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Perceived Value and Customer Adoption of Electric Vehicles in India: The Moderating Role of Government Policies and Employment Status

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Abstract

The study investigates India's perceived value and consumer adoption of electric cars (EVs) based on employment status and government policies. It uses a quantitative survey-based methodology to gather data on 386 respondents. The research reveals that social value is the most significant motivator for EV adoption in India, with policies like infrastructure expansion and financial incentives moderated by these factors. However, the study has limitations, including a cross-sectional design, a short data collection period, and specific demographics. The practical implications suggest that politicians, business leaders and scholars should focus on enhancing social standing and perception of EV ownership through improved charging infrastructure, financial incentives and environmental awareness advertising. The study also suggests manufacturers should appeal to consumers' social and functional value judegments, while policymakers should create incentives.

Keywords: Electric Vehicle, Perceived Value, Government Policies, Employment Status

Introduction

According to the IPCC, greenhouse gas emissions should be cut by 50% by 2030 to prevent the temperature from rising to 1.5°C. This calls for swift action to shift to climate-resilient development and increase ambition in order to prevent catastrophic outcomes and guarantee a sustainable future for coming generations (UN DESA, 2023). India, the second most populous country, faces air pollution and traffic congestion due to its growing road and rail networks, despite aiming to produce no emissions at all by 2070 (Riehle et al., 2023). Factors that influence the universal adoption of electric vehicles (EVs), like customer value, policy role and potential purchaser employment status, as the global EV market is rapidly expanding (Industryindia, 2019). In 2023, electric car sales climbed by 35%, accounting for 18% of all cars sold, a sixfold increase over 2018. However, sales are concentrated in important markets, with China, Europe and the United States accounting for more than 95% of global sales (Agency, 2024). India had a 70% growth in electric car registrations, totalling 80,000, compared to less than 10% in total vehicle sales. India, various variables impact the adoption of EVs, including market dynamics, customer views and government regulations and infrastructure advancements (Bhattacharyya & Thakre, 2020; Singh et al., 2020). Promoting EVs' broad acceptance and sustainable future in the transportation industry requires an understanding of how Indian customers perceive EVs. Economic viability is assessed by fuel savings, recurring costs and startup costs, while environmental appeal is emphasised (Verma et al., 2020). The purpose of this study is to examine how Indian consumers view the benefits of EVs and their adoption, with an emphasis on how employment status and government policies can contribute as moderators. The factors influencing the adoption of EV models have been the subject of several consumer behaviour research studies.

Research indicates that various factors influence the adoption of EVs, including perceived performance, infrastructure availability and financial considerations (Coffman et al., 2017; Rezvani et al., 2015; Thananusak et al., 2017). A study conducted in Thailand revealed that factors such as "performance expectancy, effort expectancy, social influence, hedonic motivation and environmental concern" significantly influence

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consumers' intentions to purchase EVs (Manutworakit & Choocharukul, 2022). Furthermore, there has been much discussion in the literature regarding the efficacy of efforts by the government like tax rebates, subsidies and charging infrastructure (Goel et al., 2021; Zhang et al., 2013; Schuitema et al., 2013). According to the study, two additional benefits of owning and using an electric car are emotionally driven features, or the pleasant experience of driving one and symbolical attributes, or the identity that comes with doing so. These associations make instrumental attributes significant. Existing studies are there that are already working on the perceived value of consumers (Higueras-Castillo et al., 2019). By investigating the moderating impact of work position on consumer opinions and adoption intention of EVs in the Indian EV industry, this research article seeks to close a knowledge gap. It aims to offer insightful information to scholars, industry experts and policymakers in the field of sustainable transportation.

A concise overview of the study model, hypotheses, sample characteristics, data collection and analytic technique is included in the article. In addition, it summarises the data, presents the analysis's findings and proposes recommendations for more research and the formulation of policies.

Literature Review

India is grappling with environmental and energy issues due to the gradual expansion of energy demand and consumption due to population growth and industrialisation (Singh et al., 2020). To enhance energy efficiency and meet the demand for eco-friendly vehicles, researchers must prioritise the shift from diesel and gasoline cars to EVs. This transition is vital, leading to a heightened interest in EV technologies and experiences (Secinaro et al., 2022). This analysis examines how EVs become prevalent in India, a populous nation with environmental issues. It emphasises how perceived value, government policies and socio-demographic characteristics affect EV adoption.

