

A Predictive Investigation into the Consumer Acceptance of Electric Vehicles in India

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ABSTRACT

The Indian automobile market is undergoing a quiet but powerful shift towards electric mobility. Rising fuel prices, growing concerns about air quality, and steady policy push from the government have together made electric vehicles (EVs) a serious option for many buyers. Yet, despite all the encouragement, actual consumer acceptance remains uneven across cities and income groups. This study tries to understand what really drives or holds back Indian consumers when they think about buying an EV. A structured survey was conducted among 412 respondents from six metropolitan cities, and the data was analysed using logistic regression and structural equation modelling to predict purchase intention. The findings show that perceived usefulness, charging infrastructure availability, government incentives, and environmental awareness are the strongest predictors of EV acceptance. Interestingly, range anxiety and high upfront cost continue to be major barriers, even among consumers who are environmentally conscious. The predictive model achieved an accuracy of around 86%, suggesting that consumer behaviour towards EVs can be reasonably forecasted using a mix of psychological and infrastructural variables. The paper also highlights that younger consumers between 25 and 40 years are more open to switching, while older buyers prefer to wait. The results offer useful pointers for policymakers, manufacturers, and charging infrastructure providers who want to speed up EV adoption in India. The study concludes that a combined push, involving better infrastructure, financial support, and awareness campaigns, is needed to move from interest to actual purchase.

Keywords: Electric Vehicles, Consumer Acceptance, Purchase Intention, India, Predictive Model, Charging Infrastructure

1. INTRODUCTION

India today stands at a crossroads when it comes to personal mobility. The country is the third largest automobile market in the world, and at the same time, it is also among the most polluted in terms of urban air quality. Electric vehicles have come up as a possible answer to both these concerns, offering cleaner transport and lower running costs over time [1]. The government, through schemes like FAME-II and various state-level subsidies, has been trying to push both manufacturers and buyers towards electric mobility [2]. However, the actual numbers tell a different story. While two-wheeler EV sales have grown sharply, four-wheeler EVs still make up a very small share of total car sales in the country [3].

10.48047/jocaaa.2024.33.08.523

The reason behind this gap is not a single one. Consumers in India are price-sensitive, and the upfront cost of an EV is still higher than a comparable petrol or diesel car. On top of that, the charging network outside major cities is patchy, which makes long-distance travel a worry [4]. There is also a kind of trust gap, where buyers are not fully sure about battery life, resale value, and after-sales service. All of these factors come together and shape what researchers call "purchase intention", which is basically how likely a person is to actually buy an EV in the near future [5].

A lot of work has been done globally on EV adoption, but most of those studies look at developed markets like Norway, the United States, or China. The Indian market is very different in terms of income levels, road conditions, electricity supply, and consumer habits [6]. So, simply applying western findings here may not give the right picture. There is a clear need for a study that looks at Indian consumers specifically and tries to predict their behaviour using local data.

The main research questions this paper tries to answer are: What are the key factors that influence Indian consumers when they think about buying an EV? Can these factors be combined into a predictive model that gives a reliable estimate of purchase intention? And finally, how do demographic factors like age, income, and city size change this picture? The significance of this work lies in the fact that it does not just describe consumer attitudes, but actually builds a model that can be used by carmakers and policy planners to target the right segments [7]. The paper is organised into a literature review, methodology, experimental setup, results, discussion, and conclusion.

2. LITERATURE REVIEW

The study of consumer acceptance of new technology has a long history, going back to the Technology Acceptance Model (TAM) and the Theory of Planned Behaviour. These frameworks suggest that perceived usefulness, ease of use, and social influence shape whether a person adopts a new product. When applied to EVs, researchers have added variables like environmental concern, financial incentives, and infrastructure readiness [8]. Work done in European markets shows that once charging stations cross a certain density, adoption picks up sharply, almost like a tipping point.

