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TAKE A RIDE ON THE GREEN SIDE: E-VEHICLE PURCHASE INTENTIONS IN THE EMERGING ECONOMY CONTEXT

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ABSTRACT. The article aims to understand individuals' E-vehicle purchase intentions. It explores the factors of the Unified Theory of Acceptance and Use of Technology (UTAUT) and Diffusion of innovation considering the individual's environmental concern and the moderating impact of income on the intention to purchase. Data was collected through the survey method and a total of 322 samples were analyzed using structure equation modelling to determine the significance of the factors affecting the intention to purchase an E-vehicle and to ascertain the sensitivity of such factors. The findings of the analysis were mixed; however, compatibility was found to be a significant factor influencing E-vehicle purchase intentions. The study's findings can assist in understanding the EV purchase intentions of Indians and those living in neighboring developing nations. This can be useful for policymakers, service providers, manufacturers, and researchers. The present study's originality lies in its proposed framework as very little research has covered UTAUT and DOI variables in the context of a developing nation to examine EV purchase intention.

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Introduction

Electric Vehicles (EVs) consume lower amounts of energy and generate fewer quantities of harmful pollutants and as such can be a potential tool used to mitigate environmental issues. Adoption of electric vehicles (EVs) has been driven by several considerations, such as reduced greenhouse gas emissions, improved energy efficiency, decreased reliance on gasoline, and cheaper operational expenses (Ahmad et al., 2018; Bayani et al., 2022; Holland et al., 2021; Sanguesa et al., 2021). Nevertheless, the expensive cost of purchasing electric vehicles, their limited driving range, slow charging speed, and concerns about the acceptance of new products restrict the widespread adoption of electric vehicles, especially in developing countries (Chawla et al., 2023; Digalwar & Rastogi, 2023). Additionally, factors such as expensive upfront costs for electric vehicles (EVs) and batteries, insufficient capacity in the power grid and charging infrastructure, dependence on imported fossil fuels, limited domestic production of EVs, and lack of consumer knowledge and interest in electric cars are all contributing to the slow adoption of EVs (Bhattacharyya & Thakre, 2021; Bryła et al., 2022; Haddadian et al., 2015; Khurana et al., 2020; Lutsey & Nicholas, 2019; Rapson & Muehlegger, 2021). Nevertheless, given the increasing levels of air pollution in developing countries, electric vehicles (EVs) have the potential to serve as an effective tool in addressing environmental concerns. An inquiry into purchase intentions for electric vehicles (EVs) among individuals in developing nations can offer valuable insights for manufacturers, service providers, legislators, and researchers in the context of a developing economy. This determined the focus of this study.

Various research exists on developed economies with a greater prevalence of electric vehicle (EV) adoption, as shown by the World Bank in 2022. Nevertheless, emerging nations continue to have sluggish adoption, mostly due to variations in individuals' economic and social circumstances (World Bank, 2022). Developing economies prioritize other concerns over reducing greenhouse gas emissions, improving air quality, increasing energy efficiency, reducing noise pollution, and promoting sustainable development. However, electric vehicles are contributing to a cleaner and healthier world compared to developed nations, primarily because developed nations have higher greenhouse gas emissions (Haddadian et al., 2015; Kabeyi & Olanrewaju, 2022; Wei et al., 2021). The current study used the Unified Theory of Acceptance and Adoption of Technology (UTAUT) (Venkatesh et al., 2003) to examine the intention of purchasing electric vehicles (EVs). UTAUT is a theoretical framework that explains users' initial intentions to embrace information systems and their future usage behavior. The statement presents fundamental concepts: enabling factors, expected performance, and anticipated effort. These factors have a direct impact on user intentions and behavior.

Moreover, the theory of diffusion, as explained by Rogers (1995), elucidates the process by which inventions, ideas, and technology spread across a civilization or culture. People possess a multitude of traits that impact their inclination to embrace innovation. Hence, it is crucial to comprehend the compatibility of the individual. The purpose of this study is to examine the impact of persons' intentions on the compatibility and purchase intention of E-vehicles. This specific area has not been thoroughly explored in the current literature. As far as the authors are aware, no previous research has suggested investigating the variables of UTAUT and DOI in the context of a developing nation to analyze the Purchase intention EVs.

This study was carried out in India, which is one of the top five countries in terms of GDP according to the World Bank in 2022. In contrast, GDP per capita experiences a significant decline (Statistics Time, 2021), indicating substantial income and wealth inequality. This further highlights its relevance, since many emerging countries also grapple with the challenge of inequality. Additionally, it is a location predominantly inhabited by medium and lowermiddle-income people, where social influence has significant sway. The study's findings can provide insights into the purchase intention of electric vehicles (EVs) among individuals in India, as well as in emerging and bordering countries that share comparable economic and social features.

This study explicitly analyzed the existing literature on the Web of Science. The purpose was to provide further support for the rationale and necessity of the present study, as well as to address any existing gaps in the literature. The search conducted on the Web of Science yielded numerous crucial aspects upon which the current study is based (refer to Fig.1). The primary focus of this investigation is to examine individuals' inclination to acquire electric vehicles. The prominent keywords that emerged concerning electric vehicles include emissions and air pollution. This might be a motivating factor for individuals to consider purchasing electric vehicles as a means to address air pollution in such a situation.

