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Predictive Analysis of Indicators of Active Mobility: A Comparative Assessment of Statistical and Machine Learning Models

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Abstract

To recognize and act upon civic mobility outgrowths, Active Mobility effectively encourages sustainability in the transport sector. This study is an attempt to identify the performance indicators that majorly affect the walkability and cyclability of people, and their mode preference in cities capable of promoting active mobility. The research aims to understand the interplay of infrastructure, physical environment factors, safety and security, and governance policy influences on active travel. Using logit, probit, and ANN models, the study assesses the relative importance of factors in predicting Active Mobility usage, considering individual and urban environment attributes. The findings reveal the significance of dedicated cycling infrastructure, traffic calming, and street connectivity in promoting active travel. Safety and security perceptions also emerge as critical factors, while the influence of government policy intervention varies across models. The Artificial Neural Network model demonstrates superior predictive accuracy, suggesting its potential for forecasting and evaluating interventions. This research contributes to the understanding of Active Mobility behavior in Bhopal City, offering practical implications for urban planners and policymakers. The study emphasizes the need for integrated interventions prioritizing infrastructure, safety, and supportive policies to promote sustainable and healthy urban mobility.

Keywords: Performance Indicators, Active Mobility, Logit, Probit, Artificial Neural Network, Cycling, Walking

1. Introduction

The growth in the demand for travelling and dependence on transportation has genuine implications for environmental issues and the consumption of energy. As a result, there has been a continuous rise in demand for non-renewable energy in the sector. The transport sector's share is about 50% of the total consumption of petroleum products in India. Therefore, the impact of transportation on the environment must be checked, and if left unbounded, may lead us to unsustainability. As cheaper energy and energy-effective readily available technologies are also not there in developing countries, alternative modes of transportation must be encouraged and its level of services should be benchmarked to attain sustainability in the transport sector. Efficient modes of transport include bicycle and walking, these modes can also be referred to as active modes of transport.Active Mobility (AM) is a regular physical activity undertaken as a means of transport. It includes walking, cycling, pedal-assisted e-bikes, kick-scooters, skateboards, and other vehicles which require physical effort to get moving, while it does not include physical activities that are undertaken for recreation purposes (EIT Urban Mobility, 2020). AM is not just a viable alternative; it is a crucial solution to effectively combat these serious issues and minimize our ecological footprint (Rainieri G. et al.2024).

The challenge lies in developing and implementing innovative technologies, policies, and practices that can mitigate the environmental impact of transportation while maintaining economic vitality and social equity. As cities worldwide seek to mitigate climate change and enhance quality of life, AM networks, including walking and cycling, have gained increasing attention in recent years as urban planners and policymakers seek to promote more sustainable and healthy modes of mobility (Auerbach, 2018; Schlosser et al., 2023).These networks encompass infrastructure and systems designed to support non-motorized modes of travel, primarily walking and cycling, but also including other human-powered modes such as skateboarding and wheelchair use.

The benefits of Active Mobility (AM) are widely acknowledged, and previous studies have explored various indicators influencing AM adoption (Jamal & Mohiuddin, 2020;Wang & He, 2015). But accurately predicting and understanding the indicators that influence the usage and adoption of active mobility modes is crucial for urban planners and policymakers to develop effective strategies to promote and support these modes (Wali et al., 2021).

Despite the growing body of research on AM, there remains a lack of understanding regarding the relative importance of various indicators influencing its adoption, particularly in the context of developing countries like India. This study addresses this gap by investigating the relative importance of indicators in the context of Bhopal, India, a city with a substantial but underserved active travel population. Bhopal, the capital city of Madhya Pradesh, was chosen as the specific study area due to its strategic position and environmental significance. Madhya Pradesh is the second-largest state in terms of forest cover in India, with over 25.14% of its geographical area classified as forested (Forest Survey of India, 2021). However, the expansion of transport infrastructure in Bhopal and its surrounding regions poses a direct threat to this forest cover, leading to deforestation, biodiversity loss, and an increased ecological footprint. The rapid urbanization, coupled with a rising dependency on motorized vehicles, has led to congestion, air pollution, and a deteriorating quality of life. Despite these challenges, Bhopal boasts a mixed land-use pattern and relatively short average trip lengths, making it conducive to Active Mobility modes such as walking and cycling.

The predictive analysis has been done using logit and probit regression modeling of indicators and artificial neural network models to verify the robustness of the results obtained. Artificial neural networks are powerful tools for uncovering complex relationships within data, making them suitable for understanding AM usage patterns (Zou et al., 2009). Combining ANN and ordered logit/probit allows for more interpretable analysis of the indicators influencing active travel behavior. By combining these methods, researchers can gain a deeper understanding of the complex interplay of factors influencing AM choices and inform effective interventions to promote sustainable transportation modes. By bridging the gap between theoretical potential and practical application, this research contributes to the development of more sustainable, healthy, and integrated urban transport systems.

2. Literature Review

Sustainable transportation is a multifaceted concept with various definitions and measurement approaches (Zhou, 2012). AM, which encompasses walking, cycling, and other non-motorized modes of travel, has emerged as a crucial component in achieving sustainability in transportation. The benefits associated with it include improved public health, reduced greenhouse gas emissions, enhanced social equity, and more livable communities (Scheepers et al., 2014). These advantages have led to increased attention from policymakers, urban planners, and researchers worldwide, seeking to promote active mobility as a viable alternative to car-dependent lifestyles. (Litman, 2015)

The initiatives to encourage AM in European countries include comprehensive cycling networks, integration with public transit, traffic calming measures, and supportive land-use policies that create compact, mixed-use developments (Robertson et al., 2015). The research on sustainable mobility indicators for Indian cities emphasizes the need for comprehensive planning that considers local socio-economic conditions, existing infrastructure, and cultural attitudes towards different modes of transport. Jain & Tiwari, 2017). The design of urban streets thus plays a crucial role in promoting AM(Ghate & Sundar, 2013). The streets need to be designed to accommodate all users safely and comfortably, regardless of age, ability, or mode of transportation (NACTO,2016; M, 2014).