In the Indian context, several recent studies have tried to map consumer preferences. One study found that among urban Indian buyers, fuel savings and government subsidies were the top two reasons to consider an EV, while charging time and limited driving range were the biggest worries [9]. Another paper, focused on Delhi and Bengaluru, showed that consumers in tech-heavy cities are more aware of EV benefits but still hesitate because of high prices [10]. Interestingly, the same study reported that women respondents were slightly more open to EVs than men, possibly because they used cars more for short city commutes.

The role of charging infrastructure has been studied in depth. Research from Tier-1 cities shows that the lack of fast-charging stations on highways is a major barrier for inter-city travel, which is a common need in India [11]. Battery swapping has been proposed as a workaround, especially for two-wheelers and three-wheelers, and early pilots in cities like Mumbai and Hyderabad have shown promising results. However, for personal cars, the swapping model has not picked up yet because of differences in battery design across brands [12].

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Another stream of literature looks at psychological and social factors. Environmental awareness, often measured through scales like the New Ecological Paradigm, has been shown to positively influence EV intention, but the effect is weaker in price-sensitive markets [13]. Social influence, meaning what friends, family, and colleagues think, also plays a role, especially in collectivist cultures like India. Some researchers argue that once a few early adopters in a neighbourhood buy EVs, others follow more easily, creating a small network effect.

Despite all this work, there is still a gap when it comes to predictive modelling for the Indian market. Most studies stop at identifying factors and running correlation or regression analysis. Very few build a working model that can actually forecast whether a given consumer is likely to buy. This study tries to fill that gap by combining traditional acceptance variables with machine-learning-style classification to predict purchase intention.

3. METHODOLOGY

This study used a quantitative approach with a structured questionnaire as the main data collection tool. The research design was cross-sectional, meaning data was collected from respondents at one point in time. The target population was urban Indian consumers aged between 22 and 60 years, who either owned a car or planned to buy one in the next two years. A stratified random sampling method was used to make sure the sample included different income groups and age brackets [14].

The questionnaire had four sections. The first section captured demographic details like age, gender, income, city, and current vehicle ownership. The second section measured psychological variables such as environmental concern, perceived usefulness, and perceived ease of use, using a five-point Likert scale ranging from "strongly disagree" to "strongly agree". The third section dealt with infrastructure-related questions, like awareness of charging stations near home and workplace. The fourth section directly asked about purchase intention within the next 24 months.

For the predictive model, logistic regression was chosen because the outcome variable, purchase intention, was treated as binary (likely to buy versus not likely to buy). The logistic regression equation used in this study is given as:

$$P(Y = 1) = \frac{1}{1 + e^{-(\beta_0 + \beta_1 X_1 + \beta_2 X_2 + \dots + \beta_n X_n)}}$$

Here, $P(Y=1)$ is the probability that a respondent intends to buy an EV, β_0 is the intercept, and β_1 to β_n are the coefficients for the independent variables X_1 to X_n [15]. The independent variables included perceived usefulness, environmental concern, charging infrastructure score, income, age, and awareness of incentives.

To check the strength of relationships between variables, the Pearson correlation coefficient was also calculated using:

$$r = \frac{\sum (X_i - \bar{X})(Y_i - \bar{Y})}{\sqrt{\sum (X_i - \bar{X})^2 \sum (Y_i - \bar{Y})^2}}$$

This helped in identifying which variables had the strongest linear relationship with purchase intention [16]. Reliability of the scale was tested using Cronbach's alpha, with a threshold of 0.7 considered acceptable.