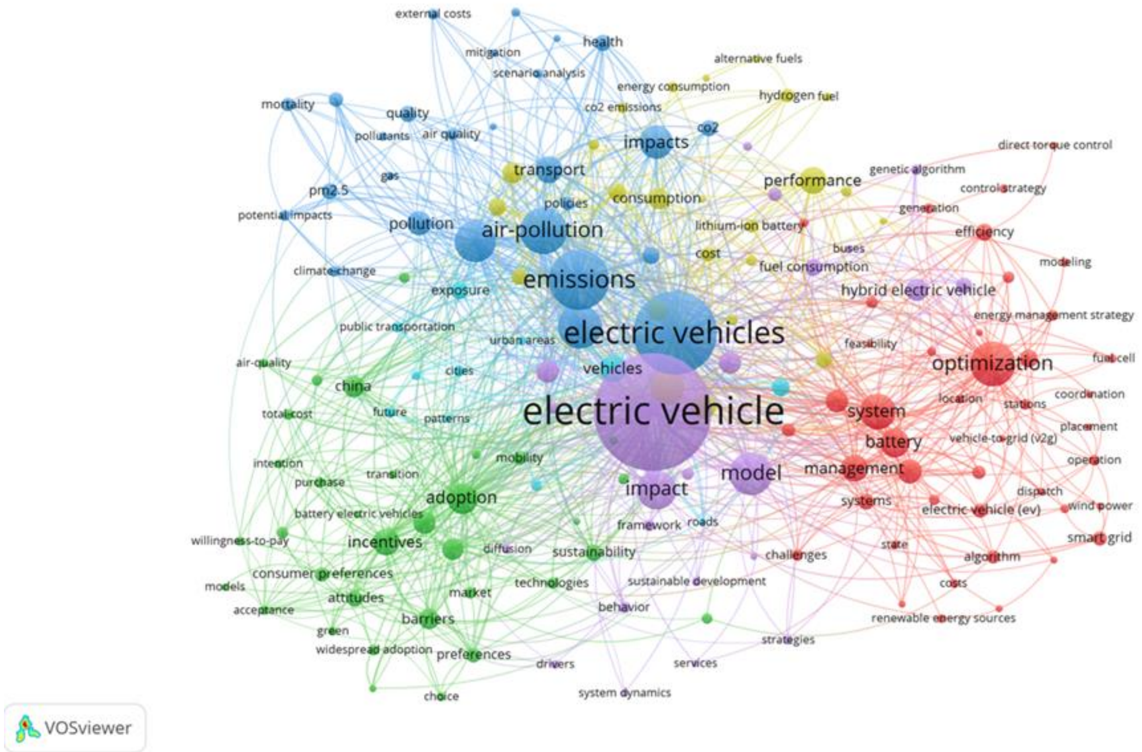


Figure 1. Author generated content using VOS viewer software
Source: *own compilation*

The present inquiry employed a dual approach to achieve the research objective. The PLS-SEM method was employed initially to assess the significance of the postulated trajectories. The second phase involved employing an artificial neural network (ANN) analysis to validate the results obtained from the PLS-SEM and assess the relative significance of the factors identified by the SEM. This article comprises the introduction, literature review, hypotheses, and research methods, followed by the data analysis, findings, conclusion, and discussion.

1. Literature review

The term Perceived Usefulness (PU) in this study pertains to the consumers' expectations that generate their interest in buying electric automobiles. The perceived utility of electric vehicles (EVs) has detrimental impacts on Compatibility, mostly because of many factors such as inadequate charging infrastructure, longer charging time compared to refueling internal combustion engine (ICE) cars, battery maintenance, and capacity concerns, limited driving range, and higher price (Leijon & Boström, 2022).

The opinions of consumers on the technical aspects of electric vehicles (EVs) and their views of the usefulness of EVs are significant elements that have been demonstrated to both encourage and impede the rate at which EVs are adopted (Leijon & Boström, 2022). According to a study by Egbue & Long (2012), consumers' impressions of the instrumental or functional features of electric vehicles (EVs) revealed that the limited range of EVs remains a significant problem, even when individuals have firsthand experience with them, since it falls short of their desired range. In addition, research have found that potential purchasers see certain factors such as performance, data security (Leijon & Boström, 2022), size, and style as hurdles to adopting electric vehicles (EVs) (Egbue & Long, 2012; Rezvani et al., 2015).

Perceived technological usefulness refers to the degree to which people believe a given technology may make their work easier or more productive. Technology's characteristics, functionality, and possible advantages all impact this perception. Compatibility in terms of users' existing attitudes, needs, and experiences, compatibility describes how well a new technology fits in. It includes things like process alignment with users' goals, simplicity of integration with current systems, and user interface design. Users are more inclined to believe that technology meets their wants and preferences when it is viewed as being very beneficial. They view it as a useful instrument that supports their goals and has the potential to increase their output or viability. In summary, perceived usefulness might act as a catalyst for compatibility by shaping users' perceptions of how well technology can meet their needs and goals. Consequently, this positive perception of usefulness might lead to increased compatibility positively.

H1: Perceived Usefulness has a positive impact on compatibility.

The perception of usefulness affects purchase intention by creating the belief among customers that a product or service will successfully fulfill their requirements and enhance their lives (Ghosh, 2024; Lim et al., 2016; Wang et al., 2023). As a result, consumers might perceive the goods more positively, trust more, and perceived risk less (Peña-García et al., 2020; X. Zhang & Yu, 2020). Consumers are more likely to favor and select a product above others when they see tangible advantages and practical value in it (Blut et al., 2023). Moreover, favorable evaluations and suggestions that emphasize the product's use might enhance consumers' inclination to purchase (Dwidienawati et al., 2020). The following hypothesis has been formulated based on the arguments presented in the available literature.

H2: Perceived usefulness has a positive impact on purchase intention.

An individual's perceived ease of use (PEOU) is influenced by their perception of the level of effort they will need to put in to utilize a certain system (Heijden et al., 2003). Research investigations have shown that the perception of ease of use has a beneficial impact on the compatibility of utilizing a system (Prastiawana et al., 2021; Asare et al., 2015). The perception of ease of use enhances the compatibility of the technology with users' existing habits and tools, hence promoting seamless incorporation into their everyday routines (Y. He et al., 2018; McCloskey, 2006). Consequently, consumers are more inclined to view the technology as a seamless match for their requirements, resulting in increased rates of adoption and further validating its compatibility with their current systems and procedures. A PEOU, or Perceived Ease of Use, offers insights into customers' perceptions of EV recharging time, charging stations and infrastructure, distance between house and charging station, and durability assurance. There is a lack of extensive research that emphasizes the relationship between perceived ease of use and compatibility. Therefore, the following aims to address this gap.

