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EXAMINING THE THEORY OF PLANNED BEHAVIOR AND PURCHASE INTENTION TOWARDS ELECTRIC VEHICLES

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ABSTRACT

The objective of the present study is to examine the theory of planned behaviour and purchase intention towards electric vehicles. Primary data have been collected through a structured online questionnaire to achieve the objective. The sample consisted of potential car buyers from various geographical regions, reached through a mixed methodology including social media, online panels, and email lists. The targeted sample size is 292 respondents, which should provide a sufficient sample for robust statistical analysis. A simple random convenience sampling method has been used for the data collection. The study's finding is that the theory of planned behaviour is positively associated with the purchase intention towards electric vehicles. It can be concluded that factors of planned behaviour lead to consumers' purchase intention toward electric vehicles.

Keywords: Theory of Planned Behavior. Purchase Intention, Electric Vehicles, Subjective Norms, Attitude and Perceived Behavioural Control.

INTRODUCTION

The growing concern for environmental sustainability has prompted a global shift towards adopting eco-friendly technologies, particularly in transportation. Electric vehicles (EVs) have emerged as a promising alternative to conventional vehicles due to their potential to significantly reduce greenhouse gas emissions (Creutzig et al., 2015). However, despite the positive environmental implications, the adoption rate of EVs still needs to catch up worldwide (Hardman & Tal, 2018). This paper explores this problem by examining the potential influence of the Theory of Planned Behavior (TPB) on consumer purchase intention towards electric vehicles.

The Theory of Planned Behavior, developed by Ajzen (1991), provides a comprehensive model to understand and predict human behaviour. According to the TPB, human action is guided by attitudes towards behaviour, subjective norms, and perceived behavioural control. Several empirical studies have shown that this model can explain consumer intention and behaviour towards various products and services (Fishbein & Ajzen, 2010), including electric vehicles (Hackbarth & Madlener, 2016).

This paper seeks to build upon existing research by employing the TPB to examine its applicability and effectiveness in predicting consumer intention to purchase electric vehicles. Additionally, we intend to identify factors that may affect this intention, such as socio-demographic characteristics, knowledge about electric vehicles, and the influence of government incentives.

This examination of the TPB's applicability to electric vehicle adoption offers valuable insights for policymakers, manufacturers, and other stakeholders in the EV industry. By better understanding the factors influencing consumer purchase intention, we can develop more effective strategies to promote the broader adoption of electric vehicles and contribute to global sustainability efforts.

LITERATURE REVIEW

Over the last decade, academics and policymakers have focused on determining the elements influencing the adoption of electric cars (EVs). Early studies on EV adoption mainly focused on technical constraints such as range anxiety, battery performance, and a lack of charging infrastructure (Pearre et al., 2011; Sovacool et al., 2020). However, recent research has underlined the importance of psychological aspects in affecting customers' purchasing intentions and actual adoption behaviours toward EVs (Schuitema et al., 2013; Rezvani et al., 2015).

Ajzen's (1991) Theory of Planned Behavior (TPB) has been extensively used to analyze customers' intentions and behaviour toward various goods and services. According to this idea, human conduct is governed by attitudes toward behaviour, subjective standards, and perceived behavioural control. TPB has been used in many research to study consumer adoption of EVs (Graham-Rowe et al., 2012; Hackbarth & Madlener, 2016). Hackbarth and Madlener (2016) discovered, for example, that perceived behavioural control and subjective norms strongly influence EV purchase intentions.

Attitudes towards behaviour, one of the three constructs of TPB, encompasses the individual's positive or negative evaluation of performing the behaviour. Many studies found that consumers' attitudes towards environmental sustainability significantly influence their intention to purchase EVs (Egbue & Long, 2012; Barbarossa & De Pelsmacker, 2016). Furthermore, consumer awareness and knowledge about the benefits and drawbacks of EVs can shape their attitudes and, consequently, their purchase intentions (Bockarjova & Steg, 2014).

Subjective norms refer to perceived social pressure to perform or not perform a particular behaviour. Lane and Potter (2007) suggest that social influence plays a significant role in EV adoption, as individuals tend to be influenced by others' opinions about EVs in their decision-making process.