Perceived Value and Customer Adoption of EVs

A consumer's evaluation of a good or service based on what is provided and received is known as perceived value. It contrasts the "give" and "get" elements and is essential to the gradual adoption of new technology, such as EVs. Essentially, it shows how customers estimate a product's usefulness about its value for money (Zeithaml, 1988). The four dimensional scale developed by (Sweeney & Soutar, 2001) is called PERVAL (perceived value scale), which consists of four components of value—emotional, social, performance/quality and price/value for money—significantly account for attitudes and actions in situations before making a purchase. The proposed conceptual framework is shown in Fig. 1.

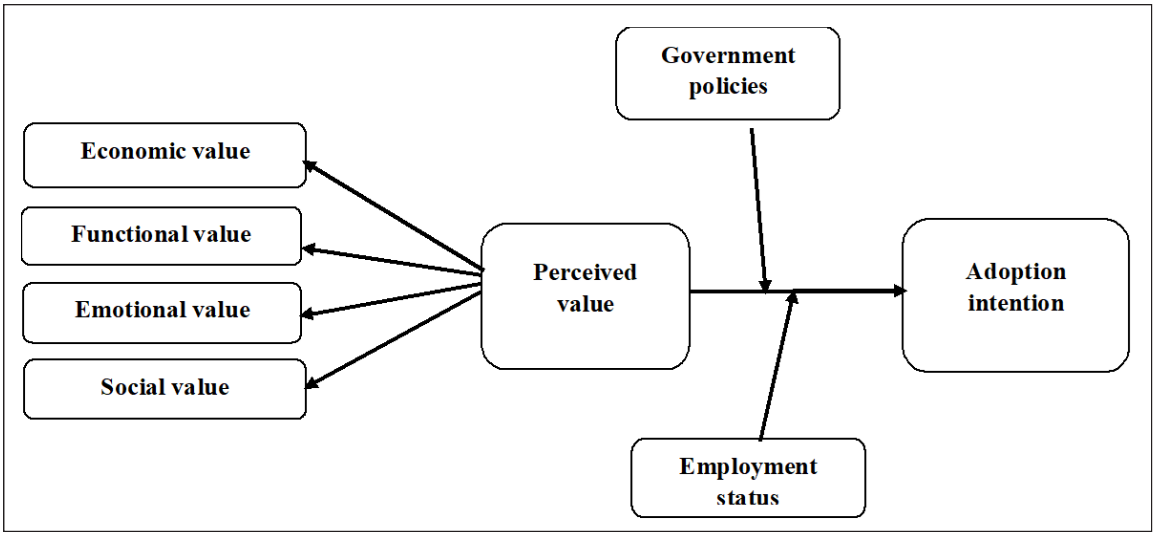

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Fig. 1

Economic Value

The cost savings from fuel, maintenance and potential government incentives significantly contribute to the perceived economic value of EVs (Wang et al., 2021). India's high fuel prices can motivate EV adoption due to economic benefits such as reduced operational costs, eco-friendly business models, tax incentives, lower business process costs and sustainable development contributions (Kim et al., 2018). Factors such as environmental responsibility, policy incentives, perceived value and purchasing intention positively influence the adoption of EVs among consumers, especially in regions facing energy price increases (Wang et al., 2017). Government incentive programs encourage the growing popularity of EVs in India, but one significant hurdle is still the absence of public charging stations (Verma et al., 2020). The study also emphasises the significance of cost-effectiveness and financial incentives in promoting the adoption of electric two-wheelers in India, pointing out that elements like price value and government assistance have a major impact on adoption intention and behaviour (Shetty & Rizwana, 2024).

H1: Economic value has a favourable impact on the adoption intention of electric passenger cars.

Functional Value

The perceived dependability and performance of EVs are referred to as their functional value. The functional significance of EVs has increased due to developments in battery technology, driving range and charging infrastructure, which has increased popularity among customers (Rezvani et al., 2015). Functional value, specifically quality, significantly influences consumers' willingness to adopt EVs, leading to increased purchase intention and favourable views on plug-in hybrids and hybrid electric cars, according to research (Zamil et al., 2023). Additionally, consumers' perceptions of the practicality of electric automobiles have a big impact on their desire to adopt green technology, highlighting the importance of functional aspects in the decision-making process (Yadav, 2024; Li et al., 2023). Research emphasises the significance of quality and functionality in promoting EV adoption, as customer interactions with their environment and salespeople significantly influence purchasing intentions.

H2: Functional value has a favourable impact on the adoption intention of electric passenger cars.