H3: Perceived ease of use positively affects compatibility.

If potential consumers see electric cars (EVs) as comprehensible and user-friendly, they are more inclined to contemplate the possibility of acquiring one (Jaiswal et al., 2022). Simplicity of use includes elements such as interfaces that are easy for users to use, charging procedures that are simple and direct, and driving experiences that are intuitive and easy to understand (Venkatesh, 2000). Consumers' confidence in adopting electric vehicles (EVs) improves when they believe that the integration of EVs into their everyday lives would be smooth and uncomplicated, requiring no effort or problems. Therefore, when electric vehicles (EVs) are viewed as easy to operate, it decreases any obstacles that may exist and increases the overall appeal of EVs, resulting in a greater probability of intending to acquire them.

H4: Perceived ease of use has a positive impact on E-vehicle purchase intention.

Facilitating circumstances (FC) refer to consumers' belief that the necessary infrastructure is there to allow technology employment (Venkatesh et al., 2003). The presence of charging infrastructure is crucial for the compatibility of electric vehicles in the specific study area (Kalthaus & Sun, 2021). In addition, it is important to have maintenance facilities and parking lots equipped with suitable charging stations to facilitate the utilization of electric vehicles. According to Khazaei and Tareq (2021), if buyers see the supporting facilities for electric vehicles (EVs) as adequate, it will directly and significantly influence their compatibility and increase their intention to purchase.

H5: Facilitating conditions positively affect compatibility.

Compatibility refers to the likelihood of a specific technology being accepted and utilized (Dutta & Hwang, 2021). Several studies have shown that compatibility has a direct and beneficial impact on the intention to purchase or utilize the latest technology. Research has demonstrated that compatibility has a favorable impact on purchase intention (Gönül et al., 2021; Schmalfuß et al., 2017). Compatibility is a vital determinant of purchase intents in several domains, such as technology adoption, consumer behaviour, and online buying. Consumers are more likely to have favorable views towards and acquire a product or service when they see it aligning with their beliefs, lifestyle, and preferences (Bednarz et al., 2023; Buranelli de Oliveira et al., 2022a; LE et al., 2020; Yang et al., 2021). In the context of this study, it pertains to the notion that customers are not obligated to adapt to electric automobiles. Specifically, electric vehicle (EV) compatibility is a crucial determinant of its usage and performance (Notter, 2010). The level of compatibility a consumer has with an electric car may directly and significantly impact their interest in acquiring one.

H6: Compatibility has a positive impact on purchase intention.

The presence of technological support, such as the accessibility of advanced technology or infrastructure like high-speed internet for online shopping or mobile payment systems, might impact consumers' intents to make purchases (Lynn et al., 2022; Rohden & Espartel, 2024). Accessibility refers to the ease of obtaining a product or service, which can be influenced by factors such as the closeness of physical storefronts or the availability of online delivery services. Customer care is available to provide assistance and address any concerns or inquiries before to, during, and following the transaction. The availability of product information, including reviews, thorough descriptions, and comparisons with similar items, can have a beneficial influence on an individual's purchasing intentions. Furthermore, financial incentives, such as discounts and financing choices, might serve as enabling conditions that influence consumers' purchasing intentions (Xue et al., 2021). Research conducted by Samarasinghe et al. (2024) revealed that conducive conditions have a favourable influence on the desire to acquire electric vehicles in developing nations. Therefore, the subsequent hypothesis has been formulated.

H7: Facilitating conditions positively affect purchase intention.

Electric cars have the potential to mitigate significant environmental issues, such as excessive dependence on oil, especially within the extensive transportation sector (Bryła et al., 2022). Furthermore, research has shown that most consumers find climate change to be a complex issue, and they lack the necessary knowledge and ability to determine which behavioral changes are worthwhile (Thøgersen, 2021). Given this situation, it is crucial to examine how consumers' environmental concerns affect the compatibility of electric vehicles with environmental safety and sustainability. Thus far, the adoption objective has been deemed inadequate (Bryła et al., 2022). The environmental benefits of electric vehicles (EVs), such as they can reduce greenhouse gas emissions, can increase and improve the quality of the air, and fit in renewable sources of energy, greatly contribute to their appeal and widespread acceptance (Chen et al., 2021; Dutta & Hwang, 2021). Nations throughout the globe are enacting measures and providing incentives to encourage the adoption of electric vehicles (EVs), while businesses are embracing eco-friendly initiatives and converting their vehicle fleets to EVs as part of their commitment to sustainability. Growing recognition among consumers regarding the environmental consequences of fossil fuels is also fuelling the market for electric vehicles (EVs), which is further bolstered by developments in battery efficiency and energy sustainability. EVs play a vital role in tackling environmental concerns and advancing a more environmentally friendly future, as stated by Dutta & Hwang (2021) and Xue et al. (2021).

H8: Environment concerns have a positive influence on compatibility.

Environmental concern is a comprehensive concept that includes several phenomena reflecting attitudes, beliefs, and intentions towards the environment (Dunlap & Jones, 2002; Rozsa et., 2023; Kalmakova et al., 2021). Environmentally conscious individuals take this element into account while making purchases (Kim & Lee, 2023; Streimikiene et al., 2023). The role of information in shaping sustainable human behaviour. Economics and Sociology, 16(3), 198-226. doi:10.14254/2071-789X.2023/16-3/11). Prior research has yielded conflicting results about the influence of environmental concerns on consumer decision-making, with some studies suggesting that it has a little effect (Ogiemwonyi et al., 2023). Environmental concerns contribute to strengthening pro-environmental purchasing intentions and enhancing customer confidence in the purchase intentions of sustainable businesses (De Canio et al., 2021; Kontautienė et al., 2024; Oliinyk et al., 2023). The following hypothesis has been formulated based on the available evidence.

