Analysing the Perception towards Electric Vehicles in India: Variation among different Classes of Cities

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Abstract: Policymakers in India are attempting to accelerate the trend towards using Electric Vehicles through schemes, and incentives, to promote cleaner energy; nevertheless, it is also necessary to comprehensively understand customer perception. This study explores factors affecting consumer willingness to adopt EV using national-level data while considering variations among different classes of cities using machine learning method and relative weights analysis. This study also uses a deep learning technique to predict the individual's willingness to spend on purchasing an EV. While education and employment status, coupled with technological advancements and policy benefits, positively impact EV purchase, the current service-related infrastructural conditions, operation, maintenance cost, and capital cost stand out as key adoption barriers. The awareness among the individuals varies within different classes of cities in India. The results can aid automotive companies to base their products and sales strategy and the policymakers to implement forthcoming EV and related policies.

Keywords: Electric Vehicle, User Perception, Machine Learning, Willingness to Pay, Developing Nations

1. INTRODUCTION

With the soar in air pollution due to passenger vehicles, it has become more imperative than ever to shift to environmentally viable mobility forms through alternative fuel vehicles (AFV). One possible solution or promising pathway to curb GHG emissions in urban areas and reduce air pollution lies in shifting towards electric vehicles (EV), including battery electric vehicles (BEVs) or plug-in hybrid electric vehicles (PHEVs) within coming decades to achieve forms of mobility that are most environmentally sustainable as well as socially acceptable and just.

While EVs witnessed an annual global upsurge in sales by 50% in 2017, the vehicle stock has risen annually at a 17.5% growth rate from 23.8 million in 2003 to 194 million by 2016 solely in China (McKinsey Center for Future Mobility, 2019). EV sales in India, excluding e-rickshaws, have grown by 20%, with 156,000 units, consisting of two-wheelers, cars, and buses, in 2019-20. India is now home to more than 1.5 million three-wheeled e-rickshaws as well. The recent advances in higher battery density related technology coupled with specific policy initiatives have lowered vehicle costs in a few countries, thereby diminishing consumer barriers; sales growth has fallen short, with International Energy Agency (2018) reporting that till 2018 only in Norway EVs had more than 5% market share. Recent trends, however, have shown that the Netherlands EV market share is over 10 percent now.

For a large-scale shift to pollution-free technology, various schemes and incentives have been launched globally and in India as well to sensitize and encourage consumers to switch to electric vehicles. Following the Paris Agreement, the Government of India unveiled the "National Electric Mobility Mission Plan 2020 (NEMMP)" in 2013 and "Faster Adoption and Manufacturing of Hybrid and Electric Vehicles (FAME) India" in 2015, respectively, endeavoring to achieve a high-level penetration in electric mobility by the year 2030. With incentives like tax cuts on EV-related loan amounts and discounting the GST rates, NEMMP aims to alleviate the harmful effects being caused to the environment due to combustion vehicles and achieve national energy security. FAME – Phase 1 (2015-2019) was instrumental in developing a rising market for EVs in India, covering various vehicle segments such as two-wheeler and four-wheeler through demand incentives and investments in public charging infrastructure. A 100 Billion Indian Rupee (INR) budget has been sanctioned to implement FAME- Phase 2 (2020-2022), with primary emphasis on increasing the number of EVs for public transport and commercial fleet, further expanding public charging facilities to selected cities. According to a KPMG report, it is estimated that by 2030 there will be a 100% incremental adoption of EVs in the Indian market (Nimesh *et al.*, 2003). Also, the Government of India (GoI) has recently joined the Electric Vehicle Initiative (EVI) of the Clean Energy Ministerial, which seeks to facilitate the deployment of 20 million EVs by 2020. The government also launched the "Go Electric" campaign at the start of 2021 to spread awareness of the benefits of electric mobility and EV charging infrastructure to ensure energy security (Ministry of Power, 2021). On the other hand, Indian car manufacturers (Reva Electric Car company, Tata Motors, Renault, Hyundai, Nissan, Maruti Suzuki, and Mahindra) and Indian app-based transportation networks like Ola are working together to produce more energy-efficient and reliable EVs (Jena, 2020).

It becomes evident that both industry stakeholders and policymakers in India, in line with the Paris agreement, are attempting hard to accelerate the trend towards investment in EVs to promote cleaner energy; however, that will only be successful with consumers' positive mindset. A comprehensive understanding of EV adoption predictors in the Indian scenario from the end-user perspective is of vital requirement to upsurge the growth in Indian EV markets and accelerate EV diffusion more effectively. Literature has evinced that lack of insight of stakeholders concerning potential EV customers (Larson *et al.*, 2014) and non-consideration of adopters' multifaceted attitudes and psychological characteristics (Nayum *et al.*,2016) have slowed down EV rollout. Therefore, this study attempted to sense the Indian buyer's willingness to pay for EV.

Recent literature has also incorporated attitudes and other psychometric constructs in understanding EV adoption. Prior work has shown that sociodemographic, socioeconomic, and psychological differences, on the one hand, and cultural views, on the other hand, distinguished between actual EV owners and potential EV adopters. Much of the dated researches have focused primarily on consumer perceptions in the United States (Egbue and Long, 2012) and European countries (Sovacool *et al.*, 2019). Among the developing nations, a study on Chinese EV consumers highlighted that the performance feature and perceived benefits of driving EV, policy support, and incentives for EV promotion were the preconditions affecting their willingness to buy EVs (Sovacool *et al.*, 2019). However, a narrower claim persists that this understanding of EV adoption has not been applied in practice, and this failure has slowed EV adoption.

The novelty of this research lies in examining the factors related to the willingness of potential Indian EV consumers to pay for EVs. The present study focuses on India, a major market that is different from other major markets but has not been thoroughly investigated to date. Furthermore, while the literature on consumer adoption rates has significantly dedicated on the willingness to adopt EV, this study, eyeing into the economic perspective, examines the willingness to pay 'more' or 'less' for EV concerning normal passenger vehicles, thereby investigating the blind spot in EV literature in the Indian scenario. This study aims to highlight the perceptions of the end-users in the automobile industry by analyzing the factors that influence their willingness to purchase an EV while categorizing the surveyed responses based on city classes (Class X, Class Y, Class Z). The independent variable through which willingness was measured is the maximum price they are willing to pay for an EV compared to a combustible vehicle by controlling for the vehicle specifications. Through the adoption of an online survey, this study objectively intends to analyze the potential EV buyers' mindset, attitude, awareness concerning technology performance and available service infrastructure, impression on energy-efficient transport modes, and their inclination to invest. Unlike the traditional data mining and lexicon-based shallow learning techniques, this study adopted machine learning techniques to extract sophisticated and comprehensive outcomes. Due to the lack of EV consumer perspective research in the Indian scenario, this study is of its initial kind, which would aid the stakeholders, including manufacturers and policymakers, in developing the EV market in India.