Demographic and socioeconomic factors also play a crucial role in influencing the effectiveness of Active Mobility infrastructure. Individuals with higher education levels are more likely to engage in walking or cycling activities, highlighting the influence of socioeconomic status on active travel behaviors (Biehl & Stathopoulos, 2020; Ferreira et al., 2022; Harumain et al., 2022; Younkin et al., 2023).

The built environment, including natural/physical and macro/micro environmental characteristics, socioeconomic factors, and sociodemographic attributes, encourages AM among urban residents, promoting physical activity and well-being (Arbab et al., 2020). A combination of infrastructure improvements, education programs, and community engagement initiatives yields the most significant increases in cycling rates (Zhang, 2015; Smith et al., 2020). It is thus important to address both physical and social barriers to Active Mobility adoption.

The presence of safe and convenient routes and urban design that includes sidewalks and bike lanes directly correlates with increased walking and cycling rates and participation in Active Mobility (Timperio et al., 2018). Land use and accessibility also contribute significantly to shaping transportation behaviors. Mixed-use developments promote walking and cycling by reducing travel distances and enhancing connectivity, thereby making active modes more appealing (Chen et al., 2024). Factors such as greenery and safety perceptions also influence individuals' choices. The environments that are perceived as safe and aesthetically pleasing may significantly increase the likelihood of choosing Active Mobility modes (Tran et al., 2020). This suggests that infrastructure and well-planned environment improvements can lead to a modal shift from motorized to non-motorized transport (Credit & O'Driscoll, 2024).

Similarly, perceived safety, particularly regarding crime and traffic conditions, plays a crucial role in individuals' decisions to engage in walking and cycling. For instance, enhanced safety measures and urban design elements that promote safety, such as well-lit pathways and visible surveillance, positively influence mode choice as individuals feel more secure in their environments (Singleton & Wang, 2014; da silva and da silva, 2020). Moreover, the fear of accidents and crime can deter individuals from choosing Active Mobility, suggesting that addressing these concerns through policy and infrastructure improvements is essential (Aziz et al., 2018).

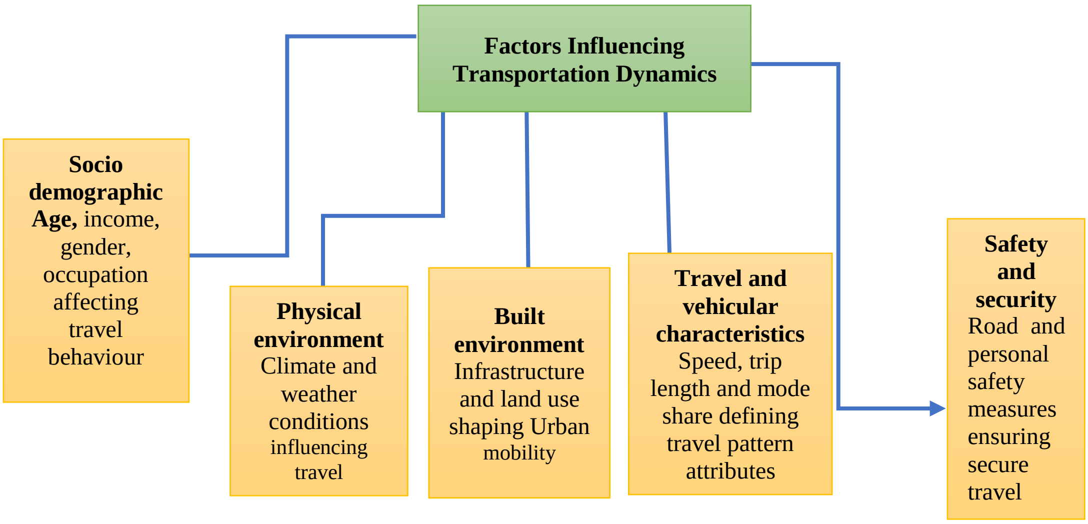


Figure 1: Factors influencing Active Mobility dynamics

However, while safety is a critical factor, it is also intertwined with other elements such as convenience and accessibility, which can complicate the decision-making process for potential active transport users (Larouche & Saidla, 2018). Like the slope of terrain has a notable impact on walking attractiveness; a 1% increase in slope can reduce walking appeal by approximately 10% (Meeder et al., 2017), it is often overlooked but plays a significant role in user experience and safety (Wen et al., 2013). For fostering sustainable and resilient communities, government intervention is also necessary. Government policies play a crucial role in influencing Active Mobility choices by addressing issues like distance and road safety and impacting cycling culture and infrastructure development (Mindell, 2015).

The adoption of Active Mobility is influenced by various key indicators, as highlighted in the figure 1. Thus, effective modeling of walking and cycling is critical for comprehending travel behavior and patterns (Schlosser et al., 2023). Many studies focus on individual elements like infrastructure or socio-economic factors, but a comprehensive understanding of how these elements interact in diverse urban contexts, particularly in developing countries, remains underdeveloped. This research aims to bridge this gap by developing a nuanced understanding of the relative importance of various AM indicators in the context of Bhopal, utilizing ordered logit, probit and Artificial neural network models. However, limitations in these studies include potential biases in self-reported data and the need for longitudinal assessments to fully understand the long-term effects of infrastructure changes. The comparative approach allows for a more robust understanding of the key indicators shaping active travel behaviors across different modeling techniques.

Building on the framework proposed by Cirianni et al. (2018), actions aimed at encouraging walking and cycling can be broadly categorized into strategic objectives (such as promoting a shift away from private motorized transport), infrastructure-based interventions, regulatory policies, and supportive programs focused on awareness and behavioral change. Integrating such classification with our modeling framework allows for a more comprehensive interpretation of how different types of interventions may influence user perceptions of walkability and cyclability—particularly in developing city contexts such as Bhopal.