Perceived behavioural control, the third construct of TPB, reflects individuals' beliefs about their ability to perform a behaviour. The availability and accessibility of charging infrastructure, for example, can affect perceived behavioural control and, in turn, influence purchase intentions towards EVs (Egbue & Long, 2012).

While TPB provides a robust theoretical framework for understanding consumer behaviour, additional factors such as government policies and socio-demographic characteristics can also influence EV adoption (Zhang et al., 2011; Jansson et al., 2017). Therefore, the current study will extend the TPB model by integrating these factors to provide a more comprehensive understanding of consumers' purchase intentions towards EVs.

RESEARCH METHODOLOGY

This study employs a quantitative research approach to examine the influence of the Theory of Planned Behaviour (TPB) on consumers' purchase intention towards electric vehicles (EVs). Data Collection

Data for this study have been collected through a structured online questionnaire. The sample consisted of potential car buyers from various geographical regions, reached through a mixed methodology including social media, online panels, and email lists. The targeted sample size is 292 respondents, which should provide a sufficient sample for robust statistical analysis. A simple random convenience sampling method has been used for the data collection.

Questionnaire Design

The questionnaire comprised variables assessing respondents' attitudes, subjective norms, and perceived behavioural control towards purchasing EVs, as outlined in the TPB and at-end variables, which assess purchase intention towards EVs.

All items related to TPB constructs and purchase intention were measured on a five-point Likert scale, ranging from "strongly disagree" to "strongly agree". These items were adapted from previously validated scales (Ajzen, 1991; Hackbarth & Madlener, 2016).

Data Analysis

Exploratory and confirmatory factor analyses have been used to validate the scales. The relationships between the TPB constructs and purchase intention have been examined using Structural Equation Modeling (SEM) via software such as AMOS or SPSS.

Hypothesis

Ha: There is a positive and significant relationship between the theory of planned behaviour and purchase intention towards electric vehicles.

Data Analysis

Table 1 Sampling Adequacy

KMO and Bartlett's Test		
Kaiser-Meyer-Olkin Measure of Sampling Adequacy.		.880
Bartlett's Test of Sphericity	Approx. Chi-Square	1974.114
	df	78
	Sig.	.000

Source: Primary Data

Table 2 shows the sampling adequacy of the study. The Chi-square value of the Bartlett Test is 1974.114, which is significant, and the KMO value is .880, more than the minimum acceptable range of .70, which indicates that the sample size is adequate in the present study.

Table 2 Results of Exploratory Factor Analysis

Sr. No.	Items	Factor loading	Eigenvalue	Variance explained	Cronbach
Factor 1: Subjective Norms					
I.	"I should purchase an electric car, according to relatives and friends".	.789	5.867	28.426	.864
I.	"Propaganda in the news media will persuade me to purchase an electric vehicle".	.774			
I.	"People using electric vehicles around me will prompt me to buy one".	.749			
V.	"My chances of buying an electric vehicle will increase if my friend buys an Electric vehicle".	.742			
V.	"Usually, I share information regarding electric vehicles with my friends".	.695			
I.	"I learn a lot about electric vehicles from my friends".	.609			
Factor 2: Attitude					
I.	"The use of electric vehicles by me will help in reducing pollution".	.859	1.589	22.748	.891
I.	"The use of electric vehicles by me will help in	.853			

	improving the environment".				
K.	"The use of electric vehicles by me will help in reducing wasteful use of natural resources."	.794			
K.	"I feel good about myself when I use electric vehicles".	.652			
Factor 3: Perceived Behavioural Control					
I.	"I am financially stable enough to purchase an electric car".	.892	1.277	15.999	.748
I.	"I have the opportunity to buy Electric vehicles."	.782			
I.	"Whether or if I purchase an electric car is up to me".	.683			
Total				67.174	.903

