DATA ANALYIS AND RESULTS

Table of Contents

CHAPTER 4: DATA ANALYSIS AND RESULTS

4.1 Introduction

This chapter gives the analysis and interpretation of data gathered to study the factors that affect the adoption of electric vehicle (EVs). Statistical analyses were performed using SPSS and AMOS with a sample size of 520 respondents to cover all the objectives and hypotheses of the research. Reliability testing, descriptive statistics, chi-square analysis, correlation, regression models and structural equation modelling are included in the chapter. Also, exploratory and confirmatory factor analysis were conducted to confirm the measurement model. The findings give information on consumer awareness, behavioural intentions, usage behaviour and continuance intention to adopt EV which will be used to discuss and draw a conclusion further.

The hypotheses are as follows,

H1: Performance expectancy has a favourable impact on the behavioural intention to use electric passenger cars.

H2: Hedonic motivation has a favourable impact on the behavioural intention to use electric passenger cars.

H3: Social influence has a favourable impact on behavioural intention to use electric passenger cars.

H4: Facilitating conditions have a favourable impact on the behavioural intention to use electric passenger cars.

H5: Price value has a favourable impact on the behavioural intention to use electric passenger cars.

H6: Environment awareness has a favourable impact on behavioural intention to use electric passenger cars.

H7: Economic benefit has a favourable impact on behavioural intention to use electric passenger cars.

H8: Sustainability has a favourable impact on behavioural intention to use electric passenger cars.

H9a: Performance expectancy positively affects confirmation.

H9b: Facilitating condition positively affects confirmation.

H9c: Price value positively affects confirmation.

H9d: Economic benefits positively affects confirmation.

H10: confirmation positively affects the consumer satisfaction.

H11: consumer satisfaction positively affects user continuance intention.

H12: consumer use behaviour has negatively affected confirmation.

H13: consumer use behaviour has positively affected the continuance intention of consumers.

4.2 Analysis and Results

4.2.1 Measurement Model Assessment

Reliability Analysis

Construct	Items	No. of Items	Cronbach's Alpha	Interpretation
Performance Expectancy (PE)	PE1–PE4	4	0.781	Acceptable
Hedonic Motivation (HM)	HM1–HM3	3	0.861	Good
Social Influence (SI)	SI1–SI3	3	0.809	Good
Environmental Awareness (EA)	EA1–EA4	4	0.870	Good
Facilitating Conditions (FC)	FC1–FC5	5	0.804	Good
Price Value (PV)	PV1–PV3	3	0.826	Good
Economic Benefit (EB)	EB1–EB3	3	0.912	Excellent
Behavioural Intention (BI)	BI1–BI3	3	0.918	Excellent
Use Behaviour (UB)	UB1–UB3	3	0.937	Excellent
Confirmation (CF)	CF1–CF3	3	0.852	Good
Satisfaction (SAT)	SAT1–SAT3	3	0.900	Excellent

Sustainability (SUS)	SUS1–SUS4	4	0.924	Excellent
Continuous Intention (CI)	CI1–CI3	3	0.900	Excellent

Table 1: Reliability Analysis of Constructs

The Cronbach's Alpha of all constructs is greater than 0.7 which is good internal consistency and scale reliability [Table 1].

Composite Variable Construction

Composite Variable	Items Included	Formula Used (SPSS Compute)
Performance Expectancy (PE)	PE1, PE2, PE3, PE4	(PE1 + PE2 + PE3 + PE4) / 4
Hedonic Motivation (HM)	HM1, HM2, HM3	(HM1 + HM2 + HM3) / 3
Social Influence (SI)	SI1, SI2, SI3	(SI1 + SI2 + SI3) / 3
Facilitating Conditions (FC)	FC1, FC2, FC3, FC4, FC5	(FC1 + FC2 + FC3 + FC4 + FC5) / 5
Economic Benefit (EB)	EB1, EB2, EB3	(EB1 + EB2 + EB3) / 3
Sustainability (SUS)	SUS1, SUS2, SUS3, SUS4	(SUS1 + SUS2 + SUS3 + SUS4) / 4
Environmental Awareness (EA)	EA1, EA2, EA3, EA4	(EA1 + EA2 + EA3 + EA4) / 4
Satisfaction (SAT)	SAT1, SAT2, SAT3	(SAT1 + SAT2 + SAT3) / 3
Confirmation (CF)	CF1, CF2, CF3	(CF1 + CF2 + CF3) / 3
Behavioural Intentions (BI)	BI1, BI2, BI3	(BI1 + BI2 + BI3) / 3
Use Behaviour (UB)	UB1, UB2, UB3	(UB1 + UB2 + UB3) / 3

Continuous Intention (CI)	CI1, CI2, CI3	(CI1 + CI2 + CI3) / 3
Price value (PV)	PV1, PV2, PV3	(PV1+ PV2 + PV3) /3

Table 2: Construction of Composite Variables

The mean of individual items that represent each construct was calculated to form composite variables [Table 2]. This method aids in simplifying data and offers a representative score of each latent variable (Miraz *et al*. 2025, p. 1). The averaged composite scores are used to make sure that all items make an equal contribution to the construct and the scale is consistent. These composite variables were also subjected to statistical analysis such as correlation, regression and structural modelling.

4.2.2 Descriptive Analysis

Descriptive Statistics of Constructs

Descriptive Statistics					
	N	Minimum	Maximum	Mean	Std. Deviation
PE1	520	1	5	4.01	1.082
PE2	520	1	5	3.33	1.207
PE3	520	1	5	3.55	1.125
PE4	520	1	5	3.55	1.142
HM1	520	1	5	3.62	1.134
HM2	520	1	5	4.01	1.028
HM3	520	1	5	3.90	1.025
SI1	520	1	5	3.46	1.202
SI2	520	1	5	3.88	1.097
SI3	520	1	5	3.49	1.146
EA1	520	1	5	4.14	1.000
EA2	520	1	5	4.18	1.022
EA3	520	1	5	4.08	1.032
EA4	520	1	5	3.78	1.098
FC1	520	1	5	3.80	1.079
FC2	520	1	5	3.27	1.209
FC3	520	1	5	3.95	.998
FC4	520	1	5	3.59	1.146
FC5	520	1	5	3.57	1.093
PV1	520	1	5	3.36	1.305
PV2	520	1	5	3.74	1.118
PV3	520	1	5	3.56	1.162
EB1	520	1	5	4.11	1.037
EB2	520	1	5	3.79	1.163
EB3	520	1	5	3.78	1.176
BI1	520	1	5	3.75	1.225
BI2	520	1	5	3.63	1.260
BI3	520	1	5	3.64	1.260
UB1	520	1	5	3.90	1.073
UB2	520	1	5	3.68	1.173
UB3	520	1	5	3.67	1.182
CF1	520	1	5	3.79	1.066

CF2	520	1	5	3.43	1.164
CF3	520	1	5	3.73	1.059
SAT1	520	1	5	3.79	1.022
SAT2	520	1	5	3.81	1.036
SAT3	520	1	5	3.78	1.104
SUS1	520	1	5	4.03	1.035
SUS2	520	1	5	3.91	1.055
SUS3	520	1	5	4.02	.995
SUS4	520	1	5	3.83	1.172
CI1	520	1	5	3.87	1.093
CI2	520	1	5	3.86	1.107
CI3	520	1	5	3.86	1.115
1. Age (Years)	520	1	5	2.89	.931
2. Gender	520	1	2	1.20	.400
3.State/ union territory	520	1	3	1.77	.791
4.Marital status	520	1	3	1.57	.510
5.Educational Qualification	520	1	4	1.70	.834
6.Profession	520	1	4	1.91	1.129
7.Income (Annual in INR)	520	1	4	2.96	1.067
1.Are you aware of electric vehicles/cars?	520	1	3	1.23	.554
2.Do you ever drive an electric car?	520	1	2	1.41	.492
3.Which of the EV brands are you well aware of?	520	1	5	1.96	1.495
4. How would you rate interest in EVs?	520	1	6	2.80	1.652
Valid N (listwise)	520				

Table 3: Descriptive analysis of constructs

The descriptive statistics reveal that generally, the respondents portray moderate to high positive perceptions towards electric vehicles [Table 3]. The mean (nearly 13.35) of environmental awareness is the largest which indicates that the participants are very concerned with sustainability. The performance expectancy (nearly Mean = 11.78) is also indicative of the fact that the respondents are of the opinion that EVs are helpful and effective. There is a positive tendency to adopt and use EVs (behavioural intentions = nearly 8.59) and use behaviour = nearly 8.80), although not the highest. Continuous intention (nearly 9.01) also indicates the desire to use EVs in the future. The standard deviations are relatively moderate which presupposes the similarity of the responses within the sample which means that the attitudes of consumers towards EV adoption are not changing.