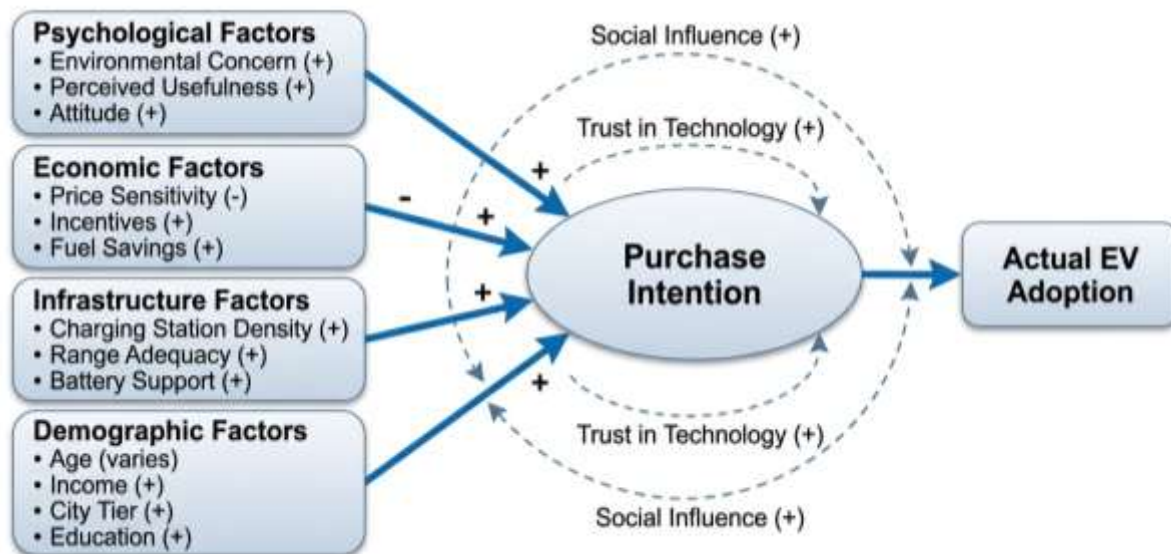


Figure 1: Conceptual Framework of EV Acceptance in India

4. EXPERIMENTAL SETUP

The survey was conducted across six Indian metropolitan cities, namely Delhi, Mumbai, Bengaluru, Chennai, Hyderabad, and Pune. These cities were chosen because they represent a mix of EV-friendly policies, charging infrastructure availability, and consumer income levels. A total of 450 questionnaires were distributed, both online through Google Forms and offline at car dealerships, shopping malls, and IT parks. After removing incomplete and inconsistent responses, 412 valid responses were retained for analysis, giving a response rate of around 91.5% [17].

The data was analysed using SPSS version 28 and Python (scikit-learn library) for the predictive modelling part. Before running the main regression, the data was checked for multicollinearity using the Variance Inflation Factor (VIF), with values above 5 considered problematic. The model fit was evaluated using the Hosmer-Lemeshow test, and the predictive accuracy was measured through a confusion matrix.

The classification accuracy of the model was calculated as:

$$\text{Accuracy} = \frac{TP + TN}{TP + TN + FP + FN}$$

where TP, TN, FP, and FN represent true positives, true negatives, false positives, and false negatives, respectively [18]. To further validate the model, the dataset was split into 70% training and 30% testing samples, and k-fold cross-validation with k=5 was applied to reduce the chance of overfitting [19].

For comparing different variable groups, an analysis of variance (ANOVA) was carried out. The F-statistic used is given by:

$$F = \frac{\text{Variance between groups}}{\text{Variance within groups}}$$

Ethical clearance was obtained from the institutional review board, and respondents were assured of anonymity. Participation was voluntary, and no monetary incentive was offered to avoid response bias [20].