3. **Methodology**

Considering the literature review, the input was based on a user perception survey was conducted in the selected study area. The data collected was subjected to factor analysis to determine the indicators affecting the level of service of AM. Based on the significance results of Bartlett’s test of sphericity with a significance level of 0.000 and the Kaiser-Meyer-Olkin measure of sampling adequacy of 0.78, the data collected was suitable for factor analysis (Field, 2018; 2024). The indicators were selected and categorized according to principal component analysis with varimax rotation (Hair et al., 2019).
The indicators are categorized into four dimensions: infrastructure (I), physical environment (PE), safety & security (SS), and government policies (GP). The collected data undergoes a comparative analysis using three modeling techniques: Logit, Probit, and Artificial Neural Network (ANN) models. While ordered logit and probit modeling were applied to gain insights into the indicators affecting Level of Service of Active Mobility as perceived by users. An artificial neural network analysis is used to understand the relative importance of different indicators and validate the models. Figure 2 represents the methodological framework followed during the research.

The parameters vary by the modeling technique used: factor loadings in PCA, regression coefficients in the ordered logit and probit models, and synaptic weight values in the artificial neural network (ANN). The ANN model also includes additional design parameters such as the number of neurons, activation functions (sigmoid), and training algorithms (Levenberg–Marquardt backpropagation).

The outputs of this methodological framework are the relative importance of each indicator in influencing the perceived Level of Service (LOS) for Active Mobility, and model performance indicators such as R-values, Mean Squared Error (MSE), and Area Under the Curve (AUC) from the ROC analysis.

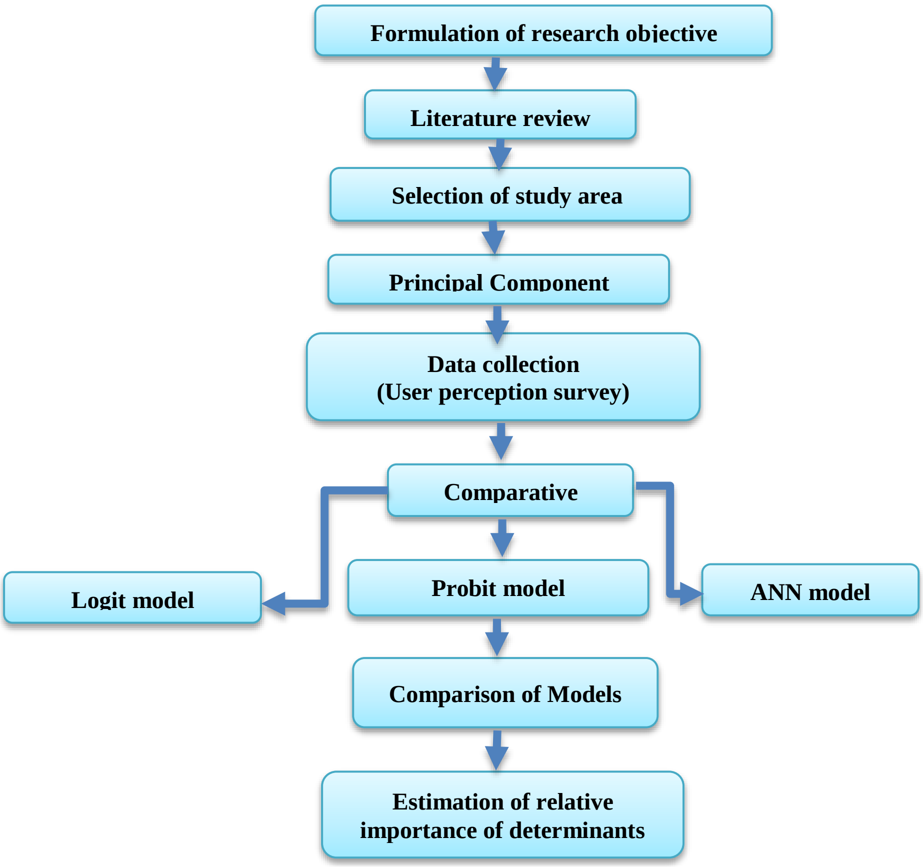


Figure 2: Methodology for assessing the relative importance of indicators of Active Mobility for Bhopal city

4. Active Mobility scenario in Bhopal

For conducting a user perception survey and identifying the role of active mobility indicators, the city of Bhopal was chosen as the study region. The second-largest Indian state, Madhya Pradesh, has Bhopal as its capital, making it both the state's and the region's economic hub. According to the latest census data, Bhopal has a population of about 1.8 million individuals, representing a diversified demographic profile with varying age groups, income levels, and career backgrounds , and the Bhopal Development Plan projects a population of 35.39 lacs by the year 2031 using the incremental rise approach. The expected population of the city in 2021 is 2.6 million (Bhopal Development Plan, 2031). In Bhopal, two-wheelers account for 25% of journeys, making them one of the most popular modes of transportation. 25% of all travel is done by public transportation. Because of the city's small and diverse land use development, the proportion of walking and bicycle journeys is quite high (43%). Figure 3 represents the average trip lengths and percentage modal share for Bhopal city (ESCAP, 2021).

