimated to be 499 Gg/year. This indicates that focus on cleaner mass transit systems like metro is crucial in mitigating GHG and reducing the burden of the transportation sector's contribution to GHG emissions. The indirect contribution of the mass transit system to GHG emissions can be further limited once the share of renewables increases in the total electricity mix.

The objective of providing accessible and affordable public transportation is connected to the larger goal of ensuring social, economic, and environmental well-being for city inhabitants, along with promoting the economic development of the city. Additionally, enhancing the use of public transport is the only way for developing countries like India, with densely populated cities, to reduce GHG emissions from transportation. The proposed policy prescriptions in this study to increase metro ridership cannot produce the desired impact if implemented in silos. A unified transport authority coordinating the city's public transportation under one umbrella organisation can provide the required synergy between individual policies and maximise the intended impact. Bengaluru has recently established a unified land use and transport authority called BMLTA, which can work towards developing a common land use and transportation plan for the city. This approach can help meet the goals of SDG target 11.2 and promote economic development and climate action.

Declaration of competing interests

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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Appendix

Table A1. Share of various transportation modes with respect to different influencing factors (values are in percentages)

	Metro	Bus	Shared Ride	Auto	Two-wheeler	Four-wheeler	Cycle	Walk
Gender								
Male	1.58	22.56	4.90	4.82	36.89	3.70	1.12	24.43
Female	1.92	24.96	4.39	5.89	11.97	1.73	0.19	48.95
Age								
<18	0.35	14.42	11.37	5.86	9.03	0.35	1.06	57.56
18-45	2.26	27.32	3.91	4.68	31.04	3.03	0.31	27.44
>=45	1.56	22.31	1.19	6.43	23.78	4.04	1.29	39.39
Occupation								
Salaried	2.36	21.40	5.80	1.57	41.30	3.15	1.00	23.41
Wage worker	0.88	28.25	1.93	6.32	25.96	1.75	0.88	34.04
Self-employed	1.35	9.73	0.81	13.51	45.14	8.65	0.54	20.27

Student	0.79	26.91	9.38	4.91	9.20	0.44	0.88	47.50
Not employed	2.53	25.77	0.94	7.31	13.68	3.28	0.00	46.49
Education								
Graduate and more	3.18	30.18	6.57	2.26	37.37	5.03	0.21	15.20
High school-intermediate	1.62	25.08	2.78	6.38	25.41	2.57	0.91	35.24
Up to primary	0.72	15.07	7.04	5.51	14.35	1.35	0.63	55.32
Vehicle ownership								
No vehicle	2.20	34.37	2.69	5.55	3.18	0.33	1.14	50.53
One vehicle	1.37	23.24	5.12	6.22	27.40	1.42	0.55	34.68
Two or more vehicle	1.93	13.10	5.89	3.34	44.59	8.00	0.44	22.69
Trip purpose								
Work	54.4	43.7	41.5	43.0	77.1	70.4	67.7	35.4
Education	26.6	22.0	3.5	20.7	7.9	22.2	0.0	10.6
Leisure	12.7	28.4	54.5	22.7	9.8	2.2	32.3	35.0
Household chores	6.3	5.9	0.5	13.6	5.1	5.2	0.0	19.0

Table A2. The questionnaire for travel survey of BBMP region.

1. Introduction

Date of Interview	....../....../........
House ID	Not to be filled by enumerator during survey. To be filled during data entry.
Nodal location (as given in the code list)	
Area name (Please enter full street address)	
Ward No/Ward name	
Predominant land use type 1. Residential 2. Commercial 3. Industrial 4. Mixed	To be filled during data entry.
Number of members in the household	
Number of working members	
Number of dependents in your household	
How long have you been living in Bangalore?	

(in years)	
Nature of accommodation 1. Own house 2. Rented House 3. Others	
Type of Vehicle owned by Household	Number of Vehicle/s
Two-wheeler	
Four-Wheeler	
Cycle	
Others (please specify)	

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2. Household Details

Member ID	Gender	Age	Relationship to respondent	Primary Occupation	If you are employed, can you please explain the nature of employment?	Monthly Income (individual)	Highest Educational Level attained
Member ID							
	1. Male 2. Female 3. Transgender 4. Others			1. Salaried with at least 11 months contracts 2. Wage work (Daily/Weekly). 3. Self-employed 4. Full time housework 5. Unemployed 6. Retired 7. Student		1. <10000 2. 10,001-30,000 3. 30,001-50,000 4. 50,001-70,000 5. 70,001-1,00,000 6. >1,00,000 7. Do not want to	1. Professional degree/postgraduate 2. Graduate (B.A/B.Sc./B.Com/Diploma) 3. Secondary School / Intermediary (ITI course, Class XII/X or Intermediate) 4. High School (class V to IX) 5. Primary School (up to Class IV) 6. Literate, no formal education 7. Illiterate 8. Can sign name 9. Others