2. CONSUMERS' PERSPECTIVE TOWARDS EV

Public perception towards EVs and general willingness to use EVs are integrally crucial for promoting electric vehicles in the market. Apart from solely improving the technological aspects like battery capacity and weight, people's personal choices and surrounding social issues should also be comprehensively investigated to increase the market share. A plethora of literature has examined and identified the predictors of acceptance or rejection of EVs (Min *et al.*, 2017). Kumar and Kumar (2019) have demonstrated an extensive systematic review of 239 articles encompassing various categories of variables: antecedents, mediators, moderators, consequences, and socio-demographics coupled with their association with the adoption of EVs, along with a few policy recommendations for different stakeholders.

Studies have proposed the trade-offs between high initial costs and long-term fuel efficiency inherently associated with adopting such newer technologies (Ingeborgrud and Ryghaug, 2019). The study interviewed 3654 EV drivers in Norway to gauge their perceptions and the reason for successful EV introduction in the nation. The results suggested that an interplay between strong economic incentives, comfortable driving experience, and environmental awareness stimulated the introduction of electric technology. Public's lifestyle (Ravi and Ravi, 2015), price, actual driving range preferences and charging rate (Yang *et al.*, 2018), fleet size, range requirements and usage patterns (Degirmenci and Breitner, 2017), future fuel advantages (Larson *et al.*, 2014), environmental consciousness and attitudes (Liu *et al.*, 2015) were the major predictors observed while evaluating EV purchase intention. A Singapore-based study identified the high cost of Certificate of Entitlement (COE) coupled with a driving range and resale value as the major concern in the path of EV adoption (Min *et al.*,2017). A similar Indian study by Jena (2020) extracts opinions of prospective buyers, marketers, and manufacturers, using a non-intrusive approach by collecting data from various social media sources (Twitter, Facebook, Internet portal, etc.) and performed sentiment analysis on them. With a short survey of sample size 200, the study found that price, maintenance, and safety were the three determining features to buy an EV for Indian customers, with price and maintenance showing negative sentiments. It also discussed inherent country-specific factors such as battery degradation and lack of awareness about the safety issues with EVs.

A measure of public exposure to any automotive technology acts as a precondition and proxy measure for future vehicle choices. Therefore, consumers' attitudes towards EVs' technical and functional attributes and perception about EV utility are significant parameters affecting EV adoption rate (Singer, 2017; Krupa *et al.*, 2014). A study in Denmark observed that hands-on experience would modify consumer sentiment towards EVs (Jensen *et al.*, 2013). A study on UK consumers revealed that while 100 miles range was suitable for EV as a second car, they would prefer 150 miles range to opt for an EV as a first car (Skippon and Garwood, 2011). Similarly, a study surveying 369 Danish drivers elucidated that the limited mile's range of EV stood out to be a vital adoption barrier (Jensen *et al.*, 2013). By using a decent sample of drivers (135 EV drivers in the UK Ultra Low Carbon Vehicle trial) and a mixed-method approach (questionnaires and interviews), Bunce *et al.* (2014) demonstrated that plug-in battery electric vehicle drivers were positive about recharging – preferring it to 'refueling' – but were concerned about the frequency of recharging. According to Carley *et al.* (2013), US urban drivers' intent to purchase plug-in vehicles was reckoned low in 2011. The cost premium, range limitations, and recharging time of PEVs were all perceived as disadvantages and were significantly associated with decreased intent to purchase. Several demographic variables (age, gender, education) were reported as strong predictors of intent to purchase.

While on the one hand, well-explained government policies, financial incentives such as tax rebates or government's cash funds could increase adoption (Sun and Xu, 2018; Lane and Poter, 2007), frequent changes in policies also create uncertainties in consumers' minds and make them resistant towards faster adoption (Greene *et al.*, 2018). Independence from foreign oil also acted as a motivation factor to adopt EV. Sovacool et al. (2019), with a relatively large sample of 805 respondents from various provinces of China, probed into an extensive set of sociodemographic, financial, and policy-related questions. The study concluded that the willingness is influenced by the policy support for promoting EVs, performance features, and perceived benefits of driving EVs, and the effect of sociodemographic factors is suppressed when other motivations are controlled for.

Despite the current increasing trend of EV and its advantages, lack of market familiarization, distance or range of EV, time to charge, availability of charging equipment, EV's performance, safety, size, and style have been reported as barriers to adoption. To gain more insights into the EV market, Rubens (2019) identified six distinctive consumer segments around prospective EV adoption by using a dataset representing the Nordic countries. The findings stated that a lot of respondents in each of the clusters, excluding the Status Seekers, expected a lower cost for EVs (<30k euros) and that affordability outperformed environmental attributes in contributing to the current EV adoption. Technical advancements of EV has increased market penetration in developed nations like Japan and the United States, whereas high price has made EVs propagate slowly in nations like South Korea, China, and India (Park *et al.*, 2018).

Consumer sentiment (White and Sintov, 2017) and feelings (Higueras-Castillo *et al.*, 2019) are also important in the domain of EV purchase, elucidating that pro-environmental behavior (Onwezen *et al.*, 2013), more positive attitude towards EV and positive perception would lead to more positive intentions to adopt EV (Schuitema *et al.*, 2013). It was observed that despite the increasing awareness for EV adoption, the price of EV and willingness to pay remains elusive, especially from the Indian buyers' perspective. From the above discussion, it was believed that finding the predictors to the willingness to pay 'more' or 'less' for an EV in comparison to combustion vehicles all for an urgent investigation.

3. DATA AND METHODS

Despite Electric Vehicles (EV) ownership increasing in Indian metropolises such as Mumbai, Delhi, and Bangalore, a significantly low EV growth rate is observed in medium and smaller towns. This phenomenon can be attributed to varying challenges related to EV penetration in metro-cities and smaller towns, such as awareness about EV and its advantages or infrastructural insufficiency. Therefore, this research focuses on understanding the factors affecting the willingness to pay for EVs from people residing in different categories of Indian urban centers, namely metropolitan cities, medium towns and small towns. The survey locations, as demonstrated in Figure 1, are classified as per the House Rent Allowance (HRA), and cities classification, Department of Expenditure, Ministry of Finance, Govt. of India (2015) included Class X cities like Mumbai, Bangalore, Delhi, Chennai, Kolkata, Hyderabad, Thane, and Pune; Class Y cities like Nagpur, Bikaner, Bhubaneswar, Lucknow, Thrissur, etc. and Class Z cities like Roorkee, Kharagpur, Buldhana, Alappuzha, Aroor, etc. The HRA-based cities are classified based on the cost of living, purchasing power, and affordability. Since this study aims to analyze the willingness to buy EVs, the aforementioned city classification was considered more acceptable than the generic city classification based on city sizes and population.