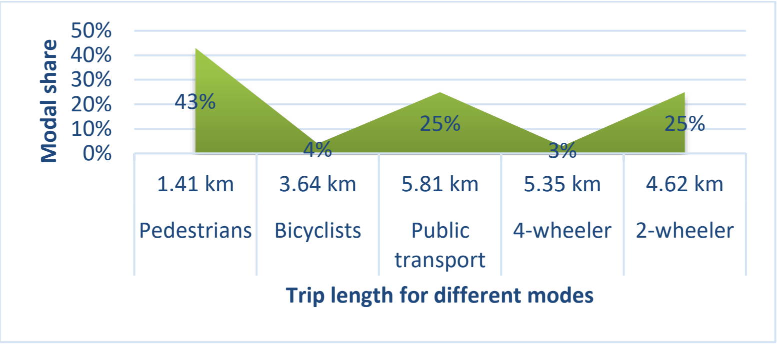


Figure 3: Average trip distances for different modes of active mobility

5. Estimation techniques

The study utilizes three alternative models, viz., ordered logit model, ordered probit model, and Artificial neural network to examine the perceptions about the indicators that affect the level of service of Active Mobility. These models are based on different assumptions and estimation techniques, as highlighted in table 1.

Table 1: Specifications of model applied

Types	Models	Assumption	Application
Ordered logit	$Y_i = \beta X_i + U_i$	The random disturbance term follows logistic distribution	Ordered dependent variable with more than two responses
Ordered probit	$Y_i = \beta X_i + U_i$	The random disturbance term follows normal distribution	Ordered dependent variable with more than two responses
Artificial Neural Network	$x_j = \sum_{i=1}^{n} W_i x_i + b_i$	The random disturbance term follows normal distribution	Utilizes nonlinear activation function (sigmoid)

5.1 Logit models

The logit and probit models differ in underlying conditions and assumptions. Logit models are an example of qualitative response regression models (Gujrati,2021). It assumes that the problem distribution of error term Ui follows a logistic probability distribution as represented by equation 3. Logistic regression is similar to a linear regression, but the curve is constructed using the natural logarithm of the “odds ratio” of the target variable, rather than the probability.

$$Y_i = \beta X_i + U_i \ldots\ldots(3)$$

While the probit model uses a cumulative normal distribution, with error term in the probit model following a normal distribution (Winship,2003). The logit models are often preferred for larger data sets and due to simplicity in calculation that they offer, while probit models hold good where normality assumptions are made. The interpretation of coefficients also differs, with logit coefficients representing odds ratios and probit coefficients reflecting changes in the z-score of the normal distribution. Understanding the nuances of each model is crucial for accurate data analysis and interpretation (Breen et al.,2018). The goodness of fit measures is not very important in binary regression models. What matters is the predicted signs of regression coefficients. the likelihood ratio (LR) measures can also be used to test the null hypothesis (Hoetkar,2007).

3.2 Artificial Neural Network (ANN) approach

A neural network model is made up of processing nodes (neurons) and interconnections (links) between them. ANN model's learning process is input-output mapping based, with synaptic weights adapted accordingly (Hua & Faghri, 1993). The network is layered because hidden units are located between the input and output units. Feed forward networks are made up of layers, with each layer connected to the previous one. The ANN model is used to develop a relationship between LOS and predictive indicators to evaluate their relative importance. Developed model has been evaluated using R and MSE values. Where R represents measures of strength of the relationship between dependent and independent variables.

The network's output is generated by the final layer (Dayhoff, 1990). Mathematically, this can be expressed in eq 4, where I_i are the input values and W_{ji} are synaptic weight values, net_j is the summation (over all the incoming neurons) of the product of the incoming neuron's activation and the synaptic weight of the connection at the typical j^{th} neuron expressed as $\sum I_i W_{ji}$. Threshold value θ_i is incorporated into the output. Thus, we have the resultant as follows:

$$net_j = \sum_{i=1}^{n} I_i W_{ji} + \theta_i \qquad (4)$$

Let n represent the initial number of neurons and I denote the vector of neurons entering the system. The synaptic weights vector is denoted as W, whereas the node cutoff is represented by θ, typically the negative weight derived from the bias unit, which emits a value of 1.The output is given by equation 5.

$$OUTPUT = f\left(net_j\right) \qquad (5)$$

Where f (net) = Activation function. It is also referred to as the threshold function, transfer function, or squashing function, and is responsible for mapping the input pattern of a neuron to the specified output range. There was use of the sigmoid function in this work. There are many good things about the sigmoid function. It has a greater slope when inputs are equal to zero, which is one of its benefits (Wu & Feng, 2018).

4. Sample size

To determine a statistically representative sample size for the population equation 6 was used

$$n = \frac{m}{1 + \frac{m-1}{N}} \qquad (6)$$

Equation 7 is used to compute the value of m, with the values of m being 1.96 and 1.645 for 95% and 90% confidence levels, respectively, and z being the statistic value of the confidence level employed. The population proportion being estimated is denoted by the symbol p, while the sampling error of the point estimate is denoted by the symbol.

$$\frac{m = z^2 * p * (1 - p)}{\varepsilon^2} \tag{7}$$

According to the formulae, 384 samples are needed to get a 95% confidence level for the population of 18, 86,100 in Bhopal. We have collected 479 samples of the user perception survey. Table 3 represents characteristics of the samples collected.

5. Predictive Analysis of Indicators

This analysis examines metrics to determine how infrastructure, physical environment, safety and security, and governance affect Active Mobility outcomes. The indicators having factor loading above 0.500 were considered statistically significant (Hair Jr. et al., 1986; 2019), as shown in Table 2. The 95% confidence intervals for the estimates substantiate the significance of the observed relationships. Most intervals do not encompass zero, providing strong evidence for the impact of these variables on AM behaviours.

The model's overall fit was evaluated using various statistical measures. A Pearson Chi-Square test revealed a statistically significant result (chi^2 = 80922.717, p < .001), suggesting that the model's predictions differed significantly from a null model. However, the Deviance statistic (1396.123, df = 3506, p = 1.000) indicated a good fit, meaning the model's predictions closely aligned with the observed data. This apparent discrepancy may be attributed to the large sample size, which can inflate the Chi-Square value. Pseudo R-squared values provided further insight into the model's explanatory power. The Cox and Snell R-squared was 0.708 , while the Nagelkerke R-squared was 0.717 , suggesting the model explained a substantial proportion of the variance in the dependent variable. The results of regression analysis for various categories (considering individual effect on LOS) are reported in tables 3 and 4 respectively.

