



DETERMINANTS OF ELECTRIC VEHICLE ADOPTION: A CROSS-SECTIONAL ANALYSIS OF INDIAN STATES AND UNION TERRITORIES

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ABSTRACT

The transformation of modern transport system into electric vehicles (EVs) is one of the significant transitions of 21st century for developing countries such as India. Though the Government of India has promoted various policy programmes on EV adoption, there is an unequal implementation rate across state and UTs. This cross-sectional empirical research studies the factors responsible for such overdispersion. The dependent variable is the number of registered EVs in each state or union territory for the year of 2024, and the independent variables include EV charging stations otherwise called infrastructure, literacy, Per Capita Income, population and rate of growth of states averaging for five years. The study tests whether economic capacity and non-economic factors such as education and infrastructure significantly explain cross-state variation in EV counts. Although the analysis is theoretical, it outlines regression model specifications, hypotheses, and interpretive insights consistent with existing literature. The results are expected to indicate that both economic and infrastructural factors are key drivers of EV diffusion, while literacy and demographic factors serve as supporting enablers. The study contributes to the growing literature on EV adoption in emerging economies and provides policy insights for targeted interventions to promote sustainable mobility.



KEYWORDS: Electric Vehicles, India, Per Capita Income, EV Infrastructure, Cross-Sectional Analysis, Policy Determinants.

1. INTRODUCTION

The global movement towards electric transition is necessary for sustainable transportation with net zero carbon emission. Electric vehicles (EVs) prove to be a desirable alternative to conventional fossil fuel-engine vehicles which reduces greenhouse gas emissions and operational costs as well as increases energy efficiency (Jesifa, & Adam. (2025). The central governmental schemes like the Faster Adoption and Manufacturing of Hybrid and Electric Vehicles (FAME) scheme (Das, A., & Sharma, S. K. (2025), the PM Electric Drive Revolution in Innovative Vehicle Enhancement (PM E-DRIVE) scheme, the National Electric Mobility Mission Plan (NEMMP) and several state-level EV programmes have regarded EV adoption as an important drive in their initiatives. However, EV practice in India is highly unequal across states and union territories. States like Delhi, Maharashtra, Karnataka, and Rajasthan have higher adoption levels due to strong policy approach and infrastructural funding whereas several northern and northeastern states show lesser EV sales underlining inequalities in income, infrastructure, and policy programmes. This unequal distributional pattern leaves an important

question to answer: Which factors influence the changes in EV adoption across states and union territories in India? Speaking of literature, it puts emphasis on the purchasing power, EV infrastructure, education and demographic features (Kousar, M., Anjum, and Asifulla 2025). But there is lack of proper quantitative research which takes to account these influencers into an aggregated picture for India. (Ehsan, F., Habib, S., Gulzar, M. M., Guo, J., Muyeen, S. M., & Kamwa, I. 2024) have shown through a study in China that not only the attitude and subjective norms but also preferential policies can have lasting impact on adoption of EVs. In addition to it multi-sectoral partnership and service-oriented models can help in faster growth of EV business in a country as has been highlighted by (Ziegler, D., & Abdelkafi, N., 2022). To be a consumer driven market EV business models should follow consumers' awareness, communication and activity-based learning. Studies in developed countries such as (Sierzchula et al., 2014) have found how financial incentives as well as number of charging stations (NITI Aayog, 2022) play a big role in embracing clean energy transportation. However, in developing countries like India sufficient amount of public EV infrastructure such as charging stations can reduce range anxiety (Wolbertus et al., 2018) among consumers and help in creating preferential market situation for EVs. Moreover, Indian EV market is tilted towards higher and middle income groups due to operational cost efficiency in long run. Education and literacy can fill the gap by enhancing awareness of the consumer on technological innovation (Kumar et al., 2022). States with higher literacy rate are found to be fruitful for social awareness campaigns. Research in China and Norway (Hasan S et al., 2020; Hasan S. 2021) accept the fact of EV acceleration with better social acceptance and information diffusion. Though several studies are found at global level on this clean transport system few have oriented on regional differences in India. National level studies such as (S Iyer et al. 2025) highlight the adoption factors and cost perceptions of Indian consumers through artificial neural networks. In order to achieve global environmental goals like Paris agreement and Net Zero Carbon emissions by 2070 (Government of India, 2023) India requires a balanced transition of sustainable transport system across its regions. In India where policy variability is observed major states have regularised EV policies with consumer subsidies, tax exemptions, Infrastructural build up but others stay behind in these aspects. This study aims for fulfilling this gap by doing a cross-sectional study on Indian states and Union Territories (UTs) about the determinants affecting their EV adoption where it follows a holistic analytical approach to study the economic, demographic, social and policy-consistent variables that put effect on EV adoption. The results pave the way for policy driven understanding to build up balanced transition of EVs across regions in India.