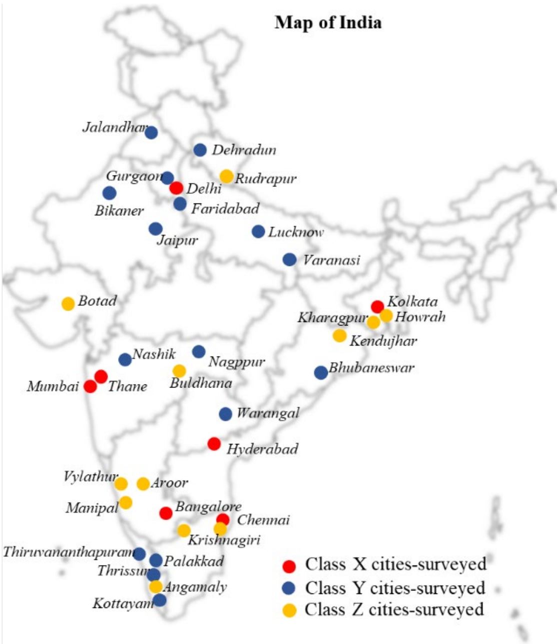

Figure 1. Class X, Class Y, and Class Z cities in India where the survey was conducted

3.1 Survey Methodology

In February-April 2020, an initial pilot interview of 35 samples followed by the online surveys collected 434 samples was conducted across Indian cities on user perception, knowledge, awareness, and attitude towards electric vehicles. The survey was offered in English, where respondents were invited to complete the survey by sharing Google online form. The survey questionnaire consisting of 34 questions was divided into five categories; Part I-Socioeconomic status of respondents, Part II- Past experiences on EVs Awareness of EVs, Part III- Importance of different features for purchasing EVs, Part IV- EV technology and EV related policies, and Part V- Willingness to pay for EVs. The questions were constructed considering factors and drawbacks discussed in the literature review and were mostly closed-ended, involving multiple choices, Likert scale, and ranking questions. The preliminary literature and pilot survey indicated a substantial difference in the price of on-road automobiles across different states and Union territories in India. Therefore, the survey questionnaire collected the information in the format of percentage difference instead of the absolute value of willingness to pay. The willingness to pay was an ordered variable with options' -40%',' -20%',' 0%', '+20%', and’+40%' for an EV compared to combustion vehicles. However, considering the very less number (less than 20) of responses for '-40%', '0%', and '+40%', the dependent variable was classified as willing to pay 'more' or 'equal or less.' This study utilized both revealed and stated preference theory for hypothetical testing.

3.2 Research Methodology

The research analyses the effect of perception and awareness regarding electric vehicles on willingness to pay for EVs. The target/output variable for the study is the maximum cost individuals are willing to pay compared to the cost of a current combustion engine vehicle with similar characteristics. The variable of WTP was elucidated as a binary variable, with the willingness to pay 'more' or 'equal or less.' The cost of a combustion engine vehicle with the model characteristics was given to the respondents to prevent ambiguity. Table 1 describes input and output variables used for the study. The study classifies the willingness to pay into two categories, namely, i) people willing to pay more (33.3% of the sample), and ii) people willing to pay an equal or lower amount compared to their current vehicle (66.7%).

This study used three types of models to study the association of user perception and awareness with the willingness to pay. In recent years, machine learning (ML) models are attaining much attention due to their robustness, capability to handle big data, and rapid improvements in the techniques. Together with transportation-related fields, several research fields have applied machine learning methods, including deep learning techniques for the analysis and predictions. The conventional logit regression models are the most common method used for choice analysis. While the logit models primarily focus on parameter estimation, the machine learning models concentrate majorly on prediction (Zhao et al., 2020). Although it is difficult to interpret the impact of variables using some ML models, certain ML models can extract behavioral insights and identify prediction accuracy. The performance of the ML model is identified with the prediction accuracy. A number of recent studies compared the prediction result of the ML models with the logit model for transport mode choice analysis, and they identified that most ML models significantly outperformed the logit model (Golshani et al., 2018; Wang & Ross, 2018; Cheng et al., 2019; Zhao et al., 2020). Looking at the recent development in the field of transport mode choice analysis using the ML model, the study focused on using the machine learning model to analyze the effect of input variables on the willingness to pay for EVs. The machine learning model, Logistic Classifier (LC) Model, was selected considering it can provide prediction accuracy and behavioral insights from the model outputs. In addition, the Relative Weights Analysis was applied to the data set to identify the relative importance of the correlated predictor variables in multiple regression analysis to compare with the LC model result (Johnson and Lebreton, 2004). Furthermore, a Deep Learning (DL) Model, which allowed the non-linear relationship among the predictor variables, was employed to compare the prediction result with the LC model.

The analysis will focus on the total sample as well as the samples based on the city classes. The results from this study can guide the government authorities towards framing EV policies and incentives specific to the city class and public need. Besides, the result also provides the guidelines on aspects to focus on vehicle manufacturers for engineering and trading the EVs in the Indian market. Figure 2 shows the comprehensive research framework.

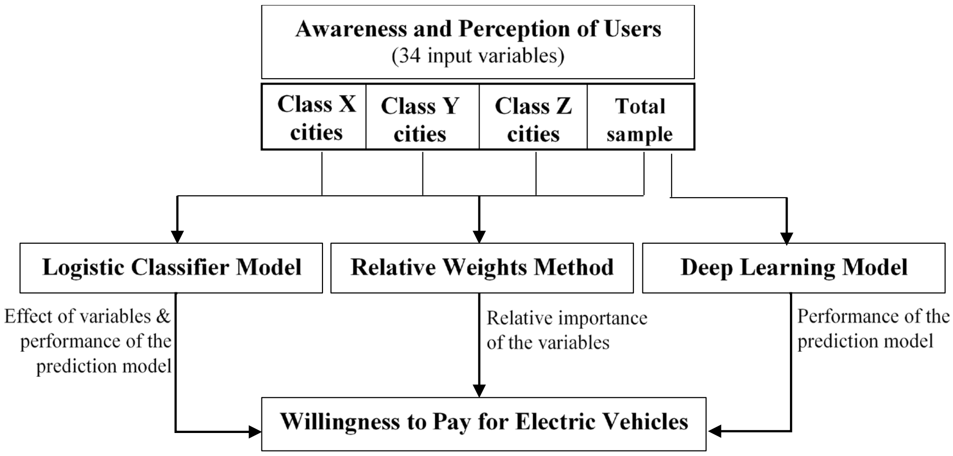

Figure 2. Research framework

Logistic Regression Classifier Model

Logistic Regression Classifier Model or Logistic Classifier Model is a statistical learning technique categorized in supervised machine learning techniques (Taboga, 2020). The technique, widely known as the logit model, uses a predictive analysis algorithm based on the concept of probability, and uses a linear regression equation to produce discrete binary outputs, and attempts to maximize the quality of output on a training set (Pant, 2020).

The logistic regression classifier is a linear model for binary classification. The net input of the model is the linear combination of the input features (z). The output is activated using a sigmoid function to transform the predicted values to probability, thus in the range [0,1]. Then, a threshold function classifies the probability output to a binary value {0, 1}. The model uses a cost function defined as the 'Sigmoid function' or 'logistic function.' The sigmoid function is used to map predicted values to probability. Thus, the study used a machine learning implementation of the statistical technique. In this research, the logistic classifier (LC) model was used to fit the input features (variables) to maximize the cost of spending on EVs. The model parameters were obtained by minimizing the logistic cost function, which is the error function. The model optimized the hyperparameter learning rate to ensure that the model converges in the least time.