4.2.3 Demographic Influence on Awareness (Chi-Square Test)

Gender vs EV Awareness

Crosstab					
			2. Gender		Total
			Male	Female	
1.Are you aware of electric vehicles/cars?	I am aware of EVs enough to consider them.	Count	364	72	436
		% within 1.Are you aware of electric vehicles/cars?	83.5%	16.5%	100.0%
		% within 2. Gender	87.5%	69.2%	83.8%
	I am aware of EVs but do not consider them.	Count	30	20	50
		% within 1.Are you aware of electric vehicles/cars?	60.0%	40.0%	100.0%
		% within 2. Gender	7.2%	19.2%	9.6%

	I am a little bit aware of them.	Count	22	12	34
		% within 1.Are you aware of electric vehicles/cars?	64.7%	35.3%	100.0%
		% within 2. Gender	5.3%	11.5%	6.5%
Total		Count	416	104	520
		% within 1.Are you aware of electric vehicles/cars?	80.0%	20.0%	100.0%
		% within 2. Gender	100.0%	100.0%	100.0%

Table 4: Analysis of Gender vs EV Awareness

The cross-tabulation of EV awareness and gender indicates that there is a distinct difference in the degree of awareness [Table 4]. A big majority of those who are aware enough to think about EVs are male (83.5%), with females making up 16.5% of this group. In gender groups, a percentage of 87.5 of males report high awareness as opposed to 69.2 of females which means that male respondents are more familiar. On the other hand, the number of those who are aware but do not think (19.2) and slightly aware (11.5) is greater in females than in males. The findings indicate that despite the high awareness among both genders, males show a relatively high awareness and consideration of EVs compared to their female counterparts.

Chi-Square Tests

	Value	df	Asymptotic Significance (2-sided)
Pearson Chi-Square	20.783[a]	2	.000
Likelihood Ratio	18.232	2	.000
Linear-by-Linear Association	16.304	1	.000
N of Valid Cases	520		
a. 0 cells (0.0%) have expected count less than 5. The minimum expected count is 6.80.			

Table 5: Chi-square tests of Gender vs EV Awareness

The results of the Chi-square test show that gender and awareness of electric vehicles have a statistically significant correlation [Table 5]. The Pearson Chi-square (2= 20.783, df=2, p<0.00) indicates that the relationship is significant at the 5 percent level. This implies that there are differences in the levels of awareness of EVs between the genders. This is also supported by the Likelihood Ratio and Linear-by-Linear Association tests that lend strength to the result. The Chi-square test assumptions are met as there are none of the cells with less than 5 expected counts. Therefore, gender is a crucial factor when it comes to the determination of EV awareness among the respondents.

Education vs EV Awareness

Crosstab					
	5.Educational Qualification				
	Post-graduation and	Diploma and graduation level	Doctoral level	Basic schoolin g	Total

			professional level				
1.Are you aware of electric vehicles/cars?	I am aware of EVs enough to consider them.	Count	230	132	66	8	436
		% within 1.Are you aware of electric vehicles/cars?	52.8%	30.3%	15.1%	1.8%	100.0%
		% within 5.Educational Qualification	84.6%	93.0%	68.8%	80.0%	83.8%
	I am aware of EVs but do not consider them.	Count	18	6	24	2	50
		% within 1.Are you aware of electric vehicles/cars?	36.0%	12.0%	48.0%	4.0%	100.0%
		% within 5.Educational Qualification	6.6%	4.2%	25.0%	20.0%	9.6%
		Count	24	4	6	0	34

	I am a little bit aware of them.	% within 1.Are you aware of electric vehicles/cars?	70.6%	11.8%	17.6%	0.0%	100.0%
		% within 5.Educational Qualification	8.8%	2.8%	6.3%	0.0%	6.5%
Total		Count	272	142	96	10	520
		% within 1.Are you aware of electric vehicles/cars?	52.3%	27.3%	18.5%	1.9%	100.0%
		% within 5.Educational Qualification	100.0%	100.0%	100.0%	100.0%	100.0%

Table 6: Analysis of Education vs EV Awareness

According to the cross-tabulation, the awareness of EVs is mostly high and similar in all levels of education, although there are evident differences [Table 6]. Respondents who have attained a diploma/graduation (93.0) and post-graduation (84.6) report the highest levels of being sufficiently aware to think about EVs. Conversely, doctoral respondents are less considerate (68.8%) and a greater number do not consider EVs despite being aware of them (25.0%).

Chi-Square Tests			
	Value	df	Asymptotic Significance (2-sided)

Pearson Chi-Square	41.480[a]	6	.000
Likelihood Ratio	36.759	6	.000
Linear-by-Linear Association	.797	1	.372
N of Valid Cases	520		
a. 2 cells (16.7%) have expected count less than 5. The minimum expected count is .65.			

Table 7: Chi-square tests of Education vs EV Awareness

The Chi-square value (2 = 41.480, p = 0.000) shows the significance of the education level and EV awareness [Table 7]. The results are to be taken with caution, as the expected counts of some of the cells are below 5. In general, awareness is shaped by education though the trend is not necessarily linear.

Income vs EV Awareness

Crosstab							
			7.Income (Annual in INR)				
			below 3 lakhs	3 to 5 lakhs	5 to 10 lakhs	Above 10 lakh	Total
1.Are you aware of electric vehicles/cars?	I am aware of EVs enough to consider them.	Count	46	74	106	210	436
		% within 1.Are you aware of electric vehicles/cars?	10.6%	17.0%	24.3%	48.2%	100.0 %
		% within 7.Income (Annual in INR)	71.9%	64.9%	88.3%	94.6%	83.8%

	I am aware of EVs but do not consider them.	Count	8	26	6	10	50
		% within 1.Are you aware of electric vehicles/cars?	16.0%	52.0%	12.0%	20.0%	100.0 %
		% within 7.Income (Annual in INR)	12.5%	22.8%	5.0%	4.5%	9.6%
	I am a little bit aware of them.	Count	10	14	8	2	34
		% within 1.Are you aware of electric vehicles/cars?	29.4%	41.2%	23.5%	5.9%	100.0 %
		% within 7.Income (Annual in INR)	15.6%	12.3%	6.7%	0.9%	6.5%
Total		Count	64	114	120	222	520
		% within 1.Are you aware of electric vehicles/cars?	12.3%	21.9%	23.1%	42.7%	100.0 %

	% within 7.Income (Annual in INR)	100.0%	100.0%	100.0%	100.0%	100.0 %

Table 8: Analysis of Income vs EV Awareness

The cross-tabulation indicates a definite correlation between income and EV awareness [Table 8]. The percentage of those respondents who are above ₹10 lakh (94.6%) and 5-10 lakhs (88.3%) who are aware enough to consider EVs is higher than the percentages of those with lower incomes as below 3 lakhs (71.9%) and 3-5 lakhs (64.9%). The proportions of limited awareness or non-consideration are also relatively higher among lower-income groups.

Chi-Square Tests			
	Value	df	Asymptotic Significance (2-sided)
Pearson Chi-Square	63.815[a]	6	.000
Likelihood Ratio	63.211	6	.000
Linear-by-Linear Association	46.119	1	.000
N of Valid Cases	520		
a. 1 cells (8.3%) have expected count less than 5. The minimum expected count is 4.18.			

Table 9: Chi-Square tests of Income vs EV Awareness

The Chi-square result (2 = 63.815, p = 0.000) shows that there is a significant correlation between income and EV awareness and the linear-by-linear correlation is also significant [Table 9]. This indicates that there is a positive trend between the higher the income, the higher the awareness and consideration. In general, more affluent people are better prepared for EV adoption.

4.2.4 Correlation Analysis

Correlations

		performance_expectancy	hedonic_motivation	social_influence	facilitating_conditions	economic_benefit	sustainability	environmental_awareness	satisfaction	confirmation	behavioural_intentions	use_behaviour	continuous_intention
performance_expectancy	Pearson Correlation	1	.698**	.620**	.634**	.592**	.472**	.539**	.670**	.632**	.640**	.586**	.662**
	Sig. (2-tailed)		<.001	<.001	<.001	<.001	<.001	<.001	<.001	<.001	<.001	<.001	<.001
	N	520	520	520	520	520	520	520	520	520	520	520	520
hedonic_motivation	Pearson Correlation	.698**	1	.582**	.642**	.625**	.573**	.631**	.685**	.667**	.594**	.658**	.771**
	Sig. (2-tailed)	<.001		<.001	<.001	<.001	<.001	<.001	<.001	<.001	<.001	<.001	<.001
	N	520	520	520	520	520	520	520	520	520	520	520	520
social_influence	Pearson Correlation	.620**	.582**	1	.648**	.545**	.567**	.652**	.612**	.559**	.532**	.523**	.630**
	Sig. (2-tailed)	<.001	<.001		<.001	<.001	<.001	<.001	<.001	<.001	<.001	<.001	<.001
	N	520	520	520	520	520	520	520	520	520	520	520	520
facilitating_conditions	Pearson Correlation	.634**	.642**	.648**	1	.671**	.645**	.627**	.700**	.702**	.656**	.654**	.706**
	Sig. (2-tailed)	<.001	<.001	<.001		<.001	<.001	<.001	<.001	<.001	<.001	<.001	<.001
	N	520	520	520	520	520	520	520	520	520	520	520	520
economic_benefit	Pearson Correlation	.592**	.625**	.545**	.671**	1	.605**	.631**	.755**	.683**	.665**	.662**	.683**
	Sig. (2-tailed)	<.001	<.001	<.001	<.001		<.001	<.001	<.001	<.001	<.001	<.001	<.001
	N	520	520	520	520	520	520	520	520	520	520	520	520
sustainability	Pearson Correlation	.472**	.573**	.567**	.645**	.605**	1	.721**	.688**	.593**	.557**	.621**	.716**