Emotional Value

Emotional value is derived from the feelings and emotions associated with using a product. For EVs, this can include the satisfaction of contributing to environmental sustainability and the prestige associated with owning advanced technology (Noppers et al., 2015). Emotional values significantly influence consumer adoption behaviour towards EVs. According to research, attitudes and buying intentions around EV adoption are strongly influenced by emotions (He & Hu, 2022). Consumer purchase intentions are impacted by both positive and negative predicted emotions (PAEs and NAEs) about EVs, with PAEs having a stronger effect on high-income customers and NAEs on low-income consumers (He et al., 2023). Additionally, interactions between sellers and customers, such as environment-customer and salesman-customer interactions, positively affect emotional experience values and ultimately influence purchasing intentions (Li et al., 2023). For marketers and legislators to create tactics that effectively encourage consumer acceptance of electric cars, they must comprehend and capitalise on these emotional values.

H3: Emotional value has a favourable impact on the adoption intention of electric passenger cars.

Social Value

Social value pertains to the perceived social implications of using a product. EVs can enhance the social image of consumers as environmentally conscious and technologically savvy individuals (Barbarossa et al., 2015). Research indicates that social factors, such as social media relevance, social influence (Axsen et al., 2013; Kim & Park, 2011) and social visibility, can impact consumer purchase intentions towards EVs. Studies have shown that social interactions and early adopters influence consumers' attitudes towards EV adoption (Chen et al., 2020), highlighting the importance of social dynamics in shaping consumer behaviour. Additionally, the perceived social value of EVs, including their environmental benefits and contribution to sustainable mobility solutions, might influence customers' intentions for purchasing (Ramesan et al., 2022), Understanding and leveraging social values are crucial for stakeholders in the EV ecosystem to develop effective strategies that promote the adoption of EVs among consumers.

H4: Social value has a favourable impact on the adoption intention of electric passenger cars.

Government Policies as Moderators

Government policies impact perceived value and adoption intentions. Favourable policies, like subsidies, lower costs and risks, while unclear policies complicate compliance. India's FAME scheme encourages EV adoption through charging infrastructure investment and network development (Li et al., 2017). Stricter emission norms and EV adoption mandates can boost consumer preference by enhancing the perceived social and emotional value of environmental compliance (He et al., 2020).

H5: Government policies moderate the relationship between perceived value (functional, economic, emotional and social) and adoption intention of electric passenger cars.

Employment Status as a Moderator

Employment status, often linked to income, significantly influences the perceived value and adoption of EVs, with higher-income individuals being better positioned to afford and appreciate their economic benefits (Carley et al., 2013). Employed individuals, particularly those in professional and technical fields, may have higher levels of awareness and knowledge about EV technology and its benefits, enhancing their perceived value (Jansson et al., 2017). Employment status can also influence access to necessary infrastructure, such as private parking with charging facilities, which is more common among higher-income households (Morton et al., 2018).

H6: Employment status moderates the relationship between perceived value (functional, economic, emotional and social) and adoption intention of electric passenger cars.

Data

Measures

Every variable measure included in the theoretical model was taken from a previous research study. A scale was used by (Walsh et al., 2014) to evaluate the PERVAL aspects, which include quality, emotional, price and social values. Employment status and government policies were measured using a scale by many researchers, as shown in Table 1.

Table 1: Summarises the Questions Used to Assess the Model's Variables

Variables	Items	Source
Functional Value	EV is well-made and remains of superior quality. EVs could operate smoothly.	
Emotional Value	EV is one that I would enjoy and would make me want to use it. EV is one that I would feel relaxed about using. EV would make me feel good and would give me pleasure.	(Walsh et al., 2014)
Economic Value	EV is reasonably priced and offers value for money	
Social Value	EV could have a positive impact on others. EV would make me feel accepted by society.	
Government Policies	Government incentives (e.g., subsidies, and tax rebates) influence my decision to purchase an EV. Government policies on EV infrastructure (e.g., charging stations) are sufficient. I am aware of the government policies promoting EV adoption. Government campaigns effectively raise awareness about the benefits of EVs. I trust the government's commitment to promoting EVs.	(Egbue et al., 2017; Hackbarth & Madlener, 2013; Jansson et al., 2017; Rezvani et al., 2015)

Variables	Items	Source
Employment Status	My employment status influences my ability to afford an EV. My job stability affects my willingness to invest in an EV. Employer-provided incentives (e.g., charging facilities at work) would encourage me to buy an EV. I believe that my work commute distance is suitable for using an EV. My employment status provides me with sufficient knowledge and resources to consider purchasing an EV.	(Bednarz et al., 2023; Bunce et al., 2014; Carley et al., 2013; Jaiswal et al., 2022; Rezvani et al., 2015; Sovacool et al., 2018)
Adoption Intention	I am likely to purchase an EV in the next five years. I have a positive attitude towards using EVs. I believe that EVs are the future of transportation. I am willing to recommend EVs to others.	(Rezvani et al., 2015) (Carley et al., 2013)

Data Collection and Sample

Part 1 of the questionnaire gathered the socio-demographic characteristics of the respondents through five questions: age, gender, employment status, education level and monthly income.