The initial weights were randomized to confirm that the features were uncorrelated, and deviation in coefficients was noted. No factor showed a variation of over 1 percent for data over 25 randomizations. Moreover, other test cases were run without various features with high absolute coefficients to ensure no correlated feature was either suppressed, under-represented, or represented inversely. Figure 3 shows the schematic of the logistic regression classifier model, which was used for the analysis.

To test the model, in addition to the full data, the data was split into training and test sets in the ratio of 0.6:0.4. Separating the training set from the testing set generalizes the results by testing it on a randomized set of responses. Hence, the performance results (F1 score) for the test dataset are relatively more accurate, and thus, the model can be applied to a larger group of people. The correctness of the predicted model was evaluated using the Receiver Operating

Characteristic curve (ROC) and F1 score. The coefficients specific to the input variable indicated the impact of that variable on the output. The multicollinearity in the features is measured using the variance inflation factors (VIF). The VIF is calculated for each feature by performing a linear regression of that feature on all other features. The R-squared value (R2) is obtained from that regression for the VIF calculation. The VIF is defined as the value, 1/(1-R2). A VIF value below 5 indicates low collinearity (Bhandari, 2020).

Table 1. Variables considered for the Models

Variables	Description of variables
Willingness to pay for EVs (Output variable) Willing to pay more than a combustion engine vehicle with similar characteristics; 1= if yes; else 0.	
City Classes (For total sample model) Whether the individual is from a particular Class of city; 1= if yes; else 0	Class X city Class Y city
Socioeconomic characteristics Whether the individual has following variable characteristics; 1= if yes; else 0	Gender: Male Qualification: Postgraduate Non-Student
Past experiences on EV use Whether the individual has following past experience of EV; 1= if yes; else 0	Driven an EV Travelled in an EVs
Awareness of EVs, EV technology, and EV related policies Whether the individual is aware of the following variable specific to EVs; 1= if yes; else 0	Aware of maintenance of EV Aware of tax rebate on EV purchase Aware of EV related policies and incentives Aware of EV charging stations near your neighbourhood Aware about EVs Aware of EVs available in the Indian market Aware of EV based public transport in India Aware of advantages of EVs Aware of disadvantages of EVs Aware of functioning of EV
Important variables while purchasing an EV Whether the individual considers the following variables as an important feature while purchasing an EV; 1= if yes; else 0	Options of EVs in the Indian automobile market Technology and performance Public charging infrastructure for EVs Service stations for EVs Separate lane and parking area for EVs Free parking spaces with charging stations for EVs EV battery charging time Quality and reliability of electricity Capital and maintenance cost Operational cost Cheaper battery charging rates Separate electricity tariff for EV charging Tax rebate on the purchase Discount on purchase Discount on the exchange of vehicle Stricter safety standards 8-year battery warranty

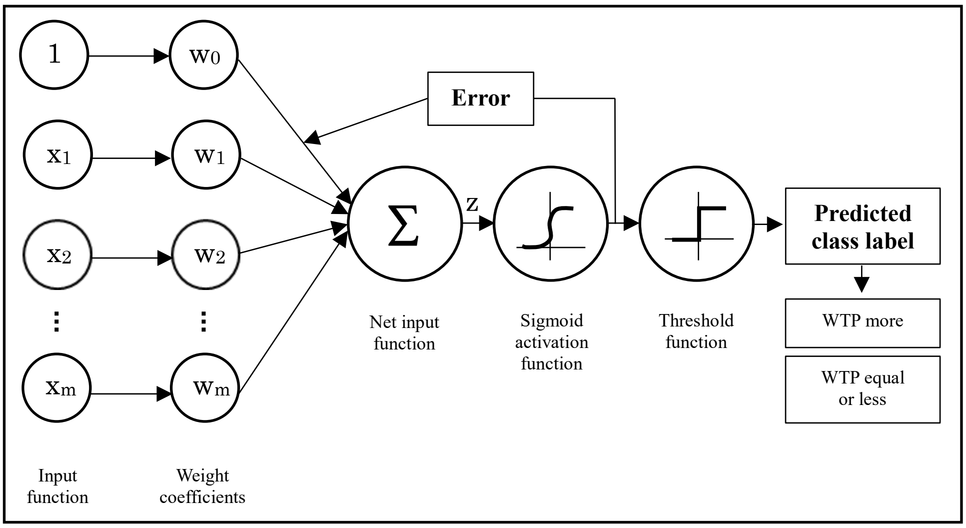

Figure 3. Schematic of the logistic regression classifier model

Relative Weights Analysis

The features with greater modulus value play higher importance in predicting the output, and thus, there could be certain discrepancies due to the correlation that is existent among the features. A particular feature with high zero correlation could have taken some credit from another heavily correlated feature. Such cases are not correctly handled by the coefficients alone. Johnson (2000) explains how Relative Weights (RW) Analysis ensures accurate weights are given to predictor features independent of their correlations. Tonidandel and LeBreton (2010) also confirm that RW Analysis can be employed to determine the relative importance level of predictor variables in the regression analysis. RW Analysis has been applied in this study on the entire data as well as data for different city classifications to obtain the relative importance of variables, which is different from the statistical significance of the features.

Deep Learning Model

Deep learning (DL) is a class of machine learning algorithms that can model non-linear relationships between input vectors to target values (Dargan, 2020). The underlying relationship between our features is likely to be non-linear as the data is high dimensional, and a linear sigmoid model like the LC model cannot capture the non-linear relation between features. Thus, the study used a deep learning model to compare the prediction result.

Figure 4 shows the general framework of the Feedforward neural network, which was used for the analysis. The node (i) in each layer is scaled by learnable weights (w_{ij}) and passed through non-linear functions to determine the values of node (j) in the next layer. The model uses an input layer with 34 input features, two hidden layers (the first layer with five nodes and the second layer with three nodes), and an output layer (1 output node) predicting a binary value classifying the WTP. After each layer, an activation layer is used to introduce non-linearity in the model. The DL model is accessible online at https://github.com/Suchetaaa/EV-Perception.