H9: Environment concern has a positive impact on purchase intention.

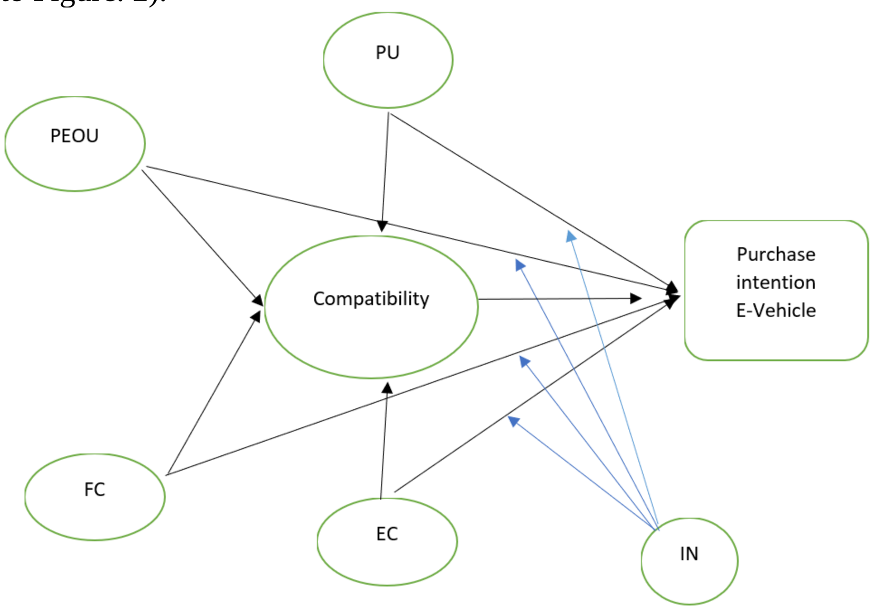
Income as Moderator

Consumers' purchasing behaviours and decision-making processes can be influenced by income levels. Customers may modify their consumption patterns to optimize their utilization of disposable money when their earnings increase. The income effect measures the extent to which variations in a consumer's income affect their preferred patterns of consumption. Income can modify additional variables such as the customer's behavioural intention and the service environment (De Canio et al., 2021; Nazir & Tian, 2022). Consumers' opinions and inclinations towards electric automobiles (EVs) and their desire to purchase one are influenced by their income level (Krishnan & Koshy, 2021; Sovacool et al., 2019). Research has revealed that income has a significant impact on an individual's propensity to make a purchase. Research indicates that there is a beneficial influence of wealth on the inclination to buy electric cars (Z. He et al., 2023). The desire to purchase electric cars is impacted by perceived obstacles, financial incentives, and policy characteristics. Purchase incentives, such as income tax credits, aim to promote the use of electric cars. However, these incentives may disproportionately benefit customers with higher incomes compared to those with lower to moderate incomes (Hardman et al., 2021). In Delhi, the income level of citizens is rising and is one of the highest compared to other states in India. Furthermore, the government incentivizes citizens to purchase electric vehicles by providing them with tax incentives. Given the current situation of increasing income levels and Delhi being afflicted with the greatest degree of air pollution globally, it is crucial to examine how wealth might influence consumers' inclination to acquire electric vehicles. The facts can be utilized to comprehend the countries and regions that have comparable demographic characteristics.

Moderators

1. *Income moderatos the relationship between environmental concerns and E-vehicle purchase intention*
2. *Income moderates the relationship between FC and E-vehicle purchase intention.*
3. *Income moderates the relationship between perceived ease of use and e-vehicle purchase intention.*
4. *Income moderates the relationship between perceived usefulness and e-vehicle purchase intention.*

Please refer to the proposed research model incorporating the variables discussed above (refer to Figure. 2).



PU: Perceived Usefulness
PEOU: Perceived ease of use
FC: Facilitating Condition
EC: Environmental Concern
IN: Income (moderator)

Figure 2. Theoretical framework
Source: *own compilation*

3. Research methodology

3.1. Research design

The current study is a quantitative study that uses self-assessed questionnaires to examine intentions to use EVs in the context of emerging markets. The study will employ a cross-sectional methodology to collect information from participants at a given point in time and analyze their EV deployment plans. The authors used structured self-report questionnaires that were considered appropriate for assessing behavioural intentions (Chan, 2009). The current investigation applies partial least squares structural equation modelling (PLS-SEM), a multivariate statistical analysis technique used to model relationships between latent variables. In addition, the collected data also revealed non-normality which motivated the use of PLS-SEM in the current investigation.

Linear statistical approaches, such as multiple regression analysis and structural equation modelling (SEM), may not always be enough to capture the intricate dynamics of human decision-making processes (Sim et al., 2014). The aforementioned techniques tend to oversimplify the intricacies of acceptance choices due to their limited ability to assess non-linear models (Tan et al., 2014). To tackle this particular problem, it is advised to employ the Artificial Neural Network (ANN) approach, which can find both linear and nonlinear correlations (Leong et al., 2013). The artificial neural network (ANN) approach does not necessitate any assumptions regarding the distribution, such as linearity, normalcy, or homoscedasticity (Leong et al., 2020; Tan et al., 2014). In addition, it has been shown that artificial neural network (ANN) models exhibit a greater degree of robustness compared to linear models, and they also demonstrate higher levels of prediction accuracy, as supported by studies conducted by Liébana-Cabanillas et al. (2018) and Tan et al. (2014). The design of artificial neural networks (ANNs) is inspired by the human brain structure, wherein the individual neurons of ANNs bear resemblance to their biological counterparts (Liébana-Cabanillas et al., 2018). The acquisition of information in the artificial neural network (ANN) technology is facilitated by its learning mechanism (Hew et al., 2018). The capacity for learning exhibited by artificial neural networks (ANNs) has positioned them as a favoured statistical approach in comparison to alternative methods (Lee et al., 2016).