Table 2: Indicators for predictive analysis of AM

Category	**Indicators**	**Abbreviation**	**Factor loadings**
Infrastructure (I)	Separate tracks	I1	.573
	Separate crossings and signage	I 2	.577
	Width of tracks	I3	.643
	Slope of terrain	I4	.676
	Network continuity	I5	.718
Physical environment (PE) `	Surface quality and cleanliness	PE1	.785
	Route aesthetics & furniture	PE2	.867

	Tree shades	PE3	.866
Safety & security(SS)	Surface and footpath lighting	SS1	.695
	Vehicular conflict	SS2	.667
	Thefts and crime	SS3	.711
Government policies (GP)	Bicycle Park and ride facility	GP1	.702
	Parking fees and charges	GP2	.832
	Government incentives	GP3	.834

Table 3: Regression results of ordered probit model

Variable	Estimate	Std. Error	Wald	df	Sig.	95% Confidence Interval	
						Lower Bound	Upper Bound
I1	0.112	0.058	3.694	1	0.055	-0.002	0.225
I2	0.246	0.066	13.984	1	0.000	0.117	0.375
I3	0.287	0.054	27.965	1	0.000	0.181	0.394
I4	0.461	0.054	72.359	1	0.000	0.355	0.568
I5	0.591	0.116	25.819	1	0.000	0.363	0.819
PE1	0.57	0.058	96.795	1	0.000	0.456	0.683
PE2	0.279	0.108	6.731	1	0.009	0.068	0.49
PE3	0.272	0.112	5.841	1	0.016	0.051	0.492
SS1	0.422	0.073	33.499	1	0.000	0.279	0.565
SS2	0.78	0.062	159.108	1	0.000	0.659	0.901
SS3	0.195	0.041	23.063	1	0.000	0.115	0.275
GP1	0.372	0.049	57.066	1	0.000	0.275	0.468
GP2	-0.259	0.104	6.226	1	0.013	-0.462	-0.055
GP3	0.635	0.099	41.002	1	0.000	0.44	0.829

Table 4: Regression results of ordered logit model

Variable	Estimate	Std. Error	Wald	df	Sig.	95% Confidence Interval	
						Lower Bound	Upper Bound
I1	0.158	0.101	2.47	1	0.116	-0.039	0.356
I2	0.464	0.115	16.353	1	0.000	0.239	0.689
I3	0.582	0.096	36.93	1	0.000	0.394	0.77
I4	0.88	0.097	81.823	1	0.000	0.689	1.07
I5	0.966	0.202	22.786	1	0.000	0.569	1.362
PE1	1.078	0.105	105.501	1	0.000	0.872	1.283
PE2	0.392	0.186	4.428	1	0.035	0.027	0.756
PE3	0.611	0.196	9.73	1	0.002	0.227	0.995
SS1	0.782	0.129	36.847	1	0.000	0.529	1.034
SS2	1.529	0.117	170.47	1	0.000	1.299	1.758
SS3	0.406	0.072	32.11	1	0.000	0.266	0.547
GP1	0.751	0.088	73.213	1	0.000	0.579	0.924
GP2	-0.58	0.18	10.419	1	0.001	-0.932	-0.228
GP3	1.277	0.175	53.216	1	0.000	0.934	1.62

The comparative analysis of logit and probit regression models reveals consistent findings regarding the significant influence of various indicators on Active Mobility in Bhopal City. Infrastructure and safety and security emerge as critical determinant categories, particularly I5 and SS2, while certain governance aspects, such as GP2, pose challenges. These insights are essential for informing targeted policy interventions aimed at enhancing Active Mobility in urban environments.

7.1 ANN model

The models employ 85% of data for training and 15 % for validation. The sigmoid function was used for activating hidden neurons. Levenberg–Marquardt backpropagation algorithm was applied as a network training function. Figure 4 illustrates the neural fitting of the model , and figure 5 shows neural network of model. The sigmoid transfer function was used in the hidden layer and a linear function in the output layer. ANN models were created using the NF (Network fitting) tools in MATLAB.The study uses a two-layer feedforward network trained with the Levenberg-Marquardt algorithm to analyse the models.