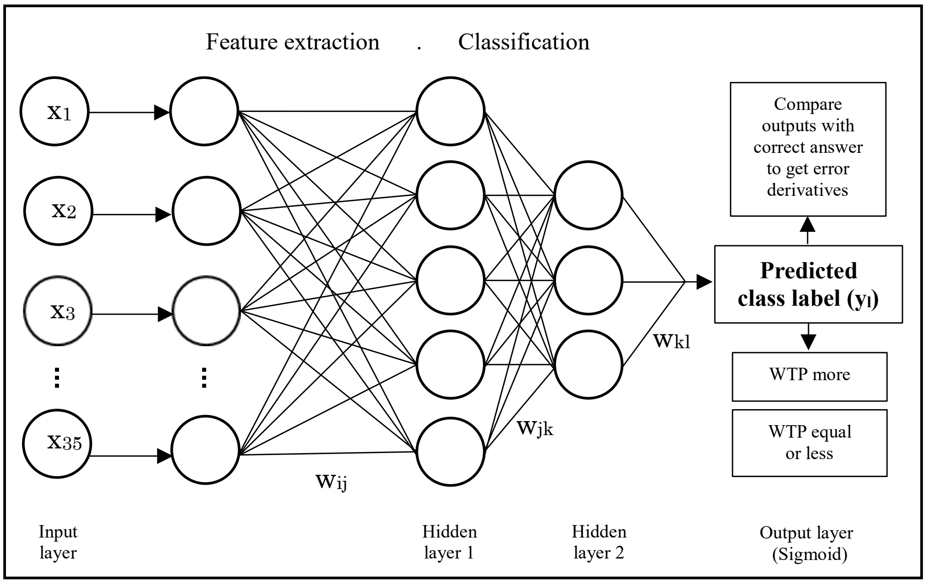

Figure 4. Schematic of the deep learning model

4. RESULTS AND DISCUSSIONS

4.1 Exploratory Findings

The post-data collection process included data sorting and descriptive analysis. Out of the 434 responses received, 18 incomplete responses were omitted. Table 2 represents the data description based on the classification of cities. 53.8 percent of the respondents belonged to the age group of 17- 23 years, while the remaining respondents were from the 24-65 years' group. Around 65 percent of the respondents were male, and 51.7 percent of the sample belonged to Class X city. The data also looked into the experience of the respondent with EVs (such as no idea about EVs, read/heard about EVs, traveled in an EV, driven an EV, and owner of an EV). A total of 39.2 percent of the respondents were reckoned to either own, drive, or traveled in an EV.

Figure 5 elucidated that majority of respondents preferred to pay equal or lesser, irrespective of their awareness concerning EV-related initiatives. Among many incentives, most conscious respondents were aware of the tax rebate policy. Figure 2 demonstrates that despite around 50 percent of the Indian buyers knowing the availability and disadvantages of EV; a lower percentage had knowledge concerning service-related maintenance (33 percent) and available charging infrastructure (16.6 percent). However, regardless of knowledge, the respondents were willing to pay equal or less for an EV.

Figure 6 showcased that around 80 percent of respondents said that stricter safety standards would make them more interested in an EV; however, with a willingness to pay equal or less than a combustion vehicle. Charging time (77 percent), public infrastructure (75 percent), and reliability of electricity (75 percent) was considered prerequisites for buying EVs. The maximum number of respondents willing to pay more prioritized charging time and public infrastructure as preconditions. Figure 7 explained that around 35 percent of the respondents belonging to the graduate and working-age group 17-23 years, 31-37 years, and 45-51 years were found willing to pay more.

Table 2. Data Description based on Classification of Cities

City Classification	Class X		Class Y		Class Z		Total
Number of respondents	217		139		65		421
	Percentage share						
	Within class X		Within class Y		Within class Z		Total
Willingness to pay for EVs							
People willing to pay more	36.9	(19.0)	30.9	(10.2)	26.2	(4.0)	33.3
Socioeconomic characteristics							
Gender: Male	68.7	(35.4)	63.3	(20.9)	72.3	(11.2)	67.5
Education level: Postgraduate	25.35	13.1)	23.7	(7.8)	12.3	(1.9)	22.8
Non-Student	45.6	(23.5)	49.6	(16.4)	43.1	(6.6)	46.6
Past experiences on EVs							
Owner of an EV	1.8	(0.9)	1.4	(0.5)	3.1	(0.5)	1.9
Driven an EV	7.3	(3.8)	9.4	(3.1)	10.8	(1.7)	8.6
Travelled in an EV	32.7	(16.9)	22.3	(7.4)	29.2	(4.5)	28.7
Read/Heard about EVs	51.2	(26.4)	59	(19.5)	49.2	(7.6)	53.4
No idea about EV	6.9	(3.6)	7.9	(2.6)	9.2	(1.4)	7.6

Note: Values are given in percentage. The values in parenthesis ( ) denote the percentages share in the total sample, i.e., 421 samples.

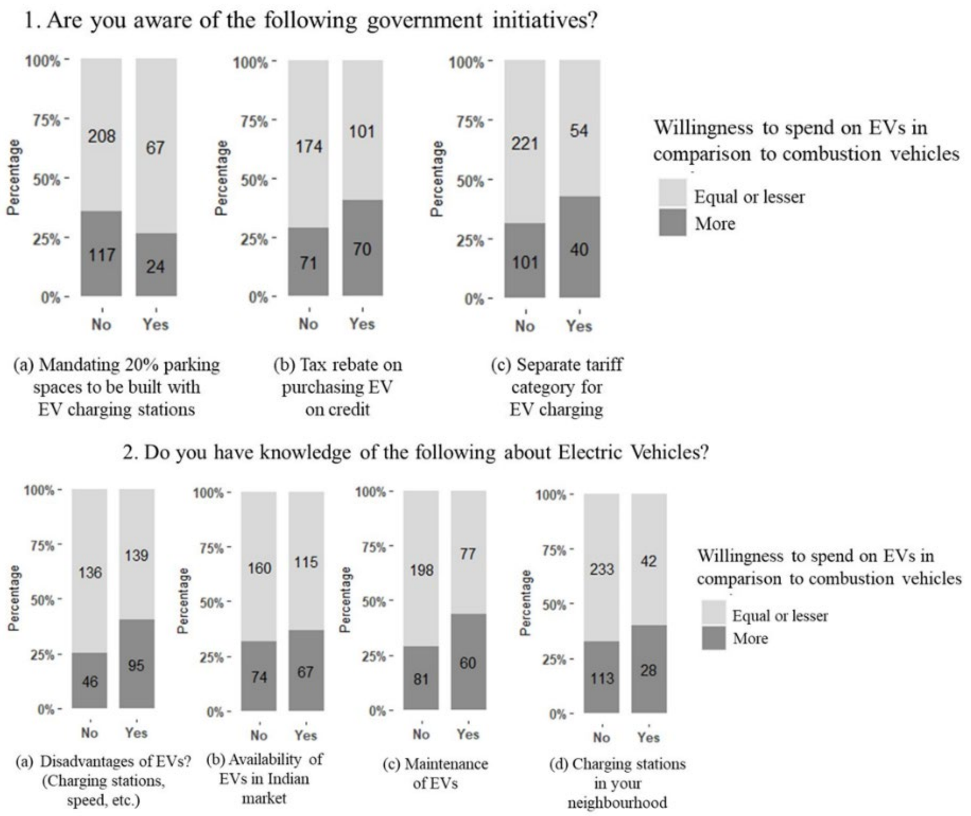

Figure 5. Awareness concerning EV policies and utility and association with WTP.