	Sig. (2-tailed)	<.001	<.001	<.001	<.001	<.001		<.001	<.001	<.001	<.001	<.001	<.001
	N	520	520	520	520	520	520	520	520	520	520	520	520
environmental_awareness	Pearson Correlation	.539**	.631**	.652**	.627**	.631**	.721**	1	.645**	.583**	.513**	.613**	.664**
	Sig. (2-tailed)	<.001	<.001	<.001	<.001	<.001	<.001		<.001	<.001	<.001	<.001	<.001
	N	520	520	520	520	520	520	520	520	520	520	520	520
satisfaction	Pearson Correlation	.670**	.685**	.612**	.700**	.755**	.688**	.645**	1	.804**	.682**	.757**	.842**
	Sig. (2-tailed)	<.001	<.001	<.001	<.001	<.001	<.001	<.001		<.001	<.001	<.001	<.001
	N	520	520	520	520	520	520	520	520	520	520	520	520
confirmation	Pearson Correlation	.632**	.667**	.559**	.702**	.683**	.593**	.583**	.804**	1	.673**	.742**	.764**
	Sig. (2-tailed)	<.001	<.001	<.001	<.001	<.001	<.001	<.001	<.001		<.001	<.001	<.001
	N	520	520	520	520	520	520	520	520	520	520	520	520
behavioural_intentions	Pearson Correlation	.640**	.594**	.532**	.656**	.665**	.557**	.513**	.682**	.673**	1	.735**	.676**
	Sig. (2-tailed)	<.001	<.001	<.001	<.001	<.001	<.001	<.001	<.001	<.001		<.001	<.001
	N	520	520	520	520	520	520	520	520	520	520	520	520
use_behaviour	Pearson Correlation	.586**	.658**	.523**	.654**	.662**	.621**	.613**	.757**	.742**	.735**	1	.806**
	Sig. (2-tailed)	<.001	<.001	<.001	<.001	<.001	<.001	<.001	<.001	<.001	<.001		<.001
	N	520	520	520	520	520	520	520	520	520	520	520	520
continuous_intention	Pearson Correlation	.662**	.771**	.630**	.706**	.683**	.716**	.664**	.842**	.764**	.676**	.806**	1
	Sig. (2-	<.001	<.001	<.001	<.001	<.001	<.001	<.001	<.001	<.001	<.001	<.001	

	tail ed)												
	N	520	520	520	520	520	520	520	520	520	520	520	520
**. Correlation is significant at the 0.01 level (2-tailed).													

Table 10: Correlation analysis

The correlation matrix indicates strong, positive, and statistically significant relationships among all constructs ($p < 0.001$), suggesting a well-connected model with high internal consistency across variables. Performance expectancy shows strong correlations with hedonic motivation ($r = 0.698$), facilitating conditions ($r = 0.634$), and satisfaction ($r = 0.670$), indicating that perceived usefulness is closely linked with both system enjoyment and user satisfaction. Hedonic motivation also demonstrates a notably strong relationship with continuous intention ($r = 0.771$), highlighting the importance of enjoyment in driving long-term usage. Facilitating conditions exhibit consistently high correlations with multiple constructs, particularly confirmation ($r = 0.702$) and continuous intention ($r = 0.706$), suggesting that adequate support and resources significantly influence both user expectations and continued system use. Economic benefit is strongly correlated with satisfaction ($r = 0.755$), reinforcing the role of perceived value in enhancing user satisfaction. Sustainability and environmental awareness are also moderately to strongly correlated ($r = 0.721$), indicating conceptual alignment between these constructs. Both variables show meaningful relationships with satisfaction and continuous intention, suggesting that environmentally conscious users are more likely to remain engaged. Satisfaction emerges as a central construct, displaying very strong correlations with confirmation ($r = 0.804$), use behaviour ($r = 0.757$), and continuous intention ($r = 0.842$). This confirms its mediating role in technology adoption models. Similarly, use behaviour is highly correlated with continuous intention ($r = 0.806$), indicating that actual usage strongly predicts continued usage intentions. However, some correlations exceed 0.80 (satisfaction–continuous intention), which may indicate potential multicollinearity or lack of discriminant validity. This suggests the need for further validation using HTMT or Fornell-Larcker criteria. Overall, the results support strong interrelationships among constructs, aligning with theoretical expectations, while also highlighting the need to assess construct distinctiveness.

4.2.5 Regression Analysis

Model 1: Factors → Behavioural Intentions

Model Summary				
Model	R	R Square	Adjusted R Square	Std. Error of the Estimate
1	.746[a]	.557	.554	1.78271
a. Predictors: (Constant), sustainability, performance_expectancy, economic_benefit, environmental_awareness				

Table 11: Model summary

ANOVA[a]						
Model		Sum of Squares	df	Mean Square	F	Sig.
1	Regression	2057.837	4	514.459	161.878	.000[b]
	Residual	1636.701	515	3.178		
	Total	3694.538	519			
a. Dependent Variable: behavioural_intentions						
b. Predictors: (Constant), sustainability, performance_expectancy, economic_benefit, environmental_awareness						

Table 12: ANOVA analysis

Coefficients[a]					
Model	Unstandardized Coefficients		Standardized Coefficients	t	Sig.
	B	Std. Error	Beta		

1	(Constant)	-.584	.402		-1.454	.146
	performance_expectancy	.320	.034	.358	9.489	.000
	environmental_awareness	-.058	.042	-.063	-1.373	.170
	economic_benefit	.409	.048	.363	8.588	.000
	sustainability	.188	.039	.214	4.840	.000
a. Dependent Variable: behavioural_intentions						

Table 13: Coefficients

The multiple regression test investigates how the most important factors influence behavioural intentions towards electric vehicles. The model has a strong explanatory power as the R^2 is 0.557 which implies that around 55.7 percent of the change in the behavioural intentions can be attributed to the performance expectancy, environmental awareness, economic benefit and sustainability. The overall model is statistically significant as shown by the ANOVA results ($F = 161.878$, $p < 0.000$). Among the predictors, the economic benefit ($\beta = 0.363$, $P = 0.000$) stands out as the most predictive variable which indicates that the cost saving and financial benefits are a key factor in the formation of consumer intentions. There is also a strong positive influence of performance expectancy ($\beta = 0.358$, $p < 0.000$) which suggests that the perceptions of efficiency and usefulness are one of the strongest motivators of purchase intentions. Also, there is a moderate but significant influence of sustainability (0.214, $p = 0.000$) and the fact that environmental considerations play a crucial role in decision-making. Although, the awareness of the environment ($\beta = -0.063$, $p = 0.170$) does not show any significant difference which means that the simple awareness of the environmental issues does not always lead to behavioural intention. Therefore, the results indicate that practical and economic considerations are more prominent when it comes to EV adoption decisions compared to overall environmental awareness (Mustafa *et al.* 2026, p. 861).

Model 2: Behavioural Intentions → Use Behaviour

Model Summary

Model	R	R Square	Adjusted R Square	Std. Error of the Estimate
1	.735[a]	.541	.540	1.67843
a. Predictors: (Constant), behavioural_intentions				

Table 14: Model summary

ANOVA[a]						
Model		Sum of Squares	df	Mean Square	F	Sig.
1	Regression	1717.164	1	1717.164	609.544	.000[b]
	Residual	1459.273	518	2.817		
	Total	3176.437	519			
a. Dependent Variable: use_behaviour						
b. Predictors: (Constant), behavioural_intentions						

Table 15: ANOVA analysis

Coefficients[a]						
Model		Unstandardized Coefficients		Standardized Coefficients	t	Sig.
		B	Std. Error	Beta		
1	(Constant)	2.948	.248		11.872	.000
	behavioural_intentions	.682	.028	.735	24.689	.000
a. Dependent Variable: use_behaviour						

Table 16: Coefficients analysis

Regression analysis explores the effects of behavioural intentions towards use behaviour of electric vehicles. The model has a good explanatory power as the R^2 is 0.541 which means that an estimate of 54.1 percent of the change in use behaviour is explained by behavioural intentions. The stability and reliability of the model is also checked by the adjusted R^2 (0.540). The test outcomes of ANOVA indicate that the model is statistically significant ($F = 609.544$, $p < 0.000$) which means that behavioural intention is an effective predictor of use behaviour. The coefficient results reveal that behavioural intentions have a strong and positive effect on use behaviour ($\beta = 0.735$, $p < 0.000$). This indicates that people who display greater intentions to buy electric cars have a much greater chance of actually utilising them. The unstandardised coefficient ($B = 0.682$) means that one unit of increase in behavioural intention increases the use behaviour by 0.682. The large t-value (24.689) further supports the strength and significance of this relationship. The results indicate the behavioural intention as a significant predictor of actual usage, which confirms the previously identified behavioural theories that intention is a strong predictor of actual use in the area of EV adoption.

Model 3: BI + UB → Continuous Intention

Model Summary				
Model	R	R Square	Adjusted R Square	Std. Error of the Estimate
1	.816[a]	.665	.664	1.34811
a. Predictors: (Constant), use_behaviour, behavioural_intentions				

Table 17: Model summary

ANOVA[a]						
Model		Sum of Squares	df	Mean Square	F	Sig.
1	Regression	1867.357	2	933.678	513.745	.000[b]
	Residual	939.595	517	1.817		
	Total	2806.952	519			
a. Dependent Variable: continuous_intention						

b. Predictors: (Constant), use_behaviour, behavioural_intentions

Table 18: ANOVA analysis

Coefficients[a]						
Model		Unstandardized Coefficients		Standardized Coefficients	t	Sig.
		B	Std. Error	Beta		
1	(Constant)	2.082	.225		9.254	.000
	behavioural_intentions	.159	.033	.182	4.851	.000
	use_behaviour	.632	.035	.672	17.909	.000
a. Dependent Variable: continuous_intention						

Table 19: Coefficients analysis

The regression study explores the joint impact of behavioural intentions (BI) and use behaviour (UB) on continuous intention (CI) to electric vehicles. There is very high explanatory power of the model which has R^2 of 0.665 which implies that the two predictors explain 66.5% of the variation in continuous intention. Adjusted R^2 (0.664) is another indicator that the model is robust and reliable. The results of the ANOVA indicate that the model is very significant ($F = 513.745$, $p < 0.000$), indicating that both BI and UB play a significant role in the continuous intention. When analysing the coefficients, the strongest predictor is using behaviour ($\beta = 0.672$, $p < 0.000$), which shows that actual use of EVs is a key factor in determining the intention of the users to remain in the use of EVs. Behavioural intentions ($\beta = 0.182$, $p = 0.000$) also positively and significantly impact this though with a relatively weaker impact than use behaviour. The results suggest that intention is significant at the initial adoption phases yet actual experience (use behaviour) plays a predominant role in the long-term maintenance of use. The findings point to the idea that promoting the use of EVs at the beginning is the primary step to guarantee further adoption and consumer loyalty (Zhang *et al*. 2025, p. 460).