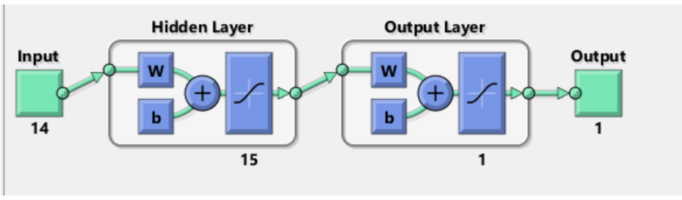


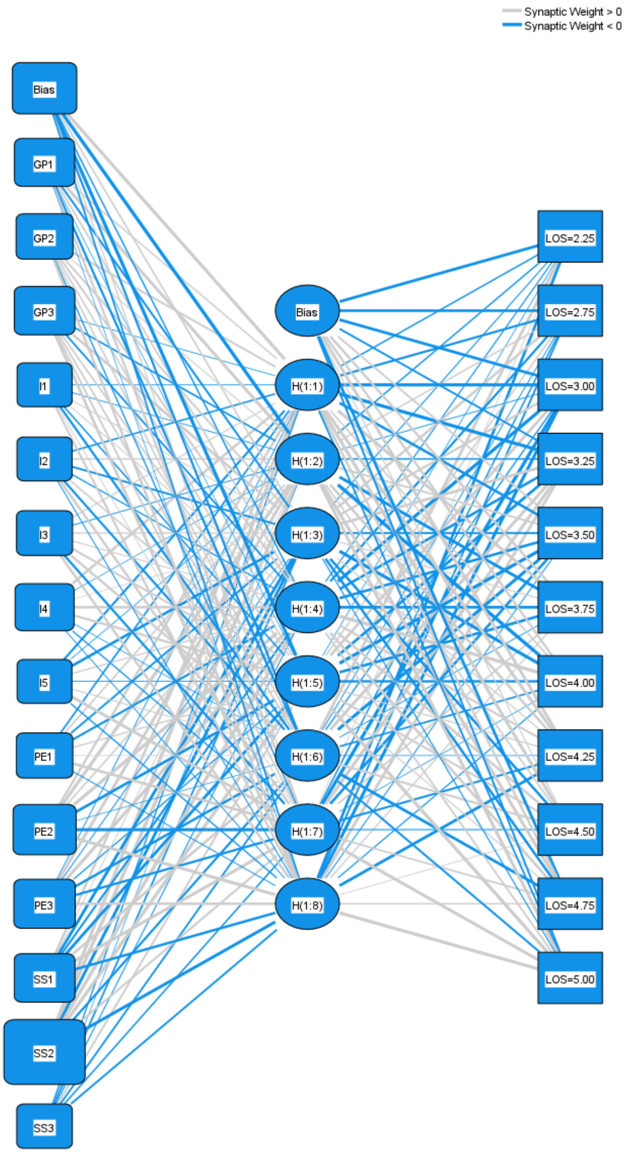
Figure 4: Neural fitting of the model (Source: Matlab data analysis)

Network performance was evaluated based on the mean of squared error (MSE). The value of statistical measures is shown in table 5 in terms of R and MSE values. It indicates that ANN1 model gives better performance results as compared to the others in terms of R value and performance measures. The model estimates neural networks for individual categories as well.

Table 5: Performance of ANN models

Model	No. of Neurons	R (Overall)	Performance (MSE)
ANN 1	15	0.98523	0.064379
ANN 2	10	0.97022	0.04202
ANN 3	5	0.96262	0.040606

It can be observed from table that ANN1 model gives better performance as compared to other models two models in terms of R value and performance measures. R represents the relationship between dependent and independent variables, it’s a statistical representation of how well the model’s prediction fits into the data, as depicted in figure 6. It ranges from 0 to 1, with 1 indicating a perfect fit.



Hidden layer activation function: Hyperbolic tangent

Output layer activation function: Softmax

Figure 5: Neural network of model (Source: Matlab data analysis)