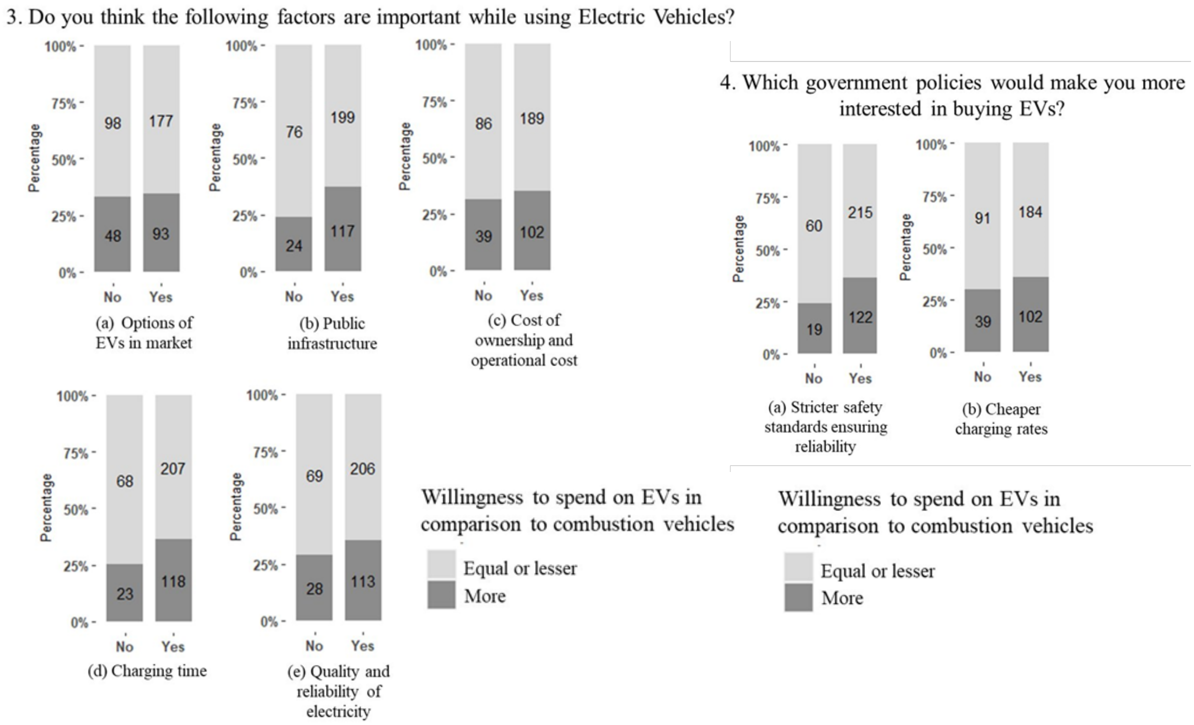

Figure 6. Prioritisation of technological and economic aspects of EV and association with WTP.

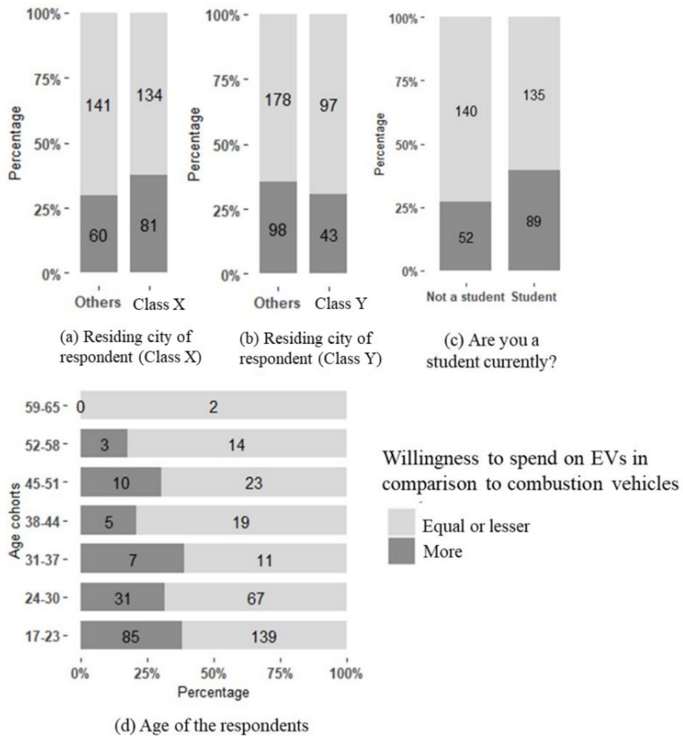

Figure 7. Difference in WTP and its association with age of the respondent.

4.2 Results from Logistic Classification (LC) Model, Relative Weights Method, and Deep Learning Model

The Logistic classification (LC) model applied here aided in describing the effect of input variables on the willingness to pay more (WTPM) for EVs, while the Relative Weights method showed the relative importance of the input variables over others. The F1 score for the LC model for full data and test data were reckoned as 0.62 and 0.39, respectively. The multicollinearity in the features was measured by using the variance inflation factors (VIF), and all features in the dataset have VIF in the range [1.113,2.374], which indicates low collinearity.

The Deep Learning (DL) technique used for the study acted as a prediction model for evaluating the performance of the model. For both full data and test data, the F1 score and accuracy of the DL models were observed to be better than the LC model. Furthermore, the performance on test data has improved by 3 percent in the DL model in comparison to that achieved in the LC model. Table 3 represents the results based on three types of models discussed in this research, and the variables are also analyzed based on the kind of city the individual resides in. The residents of metropolitan (Class X) cities show a higher tendency in willingness to spend more on EVs, followed by Class Y cities.

4.2.1 Socioeconomic characteristics

Socioeconomic characteristics such as gender, education, and employment status significantly impacted the willingness to pay more for EVs. While being male was observed to be the most significant variable for WTPM according to LC models, no significant city class-wise differences were observed for the 'gender' variable. The result from the total dataset indicated being male was one of the most important variables for choosing WTPM according to Relative weight analysis (RW Analysis), and the importance of the gender on WTPM is higher for city class X, which is followed by class Y. Overall, education background showed a high variation among city classes in effect on WTPM. Being a non-student individual negatively impacts the WTPM, and the effect is more in class Z cities than in other city classes.

4.2.2 Experience and awareness about electric vehicles and related policies

The overall sample indicates that the experience in EVs such as EV driving or traveling experience was observed to impact WTPM minimally. On the contrary, EV experience had a significant effect on WTPM when the city class-wise sample was considered, with EV driving experience having a positive effect on WTPM for Class X and Class Z cities and negatively affected Class Y cities. The high effect of driving experience in Class Z cities on WTPM can be due to the lesser population experienced in EV driving in small towns and their willingness to use the latest technology to reduce air pollution. According to the RW Analysis, the past experience on EV use are important variables affecting WTP for Class Z city citizens; however, the LC model shows that travel experience in an EV does not affect WTPM.