2. THEORETICAL BACKGROUND

This study integrates the Technology Acceptance Model (TAM), Diffusion of Innovations (DOI), and Theory of Planned Behavior (TPB) to provide a comprehensive understanding of technology adoption. TAM explains that users' behavioral intention to use a system is determined by their attitude, shaped by perceived usefulness and perceived ease of use. DOI complements this by emphasizing how the characteristics of an innovation—relative advantage, compatibility, complexity, trialability, and observability—along with communication channels, time, and social context, influence its rate of adoption across different user groups. TPB adds a psychological dimension, proposing that attitude, subjective norm, and perceived behavioral control jointly determine behavioral intention and actual behavior. Together, these frameworks highlight that technology adoption is a multidimensional process shaped by personal beliefs, innovation attributes, and social influences that collectively drive users' intention and actual use.

3. RESEARCH OBJECTIVES

To measure the relationship between the number of registered EVs in the states and UTs in India in the year of 2024 and economic, demographic, and policy variables such as state gross domestic product per capita income (PCI), literacy rate, EV infrastructure, total population, and rate of growth have been taken as the predictors. The following objectives are set to be fulfilled through this study.

1. To estimate the impact of socio-economic variables such as per-capita income and literacy rate on EV adoption.
2. To test whether policy variables like EV infrastructure and rate of growth of states have an impact on EV adoption intensity.
3. To examine how the demographic feature (population) transits the scale of EV uptake.

4. HYPOTHESES

Overall Model Hypothesis

- **H₀ (overall):** The set of predictors (PCI, literacy, EV infrastructure, growth rate, population) has no significant effect on EV adoption.
- **H₁ (overall):** At least one of the independent variables has significant effect on EV counts across states.

Specific Hypotheses

- **H1:** Higher per capita income is positively related to EV adoption.
- **H2:** Literacy rate positively influences EV adoption.
- **H3:** EV infrastructure availability positively correlates with EV adoption.
- **H4:** Population contribute positively to EV adoption through demand concentration.
- **H5:** Rate of growth positively influences the EV adoption.
- **H6:** Population has significant interaction with infrastructure in EV adoption.

5. METHODOLOGY

5.1 Data sources and Research Design

This study employs a **quantitative cross-sectional research design**, analysing secondary data collected for EV registration from 31 Indian states and union territories for the latest available year (2024-25). Five number of states and UTs have been excluded for analysis subject to unavailability of data on the predictors taken in the study. The number of registered EV in the given year is dependent on those exogenous factors as mentioned below. The analysis is structured as an empirical investigation by utilizing negative binomial regression model (E. Kim, et al 2019) in SPSS software as the outcome variable is a count data and over dispersed in nature. There is large variation in EV acquisition among states and UTs owing to various factors some of which are encountered in the study to see their marginal impact. The variance and mean aren't equal in this case so induced to take negative binomial distribution. The predictor variables can be classified in to economic indicator (Per capita income), educational indicator (Literacy rate), policy indicator (EV infrastructure, average growth rate of five years) and demographic indicator (Population) for better interpretation and understanding. The study has collected secondary data from the following trusted sources:

Variable	Description	Source
Dependent Variable	Number of registered EVs (2024-25)	VAHAN Dashboard, Ministry of Road Transport and Highways
Per Capita Income (₹)	Economic indicator	Reserve Bank of India
Literacy Rate (%)	Educational attainment	Census of India
EV Infrastructure	Number of public charging stations-policy indicators	NITI Aayog
Population (millions)	Demographic size	Census of India