The study analysed the adoption of electric cars in India and their perceived value, focusing on the moderating effects of employment status and government policy. The data was collected from 61.1% of participants aged 26–35, with the majority of males (61.1%). Most respondents held postgraduate degrees, while 67.1% were full-time employees. The largest income group (28.2%) earned between 40,000 and 60,000 per month. The study used an online survey to collect demographic information and examine how perceived value affects adoption intentions in social, functional, emotional and economic aspects. A convenience sampling technique was used to ensure demographic representation in terms of age, income, education and employment status. The sample, a subset of the population, is crucial for accurate data collection. This study examines the adoption of EVs among Indian customers. The optimal sample size was determined using power analysis with G*Power, a well-known tool in behavioural and social sciences (Erdfelder et al., 2009). Effect size is 0.05, (1-β) is 0.98, confidence level is 95% and margin of error is 5% as shown in the image.

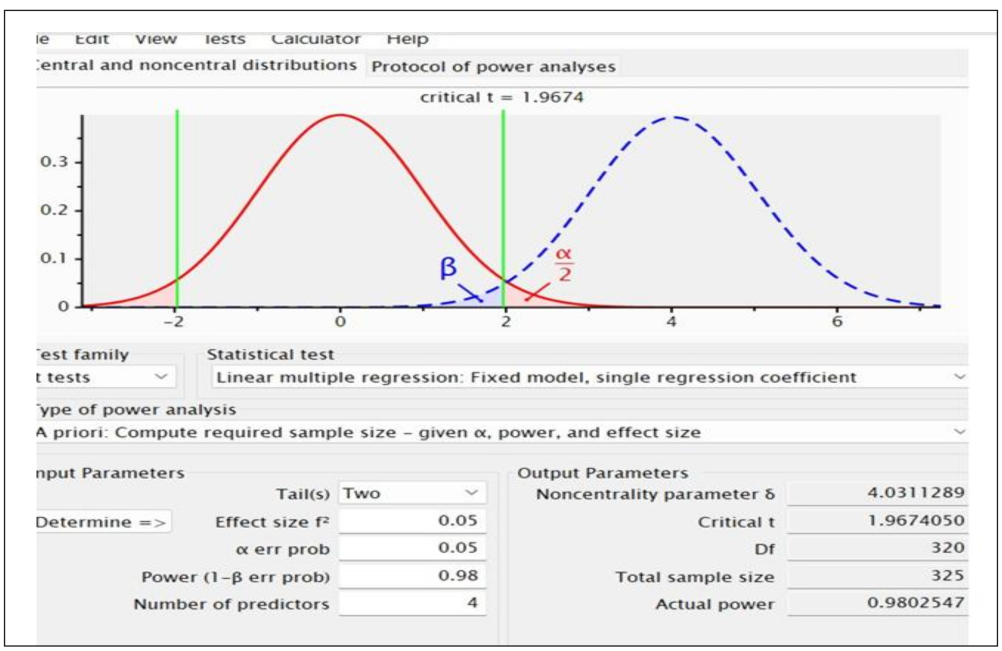

Fig. 2

Table 2: Demographics of the Study (n=386)

Variable	Category	Frequency	Percentage
Age	18-25	35	9.1
	26-35	236	61.1
	36-45	99	25.6
	46-55	16	4.1
Variable	**Category**	**Frequency**	**Percentage**
Gender	Male	236	61.1
	Female	150	38.9
Educational Level	Highschool	3	0.8
	Graduate	97	25.1
	Postgraduate	258	66.8
	Doctorate	23	6
	Others	5	1.3
Employment Status	Employed (full-time)	259	67.1
	Employed (part-time)	22	5.7
	Self-employed	62	16.1
	Student	37	9.6
	Retired	1	0.3
	Others	5	1.3
Monthly Income	Below 20,000	40	10.4
	20,000 to 40,000	88	22.8
	40,000 to 60,000	101	28.2
	60,000 to 80,000	79	20.5
	80,000 to 1,00,000	41	10.6
	Above 1,00,000	29	7.5

Table 3: Descriptives

	N	Mean	SE	Median	SD	Variance
FV	386	7.46	0.0809	8.00	1.59	2.52
EV	386	11.27	0.1289	12.00	2.53	6.42
EcV	386	3.60	0.0523	4.00	1.03	1.06
SV	386	7.51	0.0863	8.00	1.70	2.87
ADT	386	15.59	0.1807	17.00	3.55	12.60
GP	386	17.98	0.2080	19.00	4.09	16.70
ES	386	18.44	0.1969	20.00	3.87	14.97

(FV: Functional Value, EV: Emotional Value, EcV: Economic Value, SV: Social Value ADT: Adoption intention, GP: government policies, ES: employment status).