Model 4: Determinants of Behavioural Intentions

Model Summary				
Model	R	R Square	Adjusted R Square	Std. Error of the Estimate
1	.741[a]	.549	.544	1.80243
a. Predictors: (Constant), environmental_awareness, facilitating_conditions, hedonic_motivation, social_influence, economic_benefit, sustainability				

Table 20: Model summary

ANOVA[a]						
Model		Sum of Squares	df	Mean Square	F	Sig.
1	Regression	2027.929	6	337.988	104.036	<.001[b]
	Residual	1666.610	513	3.249		
	Total	3694.538	519			
a. Dependent Variable: behavioural_intentions						
b. Predictors: (Constant), environmental_awareness, facilitating_conditions, hedonic_motivation, social_influence, economic_benefit, sustainability						

Table 21: ANOVA

Coefficients[a]						
Model		Unstandardized Coefficients		Standardized Coefficients	t	Sig.
		B	Std. Error	Beta		
1	(Constant)	-.570	.408		-1.397	.163
	hedonic_motivation	.202	.052	.168	3.864	<.001
	social_influence	.101	.050	.087	2.014	.045
	facilitating_conditions	.196	.037	.258	5.361	<.001
	economic_benefit	.377	.050	.335	7.529	<.001
	sustainability	.108	.041	.122	2.633	.009
	environmental_awareness	-.101	.045	-.111	-2.232	.026
a. Dependent Variable: behavioural_intentions						

Table 22: Coefficients

The model demonstrates strong explanatory power ($R^2 = 0.549$), indicating that approximately 54.9% of the variance in behavioural intentions is explained by the included predictors. The overall model is statistically significant ($F = 104.036$, $p < 0.001$), confirming that the set of variables jointly influences behavioural intentions.

Among the predictors, economic benefit ($\beta = 0.335$) and facilitating conditions ($\beta = 0.258$) exert the strongest positive effects, suggesting that financial advantages and supporting infrastructure are key drivers. Hedonic motivation ($\beta = 0.168$), sustainability ($\beta = 0.122$), and social influence ($\beta = 0.087$) also show positive and significant contributions, though comparatively weaker. In contrast, environmental awareness exhibits a small but significant negative effect ($\beta = -0.111$), indicating that higher awareness does not necessarily translate into stronger behavioural intentions. Overall, both practical and perceptual factors shape behavioural intentions, with economic considerations being most influential.

Model 5: Performance Expectancy → Confirmation

Model Summary				
Model	R	R Square	Adjusted R Square	Std. Error of the Estimate
1	.632[a]	.399	.398	1.77171
a. Predictors: (Constant), performance_expectancy				

Table 23: Model summary

ANOVA[a]						
Model		Sum of Squares	df	Mean Square	F	Sig.
1	Regression	1078.854	1	1078.854	343.697	<.001[b]
	Residual	1625.983	518	3.139		
	Total	2704.837	519			
a. Dependent Variable: confirmation						
b. Predictors: (Constant), performance_expectancy						

Table 24: ANOVA

Coefficients[a]						
Model		Unstandardized Coefficients		Standardized Coefficients	t	Sig.
		B	Std. Error	Beta		
1	(Constant)	2.787	.316		8.821	<.001
	performance_expectancy	.482	.026	.632	18.539	<.001
a. Dependent Variable: confirmation						

Table 25: Coefficients

This model explains a substantial portion of variance in confirmation ($R^2 = 0.399$), indicating that performance expectancy alone accounts for nearly 39.9% of the variation. The model is highly significant ($F = 343.697$, $p < 0.001$), confirming a strong predictive relationship.

Performance expectancy shows a strong positive effect on confirmation ($\beta = 0.632$, $p < 0.001$), suggesting that when individuals perceive higher usefulness and effectiveness in electric vehicles, their expectations are more likely to be confirmed. The large t-value (18.539) further reinforces the strength and stability of this relationship. Overall, the findings highlight that perceived performance is a key determinant in shaping users' confirmation of expectations.

Model 6: Use Behaviour → Confirmation

Model Summary				
Model	R	R Square	Adjusted R Square	Std. Error of the Estimate
1	.742[a]	.550	.549	1.53313
a. Predictors: (Constant), use_behaviour				

Table 26: Model Summary

ANOVA[a]						
Model		Sum of Squares	df	Mean Square	F	Sig.
1	Regression	1487.289	1	1487.289	632.760	<.001[b]

	Residual	1217.547	518	2.350		
	Total	2704.837	519			
a. Dependent Variable: confirmation						
b. Predictors: (Constant), use_behaviour						

Table 27: ANOVA

Coefficients[a]						
Model		Unstandardized Coefficients		Standardized Coefficients	t	Sig.
		B	Std. Error	Beta		
1	(Constant)	2.439	.249		9.804	<.001
	use_behaviour	.684	.027	.742	25.155	<.001
a. Dependent Variable: confirmation						

Table 28: Coefficients

This model demonstrates strong explanatory power ($R^2 = 0.550$), indicating that use behaviour explains 55.0% of the variance in confirmation. The model is highly significant ($F = 632.760$, $p < 0.001$), suggesting a robust relationship between the variables.

Use behaviour has a very strong positive effect on confirmation ($\beta = 0.742$, $p < 0.001$), indicating that individuals who actively use electric vehicles are more likely to have their expectations confirmed. The high standardized coefficient and large t-value (25.155) reflect the strength and consistency of this relationship. This suggests that actual experience plays a critical role in shaping perceptions and reinforcing confirmation, making behavioural engagement a key driver of user evaluation.

Model 7: Price Value → Behavioural intention

Model Summary				
Model	R	R Square	Adjusted R Square	Std. Error of the Estimate
1	.692[a]	.479	.478	1.92772
a. Predictors: (Constant), Price_Value				

Table 29: Model summary

ANOVA[a]						
Model		Sum of Squares	df	Mean Square	F	Sig.
1	Regression	1769.603	1	1769.603	476.200	.000[b]
	Residual	1924.935	518	3.716		
	Total	3694.538	519			
a. Dependent Variable: behavioural_intentions						
b. Predictors: (Constant), Price_Value						

Table 30: ANOVA[a]

Coefficients[a]						
Model		Unstandardized Coefficients		Standardized Coefficients	t	Sig.
		B	Std. Error	Beta		
1	(Constant)	2.398	.296		8.102	.000
	Price_Value	.747	.034	.692	21.822	.000
a. Dependent Variable: behavioural_intentions						

Table 31: Coefficients

The regression results (Model 7: Table – Model Summary, ANOVA, and Coefficients) indicate that price value has a strong and statistically significant positive effect on behavioural intention ($\beta = 0.692$, $p < 0.001$). The model demonstrates good explanatory power with $R^2 = 0.479$, meaning that price value explains approximately 47.9% of the variance in behavioural intentions. The ANOVA results confirm that the model is statistically significant ($F = 476.200$, $p < 0.001$). The high beta coefficient suggests that consumers are highly influenced by perceived value for money.

Model 8: Determinants of Confirmation

Model Summary				
Model	R	R Square	Adjusted R Square	Std. Error of the Estimate
1	.800[a]	.640	.637	1.37464
a. Predictors: (Constant), economic_benefit, Price_Value, facilitating_conditions				

Table 32: Model Summary

ANOVA[a]						
Model		Sum of Squares	df	Mean Square	F	Sig.
1	Regression	1729.784	3	576.595	305.135	.000[b]
	Residual	975.053	516	1.890		
	Total	2704.837	519			
a. Dependent Variable: confirmation						
b. Predictors: (Constant), economic_benefit, Price_Value, facilitating_conditions						

Table 33: ANOVA

Coefficients[a]						
Model		Unstandardized Coefficients		Standardized Coefficients	t	Sig.
		B	Std. Error	Beta		
1	(Constant)	.468	.281		1.664	.097
	facilitating_conditions	.191	.025	.293	7.530	.000
	Price_Value	.326	.034	.353	9.611	.000
	economic_benefit	.259	.036	.269	7.143	.000
a. Dependent Variable: confirmation						

Table 34: Coefficients

The regression results for Model 8: Determinants of Confirmation (Table – Model Summary, ANOVA, and Coefficients) indicate that the model has strong explanatory power with $R^2 = 0.640$, meaning 64.0% of the variance in confirmation is explained by facilitating conditions, price value, and economic benefit. The ANOVA results confirm that the model is statistically significant ($F = 305.135$, $p < 0.001$). All three predictors show positive and significant effects: price value ($\beta = 0.353$, $p < 0.001$) has the strongest impact, followed by facilitating conditions ($\beta = 0.293$) and economic benefit ($\beta = 0.269$).