Source: Primary Data

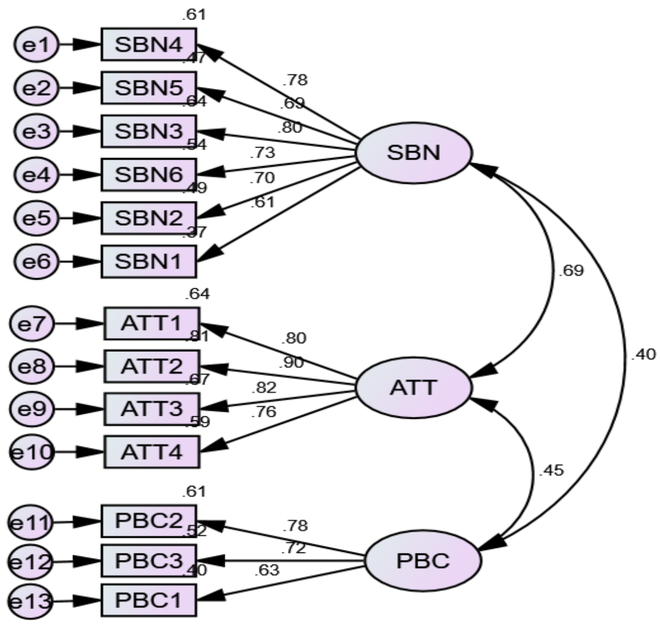
Table 2 shows the factor loadings, eigenvalues, Cronbach alpha and variance explained. The principal component method with varimax has been used as a data reduction technique on thirteen items to identify the major factors. A total of three factors have been extracted, i.e., subjective norms, attitude and perceived behavioural control. The factor loadings range from 0.609 to 0.892, which is more than the minimum acceptable value of 0.50. An eigenvalue of more than one is considered. For all three-factor eigenvalues are more than the minimum acceptable range of 1. Cronbach Alpha measures the internal consistency of the data. Value Cronbach alpha should be more than 0.70. For these factors, Cronbach alpha values are more than 0.70, indicating the data's better internal consistency. The results of the exploratory factor analysis suggested that factors are better extracted and can be used if further research is needed. The major extracted factors are explained in detail as follows.

1. **Subjective Norms**

2. Attitude

3. Perceived Behavioural Control

Figure 1: First-Order Confirmatory Factor Analysis



Source: Amos Output

Table 3 Model Fit Measures

Measure	Estimate	Threshold	Interpretation
CMIN	223.822	--	--
DF	62	--	--
P	.000		
CMIN/DF	3.610	Between 1 and 5	Acceptable
CFI	0.916	>0.85	Acceptable
GFI	0.890	>0.85	Acceptable
NFI	0.889	>0.85	Acceptable
IFI	0.917	>0.85	Acceptable
TLI	0.895	>0.85	Acceptable
RMSEA	0.095	<0.10	Acceptable

Source: Primary Data

Table 3 shows measurement model fitness. Chi-square (CMIN) value 223.822 is statistically significant (p=.000) with the degree of freedom 62. GFI=0.890, CFI=0.916, IFI=0.917, NFI=0.889, and TLI=.895 are higher than 0.80 (Moolla & Bischoff, 2013), indicating model fitness. The model was fitter with a CMIN/DF = 3.610. RMSEA was 0.073, below the recommended 0.05 to 1.00 (Browne & Cudek, 1993). The measurement model fits better.

Table 4 Standardized Regression Weights

Items	Path	Factor	Estimate
SBN4	<---	SBN	.778
SBN5	<---	SBN	.688
SBN3	<---	SBN	.801
SBN6	<---	SBN	.732
SBN2	<---	SBN	.703
SBN1	<---	SBN	.606
ATT1	<---	ATT	.801
ATT2	<---	ATT	.901
ATT3	<---	ATT	.821
ATT4	<---	ATT	.765
PBC2	<---	PBC	.782
PBC3	<---	PBC	.722
PBC1	<---	PBC	.631

Source: Primary Data

The results of the standardized regression weights are shown in Table 4. These weights varied from 0.606 to 0.901 and were determined to be significant (p 0.05). The subjective norms, attitudes, and perceived behavioural control variables were examined. There was a substantial representation of the 13 observed variables provided by the three sub-factors.

Table 5 Model Validity Measures

Factors	**CR**	**AVE**	**MSV**	**MaxR(H)**	**SBN**	**ATT**	**PBC**
SBN	0.866	0.520	0.472	0.874	**0.721**		
ATT	0.894	0.678	0.472	0.906	0.687***	**0.824**	
PBC	0.756	0.510	0.205	0.769	0.398***	0.452***	**0.714**

Source: Primary Data

Table 5 provides scale validity measures. Composite Reliability (CR) values over 0.7 improve internal consistency and concept validity (Hair et al., 2010). Subjective norms, attitude, and perceived behavioural control had CRs above the minimum acceptable value. Scales were reliable.