The table shows that the mean and median scores for FV and SV are almost 8, suggesting that respondents had similar perceptions of these elements. ADT generally shows high levels of technology adoption, with a higher mean (15.59) and median (17). GP and ES also have reasonably high values of 17.98 and 18.44, indicating favourable attitudes in these areas. EcV has the lowest variation, with a mean of 3.60 and a median of 4.00, suggesting a more limited range of scores and an overall impression of lesser economic value among participants.

Common Method Variance

The first factor in Harman's Single Factor Test represents 44.00% of the variance, which means that although it reflects a significant amount of the variance, it does not dominate it to the degree that common method bias would predict (which is often indicated by a single factor explaining more than 50% of the variance) (Podsakoff et al., 2003). As a result, even if the variance included in this analysis has considerable overlap, the lack of a single component that dominates indicates that common technique bias is probably not an issue.

Confirmatory Factor Analysis

Confirmatory factor analysis was performed to validate the perceived value constructs—Functional, Emotional, Economic and Social Values—and their impact on Adoption Intention (ADT).

PFV1 was identified as a strong indicator of Perceived Functional Value, closely representing the functional aspects of EVs. PEV1 and PEV2 effectively reflect Perceived Emotional Value, showcasing the pride and satisfaction associated with ownership. PEcV1 serves as the sole indicator of Perceived Economic Value, with a perfect standardised loading of 1.000. PSV1 and PSV2 strongly represent Perceived Social Value, capturing the social influence and societal impact of ownership. ADT1-ADT4 also exhibited strong loadings, indicating robust measurement of adoption intention.

GP1 is the strongest indicator of the government's influence on adoption intention (0.908), while ES1, ES2, ES3 and ES5 indicate that employment conditions moderately affect EV adoption. All factor loadings are significant ($p < 0.001$), reinforcing the measurement model's validity. Most standardised estimates exceed 0.80, showing strong relationships between observed variables and latent constructs.

The covariances indicate the relationships among latent variables, with a strong positive connection between functional value and emotional value and moderate relationships with economic and social values. Overall, the relationship between functional value and emotional value is the most significant.

Table 4: Confirmatory Factor Analysis (CFA) Results for the Measurement Model

Factor	Indicator	Factor Loadings	CR	AVE	Cronbach's Alpha
PFV	PFV1	0.85	0.82	0.69	0.81
	PFV2	0.81			
PEV	PEV1	0.86	0.89	0.72	0.88
	PEV2	0.84			
	PEV3	0.86			
PEcV	PEcV1	1.00	1.00	1.00	-
PSV	PSV1	0.77	0.80	0.66	0.79
	PSV2	0.86			
ADT	ADT1	0.81	0.90	0.70	0.90
	ADT2	0.84			
	ADT3	0.83			
	ADT4	0.87			
GP	GP1	0.73	0.90	0.63	0.88
	GP2	0.66			
	GP3	0.79			
	GP4	0.84			
	GP5	0.91			
ES	ES1	0.79	0.87	0.57	0.87
	ES2	0.75			
	ES3	0.80			
	ES4	0.69			
	ES5	0.79			

This table presents the results of factor loadings, Composite Reliability (CR), Average Variance Extracted (AVE) and Cronbach's alpha for various latent constructs (PFV, PEV, PEcV, PSV, ADT, GP and ES).

Two indicators (PFV1 and PFV2) for the PFV construct have high factor loadings of 0.85 and 0.81, respectively. They also show strong internal consistency, as indicated by their CR of 0.82, AVE of 0.69 and Cronbach's alpha of 0.81. The three indicators of PEV (PEV1, PEV2 and PEV3) have factor loadings that range from 0.84 to 0.86. High reliability and convergent validity are shown by Cronbach's alpha of 0.88, AVE of 0.73 and CR of 0.89. Internal consistency measures are not required since PEcV only has one indicator (PEcV1), resulting in a CR, AVE and factor loading of 1.00. The two indicators (PSV1 and PSV2) for PSV have loadings of 0.77 and 0.86, Cronbach's alpha is 0.79, AVE is 0.67 and CR is 0.80. Four indicators (ADT1–ADT4) are used to quantify ADT; they show factor loadings ranging from 0.81 to 0.87, a Cronbach's alpha of 0.90, an AVE of 0.70 and a CR of 0.90, all of which indicate good reliability. Five indicators in GP have factor loadings ranging from 0.66 to 0.91. Cronbach's alpha is 0.88, AVE is 0.63 and CR is 0.90. Finally, the five indicators that make up ES have factor loadings ranging from 0.69 - 0.80, resulting in a Cronbach's alpha of 0.87, AVE of 0.58 and CR of 0.87, all of which show strong internal consistency. In conclusion, all of the constructs in the table exhibit sufficient to exceptional levels of validity and reliability, with AVE values showing convergent validity (above 0.50 for the majority of the constructs) and CR values above the suggested 0.70 criterion.