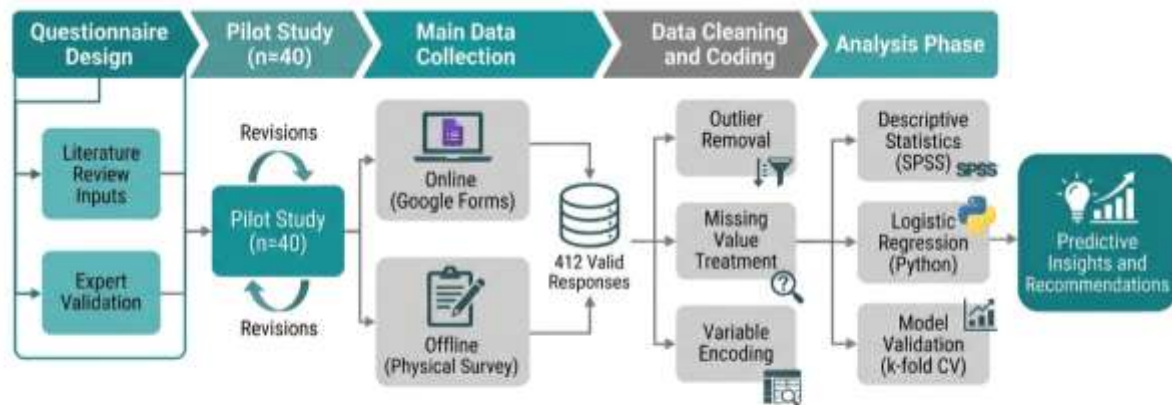


Figure 2: Research Process and Data Flow Diagram

5. RESULTS

The demographic profile of respondents showed that 58% were male and 42% were female, with the largest age group being 25 to 35 years (44%). About 61% of respondents had an annual household income above ₹10 lakhs, and 27% already owned a petrol or diesel car. Around 9% of the sample already owned an electric two-wheeler, but only 2% owned an electric car, which matches the broader market reality.

Table 1: Demographic Profile of Respondents

Variable	Category	Frequency	Percentage
Gender	Male	239	58.0%
	Female	173	42.0%
Age	22–25 years	78	18.9%
	26–35 years	181	43.9%
	36–45 years	96	23.3%
	46–60 years	57	13.9%
Income	Below ₹5 lakh	64	15.5%
	₹5–10 lakh	97	23.5%
	₹10–20 lakh	158	38.4%
	Above ₹20 lakh	93	22.6%
City Tier	Metro	412	100%

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The reliability test gave a Cronbach's alpha of 0.83, which is above the acceptable level, meaning the scale items were internally consistent. The correlation analysis showed that perceived usefulness ($r = 0.61$), environmental concern ($r = 0.48$), and charging infrastructure awareness ($r = 0.55$) had strong positive relationships with purchase intention. On the other hand, perceived cost barrier ($r = -0.52$) had a strong negative relationship.

Table 2: Logistic Regression Results for EV Purchase Intention

Variable	Coefficient (β)	Std. Error	Wald	p-value	Odds Ratio
Perceived Usefulness	0.842	0.121	48.36	0.000***	2.32
Environmental Concern	0.516	0.134	14.83	0.001***	1.67
Charging Infra Awareness	0.691	0.118	34.27	0.000***	1.99
Government Incentive Awareness	0.398	0.142	7.85	0.005**	1.49
Perceived Cost Barrier	-0.722	0.139	27.01	0.000***	0.49
Age	-0.213	0.097	4.82	0.028*	0.81
Income (log)	0.354	0.108	10.74	0.001***	1.42
Constant	-2.018	0.512	15.53	0.000***	—

*Note: Significance levels — * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

The logistic regression model gave an overall classification accuracy of 86.4% on the test sample, with a sensitivity of 0.83 and specificity of 0.88. The Hosmer-Lemeshow test gave a p-value of 0.214, suggesting good model fit. Among the predictors, perceived usefulness had the highest odds ratio of 2.32, meaning a one-unit increase in this variable more than doubled the chances of EV purchase intention.