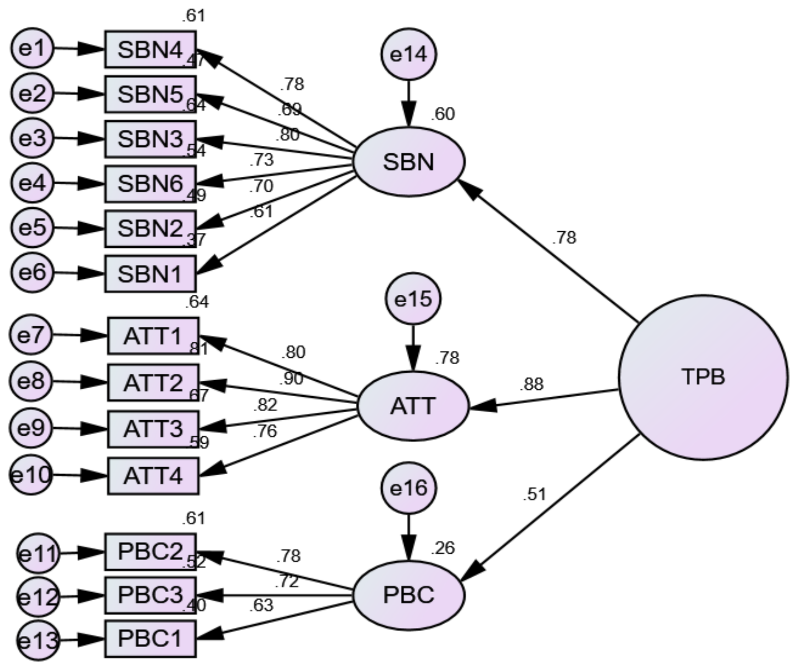
AVE should be more than MSV and less than CR. AVEs were less than CR and larger than MSV and ASV for these latent constructs, indicating convergent and divergent validity.

Discriminant validity measures how much construct variables diverge from their latent construct. Discriminant validity indicates if constructs cross load. Non-cross-loading indicates discriminant validity (Hair et al., 2006). The discriminant is valid since Larcker and Fornell (1981) assumed MSV to be smaller than AVE. Latent variable maximum shared variance (MSV) values do not have discriminant validity issues.

Another discriminant validity assumption is that the maximum shared variance (MSV) is smaller than the average variance extracted (AVE), and the square root of AVE is larger than the inter-construct correlation. Thus, discriminant validity measures verified the scales and supported the research model.

Thus, measurement scales are statistically valid and reliable.

Figure 2: Second Order Confirmatory Factor Analysis



Source: Amos Output

Table 6 Model Fit Measures

Measure	Estimate	Threshold	Interpretation
CMIN	223.822	--	--
DF	62	--	--
CMIN/DF	3.610	Between 1 and 5	Excellent
CFI	0.916	>0.85	Excellent
GFI	0.890	>0.85	Excellent
NFI	0.889	>0.85	Excellent
IFI	0.917	>0.85	Excellent
TLI	0.895	>0.85	Excellent
RMSEA	0.095	<0.10	Acceptable

Source: Amos Output

Table 6 shows that the measurement model fits the data very well. The degree of freedom is 62, and the chi-square (CMIN) value is 223.822, which is statistically significant (p=.000). The fitness scores, such as GFI=0.890, CFI=0.916, IFI=0.917, NFI=0.889, and TLI=.895, are all higher than 0.80, which means the model is more accurate. The CMIN/DF was 3.610, which is less than 5, which shows that the model fits better. The RMSEA was 0.073, which was lower than the recommended range of 0.05 to 1.00. The measurement model met the conditions for a better model fit.