5.2 Model Specification

The model that explains the annual sales of EVs in India in the year of 2024 is as follows:

Base Model

$$EV_i = \beta_0 + \beta_1 Infrastructure_i + \beta_2 Literacy_i + \beta_3 PCI_i + \beta_4 Population_i + \beta_5 Growth_i + \beta_6 Pop_infra_i + U_i \dots (1)$$

Here $i=1,2,\dots,31$ denote the states and UTs in India for the year 2024

Log-link function

$$\ln(\mu_i) = \beta_0 + \beta_1 Infrastructure_i + \beta_2 Literacy_i + \beta_3 PCI_i + \beta_4 Population_i + \beta_5 Growth_i + \beta_6 Pop_infra_i + U_i \dots (2)$$

Here $\ln(\mu_i)$ is the natural logarithm of the expected count (μ) which is the mean of dependent variable EV sales and it is modelled as a linear combination of the predictors as explained above.

6. CONCEPTUAL FRAMEWORK

The conceptual model integrates economic, demographic, infrastructural and policy determinants to influence EV adoption in India. This framework suggests that population influences EV adoption both directly and indirectly through infrastructure availability, while literacy, rate of growth, and per capita income provide supporting contextual effects.

7. RESULTS

7.1 Descriptive Characteristics of the Variables

The study analyzed data from 31 Indian states and union territories in SPSS software for the year 2024. As it is shown in Table 1, the dependent variable, the number of registered electric vehicles (EVs), showed substantial variability, ranging from 21 to 465,432 vehicles ($M = 69,824.77$; $SD = 97,776.87$). This wide dispersion is characteristic of count data with overdispersion, supporting the appropriateness of a negative binomial regression model.

Table 1: Continuous Variable Information

		N	Minimum	Maximum	Mean	Std. Deviation
Dependent Variable	EVs	31	21	465432	69824.77	97776.868
Covariate	Infrastructure	31	4	5765	781.45	1223.854
	Literacy rate	31	63.8000	93.9000	77.716129	7.9514819
	Population	31	404	238078	43854.94	52556.163
	PCI	31	60.3400	587.7400	229.074839	119.7478222
	Growth	31	5.1400	13.3300	9.468387	1.8135768
	pop_infra	31	1616.00	474798080.00	65448099.2581	131273500.23005

The predictors also demonstrated considerable variability. Infrastructure, measured as the number of public charging stations, ranged from 4 to 5,765 ($M = 781.45$; $SD = 1,223.85$). Population varied greatly across states ($Min = 404$ thousand; $Max = 238,078$ thousand), with a mean of 43,854.94 thousand ($SD = 52,556.16$). Literacy rates were comparatively less varied, ranging from 63.8% to 93.9% ($M = 77.72\%$). Per capita income (PCI) showed a wide spread, ranging from ₹60,340 to ₹587,740 ($M = 229,074.84$; $SD = 119,747.82$). Economic growth ranged from 5.14% to 13.33% ($M = 9.47\%$). The constructed interaction variable, population $\times$ infrastructure (pop_infra), displayed a large spread, consistent with the interaction of two high-variance variables ($M = 65,448,099$; $SD = 131,273,500$).

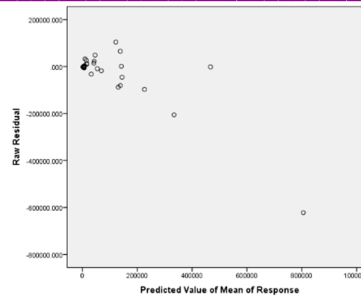


Figure 1: Negative binomial regression

Figure 1 presents the residual plot of the negative binomial regression model, in which raw residuals are plotted against the predicted mean EV counts. Most observations are clustered toward the lower end of the predicted values, reflecting the fact that the majority of Indian states have relatively modest EV adoption. For these states, residuals remain small and generally close to zero, suggesting that the model predicts their EV counts with reasonable accuracy. A few states with very high predicted EV values show larger positive or negative residuals, indicating greater discrepancies between observed and predicted counts. This pattern is expected given the highly skewed distribution of EV adoption, where a small number of states dominate the national total. Importantly, the residuals do not display any systematic shape or trend, suggesting no evidence of major model misspecification. Overall, the residual plot supports the appropriateness of the negative binomial model for handling overdispersion in EV adoption data across states.