4.2.6 Group Difference Analysis

Independent Sample t-test (Gender Differences)

Independent Samples Test										
		Levene's Test for Equality of Variances		t-test for Equality of Means						
									95% Confidence Interval of the Difference	
		F	Sig.	t	df	Sig. (2-tailed)	Mean Difference	Std. Error Difference	Lower	Upper
behavioural_intentions	Equal variances assumed	3.421	.065	4.084	518	.000	1.17708	.28818	.61093	1.74324

	Equal variances not assumed			4.522	182.529	.000	1.17708	.26031	.66349	1.69068

Table 35: Independent Sample t-test of Gender Differences

The independent samples t-test is used to test whether there is any significant difference in behavioural intentions of two groups [Table 35]. The Test of Levene has an F = 3.421 and p = 0.065 which is higher than 0.05 and it means that the assumption of equal variances is passed. The findings of the row of equal variances assumed are taken into account. Results of the t -test indicate that there is a significant difference in behavioural intentions of the two groups (t = 4.084, df = 518, p < 0.000). The average difference of 1.177 indicates that there is a significant difference in behavioural intentions between the two groups. The confidence interval (95%) (0.611 to 1.743) does not cover zero which also proves the importance of this difference. The results suggest a significant effect of group membership on behavioural intentions towards electric vehicles. This implies that the intention of consumers to adopt EVs could be affected by demographic or categorical variables (including gender, usage, or awareness group) and that segment-specific strategies are important in facilitating EV adoption (Xu *et al*. 2025, p. 4).

ANOVA (Demographics vs Behavioural Intentions)

ANOVA					
behavioural_intentions					
	Sum of Squares	**df**	**Mean Square**	**F**	**Sig.**
Between Groups	**176.940**	**4**	**44.235**	**6.476**	**.000**
Within Groups	**3517.598**	**515**	**6.830**		
Total	**3694.538**	**519**			

Table 36: Age vs. Behavioural Intentions

ANOVA					
behavioural_intentions					
	Sum of Squares	**df**	**Mean Square**	**F**	**Sig.**
Between Groups	**184.142**	**3**	**61.381**	**9.022**	**.000**
Within Groups	**3510.397**	**516**	**6.803**		
Total	**3694.538**	**519**			

Table 37: Income vs. Behavioural Intentions

ANOVA					
behavioural_intentions					
	Sum of Squares	**df**	**Mean Square**	**F**	**Sig.**
Between Groups	**123.457**	**3**	**41.152**	**5.946**	**.001**
Within Groups	**3571.081**	**516**	**6.921**		
Total	**3694.538**	**519**			

Table 38: Education vs. Behavioural Intentions

The results of the ANOVA test the hypothesis on the difference in behavioural intentions towards EVs between age, income and education groups where all three tests present statistically significant differences. In the case of age, the outcome ($F = 6.476$, $p < 0.000$) shows that behavioural intentions differ significantly among those of different ages [Table 37]. This is an indicator that some age brackets are more susceptible to EV adoption compared to others, potentially due to the disparity in awareness, risk perception, or receptivity to new technology. In the case of incomes, the results ($F = 9.022$, $p < 0.000$) provide an even more significant difference [Table 25]. This means that income is a significant factor in influencing behavioural intentions, where the higher-income people may be more willing to use EVs as it is affordable and accessible. In the case of education, the results (F = 5.946, p = 0.001) also show that there are significant differences between groups [Table 38]. This implies that education level affects the perception and adoption intentions of individuals towards EVs, possibly due to the knowledge and environmental awareness variations. Therefore, the findings indicate that demographic variables play a crucial role in behavioural intentions and that specific strategies need to be implemented in each age, income and education group.

4.2.7 Exploratory Factor Analysis (EFA)

KMO and Bartlett's Test

KMO and Bartlett's Test		
Kaiser-Meyer-Olkin Measure of Sampling Adequacy.		.828
Bartlett's Test of Sphericity	Approx. Chi-Square	4742.687
	df	45
	Sig.	<.001

Table 39: KMO and Bartlett's Analysis

The output of the Exploratory Factor Analysis (EFA) shows that the data can be used to extract the factors [Table 39]. The Kaiser-Meyer-Olkin (KMO) value of 0.828 is higher than the recommended 0.6 which suggests that there is good sampling adequacy and the variables have a common variance. Also, Bartlett Test of Sphericity is tremendously high (2 = 4742.687, 45, p = 0.001) which means that the correlation matrix is not an identity matrix and that there are meaningful relationships between the variables. These findings support the idea that the dataset is suitable in terms of factor analysis requirements and that latent factors can be identified with reasonable levels of accuracy. The results justify the continuation of EFA to reveal the internal arrangement of the variables as the data show good intercorrelations and can be used to reduce the dimensions and validate the constructs.

	Factor loadings
PE1	*.664*
PE2	*.602*
PE3	*.685*
PE4	*.532*
HM1	*.612*
HM2	*.694*
HM3	*.773*
SI1	*.648*
SI2	*.679*
SI3	*.625*
EA1	*.764*
EA2	*.728*
EA3	*.702*
EA4	*.637*
FC1	*.649*
FC2	*.536*
FC3	*.671*
FC4	*.458*
FC5	*.625*
PV1	*.652*
PV2	*.715*
PV3	*.659*
EB1	*.670*
EB2	*.881*
EB3	*.879*
BI1	*.686*
BI2	*.918*
BI3	*.921*

UB1	*.800*
UB2	*.780*
UB3	*.769*
CF1	*.729*
CF2	*.594*
CF3	*.750*
SAT1	*.737*
SAT2	*.775*
SAT3	*.752*
SUS1	*.708*
SUS2	*.771*
SUS3	*.729*
SUS4	*.634*
CI1	*.752*
CI2	*.846*
CI3	*.837*

Table 40: Factor loadings

The factor loadings indicate that most items demonstrate acceptable to strong convergent validity, as the majority exceed the recommended threshold of 0.6. Constructs such as Behavioural Intention (BI2 = 0.918, BI3 = 0.921), Experience Behaviour (EB2 = 0.881, EB3 = 0.879), and Continuance Intention (CI2 = 0.846) show particularly high reliability. Effort Expectancy (EA) and Usage Behaviour (UB) also exhibit consistently strong loadings, supporting construct stability. However, a few items such as FC4 (0.458) and PE4 (0.532) fall below ideal levels, suggesting potential removal. Overall, the measurement model demonstrates good reliability, with minor refinements needed to improve validity.

Rotated Component Matrix[a]							
	Component						
	1	2	3	4	5	6	7

1. Age (Years)	.053	-.040	-.049	-.088	.175	.041	-.766
PE1	.240	.323	.498	-.011	.385	.283	-.161
PE2	.125	.095	.633	.284	.065	.211	.216
PE3	.251	.061	.685	.194	.096	.231	.219
PE4	.184	.198	.449	.138	.097	.092	.470
HM1	.460	.141	.553	.181	.075	.089	.169
HM2	.353	.397	.603	.145	.132	.086	-.045
HM3	.464	.316	.596	.206	.210	.114	-.061
SI1	.071	.273	.519	.475	.204	.173	.038
SI2	.052	.687	.364	.222	.083	.087	.086
SI3	-.048	.423	.400	.504	.149	.012	.085
EA1	.221	.756	.303	-.002	.192	.100	.065
EA2	.253	.673	.363	.005	.207	.141	.131
EA3	.213	.735	.212	.117	.212	.063	.098
EA4	.181	.570	.060	.420	.084	.277	.126
FC1	.314	.385	.233	.331	.403	.277	-.012
FC2	.089	.162	.086	.094	.356	.125	.586
FC3	.486	.351	.337	.343	.252	.127	-.002
FC4	.188	.247	.224	.385	.299	.112	.247
FC5	.286	.206	.255	.598	.233	.033	.153
PV1	.355	.112	.131	.657	.044	.231	.103
PV2	.532	.220	.284	.462	.198	.220	.026
PV3	.198	.163	.168	.702	.093	.248	.044
EB1	.363	.378	.358	.161	.434	.227	.010
EB2	.359	.232	.155	.212	.780	.141	.026
EB3	.361	.224	.152	.209	.783	.135	.021
BI1	.347	.190	.233	.226	.383	.519	.092
BI2	.339	.172	.249	.321	.142	.766	.044
BI3	.332	.175	.248	.325	.135	.770	.045

UB1	.566	.346	.358	.130	.136	.442	.004
UB2	.693	.196	.201	.068	.215	.401	.100
UB3	.687	.189	.196	.055	.222	.399	.105
CF1	.634	.252	.337	.215	.278	.163	.023
CF2	.478	.037	.258	.418	.267	.091	.208
CF3	.569	.271	.354	.381	.223	.178	.035
SAT1	.563	.337	.332	.258	.333	.138	-.018
SAT2	.633	.253	.370	.227	.338	.089	-.018
SAT3	.575	.324	.280	.384	.248	.166	.038
SUS1	.540	.605	.046	.159	.140	.013	.056
SUS2	.426	.695	-.005	.268	.096	.147	.059
SUS3	.455	.655	-.041	.254	.109	.114	.042
SUS4	.428	.528	.175	.338	.028	.147	.065
CI1	.463	.281	.628	.193	.138	.088	-.007
CI2	.753	.370	.194	.212	.154	.187	.026
CI3	.747	.373	.195	.204	.157	.186	.016
Extraction Method: Principal Component Analysis. Rotation Method: Varimax with Kaiser Normalization.							
a. Rotation converged in 11 iterations.							