Table 7 Standardized Regression Weights

Items	Path	Factors	Estimate
SBN	<---	TPB	.777
ATT	<---	TPB	.883
PBC	<---	TPB	.512
SBN4	<---	SBN	.778
SBN5	<---	SBN	.688
SBN3	<---	SBN	.801
SBN6	<---	SBN	.732
SBN2	<---	SBN	.703
SBN1	<---	SBN	.606
ATT1	<---	ATT	.801
ATT2	<---	ATT	.901
ATT3	<---	ATT	.821
ATT4	<---	ATT	.765
PBC2	<---	PBC	.782
PBC3	<---	PBC	.722
PBC1	<---	PBC	.631

Source: Primary Data

Table 7 and Figure 2 showed that all variables of three latent factors had standardized regression weights (factor loadings) between 0.606 and 0.901, indicating more incredible goodness of fit. The central factor hypothesis of planned behaviour is based on subjective norms, attitude, and perceived behavioural control. Standardized regression weights (factor loadings) should be more than 0.5 for each variable to determine the factor structure.

Exploratory Factor Analysis of Purchase Intention

Table 8 Sampling Adequacy

<table>
<tr><th colspan="3">KMO and Bartlett's Test</th></tr>
<tr><td colspan="2">Kaiser-Meyer-Olkin Measure of Sampling Adequacy.</td><td>.844</td></tr>
<tr><td rowspan="3">Bartlett's Test of Sphericity</td><td>Approx. Chi-Square</td><td>562.137</td></tr>
<tr><td>df</td><td>10</td></tr>
<tr><td>Sig.</td><td>.000</td></tr>
</table>

Source: Primary Data

Table 8 shows the sampling adequacy of the study. The Chi-square value of the Bartlett Test is 562.137, which is significant, and the KMO value is .844, more than the minimum acceptable range of .70, which indicates that the sample size is adequate in the present study.

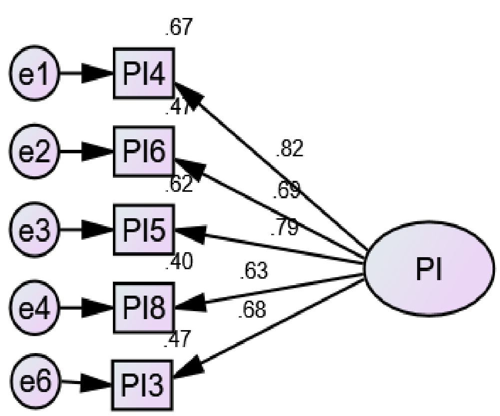
Table 9 Results of Exploratory Factor Analysis

Sr. No.	Items	Factor loading	Eigenvalue	Variance explained	Cronbach
Factor 1: Purchase Intention					
1.	"I do not trust EV technology because of EV fires".	.844	3.092	61.841	.845
2.	"I am hesitant to purchase an EV since it is a new technology".	.825			
3.	"The lack of service assistance for EVs in India deters me from buying".	.771			
4.	"I do not want to take a risk on an EV since I know so little about them".	.755			
5.	"Because of the poor resale value, purchasing an EV is not a wise choice".	.732			

Source: Primary data

The principal component factor analysis with varimax rotation is applied to reduce the data. Provided with all preconditions fulfilled, the factor analysis was applied to the data collected. Factor loadings of the items ranged between 0.732 and 0.844, which can be considered suitable for factor analysis. Hair et al. (2014) classified the significance of factor loadings based on sample size; for a sample of 350 or more 0.50-factor loadings are acceptable. So, in this study, factor loading >0.50 is considered for item retention. In total, one was extracted with eigenvalues greater than one, which included a total of five items.

Figure 3: First-Order Confirmatory Factor Analysis of Purchase Intention



Source: Amos Output

Table 10 Model Fit Measures

Measure	Estimate	Threshold	Interpretation
CMIN	14.233	--	--
DF	5	--	--
P	.000		
CMIN/DF	2.847	Between 1 and 5	Excellent
CFI	0.983	>0.85	Excellent
GFI	0.981	>0.85	Excellent
NFI	0.975	>0.85	Excellent
IFI	0.984	>0.85	Excellent
TLI	0.967	>0.85	Excellent
RMSEA	0.080	<0.10	Acceptable

Source: Primary Data

Table 10 shows that the measurement model's fitness is outstanding. With a degree of freedom of 5, the chi-square (CMIN) value is 14.233, which is statistically significant (p=.000). The fitness indices GFI=0.981, CFI=0.983, IFI=0.984, NFI= 0.8975, and TLI=.90967 are more than the required 0.80, indicating that the model is more fit. The CMIN/DF was 2.847, which is less than five and indicates that the model is more fit. The RMSEA was 0.080, lower than the recommended range (0.05 to 1.00). The measurement model meets the criteria for improved model fit.