Table 5: Correlation Matrix

		PFV		PEV		PEcV		PSV		ADT		GP		ES	
PFV	Pearson's r	—													
	Df	—													
	p-value	—													
PEV	Pearson's r	0.777	***	—											
	Df	384		—											
	p-value	<.001		—											
PEcV	Pearson's r	0.600	***	0.665	***	—									
	Df	384		384		—									
	p-value	<.001		<.001		—									
PSV	Pearson's r	0.675	***	0.757	***	0.676	***	—							
	Df	384		384		384		—							
	p-value	<.001		<.001		<.001		—							
ADT	Pearson's r	0.687	***	0.730	***	0.649	***	0.716	***	—					
	Df	384		384		384		384		—					
	p-value	<.001		<.001		<.001		<.001		—					
GP	Pearson's r	0.626	***	0.622	***	0.583	***	0.641	***	0.642	***	—			
	Df	384		384		384		384		384		—			
	p-value	<.001		<.001		<.001		<.001		<.001		—			
ES	Pearson's r	0.608	***	0.611	***	0.577	***	0.615	***	0.636	***	0.739	***	—	
	Df	384		384		384		384		384		384		—	
	p-value	<.001		<.001		<.001		<.001		<.001		<.001		—	

Note. H_a is positive correlation.

Note. * $p < .05$, ** $p < .01$, *** $p < .001$, one-tailed.

Discriminant Validity

By comparing each construct's AVE with its squared correlations with other constructs, discriminant validity is evaluated. The AVE of a factor must be greater than these squared correlations to prove discriminant validity. The squared correlations are obtained from the correlations between constructs, whereas the AVE is computed by averaging the squared factor loadings. For instance, if the AVE for a factor such as PFV is 0.6893 and its correlation with PEV is 0.777 (which squares to approximately 0.6045), PFV demonstrates discriminant validity since its AVE exceeds the squared correlation. This method is applied to each construct, ensuring that all show higher AVE than their respective squared correlations, confirming that they are distinct and measuring different aspects without overlap.

To evaluate discriminant validity using the data provided, we can apply the (Fornell & Larcker, 1981) criterion. It asserts that each construct's AVE ought to be higher than the squared correlations between it and each subsequent component.

Table 6: Discriminant Validity Table Based on Fornell-Larcker Criterion

Factor	AVE	Squared Correlation With Other Factors	Conclusion
PFV	0.69	PEV: 0.6045, PEcV: 0.3600, PSV: 0.4556, ADT: 0.4717, GP: 0.3919, ES: 0.3696	**Yes** – All AVE > squared correlations
PEV	0.72	PFV: 0.6045, PEcV: 0.3600, PSV: 0.4556, ADT: 0.4717, GP: 0.3919, ES: 0.3696	**Yes** – All AVE > squared correlations
PEcV	1.00	PFV: 0.3600, PEV: 0.3600, PSV: 0.4556, ADT: 0.4717, GP: 0.3919, ES: 0.3696	**Yes** – AVE is highest for this construct
PSV	0.66	PFV: 0.4556, PEV: 0.4556, PEcV: 0.4556, ADT: 0.4717, GP: 0.3919, ES: 0.3696	**Yes** – All AVE > squared correlations
ADT	0.70	PFV: 0.4717, PEV: 0.4717, PEcV: 0.4717, PSV: 0.4717, GP: 0.3919, ES: 0.3696	**Yes** – All AVE > squared correlations
GP	0.63	PFV: 0.3919, PEV: 0.3919, PEcV: 0.3919, PSV: 0.3919, ADT: 0.3919, ES: 0.3696	**Yes** – All AVE > squared correlation
ES	0.57	PFV: 0.3696, PEV: 0.3696, PEcV: 0.3696, PSV: 0.3696, ADT: 0.3696, GP: 0.3696	**Yes** – All AVE > squared correlations

The AVE values for each construct are greater than their respective squared correlations with other constructs, indicating discriminant validity according to the Fornell-Larcker criterion. Each construct demonstrates adequate separation from others in the model.