The overall sample showcased that variables related to awareness concerning EVs positively affect the WTPM except for awareness regarding EV-based public transport and available EV options in the Indian market, thereby indirectly impacting EV adoption. Both LC model and RW Analysis indicated that individuals who are aware of the EV policies and incentives were observed to be more associated with WTPM, and this effect was found significant in Class Y and Class Z cities. The comparison of city classes indicates no other awareness variable other than awareness of the EV policies and incentives have the same direction of impact on WTPM.

Table 3. Effect of Variables on Willingness to Pay for the Electric Vehicles

Variables	VIF	Class X (N=217)	Class Y (N=139)	Class Z (N=65)	Total (N=421)
Intercept		-1.49	-2.57	-2.79	-2.104
City Class (For total sample model)					
Class X city	1.60	NA	NA	NA	0.36(2.12)
Class Y city	1.64	NA	NA	NA	0.08(0.57)
Socioeconomic characteristics					
Gender: Male	1.25	0.92(9.54)	0.88(4.18)	1.01(2.12)	0.65(11.71)
Qualification: Post graduate	1.15	0.34(0.10)	-0.03(0.16)	0.77(2.56)	0.38(0.61)
Non-Student	1.64	-0.12(2.63)	-0.97(4.74)	-2.34(1.65)	-0.31(5.46)
Past experiences on EV use					
Driven an EV	1.24	0.96(1.59)	-1.41(1.34)	1.83(6.59)	0.06(0.41)
Travelled in an EVs	1.18	-0.05(0.97)	0.32(1.37)	0(4.59)	-0.17(0.31)
Awareness of EVs, EV technology and EV related policies					
Aware about EVs	1.18	0.13(0.5)	-0.91(1.22)	-1.49(2.28)	0.21(2.05)
Aware of EVs available in Indian market	1.39	-0.39(0.92)	0.55(0.97)	-1.5(1.5)	-0.26(0.79)
Aware of EV based public transport in India	1.33	0.11(0.5)	-1.87(4.67)	1.38(4.74)	-0.15(0.28)
Aware of advantages of EVs	1.32	-0.95(1.88)	2.44(14.02)	4.37(6.17)	0.29(3.47)
Aware of disadvantages of EVs	1.30	1.16(10.69)	-0.52(1.14)	-1.29(0.92)	0.19(4.23)
Aware of functioning of EV	1.26	-0.13(1.78)	1.41(9.85)	-1.54(0.63)	0.26(6.1)
Aware of maintenance of EV	1.37	0.17(1.53)	-0.26(3.68)	4.4(3.07)	0.18(3.63)
Aware of tax rebate on EV purchase	1.37	0.3(5.63)	0.46(0.58)	-0.96(1.24)	0.22(3.6)
Aware of EV related policies and incentives	1.44	0.45(4.74)	1.53(9.65)	1.58(9.53)	0.97(13.29)
Aware of EV charging stations near your neighbourhood	1.31	-0.4(1.63)	0.87(4.86)	-3.22(1.1)	0.12(0.88)
Important variables while purchasing an EV					
Options of EVs in Indian automobile market	1.37	-0.13(0.64)	-1.76(2.08)	1.13(5.64)	-0.32 (1.01)
Technology and performance	1.53	-0.11(1.72)	0.67(4.58)	-4.95(3.3)	0.15(0.67)
Public charging infrastructure for EVs	1.55	0.48(2.57)	-0.55(1.34)	7.24(2.61)	0.6(3.22)
Service stations for EVs	1.96	-0.01(0.57)	-0.53(4.5)	3.82(3.1)	-0.24(1.1)
Separate lane and parking area for EVs	1.21	-0.56(1.61)	0.34(0.92)	1.28(0.87)	-0.13(0.21)
Free parking spaces with charging stations for EVs	1.44	-2.3(15.27)	-1.33(3.26)	2.06(1.57)	-1.3510.85)
EV battery charging time	1.94	0.33(2.45)	-1.01(1.2)	0.73(5.34)	0.2(1.76)
Quality and reliability of electricity	1.84	0.52(4.02)	-1.48(1.5)	-0.9(1.13)	0.07(0.93)
Capital and maintenance cost	1.36	-0.49(4.44)	-1.26(6.43)	-2.19(0.00)	-0.66(9.93)
Operational cost	1.58	-1.18(1.93)	0.16(1.66)	-6.04(3.3)	-0.66(1.18)
Cheaper battery charging rates	1.50	0.34(1)	-1.71(0.77)	0.98(2.54)	0.13(0.56)
Separate electricity tariff for EV charging	1.49	2.01(10.76)	-0.17(0.55)	-1.69(0.46)	0.7(4.93)
Tax rebate on purchase	1.36	-0.18(0.67)	0.78(2.67)	0.02(1.36)	-0.03(0.4)
Discount on purchase	1.39	-0.25(0.78)	1.06(3.07)	1.91(3.24)	0.19(0.52)
Discount on exchange of vehicle	1.31	0.84(3.43)	-0.31(1.34)	-2.9(4.56)	0.09(0.14)
Stricter safety standards	1.56	0.76(1.48)	-0.04(0.37)	-2.9(2.46)	-0.04(0.31)
8-year battery warranty	1.47	-1.26(1.39)	0.5(0.53)	2.39(3.01)	-0.3(0.29)
Model evaluation		Class X	Class Y	Class Z	Total
F1 score - Full data		0.68	0.74	0.83	0.62 [0.85]
Test F1 score (0.6:0.4)		0.39	0.39	0.39	0.39 [0.42]
Accuracy - full train		0.76	0.80	0.90	0.72 [0.90]
Accuracy - 0.6:0.4 train test		0.52	0.52	0.52	0.52 [0.57]

Note: The values in parenthesis ( ) denote the results from Relative Weights Method & the values in square bracket [ ] denote the results from Deep Learning Model.

Interestingly, while the awareness of the advantages of EVs negatively affects WTPM, the awareness of disadvantages of EVs has a significant and positive effect in Metropolitan (Class X) cities. However, the results from Class Y and Z cities show the finding as expected: the awareness of the advantages of EVs has a positive effect, and awareness of disadvantages of EVs negatively affects WTPM. RW Analysis confirms that the advantages of EVs are a significant variable for Class Y and Z cities, while awareness of disadvantages of EVs is a significant variable for Class X cities. RW Analysis also indicates that the awareness of the functioning of EV vehicles is a significant variable for Class Y.

4.2.3 Importance of variables while purchasing EVs

Capital cost, maintenance, and operational cost acted as vital EV purchase barrier variables indicating that the individuals giving more importance to the aforementioned variables had shown a negative tendency towards paying more for EV. On the contrary, the individuals giving increased priority to technology and performance, charging infrastructure, recharging time, inexpensive charging rate, and distinct charging electricity tariff were inclined towards paying more for EVs, majorly owing to their amplified awareness concerning EV utility. However, the individuals who were reckoned to probe into EV options, parking facilities, service options, safety standards, and long-term battery warranty tend to have a negative effect on WTPM. The overall sample result from the Relative Weight analysis indicated that the significant variables that would affect WTP are free parking spaces with charging stations, capital and maintenance cost, separate electricity tariff, and public charging infrastructure for EVs. These results can be attributed to the current scenario of service level and road infrastructure of EVs in the Indian context as well as a lower driving range and reduced battery capacity, which might need up-gradation for transforming people's mindset towards an increased EV purchase.