Table 11: Standardized Regression Weights

Items	Path	Factors	Estimate
PI5	<---	PI	.788
PI8	<---	PI	.632
PI4	<---	PI	.819
PI6	<---	PI	.687
PI3	<---	PI	.685

Source: Primary Data

Table 11 and Figure 3 demonstrated that the values of standardized regression weights (factor loadings) for all the variables of three latent factors lay in the range of 0.632 to 0.788, which confirmed better goodness of fit. The Standardized regression weights (factor loadings) should be higher than 0.5 for each variable (to confirm the structure of the factors.

Table 12 Model Validity Measures

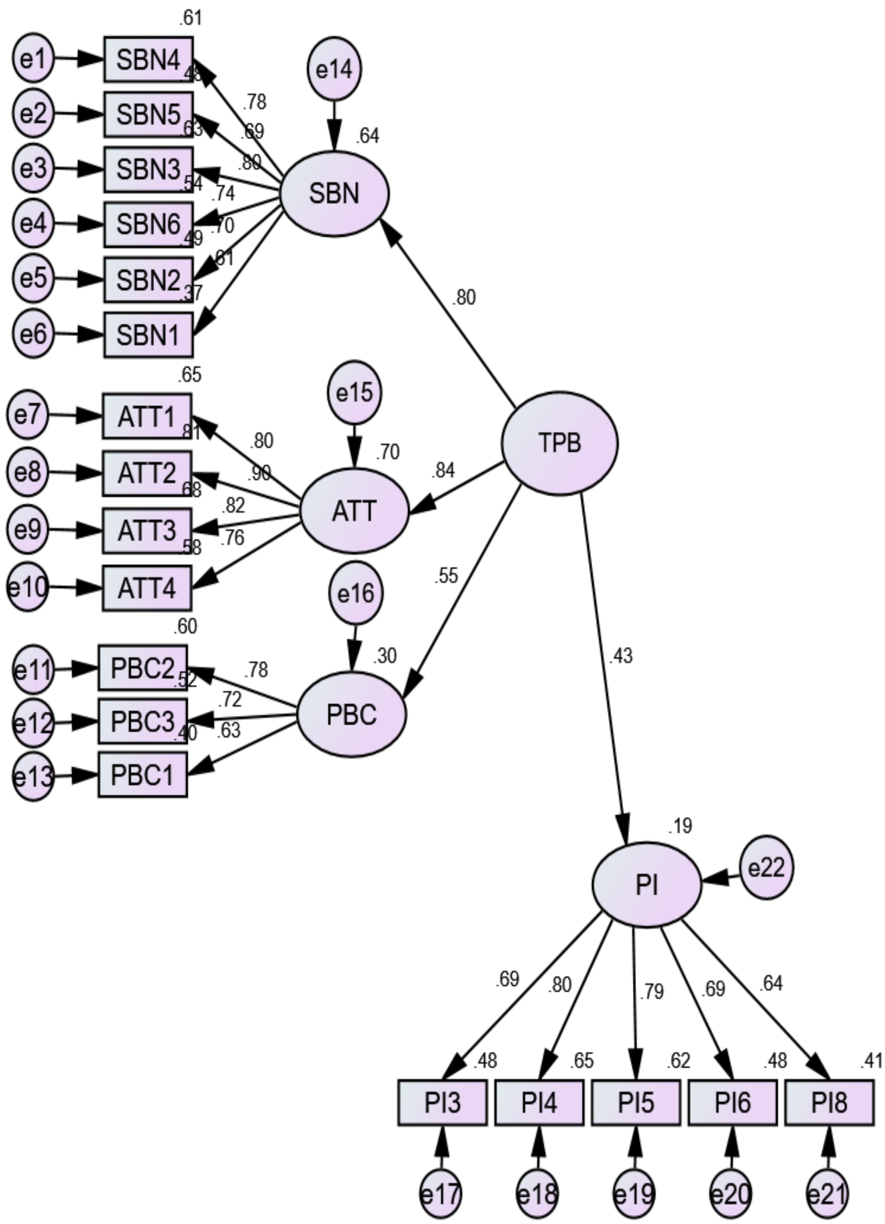
Factors	**CR**	**AVE**	**MaxR(H)**	**PI**
PI	0.846	0.526	0.859	

Source: Primary Data

Table 12 shows the different validity measures; CR is more than the minimum acceptable value of 0.70, and AVE is in a more acceptable range of 0.50. CR is also more than AVE. So no validity concern is found on the scale.