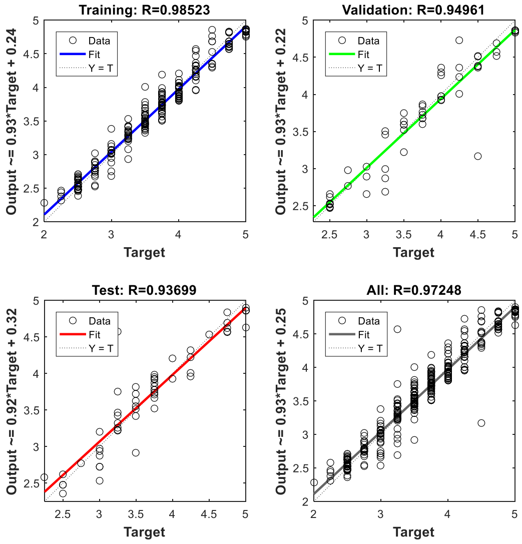


Figure 6: ANN Model Fitting Curve

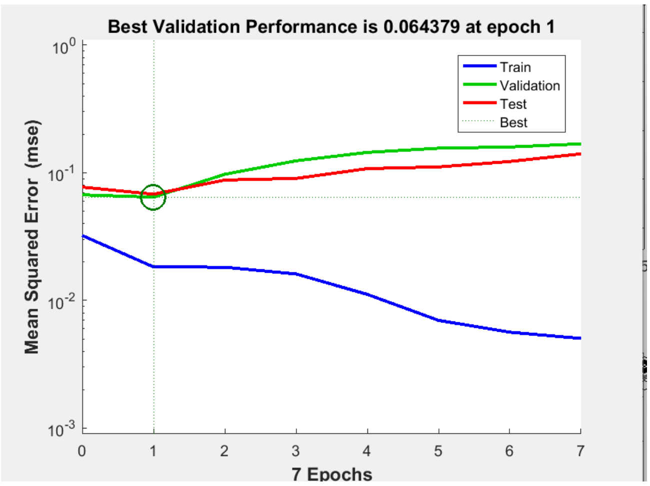


Figure 7: Performance validation curve

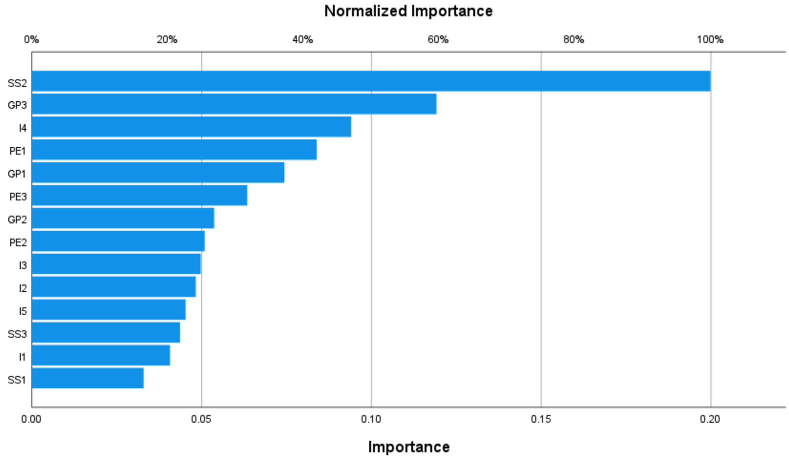


Figure 8: Normalized importance of indicators of Active Mobility

The normalized importance values reveal key drivers of Active Mobility behavior in Bhopal City. Vehicular conflict under Safety and security emerges as the most influential indicator, with a normalized importance of 100%. This highlights the critical role of safety perceptions in encouraging active travel. Governance aspects, specifically GP3, also hold substantial weight (59.6%), suggesting that effective policies and regulations are crucial for promoting Active Mobility. Infrastructure indicators, particularly I4 (47.1%), demonstrate significant importance, underscoring the need for well-designed and maintained facilities. Physical environmental factors, notably PE1 (42.0%) and PE3 (31.7%), also contribute significantly, emphasizing the importance of creating a conducive and appealing environment for active travel. While all indicators demonstrate some level of influence, I1 (20.4%) and SS1 (16.5%) appear to be relatively less impactful compared to others. These findings provide valuable insights for prioritizing interventions and resource allocation to effectively promote Active Mobility in Bhopal City. They suggest that focusing on safety, governance, and key infrastructure improvements can yield the most significant impact on active travel behavior.

6. Results and discussion

The results of this analysis highlight the complex characteristics of indicators of AT in Bhopal City, demonstrating that diverse modelling methodologies produce distinct perspectives on the impact of particular indicators. The analysis employed three distinct modeling approaches: Logit, Probit, and Artificial Neural Network (ANN). The estimates from each model for the various indicators are summarized in Table 6, and Figure 9 illustrates eigen values for factors influencing level of service.

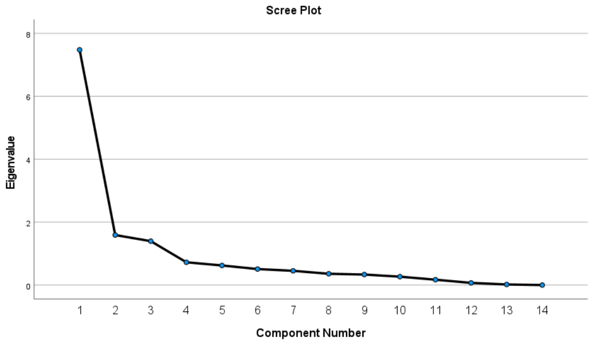


Figure 9: Scree plot showing eigen values for factors influencing level of service

The logit model consistently yielded elevated estimates across numerous measures, especially for infrastructure and safety and security, indicating a greater sensitivity to the subtleties of these elements as reflected in table 6. While the probit and ANN models provide valuable insights into the relationships as well. Each model highlights different aspects of how various factors influence Active Mobility behaviors in Bhopal City.

Table 6: Summary of estimates of each determinant across the three models

Indicators	Logit	Probit	ANN
I1	0.158	0.112	0.077
I2	0.464	0.246	0.135
I3	0.582	0.287	0.235
I4	0.88	0.461	0.356
I5	0.966	0.591	0.197
PE1	1.078	0.57	0.428
PE2	0.392	0.279	0.273
PE3	0.611	0.272	0.3
SS1	0.782	0.422	0.212
SS2	1.529	0.78	0.543
SS3	0.406	0.195	0.245
GP1	0.751	0.372	0.456
GP2	-0.58	-0.259	0.149
GP3	1.277	0.635	0.395

Infrastructure indicators (I1 to I5) demonstrated varying levels of impact across models. The logit model produced the highest estimates, particularly for I4 (0.880) and I5 (0.966), suggesting a strong positive influence on Active Mobility. In contrast, the ANN estimates for these indicators were significantly lower, indicating a more conservative estimate of their impact. Physical environment indicators yielded noteworthy results, with PE1 showing the highest logit estimate (1.078), emphasizing its critical role in facilitating Active Mobility. The ANN model also recognized PE1 as influential, but with a lower estimate (0.428). The discrepancies across models suggest the complexity of the physical environment's influence, warranting further investigation.

Among the safety and security indicators, SS2 exhibited the highest logit estimate (1.529), reinforcing the importance of social support in promoting Active Mobility. The ANN model's lower estimate (0.543) for SS2 suggests a potential underestimation of social support's influence when using ANN, highlighting the need for a nuanced understanding of these factors.

Governance and policy indicators varied significantly, with GP2 showing a negative logit estimate (-0.580), indicating potential barriers to Active Mobility. This contrasts with GP3's strong positive influence in both logit (1.277) and probit (0.635) models. The ANN model's estimates for governance indicators were generally lower, suggesting a less pronounced role in promoting Active Mobility.

6.1 The Receiver Operating Characteristic (ROC)

A receiver operating characteristic (ROC) curve is a graphical depiction that demonstrates the enhancement in diagnostic quality of a binary classifier system with an increase in the discrimination threshold.Figure 10 represents the ROC curve for the model .The True Positive Rate (Sensitivity) is represented by the y-axis, and the False Positive Rate (1 - Specificity) is shown by the x-axis. The performance of a random classifier is represented by the diagonal line. It can be seen that all curves are well above the diagonal line, indicating that the classifier performs much better than random for all severity levels. The curves rise steeply and quickly approach the top-left corner of the plot, which is ideal, as it represents high true positive rates and low false positive rates. These AUC(Area under curve) values are all very close to 1 as shown in table 7, which indicates excellent classification performance across all levels. The data shows that the model’s performance, as measured by AUC, varies with different thresholds.