Structural Equation Modelling

Based on 386 data and 45 free parameters, the study's statistical model was estimated using Maximum Likelihood techniques and the NLMINB optimisation methodology. After 53 iterations, the model has effectively converged, and standard errors are presented as standard without any scaling modifications. The model looks at several relationships: PFV1 and PFV2 represent the latent variable PFV; PEV1, PEV2 and PEV3 indicate PEV; PEcV1 indicates PEcV; PSV1 and PSV2 indicate PSV; and ADT1 through ADT4 indicate ADT. Furthermore, the latent variables PFV, PEV, PEcV and PSV are regressed on ADT, indicating an exploratory framework in which the latent constructions impact the ADT results. After 53 iterations, the model shows substantial convergence, and a significant Chi-square value of 161 ($p < .001$) indicates that it fits the baseline model well (3636, $p < .001$). With a Goodness of Fit Index of 0.987, Tucker-Lewis Index of 0.952 and Comparative Fit Index of 0.967, key fit indices perform well and indicate a sufficient fit to the data. ADT was impacted by PFV, PEV, PEcV and PSV, according to the model's estimation of the links between latent variables. PEV and PEcV did not exhibit significant impacts, while PFV and PEV had path coefficients of 0.3234 ($p = 0.042$) and 0.5652 ($p = 0.003$), respectively. Estimates from measurement models show significant factor loadings, especially for PSV2 (1.189, $p < .001$) and

PFV2 (0.936, p < .001). Each observed variable's variance is presented, and its reliability is confirmed by significant values and confidence ranges. With Cronbach's alpha and omega values for the majority of the constructs over 0.8, the model as a whole exhibits strong internal consistency and dependability. Furthermore, Mardia's coefficients show notable kurtosis and skewness, suggesting that the data distribution may not be normal.

Path Analysis

The model uses maximum likelihood estimation to analyse the impact of various predictors on the dependent variable ADT. It was successfully estimated using 386 observations and includes eight free parameters. The model is flexible and matches observed data.

Table 7: Path Analysis Results

Hypothesis	Predictor	Estimate	SE	β	z	p-value	Conclusion
H1	PEcV	0.457	0.166	0.132	2.758	0.006	Supported
H2	PFV	0.357	0.119	0.159	2.988	0.003	Supported
H3	PEV	0.270	0.086	0.193	3.118	0.002	Supported
H4	PSV	0.455	0.116	0.217	3.928	<.001	Supported
H5	PVGP	0.001	0.001	0.053	0.688	0.492	Not supported
H6	PVES	0.002	0.001	0.140	1.748	0.081	Not supported

By assessing the assumptions about predictors' influence on ADT, this table provides a summary of the path analysis results: Supported Hypotheses (Significant Predictors): ADT is strongly predicted ($p < 0.05$) by FV (H1), EV (H2), SV (H3) and EcV (H4), all of which have positive estimates. The strength of each predictor's link with ADT is shown by their standardised coefficients (β), with SV having the largest correlation (β = 0.2176). Not Supported Hypotheses (Non-Significant Predictors): According to their respective p-values of 0.492 and 0.081, PVGP (H5) and PVES (H6) did not substantially predict ADT. This implies that ADT in this model is not much impacted by changes in PVGP and PVE.