Furthermore, while EV has penetrated Indian markets in the last decade, the choice alternatives, often acting as a significant user-based parameter, are lower for EVs with respect to conventional combustion vehicles. However, EV options having a negative coefficient indicate that the buyers currently do not care much about having more choices of EVs to buy from. This as well seems counterintuitive, but for a relatively new industry, the following could be the plausible explanations: (i) the people interested in buying are already highly motivated by the positive impact of EVs, and hence the unavailability of options does not refrain them to buy one, (ii) people are satisfied with the available options and hence having more choices is not their primary concern.

In Class X cities, individuals who prioritized separate electricity tariffs for EVs and free parking spaces with charging stations have a significant positive and negative effect on WTPM, respectively. Whereas, classified model estimates showcased that the individuals from Class Y and Class Z cities considering tax rebates and incentives as a significant precondition during EV purchase were noticed to affect WTPM positively. Purchase-based incentives and tax benefits have been established to impact significantly and are utilized worldwide to encourage EVs (Melton et al., 2017; Sierzchula et al., 2014). Also, Norway, the Netherlands, and the State of California have the highest PHEV/EV market share, mainly due to supportive incentive policies. The results are also in accordance with a study wherein a high correlation was observed between financial incentives and EV market share across 30 countries and another study that concluded that exemptions from taxes were significant motivators for more than 80% of the respondents (Bjerkan et al., 2016; Sierzchula et al., 2014). However, in Class Z city, the individuals considering public charging infrastructure and service stations as an important variable for EV purchase exhibit the choice of WTPM for EVs. Since Class Z cities lack progression in terms of EV and related upgraded service infrastructure, small-town residents might have a tendency to prioritize and ensure fulfilling the essential prerequisite of charging infrastructure availability before opting for EV.

5. CONCLUSIONS

Owing to the lack of adequate literature regarding EV emergence, its usage, and especially user perception concerning EV adoption in the Indian scenario, this study is of its initial kind, which explores the public opinion, attitude, and concern towards purchasing electric vehicles in India. While worldwide literature has looked into general willingness to adopt EV among the end-users, this study eyeing into the economic perspective, investigates the willingness to pay more or less for an EV in comparison to conventional combustion vehicles. This study has attempted to identify the predictors that influence a potential Indian buyer to purchase an EV by utilizing Machine Learning techniques. On the one hand, the advent of pollution-free technology of EVs would facilitate the users with an emission-free liveable environment. In contrast, the technological challenges of EVs like the dearth of service infrastructure, battery capacity, lower driving range, and increased charging time is a sign of gaps that still impose challenges in public adoption of EVs in India. However, the EV industry has witnessed escalated growth in the last decades and can further be amplified if upcoming policies turn user-centric. This research broadly aims to capture the user perception in the Indian scenario by centering on public individualities, opinions, and values held by respondents to answer a primary question: "Are you willing to pay more for an EV than a combustion vehicle?" The analysis was categorized based on the city classes that the respondents belong to. Due to the variation in socioeconomic conditions and job aspects of the residents and service infrastructure levels, this classified analysis was performed to understand the specific differences in opinion and public needs based on city infrastructure. The learning from the study would ease EV diffusion in markets more effectively from EV manufacturers' side and aid policymakers in adjudicating EVs efficacy rationally and formulating forthcoming EV policies efficiently.

The finding from the study offered a general perspective regarding the user attitude towards EV and identified that male respondents, respondents with employment status, higher education, and belonging to metropolises were found willing to pay more for an EV than those in other classes of cities. The experience of driving or riding an EV also had a positive impact, indicating that individuals already experienced with EV, being aware of its benefits and disadvantages, are willing to pay more for an EV in smaller cities and towns. This indicates the need for more public campaigns of EVs for improved EV adoption rate. While capital cost, maintenance, and operational cost acted as vital EV purchase barriers, the individuals giving increased priority to technology and performance, charging infrastructure, recharging time, inexpensive charging rate, and distinct charging electricity tariff preferred to pay more for EV. The variables of EV options, parking facilities, service options, safety standards, and long-term battery warranty had a negative impact on EV purchase. This calls for the up-gradation of technical services for transforming people's mindset towards an increased EV purchase. Among all the variables studied, the most significant was the individual's awareness concerning policy benefits and tax rebates.

As India is at a nascent stage in the adoption of EVs, the result from this consumer analysis study is vital, and the study highlighted the differences in opinion observed for different city classes owing to variation in economic activities, general socioeconomic status of residents, and population density. The study found that the awareness among the prospective buyers varies within different classes of cities in India and, therefore, might affect the viability of EV geographically. The results from this study can be a significant aid to automotive companies to base their products and sales strategy and the policymakers to implement forthcoming policies to ensure a seamless diffusion of EVs while fulfilling the customer requirements.

A significant change in terms of EV options and policies has occurred in India since 2020. The study does not capture their effect as the survey was conducted in early 2020, which can be considered a major limitation. The government launched the Go Electric campaign at the start of 2021 to encourage the adoption of electric mobility vehicles and electric cooking appliances and ensure energy security in the country (Renewable Energy 2050, 2021). The sale of EVs grew 109.84% from FY2020 (Apr 19-Mar 20) to FY2021 (Apr 2020- Mar 2021) despite the global COVID-19 pandemic (Society of Manufacturers of Electric Vehicles, 2021). The increasing EV options with better specifications in the Indian market is expected to have contributed to the increased sale of EVs in 2021.

Moreover, the increasing awareness on the current government policies like reduction of GST on EVs and chargers, allowing the sale of electricity as a 'service' for charging of electric vehicles, provision of additional income tax deduction up to 0.15 Million INR on the interest paid on loans taken to purchase EVs would also have increased the sales of EV significantly (Ministry of Heavy Industries & Public Enterprises, 2020). Currently, EV's share in car sales is less than 0.5%, and the Indian government targets a 30% EV share by 2030. Thus, EV sales in India need to be increased faster through better policies, infrastructure, and EV specifications. Future research may conduct a detailed analysis based on the new policies, infrastructure, and economic aspects to understand the EV adaptation and value of WTP.

The reservations and unreliability intertwined with EV's technological progressions, especially in India, have been recognized here. Numerous queries in this field remain under-explored, which can be speculated with the real implementation of EVs on the field on a larger scale. Further research on globally accepted EV-related policies and schemes can enhance the depth of the epistemology of the evolving arena of EV addressing macro-level matters regarding the effect of global EV adoption on urbanization, etc. With the aid of these researches, the efficacy of EVs can be adjudicated rationally.

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