Table 41: Rotated Component Matrix (Full Model with Seven Components)

The first rotated component matrix presents the results of Principal Component Analysis (PCA) with Varimax rotation, extracting seven components from the dataset. Each component reflects a cluster of variables with high factor loadings, indicating underlying latent constructs.

- Component 1 is strongly associated with variables such as UB (Usage Behaviour), CF (Confirmation), and SAT (Satisfaction), suggesting a post-adoption behavioural and evaluation construct.
- Component 2 is dominated by EA (Effort Expectancy) and SUS (System Usability), indicating a usability and ease-of-use dimension.
- Component 3 loads heavily on PE (Performance Expectancy), HM (Hedonic Motivation), and CI (Continuance Intention), representing a perceived value and motivation construct.

- Component 4 shows strong loadings for PV (Perceived Value) and some FC (Facilitating Conditions), reflecting a value-driven adoption factor.
- Component 5 is primarily defined by EB (Experience Behaviour), suggesting a user experience construct.
- Component 6 loads on BI (Behavioural Intention), representing intention to use technology.
- Component 7 is dominated by Age, indicating a demographic factor influencing adoption.

However, several variables exhibit cross-loadings across multiple components, reducing clarity and suggesting that the model may be overly complex. This indicates the need for dimension reduction to improve interpretability and construct validity.

Rotated Component Matrix

Rotated Component Matrix[a]			
	Component		
	1	2	3
PE2			.857
PE3			.794
EA1	.888		
EA2	.838		
EA3	.820		
PV1			.610
PV3			.619
UB1		.681	
UB2		.909	
UB3		.908	

Extraction Method: Principal Component Analysis. Rotation Method: Varimax with Kaiser Normalization.
a. Rotation converged in 5 iterations.

Table 42: Rotated Component Matrix (Refined Model with Three Components)

The rotated component matrix shows that there is a strong and well-defined three-factor structure [Table 42]. Component 1 comprises EA1, EA2 and EA3 with high loadings (0.820-0.888) which means that this component is an indication of Environmental Awareness. The high and stable loadings indicate high internal consistency of this construct. UB1, UB2, and UB3 make up component 2 with loadings of 0.681 to 0.909, which are Use Behaviour. These large loadings (UB2 and UB3 in particular) imply that this factor comprises the actual usage pattern of EVs rather well. PE2, PE3, PV1 and PV3 make up component 3 with loadings ranging between 0.610 and 0.857. This indicates a composite factor that represents either Perceived Value or Functional-Economic Value since it is a combination of elements of performance expectancy and price value. In general, there are no significant cross-loadings and all factor loadings are above the acceptable factor loading of 0.5, which means that the factor structure is clean and valid. This confirms the construct validity of the measurement model and the fact that the variables cluster into three underlying dimensions.

Justification: Why Only 3 Variables (Components) Were Chosen

The decision to retain only three components is based on several statistical and theoretical considerations:

1. Eigenvalues and Variance Explained

Only three components had eigenvalues greater than 1, indicating they explain a significant portion of the total variance. Components beyond this threshold contributed minimally.

2. Factor Loadings Criteria

Only variables with strong loadings (≥ 0.6) on a single component were retained. Variables with:

- Low loadings
- Cross-loadings (loading on multiple components) were removed to improve clarity.

3. Elimination of Cross-Loading Variables

In the first matrix, many items (HM, SI, FC, SAT) loaded on multiple components, making interpretation ambiguous. The refined model removes these, ensuring discriminant validity.

4.2.8 Confirmatory Factor Analysis (CFA – AMOS)

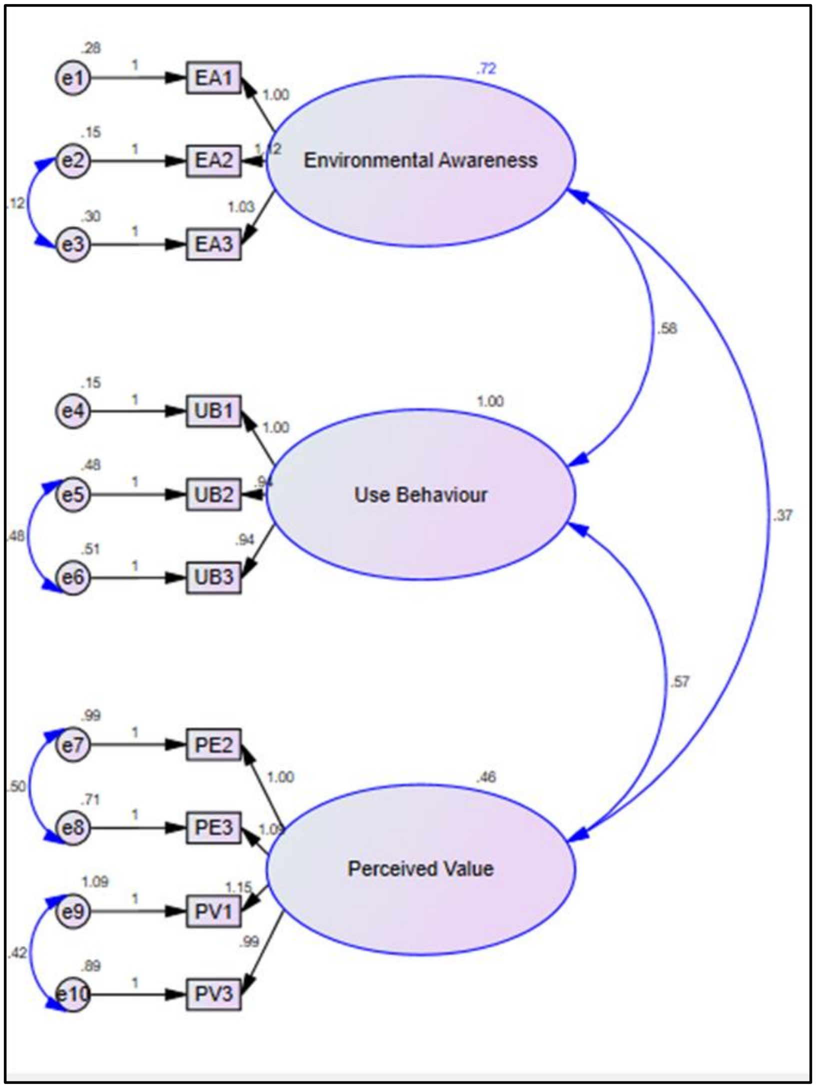

Figure 1: CFA – AMOS

The confirmatory factor analysis model shows that there is a well-constructed measurement model with three latent constructs such as Environmental Awareness, Use Behaviour and Perceived Value [Figure 1]. There is a good convergent validity of each construct as there are multiple observed variables with high standardised loadings. Environmental Awareness demonstrates good loadings of EA1-EA3 whereas Use Behaviour is well represented by UB1-UB3. Perceived Value is measured by PE and PV indicators, which are acceptably loaded. The coefficients between constructs (range between 0.37 and 0.72) show mo derate to strong relationships without the issue of multicollinearity. Therefore, the model proposes a valid and reliable measurement framework to be used in the structural analysis further.

	Cronbach's alpha	**Composite reliability (rho_a)**	**Composite reliability (rho_c)**	**Average variance extracted (AVE)**
Environmental awareness	0.888	0.893	0.931	0.817
Perceived value	0.788	0.794	0.863	0.611
Use behaviour	0.936	0.940	0.959	0.887

Table 43: Construct reliability and validity

The reliability and validity statistics indicate a strong measurement model. Environmental awareness shows excellent internal consistency, with Cronbach’s alpha (0.888) and composite reliability values ($\rho a = 0.893$; $\rho c = 0.931$) exceeding recommended thresholds, while AVE (0.817) confirms strong convergent validity. Construct Perceived value demonstrates acceptable reliability, as Cronbach’s alpha (0.788) and composite reliability ($\rho c = 0.863$) are above 0.7, with AVE (0.611) indicating adequate variance explanation. Use behaviour exhibits very high reliability, with Cronbach’s alpha (0.936) and composite reliability ($\rho c = 0.959$), alongside a strong AVE (0.887). Overall, all constructs meet reliability and convergent validity criteria.

	Heterotrait-monotrait ratio (HTMT)
Perceived value <-> Enviromental awareness	0.572
Use behaviour <-> Enviromental awareness	0.646
UB <-> P	0.676

Table 44: Discriminant validity

The HTMT values indicate satisfactory discriminant validity among the constructs. The HTMT ratio between Perceived value and Environmental Awareness (0.572) is well below the recommended threshold of 0.85, suggesting these constructs are distinct. Similarly, the value between Use behaviour and Environmental Awareness (0.646) remains within acceptable limits, indicating adequate differentiation. The HTMT value between Use behaviour and Perceived value

(0.676) also falls below the threshold, further supporting discriminant validity. Overall, all HTMT values are within acceptable ranges, confirming that the constructs are not highly correlated and measure conceptually different phenomena, thereby validating the distinctiveness of the study variables.