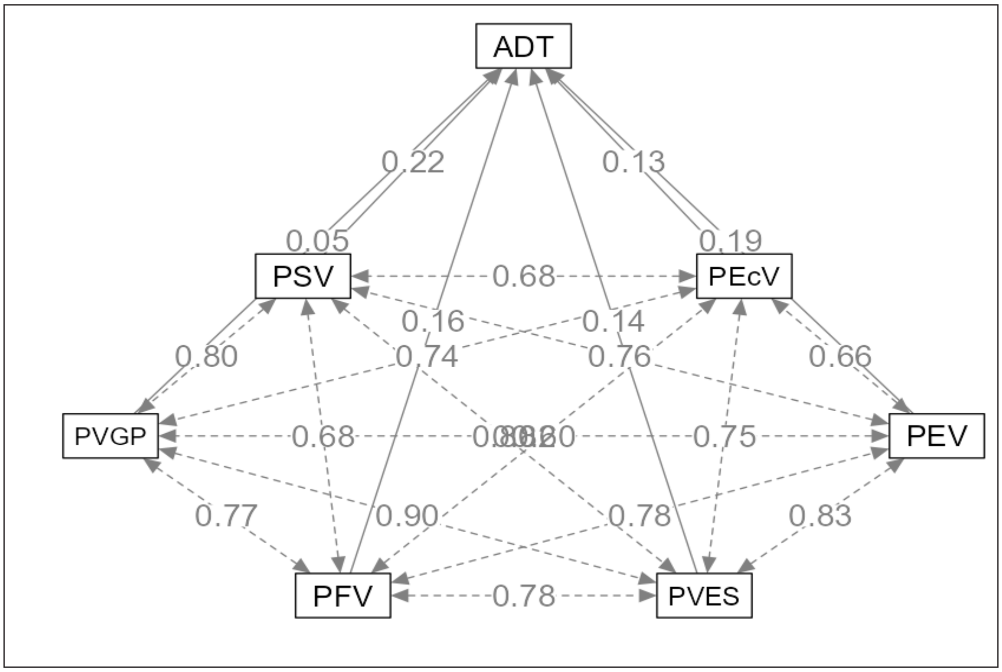

Fig. 3: Path Model

Moderation Analysis

The moderation study looks at how the predictor variable (PV) affects the dependent variable (ADT) at various moderator variable (GP) levels. It is evident that GP moderates the association between PV and ADT since the interaction term (PV * GP) has a substantial negative effect (Estimate = −0.0163, SE = 0.00326, Z = −5.02, $p < .001$) as it reduces as GP increases. The simple slope analysis demonstrates how the effect of PV on ADT varies with the extent of government policy support. When government policy support is weak (1 standard deviation below the average, or −1 SD), PV has a greater effect on ADT (Estimate = 0.401, $p < .001$). This means that in the absence of significant government support, people rely more largely on their assessment of the value of a product or service to decide whether to use it. When government policy support is high (1 SD above average), PV's effect on ADT declines (Estimate = 0.268, $p < .001$). In this instance, the presence of strong government policies diminishes the role of perceived value in motivating adoption intentions, most likely because government incentives or support make adoption easier or more appealing independent of individual value assessments. At the average level of government policies, the effect of PV on ADT is still substantial but rests between these extremes (Estimate = 0.335, $p <.001$), indicating that the link between PV and ADT minimises as government policy support rises.

With employment status (ES) serving as a moderator, this analysis uses a moderation model to examine the relationship between a predictor variable PV and a ADT. The moderation estimates show that PV has an effect on ADT, with a direct effect estimate of 0.354, which is statistically significant ($p < .001$), suggesting a positive relationship between PV and ADT; ES also significantly predicts ADT (estimate = 0.1218, $p < .001$); and the interaction between PV and ES (PV * ES) is negative and significant (estimate = -0.0131, $p < .001$), suggesting that the relationship between PV and ADT weakens as ES increases. The effect of PV on ADT demonstrates a stronger slope for individuals with low ES (-1 SD; estimate = 0.405, $p < .001$) and a weaker slope for those with high ES (+1 SD; estimate = 0.303, $p < .001$) in the simple slope analysis. This indicates that the interaction's negative coefficient correlates with a stronger positive effect of PV on ADT when ES is lower.

Findings

The study reveals that social and functional values significantly influence EV adoption in India, with government initiatives like tax breaks and subsidies playing a significant role. Employment position moderates this association, with higher income or job stability increasing adoption likelihood.

Summary of Key Findings

EV Adoption in India: Influence of Perceived Value and Government Policies

- *Social Value:* Buyers prioritise EV ownership for social image.
- *Functional Value:* Dependability and performance of EVs significantly influence adoption intentions.
- *Government Policies:* Financial incentives and infrastructure development enhance perceived value, but do not fully address consumer needs.
- *Employment Status:* Higher income individuals with stable jobs are more likely to adopt EVs due to higher economic value perception and resource access.
- Employment-related incentives like workplace charging infrastructure could boost adoption rates.

Discussion and Future Direction

The findings highlight the significance of social value and deepen our knowledge of the factors affecting India's willingness to accept EVs. This implies that customers are motivated by the way their decision to acquire EVs impacts their social standing, indicating a major social effect component. This is in accordance with earlier research, including that done by (Axsen et al., 2013) highlighting the importance of social impact in shaping consumer preferences, particularly in India, where customers prioritise long-term environmental benefits over short-term cost reductions. This result departs from conventional economic theories of adoption, but it is consistent with research such as (He & Hu, 2022). The study suggests that environmental concerns may outweigh financial constraints in EV adoption, with government policies promoting green technology use and targeting different income groups, particularly steady-employed individuals.

To boost EV adoption in India, future initiatives should enhance social perception, environmental consciousness, charging infrastructure and tax breaks. Government campaigns, innovative finance strategies and psychological drivers like environmental responsibility could also boost adoption.

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