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				8. Other		reveal	

3.Daily Household Travel needs

Member ID	Trip Purpose (Weekdays)	Time of travel (In hours)	Time of the day (in am/pm)	Mode of travel	Trip Purpose (Weekends)	Time of travel (In hours)	Time of the day (in am/pm)
	Work/Business				Work/Business		
	Leisure				Leisure		
	Education				Education		
	Household chores				Household chores		
	**1.Metro; 2.BMTC Bus; 3.Feeder Bus;4.Shared cabs; 5. Auto-rickshaws 6. Taxi 7.Private vehicle(2W); 8.Private vehicle(4W); 9.Cycling; 10.Walk. *Morning peak = 0830-1000 hrs, evening peak =1600-1830 hrs,						

4. Mode of commute (prior to December 2019)

Member id (Same as Q. No. 2)	#Main Purpose of travel	Origin (street/ station name)	Destination (street/ station name)	Main commute detail							Distance (km)	Amount incurred (Rs.)
				*Mode of travel 1	Mode of travel	If the mode of travel is (1) – (3)			If the mode of travel is (4) – (8)			
						WT	$IVTT	$OVTT	$TT			

*1.BMTC Bus;2.Shared cabs; 3. Auto-rickshaws 4. Taxi 5.Private vehicle(2W); 6.Private vehicle(4W); 7.Cycling; 8.Walk.

#1.Work; 2.Leisure; 3.Education; 4.Household chore

WT- Wait Time; IVTT – In Vehicle Travel Time; OVTT – Out of Vehicle Travel Time

5. If you use any of the following modes of transport as your first/last mile connectivity (on a scale of 1 to 5), please rank the following attributes for the given mode.

Member ID (Q. No.		Safety	Frequency of service	Accessibility	Comfort	Cost feasible

2)						
	BMTC Bus service					
	BMTC Feeder Bus service					
	Shared cabs					
	Auto rickshaws					
	Private vehicle (2W/4W)		NA	NA		

1=Very Poor, 2=Poor, 3=Average, 4=Good, 5=Very Good

5.1 In case you are using BMTC Bus or BMTC metro feeder as first and last mile services, please specify.

Member ID	Origin bus stop	Destination bus stop
(Q. No. 2)		

6. Please rank the following reasons (on a scale of 1 to 5) for not using metro even after its construction (prior to December 2019)

Memb	Reasons

er ID (Q. No. 2)	Expensive	Frequency of service is low	Lack of parking facility at metro station	Lack of accessibility	Metro goes in opposite direction to your work location	Lack of first and last mile connectivity	Safety and security concern	Comfort (Availability of seating/standing space)

1=Very Poor, 2=Poor, 3=Average, 4=Good, 5=Very Good

7. When metro comes to your locality, will you use it?

Member ID	Answer (Yes=1,No=2)	If Yes, please specify	If No, Please specify

8. Do you think Bengaluru is safe for

Member ID	Walking Yes=1,No=2	If not, why?	Cycling Yes=1, No=2	If not, why?

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8.1 Answer for the response which think Bengaluru is not safe for cycling/walking.

Walking	If not, why?	Cycling	If not, why?
1.Yes 2.No	1.Lack of separate walking facility 2.Fast moving traffic 3. Lack of foot overbridges 4. Routes do not have good night lighting facility 5. Inconvenient to walk (lack of shades, waterlogging, bad surface quality) 6.Others	1.Yes 2.No	1.Lack of separate walking facility 2.Fast moving traffic 3.Lack of foot overbridges 4.Routes do not have good night lighting facility 5.Inconvenient to cycle (lack of shades, waterlogging, bad surface quality) 6.Others

9.After the construction of metro, do you experience reduction in

Member ID	Vehicular density in your locality	Pollution level in your locality

Highlights

Socio-economic survey of 1,350 households around existing and proposed metro stations in Bengaluru.

Random Forest model to assess key determinants of mode-choice.

Affordability is the most significant determinant of mode choice for low- and middle-income commuters in Bengaluru.

Developed two scenarios to evaluate the environmental and economic benefits of increased metro ridership

Affordable and Sustainable Transportation: Key Drivers and Policy Choices for a Megacity in India

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R. Srikanth: Conceptualization, Methodology, Writing - review and editing, Funding acquisition, Project administration.