3.2 Sampling procedure

A stratified sampling method was used to ensure that participants in the Indian capital, New Delhi, represented different age categories, genders, educational levels, and geographical locations. The national capital represents some of the country's most influential population groups but is also one of the most polluted cities in the world, which is the reason for the selection of New Delhi for the data collection. Face-to-face interviews were used to collect primary data from January to April 2023. The authors used targeted random sampling to collect data from the target audience. A priori performance evaluation was performed using G*Power 3.1.9.4 software to determine the minimum sample size required for analysis. The priori analysis highlighted the need to collect at least 89 samples to achieve a mean effect (0.15) at the 95 per cent confidence level. The authors collected 322 samples, excluding the samples collected to validate the construct, which meets the minimum sample criterion (Bagozzi and Yi, 2012) (see Table 1).

3.3 Questionnaire design

The authors created a questionnaire to validate the proposed model using adapted constructs from established theories. The questionnaire is divided into two sections, including the demographics section. Section two of the questionnaire contains all items requiring responses on a five-point Likert scale. The authors used reverse scaling and blending to avoid common method bias (CMB) (Podsakoff and Organ, 1986). In addition, to rule out the possibility of CMB in the considered data, the authors performed Harman's one-factor test, which was within the threshold.

Table 1. Sample Profile

Age	**In number**	**In percentage**
Below 25	134	41.61
Below 35	94	29.19
Below 45	73	22.67
Below 55	14	4.35
Below 65	7	2.17
	322	**100**
Level of education	**In number**	**In percentage**
High School	40	12.42
Secondary School	53	16.46
Bachelor	121	37.58
Master	74	22.98
PhD	20	6.21
No formal education	14	4.35
	322	**100**
Income Level in INR (Monthly)	**In number**	**In percentage**
Below 40K	175	54.35
Between 40k to 60k	44	13.66
Between 60k to 80k	29	9.01
Between 80k to 100k	43	13.35
Between 100k to 120k	13	4.04
Above 120k	18	5.59
	322	**100.00**

Source: *own data*

4. Results

The authors implemented the PLS-SEM analysis using Smart PLS 4 software. This analysis method is often used in behavioural research, where cross-sectional data is used to study complex relationships. In addition, the method can also process data representing non-normality (Ringle et al., 2015; Sarstedt et al., 2020). At this point, the factor loadings of the indicators were calculated and the indicators that did not represent the expected loadings (0.70) were excluded from further analysis. Cronbach's Alpha, Composite Reliability, AVE, and HTMT scores were used in this study to determine reliability, convergent validity, and discriminant validity (Henseler et al., 2009, 2014; F. Hair Jr et al., 2014). Calculated.

Construct reliability was determined by Cronbach's alpha and composite reliability being greater than 0.7.

$$\text{Cronbach's } \alpha = \left(\frac{M}{M-1}\right)\left(1 - \frac{\sum_{i=1}^{M} s_i^2}{s_i^2}\right) \qquad CR = \frac{\left(\sum_{i=1}^{M} l_i\right)^2}{\left(\sum_{i=1}^{M} l_i\right)^2 + \sum_{i=1}^{M} var\ (e_i)}$$

$$AVE = \left(\frac{\sum_{i=1}^{M} l_i^2}{M}\right)$$

All reported AVE values were above 0.5, further confirming the convergent validity (see Table 2) (Hair et al., 2017, 2019).

Table 2. Reliability and Validity of variants

Construct	**Item**	**Factor Loading**	**Cronbach's Alpha**	**Composite Reliability**	**AVE**	**Sources**
Perceived Usefulness (PU)	PU1	0.893	0.926	0.930	0.772	Davis et al., 1989
	PU2	0.914				Venkatesh, 2003
	PU3	0.906				Wu et al. 2015
	PU4	0.809				
	PU5	0.867				
Perceived Ease of Use (PEOU)	PEOU1	0.869	0.943	0.946	0.746	Davis et al., 1989
	PEOU2	0.894				Venkatesh, 2003
	PEOU3	0.865				Choi and Ji, 2015
	PEOU4	0.769				Wang et al., 2019
	PEOU5	0.90				
	PEOU6	0.905				
	PEOU7	0.835				
Facilitating Conditions (FC)	FC2	0.722	0.925	0.940	0.658	Venkatesh et al., 2012 Kasper and Abdelrahman, (2020)
	FC3	0.798				
	FC4	0.805				
	FC5	0.860				
	FC6	0.881				
	FC7	0.866				
	FC8	0.874				
Environmental Concern (Concern)	Concern1	0.855	0.786	0.923	0.816	(Dunlap et al., 2000)
	Concern2	0.949				
Compatibility (COM)	COM1	0.880	0.952	0.952	0.805	E M Rogers, 1962
	COM2	0.881				Yuen et al., 2020
	COM3	0.903				
	COM4	0.914				
	COM5	0.903				
	COM6	0.902				
Purchase Intention (PI)	PI1	0.801	0.946	0.948	0.727	Davis et al., 1989
	PI2	0.870				Venkatesh, 2003
	PI3	0.889				Wu et al. 2015
	PI4	0.854				
	PI5	0.861				
	PI6	0.877				
	PI7	0.789				
	PI8	0.876				

Source*: own calculated values through SmartPLS 4*

The specified Fornell-Larcker criterion falling below the cut-off values established discriminant validity (see Table 3) (Sarstedt et al., 2020; Farrell, 2010; Henseler et al., 2014).

Table 3. Discriminant Validity

	COM	Concern	FC	PEOU	PI	PU
COM	0.897					
Concern	-0.203	0.903				
FC	0.849	-0.148	0.811			
PEOU	0.595	-0.111	0.625	0.864		
PI	0.713	-0.203	0.683	0.615	0.853	
PU	0.629	-0.101	0.614	0.728	0.697	0.879

Source: *Author calculated values through SmartPLS 4*

The calculated VIF values ranged from 1.023 to 2.534, which is within the collinearity threshold (see Table 4) (Hair et al., 2014; Becker et al., 2015).