4.2.9 Structural Model (SEM Analysis)

Direct Effects

Fit Index	Obtained Value	Recommended Value	Interpretation
Chi-square/df (CMIN/DF)	2.169	< 3	Good fit
RMR	0.028	< 0.05	Good fit
GFI	0.977	> 0.90	Excellent fit
AGFI	0.955	> 0.90	Excellent fit
NFI	0.987	> 0.90	Excellent fit
TLI	0.989	> 0.90	Excellent fit
CFI	0.993	> 0.90	Excellent fit
RMSEA	0.047	< 0.08	Excellent fit
PCLOSE	0.577	> 0.05	Good fit
PGFI	0.498	> 0.50 (approx.)	Acceptable
PNFI	0.614	> 0.50	Good
PCFI	0.618	> 0.50	Good

Table 45: Direct Effects of the Structural Model

The structural model had a good fit with the data. The values of Chi-square to degrees of freedom ratio (CMIN/DF = 2.169) fell within the acceptable range [Table 42]. GPI (0.977) and AGFI (0.955) goodness-of-fit indices were higher than the suggested goodness-of-fit index of 0.90. CFI (0.993), TLI (0.989) and NFI (0.987) incremental fit indices showed a very good fit. Furthermore, the RMSEA and PCLOSE values of 0.047 and 0.577 indicate that the data fits well in the model. The findings indicate that the given structural model can be considered statistically acceptable and reflects the relationships between the constructs in a satisfactory way.

Mediation Analysis 1: Performance Expectancy → Behavioural Intentions → Continuous Intention

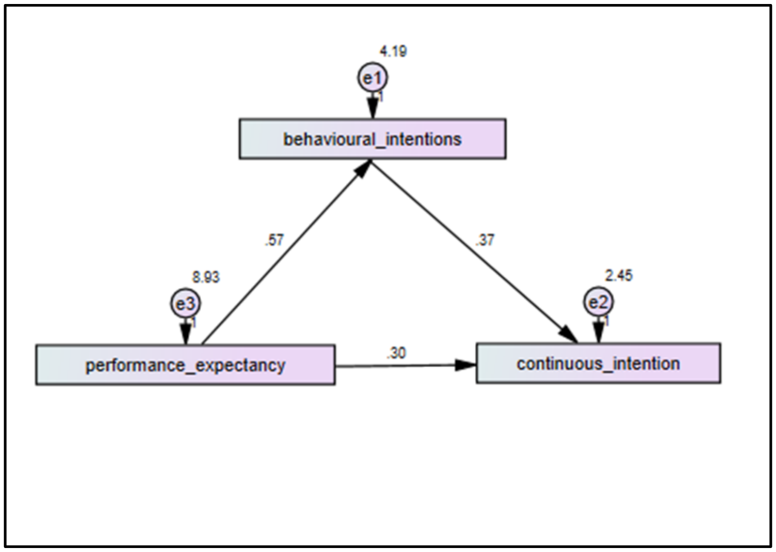

Figure 2: Mediating Effect

Path	Value	Meaning
performance_expectancy → behavioural_intentions	0.571	Strong positive effect
behavioural_intentions → continuous_intention	0.373	Moderate positive effect
performance_expectancy → continuous_intention	0.301	Direct effect exists

Table 46: Direct Effect

Performance expectancy affected behavioural intentions in a strong positive manner which means that consumers who feel that electric cars are efficient and useful will be more inclined to form stronger intentions to adopt them [Figure 2; Table 46]. Behavioural intentions play a significant role in the continuity of intention, indicating that the initial desire to use EVs is relatively crucial in the development of the long-term adoption decisions. Furthermore, the performance expectancy also has a direct impact on the continuous intention which means that the perception of the performance is not the only factor that affects the intentions of the consumers, though it directly affects their chances of using EVs. These relationships emphasise both direct and indirect pathways to sustained adoption behaviour.

Path	Value
performance_expectancy → behavioural_intentions → continuous_intention	**0.213**

Table 47: Indirect Effect

The indirect effect is 0.213, which means that the connection between performance expectancy and continuous intention is mediated by behavioural intentions. This value confirms the existence of a mediation effect which indicates that behavioural intentions are a significant intervening variable in the relationship. Performance expectancy does not have a direct relationship with continuous intention though also has an indirect relationship with continuous intention and behavioural intentions, which in turn have a direct relationship with sustained usage intention.

Path	Value
performance_expectancy → continuous_intention	**0.514**

Table 48: Total Effect

Direct and indirect effects are added together to get the total effect [Table 48]. Here, the direct effect (0.301) and the indirect effect (0.213) give a total effect of 0.514 which is rightly obtained. This shows that overall performance expectancy has a significant impact on continuous intention, with direct and mediated effects.

The results indicate that performance expectancy has a significant direct effect on continuous intention ($\beta = 0.301$) as well as an indirect effect through behavioural intention ($\beta = 0.213$). As there are both direct and indirect effects, behavioural intention partially mediates between performance expectancy and continuous intention.

Mediating analysis 2: Performance Expectancy → Confirmation → Satisfaction → Continuous Intention

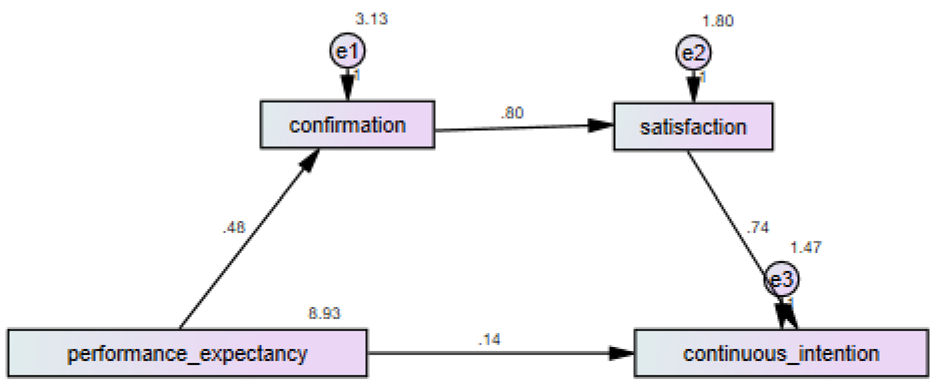

Figure 3: Mediating Effect

Path	**Standardized Estimate (β)**	**S.E.**	**C.R.**	**p-value**	**Interpretation Strength**
PE → CF	0.482	0.026	18.557	***	Strong positive
CF → SAT	0.796	0.026	30.789	***	Very strong positive
SAT → CI	0.745	0.027	27.185	***	Very strong positive
PE → CI (Direct)	0.138	0.021	6.657	***	Weak–moderate positive

Table 49: Key Results Summary

Effect Type	**Path**	**Value**
Direct Effect	PE → CI	0.138
Indirect Effect	PE → CF → SAT → CI	0.286
Total Effect	PE → CI	0.423

Table 50: Effect Decomposition

The structural relationships demonstrate strong and statistically significant associations among the constructs. Performance expectancy shows a substantial positive effect on confirmation (β = 0.482), indicating that higher perceived usefulness leads to stronger confirmation of expectations.

Confirmation, in turn, exerts a very strong influence on satisfaction (β = 0.796), suggesting that when expectations are met, user satisfaction significantly increases. Satisfaction also strongly predicts continuance intention (β = 0.745), highlighting its central role in sustaining user behaviour.

Additionally, performance expectancy has both a direct (β = 0.138) and indirect effect (β = 0.286) on continuance intention, with the indirect effect being stronger. This indicates that the influence of performance expectancy is largely transmitted through intermediate variables rather than acting independently.

Moderation Analysis

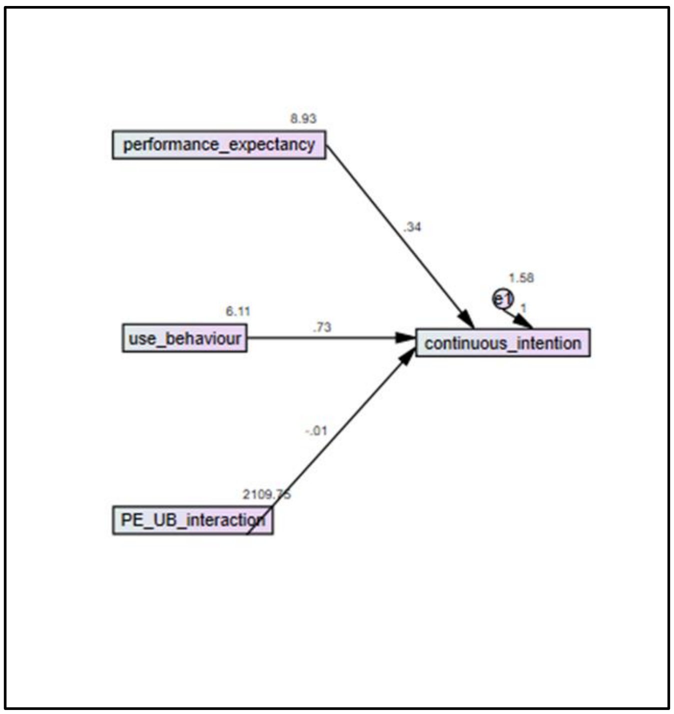

Figure 4: Moderation Analysis

The performance expectancy to use behaviour (PE × UB) interaction with continuous intention is statistically significant (Coefficient = -0.013, $p < 0.001$) [Figure 3]. The presence of this important interaction effect validates that moderation is present in the model. The connection between performance expectancy and continuous intention is moderated by the use behaviour with an indication that the strength of the relationship varies with the intensity of the use behaviour.