No Validity Concerns

Figure 4: Structural Equation Modelling:



Source: Amos Output

Table 13 model fit measures

Measure	Estimate	Threshold	Interpretation
CMIN	333.120	--	--
DF	131	--	--
P	.000		
CMIN/DF	2.543	Between 1 and 5	Excellent
CFI	0.921	>0.85	Excellent
GFI	0.881	>0.85	Excellent
NFI	0.877	>0.85	Excellent
IFI	0.922	>0.85	Excellent
TLI	0.908	>0.85	Excellent
RMSEA	0.073	<0.10	Acceptable

Source: Primary data

Table 13 shows that the structural model's fitness is outstanding. With a degree of freedom of 131, the chi-square (CMIN) value is 333.120, which is statistically significant (p=.000). The fitness indices GFI=0.881, CFI=0.921, IFI=0.922, NFI= 0.877, and TLI=.908 are more than the required 0.80, indicating that the model is more fit. The CMIN/DF was 2.543, which is less than five and indicates that the model is more fit. The RMSEA was 0.073, lower than the recommended range (0.05 to 1.00). The structural model meets the criteria for improved model fit.

Table 14: Standardized Regression Weights

Factors	Path	Factors	Estimate	P
SBN	<---	TPB	.803	.***
ATT	<---	TPB	.838	.***
PBC	<---	TPB	.551	.***
PI	<---	TPB	.432	.***

Source: Primary data

The effect of the theory of planned behaviour on purchase intention towards electric vehicles was found to be significant and positive **(Figure 4).** theory of planned behaviour is positively associated with the purchase intention towards electric vehicles. The standardized regression weight ($p<0.001$) of the theory of planned behaviour is 0.432. it can be concluded that factors of the theory of planned behaviour lead to consumers' purchase intention toward electric vehicles. *Thus, the hypothesis (Ha)* there is a positive and significant relationship between the theory of planned behaviour and purchase intention towards electric vehicles *is accepted.*

LIMITATIONS AND FUTURE RESEARCH DIRECTIONS

Like any research, this study has limitations that can provide avenues for future research.

LIMITATIONS

First, the Theory of Planned Behavior (TPB) does not account for factors outside volitional control, such as the availability of infrastructure or financial capabilities (Sierzchula et al., 2014). While the TPB provides valuable insights, it may only capture some of the complexities of purchasing behaviours, particularly for high-involvement decisions such as buying an electric vehicle.

Second, self-reported intentions and behaviours measured through an online survey can potentially suffer from social desirability bias, where respondents may overstate their intention to buy an electric vehicle due to the socially desirable nature of sustainable behaviours (Davies et al., 2002).

Third, the sample is constrained by the nature of online data collection. It might not adequately represent the entire population, particularly those with limited internet access or older generations who might need to be more familiar with online surveys.

Finally, the cultural and geographical limitations of the study may reduce the generalizability of the findings. The study's respondents are limited to a particular region, and attitudes towards electric vehicles and their adoption might differ across cultures (Liao et al., 2020).

FUTURE RESEARCH DIRECTIONS

Future research should address these limitations. Including other theories that account for external constraints, such as the Diffusion of Innovations theory, could provide a more comprehensive framework for understanding electric vehicle adoption.

A mixed-methods design, integrating qualitative methods such as interviews or focus groups, could offer more nuanced insights into consumers' perceptions and attitudes towards electric vehicles.

Future studies could also consider stratified or quota sampling methods to ensure a more representative sample. Researchers could also focus on expanding the geographical and cultural range of the study, allowing for a broader understanding of consumer intentions across different contexts.

Finally, longitudinal studies could be beneficial to track changes in consumer behaviour and attitudes over time and provide insights into how intentions translate into actual purchase behaviour.

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