Table 4. Collinearity Statistics

	COM	Concern	FC	PEOU	PI	PU
COM					1.941	
Concern	1.023				1.077	
FC	1.817					
PEOU	2.386				2.307	
PI						
PU	2.334				2.534	

Source: *The author calculated values through SmartPLS 4*

5. Assessment of the structural model

The formulated hypotheses were tested using a two-sided percentile bootstrapping test with 10,000 subsamples and a relevance requirement of 5 per cent (Streukens & Leroi-Werelds, 2016).

5.1. Direct effects

Analysis revealed that perceived usefulness (PU) has a positive impact on compatibility (COM) and purchase intent (PI), with (β=0.166, $p<0.05$) and (β =0.329, $p<0.05$) respectively leading to the acceptance of the formulated hypotheses (H1) and (H2). However, the other driver of technology adoption, perceived ease of use (PEOU), had no impact on COM and PI with ($\beta = 0.01$, $p > 0.05$) and ($\beta = 0.01$, $p > 0.05$), respectively, which led to the rejection of the formulated hypotheses (H3) and (H4). The other key variable of the model facilitating condition (FC) has a positive effect on the COM ($\beta = 0.729$, $p < 0.05$) and leads to the acceptance of the formulated hypotheses (H5). The other key variable, Environmental concern (Concern), negatively impacts the COM at ($\beta = -0.077$, $p < 0.05$) but fails to detect a significant impact on the PI at ($\beta = -0.059$, $p > 0.05$), so (H8) is accepted, but (H9) is rejected (see Table 5 and Figure 2).

5.2. Indirect effects

The examination of Compatibility (COM) as a mediating variable positively impacts purchase intent (PI) through FC with (β= 0.418, p > 0.05) and (β= 0.304, p > 0.05), leading to acceptance of the formulated hypotheses (H6) and (H7). The examination of the moderating variable, income, failed to impact PI at (β = -0.04, p > 0.05), hence (H10) was rejected. Likewise, the moderating variables failed to affect PI through concern and PU with (β = -0.052, p > 0.05) and (β = -0.061, p > 0.05), respectively, leading to the rejection of (H11) and (H14). However, the moderating variable positively affected the relationship between COM and PI, with (β = 0.14, p > 0.05) leading to acceptance of (H12). Similarly, the moderating variable negatively affected the relationship between PEOU and PI, with (β = -0.092, p > 0.05) leading to acceptance of (H13) (see Table. 5 and Figure. 2).

Table 5. Hypothesized relationships

Hypotheses			Original sample (O)		Sample mean (M)	Standard deviation (STDEV)	T statistics (|O/STDEV|)
H1	PU -> COM	0.166	0.167	0.048	3.447***	P values	Result
H2	PU -> PI	0.329	0.329	0.062	5.286***	**0.001*** **	Accepted
H3	PEOU -> COM	0.01	0.009	0.055	0.179	**0*** **	Accepted
H4	PEOU -> PI	0.105	0.104	0.06	1.762	0.858	Rejected
H5	FC -> COM	0.729	0.729	0.042	17.529***	0.078	Rejected
H6	COM -> PI	0.418	0.418	0.063	6.599 ***	**0*** **	Accepted
H7	*FC -> PI*	*0.304*	*0.305*	*0.051*	*6.014****	**0*** **	Accepted
H8	Concern -> COM	-0.077	-0.076	0.027	2.877***	*0****	Accepted
H9	Concern -> PI	-0.059	-0.06	0.034	1.734	**0.004*** **	Accepted
H10	Income -> PI	-0.04	-0.04	0.031	1.259	0.083	Rejected
H11	Income x Concern -> PI	-0.052	-0.051	0.032	1.614	0.208	Rejected
H12	Income x COM -> PI	0.14	0.144	0.053	2.625***	0.107	Rejected
H13	Income x PEOU -> PI	-0.092	-0.092	0.047	1.964***	**0.009*** **	Accepted
H14	Income x PU -> PI	-0.061	-0.065	0.055	1.115	**0.05*** **	Accepted
						0.265	Rejected