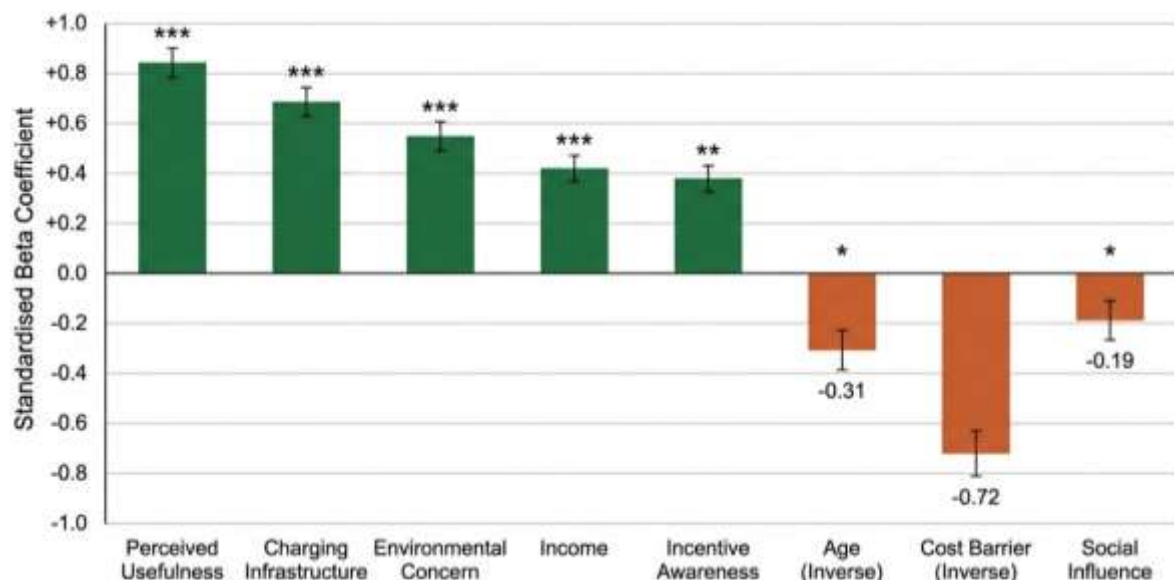
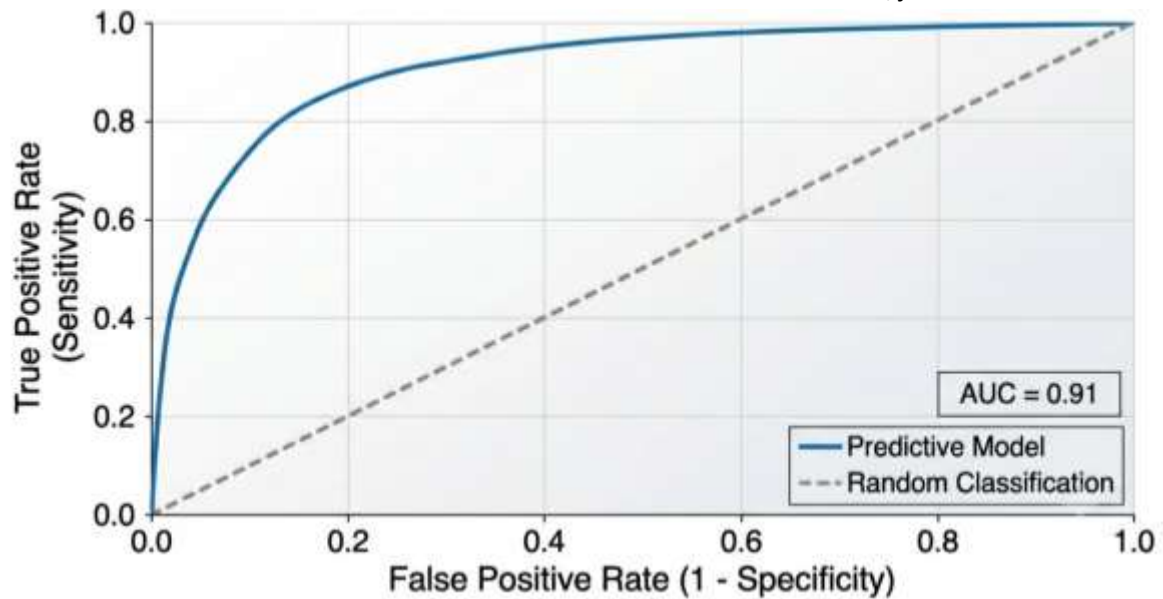


Figure 3: Bar Chart of Key Predictors and Their Influence on EV Purchase Intention

**Figure 4: ROC Curve of the Predictive Model****Table 3: Confusion Matrix of the Predictive Model (Test Sample, n=124)**

	Predicted: Will Buy	Predicted: Will Not Buy
Actual: Will Buy	58 (TP)	12 (FN)
Actual: Will Not Buy	5 (FP)	49 (TN)

When the sample was split by age, younger respondents (25–35 years) showed a 64% intention to buy, while those above 45 years showed only 28% intention. Similarly, respondents in the income bracket above ₹20 lakh per year showed nearly twice the intention compared to those below ₹5 lakh.