7.2 Model Fit and Diagnostics

The goodness of fit of the data is shown in Table 2 below. The Pearson chi-square statistic divided by its degrees of freedom (Pearson/df = 1.194) was close to 1, indicating that the negative binomial specification successfully accounted for overdispersion in EV counts. The deviance statistic similarly indicated no evidence of poor fit (Deviance/df = 2.374). The model's log-likelihood value (-348.792) along with the Akaike Information Criterion (AIC = 711.585) suggested improved fit compared to simpler specifications without the interaction term.

Table 2: Goodness of Fit			
	Value	df	Value/df
Deviance	56.986	24	2.374
Scaled Deviance	56.986	24	
Pearson Chi-Square	28.667	24	1.194
Scaled Pearson Chi-Square	28.667	24	
Log Likelihood ^b	-348.792		
Akaike's Information Criterion (AIC)	711.585		
Finite Sample Corrected AIC (AICC)	716.454		
Bayesian Information Criterion (BIC)	721.622		
Consistent AIC (CAIC)	728.622		

The omnibus likelihood ratio test in Table 3 confirmed that the full model significantly improved over the intercept-only model, $\chi^2(6) = 55.948$, $p < .001$, indicating that the set of predictors collectively contributed to explaining variation in EV adoption across states.

Table 3: Omnibus Test

Likelihood Ratio Chi-Square	df	Sig.
55.948	6	.000

7.3 Tests of Model Effects

The Type III Wald chi-square tests identified several significant predictors. Population emerged as the strongest predictor, $\chi^2(1) = 16.141$, $p < .001$. Infrastructure also had a statistically significant effect, $\chi^2(1) = 7.256$, $p = .007$. The interaction term (population $\times$ infrastructure) was also significant, $\chi^2(1) = 8.571$, $p = .003$, indicating that the effect of infrastructure on EV adoption depends on population size.

Table 4: Tests of Model Effects

Source	Type III		
	Wald Chi-Square	df	Sig.
(Intercept)	2.976	1	.085
Infrastructure	7.256	1	.007
Literacyrate	.005	1	.945
Population	16.141	1	.000
PCI	1.397	1	.237
Growth	3.375	1	.066
pop_infra	8.571	1	.003

It is evident from Table 4 that other variables did not contribute significantly: literacy rate ($p = .945$), PCI ($p = .237$), and growth ($p = .066$) were all statistically non-significant. The growth rate approached significance level of 10% crossing the conventional $\alpha = .05$ threshold.

7.4 Parameter Estimates

Population had a positive coefficient ($B = 3.690 \times 10^{-5}$), with a 95% confidence interval fully above zero (1.890×10^{-5} to 5.490×10^{-5}), confirming its substantial and reliable positive effect on EV adoption. Infrastructure also exhibited a positive coefficient ($B = .001$), with a confidence interval between .000 and .002.

Table 5: Parameter Estimates

Parameter	B	Std. Error	95% Wald Confidence Interval		Hypothesis Test		
			Lower	Upper	Wald Chi-Square	df	Sig.
(Intercept)	5.201	3.0151	-.708	11.111	2.976	1	.085
Infrastructure	.001	.0005	.000	.002	7.256	1	.007
Literacyrate	.002	.0350	-.066	.071	.005	1	.945
Population	3.690E-005	9.1841E-006	1.890E-005	5.490E-005	16.141	1	.000
PCI	.003	.0029	-.002	.009	1.397	1	.237
Growth	.252	.1370	-.017	.520	3.375	1	.066
pop_infra	-1.364E-008	4.6600E-009	-2.278E-008	-4.509E-009	8.571	1	.003
(Scale)	1 ^a						
(Negative binomial)	1 ^a						

In Table 5 the interaction term showed a small but statistically significant negative coefficient ($B = -1.364 \times 10^{-8}$; $CI = -2.278 \times 10^{-8}$ to -4.509×10^{-9}), suggesting that the positive effect of infrastructure diminishes at very high levels of population. This indicates a moderating effect, where infrastructure alone cannot compensate for extremely high population pressures without proportional scaling.