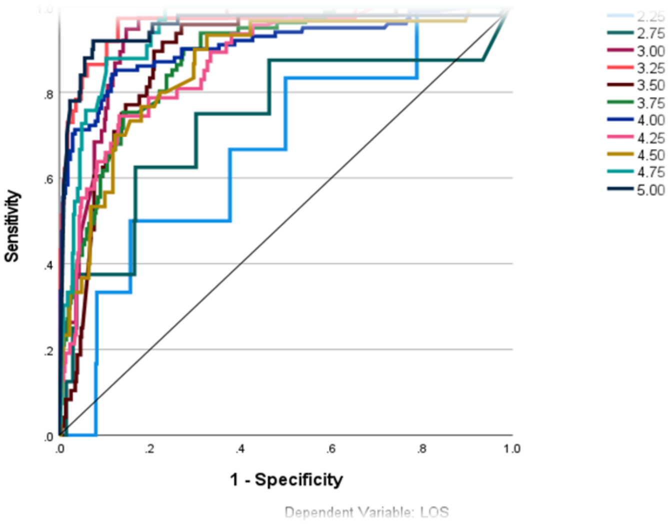


Figure 10: ROC curve

Table 7: Area Under the Curve

LOS	Area
2.25	.669
2.75	.732
3.00	.931
3.25	.960
3.50	.884
3.75	.883
4.00	.909
4.25	.875
4.50	.863
4.75	.944
5.00	.953

The AUC values range from 0.669 to 0.960, with higher values indicating better discrimination. The model demonstrates excellent discrimination for LOS 3.25 (AUC = 0.960) and LOS 5.00 (AUC = 0.953). Good discrimination is also observed for LOS 3.00 (AUC = 0.931) and LOS 4.75 (AUC = 0.944). The lowest discrimination is observed for LOS 2.25 (AUC = 0.669), suggesting that the model may have difficulty differentiating between this LOS and adjacent categories. Overall, the AUC values indicate that the model performs well in discriminating between different LOS categories, particularly for moderate to high levels of service.

The ANN model confirms the results of logit and probit models and also identifies additional indicators that may influence the level of service like bicycle park and ride facilities (GP1) (Durao, et al., 2023;Pucher, et al., 2010). The model also provides a better predictive accuracy as suggested by higher R^2 values. Attributes like distance, walkability, dedicated walking and cycling infrastructure, and traffic safety contribute significantly to Active Mobility among children Multi modalism (Timperio, et al., 2018). Smith, et al., (2020) highlight that a well-designed infrastructure, such as dedicated bike lanes and pedestrian pathways, encourages higher rates of walking and cycling, particularly in urban areas where accessibility is crucial. Incorporating these critical insights can help planners and policymakers to make more informed decision to improve and promote the infrastructure and physical environment of AT for users (Harumain, et al., 2022). It is thus important to address both physical and social barriers to Active Mobility adoption.

The analysis demonstrates the significance of employing several modelling techniques to encapsulate the intricacies of Active Mobility dynamics. Each model offers distinct insights, and their collective analysis can guide targeted activities and policies to promote active transport in Bhopal City. Bhopal serves as a representative case for other tier-2 cities in India that face similar urbanization and transportation challenges. Insights from this study can guide policymakers in formulating sustainable mobility strategies not only for Bhopal but also for other cities in India and comparable regions worldwide. The findings can contribute significantly to achieving national and international goals, such as India’s commitment to achieving net-zero emissions by 2070 and the United Nations Sustainable Development Goals (SDGs), particularly SDG 11 on sustainable cities and communities.

7. **Conclusions**

This study's multi-faceted approach combined traditional models and advanced techniques to provide a comprehensive understanding of Active Mobility. The findings offer valuable insights for urban planners and policymakers in Bhopal City and similar contexts, emphasizing the need for integrated interventions addressing infrastructure, safety, and policy environments to foster sustainable and healthy urban mobility.

Key determinants of Active Mobility identified include network continuity (I5), slope of terrain (I4), and vehicular conflict (SS2), with respective logit coefficients of 0.966, 0.880, and 1.529, indicating strong positive influence. The ANN model further validated these with normalized importance values of 47.1% (I4) and 100% (SS2), reflecting their dominant roles in shaping active travel behavior. The model’s predictive strength is further evidenced by high R^2 values (up to 0.985) and AUC values ranging from 0.669 to 0.960, signifying excellent classification accuracy.

The findings underscore the multifaceted nature of active travel behavior, revealing the interplay of various indicators. While infrastructure provisions like dedicated network continuity (I5) and slope of terrain (I4) emerged as significant across models, the logit model highlighted their particularly strong positive influence. This aligns with existing literature emphasizing the importance of safe and accessible infrastructure in promoting active mobility.

Furthermore, the consistent influence of physical environmental factors like surface quality and cleanliness (PE1) underscores the need for creating walkable and bikeable urban environments. The critical role of safety and security (SS2) is further reinforced, addressing safety and security concerns as paramount, as these indicators emerged as primary drivers of active travel behavior. This could involve implementing improved lighting, enhanced surveillance, and public awareness campaigns to promote safe active travel practices. Interestingly, the models diverged in their assessment of governance/policy indicators, with GP2 exhibiting a negative influence in the logit model, potentially indicating barriers related to specific policies or regulations. This warrants further investigation to understand the nuanced interplay of governance mechanisms and active travel behavior. Finally, the study underscores the need for supportive policy environments, including regulations and incentives that encourage Active Mobility and address potential barriers identified through the governance/policy indicators.

8. Limitation and Future scope

Future research should explore the causal relationships between identified factors and active travel behavior, potentially employing experimental or quasi-experimental designs and incorporating qualitative data to understand the underlying motivations and barriers. Comparative studies across diverse urban contexts could further enhance the generalizability of these findings. Investigating the long-term impacts of interventions and integrating advanced modeling techniques, such as agent-based modeling or machine learning, are also promising avenues for future research. The study establishes a foundation for further inquiry into the complex interplay of urban indicators. By addressing the limitations of existing models and offering practical recommendations, this study contributes significantly to the ongoing discourse on sustainable urban mobility and the promotion of Active Mobility. However, limitations in these studies include potential biases in self-reported data and the need for longitudinal assessments to fully understand the long-term effects of infrastructure changes. The comparative approach allows for a more robust understanding of the key indicators shaping active travel behaviors across different modeling techniques.

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