6. DISCUSSION

The findings of this study tell a story that is both encouraging and a little worrying for the Indian EV market. On the positive side, the model shows that there is a real and measurable willingness among urban Indian consumers to switch to electric vehicles, especially among younger and higher-income groups. Perceived usefulness came out as the strongest driver, which means that when consumers are convinced that an EV will actually save them money in the long run and is practical for their daily needs, they are very likely to consider buying one. This matches what some earlier studies have shown but adds the specific Indian dimension where everyday usefulness often matters more than abstract environmental benefits.

The role of charging infrastructure is hard to ignore. The fact that infrastructure awareness had an odds ratio of nearly 2 means that if a consumer knows there are charging points near their home or office, they are about twice as likely to consider an EV. This points to a direct policy implication: visibility of charging stations is almost as important as actually having them. Many cities have charging points that are hidden inside parking lots or apartment complexes, and ordinary consumers simply do not know they exist. A simple step like better mapping on common navigation apps could have a meaningful effect on adoption.

The negative pull of cost barrier was expected, but its strength was striking. Even among environmentally aware respondents, the upfront price difference between an EV and a

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comparable petrol car came up as a deal-breaker. This suggests that subsidies need to be more visible at the point of sale, not just available on paper. Some respondents in informal follow-up conversations mentioned that they were unsure whether they would actually get the promised state subsidy, which created hesitation.

The age effect is also worth thinking about. Younger consumers are clearly more open, possibly because they are more comfortable with new technology and also have a longer time horizon to recover the higher upfront cost through fuel savings. Older consumers, who often have more disposable income, are still cautious, partly because of resale value worries and partly because of habit. This means marketing campaigns might need different messages for different age groups, rather than a single one-size-fits-all approach.

One limitation of the study is that it focused only on metropolitan cities. Tier-2 and Tier-3 cities, where road conditions and electricity supply are different, may show very different patterns. Also, the cross-sectional design means we are capturing intention at one point in time, and intention does not always translate into actual purchase. Future studies could use a longitudinal design and include smaller cities to get a fuller picture.

7. CONCLUSION

This study set out to understand and predict consumer acceptance of electric vehicles in India, and the results give a fairly clear answer. The Indian urban consumer is not against EVs, but is also not yet fully ready to make the switch. The decision is shaped by a mix of practical, financial, and emotional factors, with perceived usefulness, charging infrastructure, and cost playing the biggest roles. The predictive model built in this study, with an accuracy of around 86% and an AUC of 0.91, shows that consumer behaviour in this space can be forecasted with a reasonable degree of confidence.

The contribution of this paper lies in moving beyond just listing factors and actually combining them into a working predictive framework that is tuned to the Indian context. For policymakers, the message is clear: subsidies alone will not do the job. What is needed is a combined effort that includes visible and reliable charging infrastructure, simpler subsidy disbursement, and awareness campaigns that focus on practical benefits rather than only environmental ones. For manufacturers, the takeaway is that the 25 to 40 age group with mid-to-high income is the sweet spot to target first, and product design should focus on reducing both real and perceived cost gaps.

In the bigger picture, India's shift to electric mobility will not happen in one big jump. It will happen slowly, neighbourhood by neighbourhood, as charging points become more visible, as early adopters share their experiences, and as the price gap narrows. This study provides a small but useful map of where to push next. Future research can build on this by tracking the same respondents over two or three years to see how intention turns, or does not turn, into actual purchase, and by extending the work to smaller cities where the next wave of growth is likely to come from.

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