PCI had a positive but non-significant coefficient ($B = .003$), while literacy rate ($B = .002$) and growth ($B = .252$) displayed wide confidence intervals including zero, indicating a lack of reliability in their effects.

The intercept ($B = 5.201$) was not statistically significant ($p = .085$), which is not unusual in multivariate count models where interpretation of the intercept is not central to theoretical understanding.

8. DISCUSSION

8.1 Overview of Main Findings

The results reveal a complex interplay of demographic, infrastructural, and economic factors shaping EV adoption across Indian states. The strongest and most consistent determinants in the model were population, infrastructure, and the interaction between them.

The positive and significant effect of population underscores the importance of market size in EV adoption. Larger states, characterized by dense urban settlements and greater mobility requirements, tend to have greater EV uptake. This finding aligns with macro-level mobility patterns in India, where populous states such as Maharashtra, Karnataka, Tamil Nadu, and Uttar Pradesh consistently account for a disproportionate share of national EV registrations.

Infrastructure also emerged as a significant predictor: states with more public charging stations tend to have higher EV adoption. This is consistent with existing literature emphasizing the role of charging infrastructure in alleviating range anxiety and supporting consumer confidence in EV usability.

The significant interaction effect adds an important nuance. While infrastructure contributes positively to EV adoption, its marginal effect decreases as population grows beyond a certain threshold. In very highly populated states, infrastructure must scale aggressively to keep pace with mobility demand. If infrastructure expands slowly relative to demand, its potential to stimulate EV adoption diminishes. This finding highlights the importance of proportional investment in infrastructure, particularly in megastates where small infrastructure gains are insufficient to create measurable behavioral change.

8.2 Non-Significant Predictors and Their Implications

The non-significance of literacy rate suggests that informational and cognitive factors may not currently be primary drivers of EV adoption in India. This finding challenges the common assumption that more educated populations adopt environmentally friendly technologies at higher rates. It appears that EV adoption at the state level is driven less by awareness or environmental consciousness and more by structural and economic conditions.

The insignificance of PCI is noteworthy. While household income is known to influence individual EV purchasing decisions, state-level per capita income did not independently predict EV adoption in this multivariate framework. This could be due to several reasons. First, PCI varies considerably across states, but EV adoption may be concentrated in wealthier urban pockets within states, making statewide averages a weak proxy for true affordability patterns. Second, generous subsidies offered under national and state EV policies may reduce the role of income in early adoption stages. Third, the inclusion of population and infrastructure in the model may overshadow PCI's independent effect, given their stronger explanatory power.

Economic growth, although approaching significance ($p = .066$), did not reach statistical reliability. The direction of its coefficient, however, suggests that economically dynamic states tend to show greater EV adoption. While not statistically definitive, this trend highlights the possibility that

growth may become more influential in later stages of EV market maturity, when industrial diversification and income gains become more evenly distributed.

8.3 Interpretation of Interaction Effects

The inclusion of the population $\times$ infrastructure interaction term provides valuable insight into contextual variations in EV adoption. The negative coefficient indicates that infrastructure's positive effect weakens in extremely high-population contexts. This finding helps explain why some highly populated states lag behind despite having charging infrastructure. Merely adding charging stations does not guarantee proportional increases in EV adoption when population density is extremely high.

This moderation effect may reflect constraints such as traffic congestion, limited land availability for infrastructure expansion, and uneven intrastate distribution of charging networks. The result emphasizes that infrastructure planning must consider both absolute numbers and ratios per capita or per square kilometer.

Theoretical Implications

The findings reinforce elements of diffusion theory, which suggests that early adoption of new technologies is driven by market size, accessibility, and infrastructural readiness rather than awareness or income alone. The strong effect of population supports the idea that network effects are critical—larger populations offer larger early-adopter bases, which accelerates diffusion.