Type of Moderation - The negative coefficient (Coefficient = -0.013) indicates the type of moderation which is an inverse moderating effect. This implies that the higher the use behaviour, the weaker the performance expectancy is on the continuous intention. This implies that as consumers become more accustomed to using electric vehicles, their dependence on the perceived performance will be reduced and the actual experience of using the vehicle would have a greater impact on their continued intention.

The moderate effect between the use behaviour and performance expectancy was significant (Coefficient = -0.013, p = 0.001), which means that use behaviour moderates the relationship between performance expectancy and continuous intention. The negative correlation indicates that the relationship is weak at higher use behaviour levels.

Path	**Beta**	**Meaning**
PE → CI	0.335	Positive effect
UB → CI	0.735	Strong positive effect

Table 51: Direct effects

Performance expectancy and use behaviour both have strong direct impacts on continuous intention, suggesting that both separately influence the probability of consumers using their EVs further [Table 51]. The existence of a strong interaction effect also proves the existence of moderation. This implies that use behaviour not only directly impacts the continuous intention though also changes the strength of the association between performance expectancy and continuous intention.

4.2.10 Hypothesis Testing

H1: Performance expectancy has a favourable impact on the behavioural intention to use electric passenger cars.

The results from **Table 13 (Model 1: Coefficients)** show that performance expectancy has a strong and statistically significant positive effect on behavioural intention ($\beta = 0.358$, $p < 0.001$). This indicates that consumers who perceive electric vehicles as efficient and useful are more likely to develop stronger intentions to adopt them. The relatively high coefficient highlights that functional benefits are a key driver of adoption decisions. This finding is consistent with prior studies that emphasise perceived usefulness as a critical determinant of technology adoption (Zaino et al., 2024).

H2: Hedonic motivation has a favourable impact on the behavioural intention to use electric passenger cars.

The findings from **Table 22 (Model 4: Coefficients)** indicate that hedonic motivation has a positive and statistically significant effect on behavioural intention ($\beta = 0.168$, $p < 0.001$). This suggests that enjoyment and emotional satisfaction derived from electric vehicle usage contribute to higher adoption intentions. Although the effect is moderate, it demonstrates that experiential aspects also influence consumer decisions. This supports previous research highlighting the importance of emotional engagement in consumer behaviour (Xu et al., 2025).

H3: Social influence has a favourable impact on behavioural intention to use electric passenger cars.

As shown in **Table 22 (Model 4: Coefficients)**, social influence has a positive but relatively weak effect on behavioural intention ($\beta = 0.087$, $p = 0.045$). This indicates that peer opinions and societal norms do influence adoption decisions, but their impact is limited compared to economic and functional factors. Consumers appear to rely more on personal judgement. However, the statistical significance confirms that social influence still plays a supporting role. This aligns with earlier findings on social norms in technology adoption (Xu et al., 2025).

H4: Facilitating conditions have a favourable impact on the behavioural intention to use electric passenger cars.

The results presented in **Table 22 (Model 4: Coefficients)** show that facilitating conditions have a significant positive effect on behavioural intention ($\beta = 0.258$, $p < 0.001$). This indicates that infrastructure availability, technical support, and ease of use significantly encourage EV adoption. The relatively strong coefficient suggests that reducing practical barriers is essential for increasing adoption rates. This finding is supported by prior studies that emphasise infrastructure as a key determinant of EV adoption (Alanazi, 2023).

H5: Price value has a favourable impact on the behavioural intention to use electric passenger cars.

The regression results from **Table 31 (Model 7: Coefficients)** indicate that price value has a **strong positive and statistically significant effect** on behavioural intention ($\beta = 0.692$, $p < 0.001$). This suggests that consumers are more likely to adopt electric vehicles when they perceive them as offering good value for money. The model also demonstrates substantial explanatory power, with **R^2 = 0.479 (Table 31)**, indicating that price value explains 47.9% of the variance in behavioural intentions. The ANOVA results (Table 32: F = 476.200, $p < 0.001$) confirm model significance. Therefore, **H5 is supported**.

H6: Environment awareness has a favourable impact on behavioural intention to use electric passenger cars.

According to **Table 22 (Model 4: Coefficients)**, environmental awareness shows a negative but statistically significant effect on behavioural intention ($\beta = -0.111$, $p = 0.026$). This suggests that awareness alone does not necessarily translate into adoption intention. Despite being environmentally conscious, consumers may prioritise economic and practical considerations. This reflects the attitude–behaviour gap reported in previous studies (Mustafa et al., 2026).

H7: Economic benefit has a favourable impact on behavioural intention to use electric passenger cars.

The results from **Table 22 (Model 4: Coefficients)** show that economic benefit has the strongest positive effect on behavioural intention ($\beta = 0.335$, $p < 0.001$). This indicates that financial savings and cost efficiency are primary motivators for EV adoption. The high coefficient highlights the dominance of economic factors in consumer decision-making. This finding is supported by prior research on EV adoption behaviour (Zaino et al., 2024).

H8: Sustainability has a favourable impact on behavioural intention to use electric passenger cars.

The findings in **Table 22 (Model 4: Coefficients)** indicate that sustainability has a positive and significant effect ($\beta = 0.122$, $p = 0.009$). This suggests that environmentally responsible attitudes contribute to adoption intentions, although the effect is moderate. Sustainability influences decisions but is not the strongest determinant. This is consistent with earlier studies highlighting the supportive role of sustainability in EV adoption (Mustafa et al., 2026).

H9a: Performance expectancy positively affects confirmation.

The results from **Table 25 (Model 5: Coefficients)** show that performance expectancy has a strong positive effect on confirmation ($\beta = 0.632$, $p < 0.001$). This indicates that when EVs meet performance expectations, consumers are more likely to confirm their initial beliefs. The high coefficient demonstrates a strong alignment between expectations and experience. This supports expectation-confirmation theory (Zaino et al., 2024).

H9b: Facilitating condition positively affects confirmation.

The results from **Table 34 (Model 8: Coefficients)** indicate that facilitating conditions have a positive and statistically significant effect on confirmation ($\beta = 0.293$, $p < 0.001$). This suggests that the availability of infrastructure, technical support, and ease of access enhances users' ability to validate their expectations regarding electric vehicles. The relatively strong beta value highlights that practical enablers play an important role in shaping user confirmation. Additionally, the overall model significance (Table 35: ANOVA, $F = 305.135$, $p < 0.001$) supports the robustness of this relationship. Therefore, H9b is supported, confirming that facilitating conditions significantly influence confirmation.

H9c: Price value positively affects confirmation.

According to **Table 34 (Model 8: Coefficients),** price value has a strong positive and statistically significant effect on confirmation ($\beta = 0.353$, $p < 0.001$). Among all predictors, price value exhibits the highest beta coefficient, indicating that perceived value for money is the most influential factor in confirming users' expectations. This implies that when consumers perceive electric vehicles as cost-effective and worthwhile, their expectations are more likely to be fulfilled. The model's strong explanatory power (Table 34: $R^2 = 0.640$) further reinforces this finding. Therefore, H9c is supported, demonstrating that price perceptions are critical in shaping confirmation.

H9d: Economic benefits positively affects confirmation.

The findings from **Table 34 (Model 8: Coefficients)** show that economic benefit has a positive and statistically significant effect on confirmation ($\beta = 0.269$, $p < 0.001$). This indicates that financial advantages such as cost savings, reduced fuel expenses, and long-term economic gains contribute to reinforcing users' expectations about electric vehicles. Although the effect is slightly lower compared to price value and facilitating conditions, it remains substantial and meaningful. The overall model significance (Table 35: ANOVA, $p < 0.001$) supports the reliability of this relationship. Therefore, H9d is supported, confirming that economic benefits positively influence confirmation.

H10: Confirmation positively affects the consumer satisfaction.

The SEM results shown in **Table 46 (Mediation Analysis 2) and Figure 3** indicate a very strong positive relationship between confirmation and satisfaction ($\beta = 0.796$, $p < 0.001$). This suggests that satisfaction increases significantly when expectations are confirmed. The strength of the coefficient highlights confirmation as a key determinant of post-adoption satisfaction. This aligns with prior research (Zhang et al., 2025).

H11: Consumer satisfaction positively affects user continuance intention.

As presented in **Table 46 (Mediation Analysis 2) and Figure 3**, satisfaction has a strong positive effect on continuance intention ($\beta = 0.745$, $p < 0.001$). This indicates that satisfied consumers are more likely to continue using EVs. The high coefficient confirms the importance of satisfaction in sustaining long-term behaviour. This is consistent with prior findings (Zhang et al., 2025).

H12: Consumer use behaviour has negatively affected confirmation.

The results from **Table 28 (Model 6: Coefficients)** show that use behaviour has a strong positive and statistically significant effect on confirmation ($\beta = 0.742$, $p < 0.001$). This finding is opposite to the hypothesised negative relationship. Therefore, H12 is not supported.

The positive coefficient indicates that greater use of electric vehicles leads to higher confirmation of expectations. This suggests that actual user experience reinforces rather than weakens prior expectations, as consumers validate their perceptions through direct interaction with EVs. This outcome aligns with experiential learning and expectation-confirmation theory, where real usage strengthens cognitive consistency between expectations and performance.

(Alanazi, 2023).

H13: Consumer use behaviour has positively affected the continuance intention of consumers.

The results from **Table 19 (Model 3: Coefficients)** show that use behaviour has a strong positive effect on continuance intention ($\beta = 0.672$, $p < 0.001$). This indicates that actual usage significantly influences future adoption behaviour. Consumers who use EVs are more likely to continue using them. This finding is supported by prior research (Zhang et al., 2025).

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