Source: *own calculated values through SmartPLS 4*

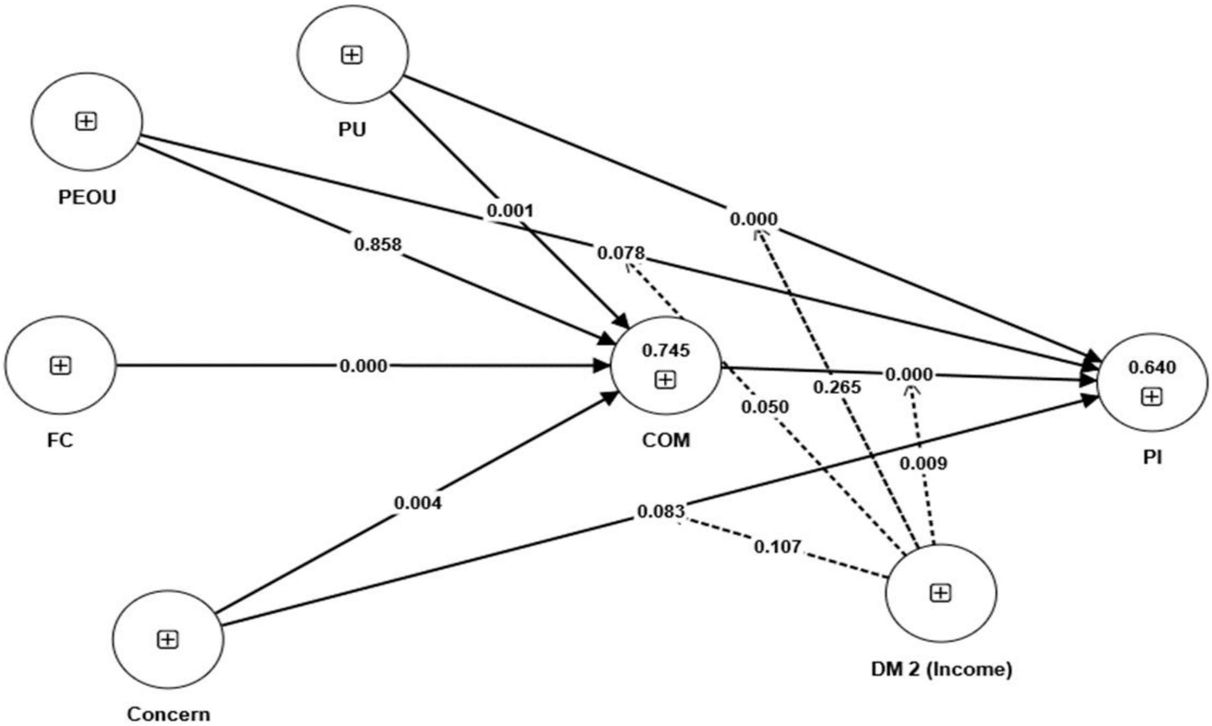


Figure 3. Author-generated model using Smart PLS 4
Source: *own data compilation*

5.3. R-Square

The model's adjusted R^2 values demonstrate that the associated constructs account for 62.9 per cent of the variance in the dependent variable (PI), which, by the researchers' standards, comes within the moderate range (Hair et al., 2019). The mediating variable (COM) explains 74.5 per cent of the variation in the dependent variable thereby satisfying the mediation criterion (see Table 6).

$$Adjusted\ R^2 = 1 - \left(\frac{(1-R^2)(n-1)}{(n-k-1)}\right)$$

Table 6. R-Square

	R-square	R-square adjusted
COM	0.745	0.741
PI	0.64	0.629

Source: own calculated values through SmartPLS 4

5.4. Model fit

The results of the present study showed that the SRMR = 0.05, which is well within the threshold (0.08) suggested in the literature (Hu and Bentler, 1998; Clark and Bowles, 2018). In addition, the investigation yielded a chi-square value of 1897.801 and an NFI of 0.839, showing that an appropriate model fit was achieved for the study (Parry, 2020) (see Table 7).

Table 7. Model fit

	Saturated model	Estimated model
SRMR	0.049	0.05
d_ULS	1.682	1.732
d_G	1.071	1.077
Chi-square	1892.474	1897.801
NFI	0.84	0.839

Source: own calculated values through SmartPLS 4

5.5. ANN analysis

In this study, a multilayer perception ANN analysis was performed. Researchers have outlined in detail how neurons learn and apply this information to anticipate the output neuron nodes (Hew et al., 2019; Ooi et al., 2018). Since one hidden layer is sufficient to represent any continuous function (Negnevitsky, 2011), we followed the practice used by numerous researchers in the majority of neural network models for behavioural research (Leong et al., 2020; Liébana-Cabanillas et al., 2018; Ooi et al., 2018) and used one hidden layer in this study. Using a ten-fold cross-validation approach, 70% of the data was used for training and 30% for assessing the networks to prevent over-fitting concerns (Talukder et al., 2020).

Root means square error (RMSE) was measured for both the testing and training phases of each iteration of the ANN model to establish its prediction accuracy. See Table 8 and Figure 3 for average RMSE values during testing (0.458) and training (0.419). The research model's high accuracy and robust prediction power are indicated by the tiny and comparable values in the test and training datasets (Talukder et al., 2020).

Table 8. RMSE values during testing and training stages (N=322)

Network	Sum of square error (Training) (The name of the dependent variable)	Sum of square error (Testing) (The name of the dependent variable)	RMSE (Training) (The name of the dependent variable)	RMSE (Testing) (The name of the dependent variable)
ANN1	46.231	15.598	0.450	0.407
ANN2	47.692	21.365	0.471	0.447
ANN3	54.168	18.338	0.484	0.449
ANN4	47.166	16.976	0.467	0.400
ANN5	41.955	17.59	0.436	0.417
ANN6	44.356	17.381	0.444	0.423
ANN7	45.413	18.385	0.465	0.405
ANN8	47.444	17.26	0.460	0.420
ANN9	46.364	15.353	0.460	0.386
ANN10	43.687	18.786	0.443	0.436
Mean	46.448	17.703	0.458	0.419
Std Dev	3.097829537	1.62006906	0.014111818	0.019319477