The results also align with structural determinants emphasized in environmental economics. Infrastructure and population emerge as core structural variables shaping mobility choices. The limited role of literacy and PCI suggests that in early stages of EV diffusion, structural factors outweigh socio-psychological or economic capacity variables.

9. POLICY IMPLICATIONS

Several practical insights emerge from the results. First, the strong influence of population underscores the need for differentiated EV policies. Heavily populated states such as Uttar Pradesh, Maharashtra, and West Bengal require much more extensive charging networks than smaller states in order to create the same level of impact. National EV goals will be difficult to achieve unless infrastructure policies account for these differences in scale and demand.

Second, although infrastructure is often discussed in broad terms, this study shows that the distribution and density of charging stations matter significantly. Merely increasing the total number of chargers may not be sufficient if they are not proportionate to the size of the potential user base. Policies should therefore prioritize not only the quantity of infrastructure but also its strategic placement in areas of high mobility, such as urban corridors, state highways, commercial zones, and industrial clusters.

Third, the lack of significance for literacy rate and per capita income suggests that awareness campaigns and income-based incentives alone cannot drive adoption. Instead, stronger emphasis is needed on the structural aspects of EV readiness—such as electricity network reliability, integration of renewable energy, and simplifying permissions for installing public and private chargers. Incentives will continue to play a role, but without accessible charging opportunities, their impact will remain limited.

Fourth, although economic growth was not a statistically significant predictor in the model, the general direction of its effect indicates that economically dynamic states may gradually become hubs for EV uptake. States seeking to promote both industrial development and sustainable mobility may benefit from encouraging EV-related industries, including battery production, component manufacturing, recycling units, and EV servicing infrastructure.

In essence, policymakers need to view EV adoption as part of a broader mobility and infrastructure ecosystem. Coordinated strategies that involve urban planning, power distribution companies, highway authorities, and local bodies will be essential for creating an environment where EVs become a practical and attractive choice for large numbers of people.

10. LIMITATIONS

Several limitations should be considered when interpreting the findings. The analysis relied on state-level data, which may mask internal variations within states. For example, a state with low overall EV adoption might still contain a few cities with relatively high uptake. A more detailed district-level or city-level analysis would capture these nuances more clearly.

The study also did not include state-specific EV policies, such as subsidies, road tax exemptions, parking incentives, or scrappage benefits, largely because such data vary widely in structure and availability. These policies may influence adoption but were not directly assessed here.

Additionally, the interaction between population and infrastructure was modelled linearly. In reality, the relationship may not be strictly linear. Highly dense states may experience diminishing returns on infrastructure investments due to congestion, space constraints, or uneven distribution of charging points. Future research could explore nonlinear models or spatial analyses to capture these complexities.

Another limitation of the study is its cross-sectional nature. EV adoption is an evolving process influenced by technological changes, policy shifts, and consumer preferences over time. Because this study captures only one year, it cannot trace how earlier policies or market conditions may have shaped current adoption patterns. Longitudinal data would allow for stronger conclusions about causality.

Finally, although the negative binomial model accounts for overdispersion, EV adoption may also be influenced by factors not included in the dataset, such as consumer perceptions of EV performance, availability of affordable models, or local environmental concerns. Including such variables in future studies could provide a more detailed picture of the adoption process.

CONCLUSION

The analysis shows that differences in EV adoption across Indian states are shaped primarily by population size and the availability of charging infrastructure, with infrastructure becoming less effective when population levels are extremely high. Socioeconomic variables such as literacy, income, and growth did not independently predict adoption once structural factors were considered. These findings suggest that India's EV transition is driven more by demographic scale and infrastructural readiness than by individual-level characteristics. Strengthening and strategically expanding charging networks, particularly in high-population states, will be essential for sustaining future growth in EV adoption. Future researchers should expand the scope of analysis by including policy variables, spatial factors, and multi-year data. This would make it possible to understand not only the structural determinants of adoption but also the temporal evolution of the EV market and the real-world effects of government interventions.

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