Source: own *calculated values through IBM-SPSS*

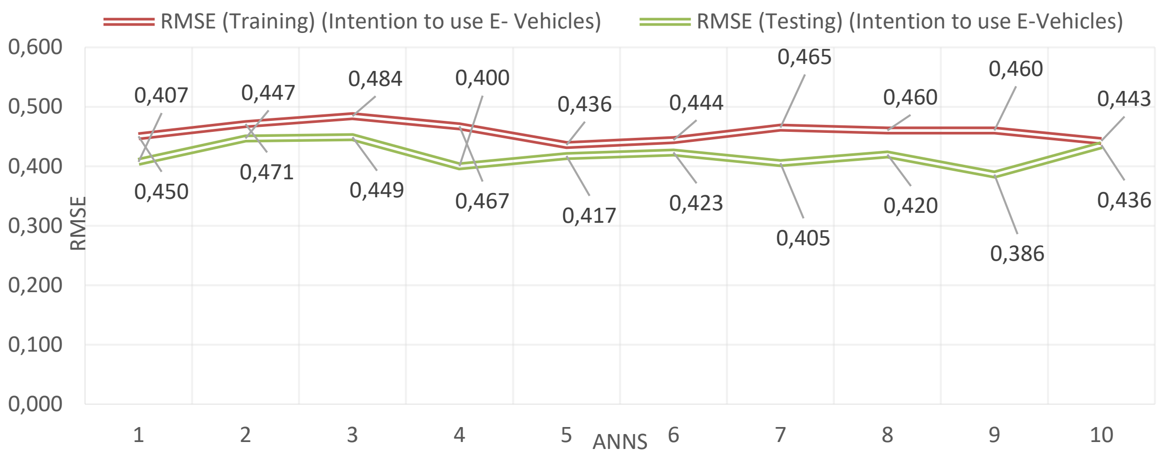


Figure 4. Author-generated model using IBM-SPSS
Source: *own data compilation*

To evaluate the input neurons' prediction ability, a sensitivity analysis was performed. Ranking exogenous constructs by their relative importance is accomplished using sensitivity analysis. 'One-at-a-time' simulations, which assess the impact of each independent variable separately while disregarding their interactions, are commonly used for sensitivity analyses of models (Beres & Hawkins, 2001). Sensitivity analysis in ANN allows for the evaluation of input variables based on the significance of their influence on the output variable and for the identification of components that might be deleted without affecting network quality and the crucial key factors (Mrzygód et al., 2020). Table 9 displays the results of the ANN sensitivity analysis, which found that PU, followed by FC, COM, PEOU, and Concern was the most significant variable in this study.

Table 9. Sensitivity analysis with normalized importance

	COM	Concern	FC	PEOU	PU
ANN1	97.4%	5.7%	78.9%	33.1%	100.0%
ANN2	56.8%	23.2%	76.8%	46.9%	100.0%
ANN3	48.6%	16.5%	100.0%	27.7%	90.6%
ANN4	63.6%	28.4%	83.4%	35.9%	100.0%
ANN5	100.0%	2.8%	74.6%	51.5%	84.2%
ANN6	55.2%	25.4%	100.0%	26.3%	87.6%
ANN7	100.0%	40.6%	64.3%	34.9%	64.1%
ANN8	78.2%	18.1%	97.2%	31.2%	100.0%
ANN9	60.6%	40.0%	87.7%	38.6%	100.0%
ANN10	62.2%	22.0%	100.0%	21.5%	95.0%
Average relative importance	72.3%	22.3%	86.3%	34.8%	92.2%

Source: *own data compilation*

Discussion

The main objective of the present study is to examine the purchase intention of E-vehicles among individuals living in metropolitan cities that have the worst air quality and are among the top polluted air quality in the world. The study intends to investigate how people think about curbing air pollution by reflecting on their intention to use E-vehicles. The study tested the connection between the variables of UTAUT to check their intention. More so, how does individuals' concern over the environment affect their E-vehicle purchase intention? The study also examined the role of income on the framed hypotheses to check its moderation effect.

The results from each examined hypothesis have a substantial connection with the existing literature. Several studies support the idea of the first hypothesis which is that perceived usefulness has a positive impact on compatibility (Buranelli de Oliveira et al., 2022b; Isaac et al., 2016a; Lashari et al., 2021; Tu & Yang, 2019). Hypothesis two also found support in the existing literature (Cho & Sagynov, 2015b; Mican & Sitar-Taut, 2023). Third and fourth hypotheses PEOU impact on compatibility and PEOU impact on purchase intention were found insignificant which is against the perceived compatibility positively associated with PEOU(Isaac et al., 2016b). It has been found that compatibility has a connection with perceived ease of use. When a technology is compatible with pre-existing work practices and prior experience, it lessens the cognitive load it imposes, which promotes a more positive view of ease of use (Karahanna et al., 2006) but the results of the present study deny the positive connection between the two. Not every study shows the same effect of perceived ease of use on purchase intention. Purchase intention and perceived ease of use are positively correlated in some research (Cho & Sagynov, 2015a; Fachrulamry & Hendrayati, 2021), and negatively correlated in others (Herzallah et al., 2022). Therefore, depending on the environment and user experience, the effect of perceived ease of use on purchase intention may differ.

Hypotheses H5, H6, H7 and H8, were found significant and support the positive relationship between the dependent and independent variables. H5, facilitating conditions have a positive impact on compatibility, is probably less focused in the existing literature and has less evidence of the association between facilitating conditions and compatibility. Compatibility which is supported by In the UTAUT paradigm, compatibility—defined as users' perceptions of how well a technology suits their needs, values, and current work practices—is a crucial component that shapes users' views and actions toward embracing and making use of technology (Karahanna et al., 2006). Based on this, facilitating conditions might affect compatibility, therefore the present study examined it and found its positive impact on compatibility, and this adds new knowledge to the existing literature.

H6, compatibility and purchase intention, according to the findings, compatibility influences purchase intention positively across a range of situations. This means that when a technology or platform is well-matched with consumers' needs, values, and current behaviours, it can increase their intention to make a purchase, Many studies support this hypothesis(Peña-García et al., 2020; W. Zhang & Luo, 2023). Hypothesis seven found significant that facilitating conditions positively impact purchase intention. Existing studies have mixed results, and found positive and negative impacts in different contexts (Rehman et al., 2022; M. Zhang et al., 2023). Next are hypotheses 8 and 9, whereas H8 was found significant and 9 insignificant. There is a positive connection between environmental concern and compatibility.

The present study found mixed results on the moderating impact of income on the dependent variables, which attracts further investigation with a bigger and with rigorous methodology.

Conclusion

The purpose of the study is to understand the determinants of the E-vehicle purchase intention of individuals suffering from high levels of pollution in the context of an emerging economy. The study contributes useful insight to understanding the individuals' intention and the key factors relevant to affecting the consumer choice for E-vehicle purchase. The study investigated within the scope of UTAUT, diffusion of innovation theory and individual environmental concerns and attempted to add to the existing literature. The objective of the study is to draw the attention of the researchers further towards the sustainability of the environment. Although the study contributes to the literature the results of the study might be useful to the researchers, policymakers and individuals. However, the study possesses various weaknesses which might be overcome with further investigation. To name some, the size of the sample is relatively very small compared to the population the study is intended to cover. The methodology can be more robust and can cover other determinants including direct, indirect and moderation factors wish might have a significant impact on individuals' E-vehicle purchase intention. In short, the study has limitations but can bring out some relevant factors and issues which are considerably relevant in the case of E-vehicle choice.

Founding

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