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Determinant of Electric Car Adoption in the Case of Dire Dawa Consumers Perspectives

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Abstract

This study investigates the key factors influencing Electric Vehicle (EV) Purchase Intention, focusing on Performance Expectancy, Effort Expectancy, Social Influence, and Price Value, using a sample of 247 respondents. Correlation and multiple regression analyses reveal significant positive relationships between these predictors and EV Purchase Intention. Performance Expectancy ($r = 0.878$) and Price Value ($r = 0.873$) have the strongest correlations, indicating that consumers who perceive higher performance and better value for money are more likely to intend to purchase an EV. The model explains 81.7% of the variance in EV Purchase Intention ($R^2 = 0.817$), with Price Value being the most influential factor (Beta = 0.336). Despite moderate multicollinearity, particularly between Performance Expectancy and Price Value, the regression model remains statistically significant ($p < 0.01$), highlighting the importance of these factors in shaping purchase intentions. These findings suggest that strategies to increase EV adoption should focus on enhancing perceived performance, ease of use, and affordability, while leveraging social influences. The results provide actionable insights for both marketers and policymakers aiming to boost EV adoption.

Keywords: *Electric Vehicles, Purchase Intention, Performance Expectancy, Price Value, Social Influence*

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1. Background of the Study

The rapid advancement of electric vehicles (EVs) as a solution to environmental challenges has led to increasing global interest in their adoption. As nations strive to meet climate change goals and reduce carbon emissions, EVs are seen as a promising alternative to conventional gasoline-powered vehicles. In developed nations, the adoption of EVs has been propelled by various factors such as environmental consciousness, governmental incentives, and advanced infrastructure. However, in developing countries like Ethiopia, the adoption of EVs remains limited due to challenges such as affordability, infrastructure, and societal perceptions.

In Ethiopia, particularly in secondary cities like Dire Dawa, the adoption of EVs is still in its infancy. While there is a global movement toward sustainable transportation, Ethiopia's unique socio-economic context presents distinct barriers to widespread EV adoption. Factors such as low income levels, limited knowledge of EV technology, and inadequate infrastructure for charging stations hinder the potential growth of the EV market in Ethiopia. However, understanding the drivers that influence consumer decision-making processes in this context is crucial for enabling a successful transition toward electric mobility.

Existing studies on EV adoption have predominantly focused on developed economies, with a heavy emphasis on environmental concerns and technological factors (Sierzchula et al., 2014; Egbue & Long, 2012). In contrast, limited research has been conducted on the determinants of EV adoption in sub-Saharan Africa, and specifically in Ethiopian cities like Dire Dawa. Furthermore, most studies in this area have emphasized environmental factors, neglecting other critical determinants such as performance expectancy, effort expectancy, social influence, and price value.

This study aims to bridge this gap by exploring the factors that influence EV adoption from the perspective of consumers in Dire Dawa, Ethiopia. Specifically, it focuses on performance expectancy, effort expectancy, social influence, and price value as the primary determinants, while intentionally excluding environmental concerns. The research will contribute to the understanding of the local market dynamics and offer recommendations for policymakers and industry stakeholders looking to promote EV adoption in the region.

2. Literature Review

2.1. Determinants of EV Adoption: A Global Perspective

Several studies have been conducted globally to identify the key determinants influencing the adoption of electric vehicles. The most widely used theoretical frameworks for understanding technology adoption are the Technology Acceptance Model (TAM) and its extensions, such as the Unified Theory of Acceptance and Use of Technology (UTAUT). These models posit that performance expectancy (the perceived benefits or advantages of using the technology) and effort expectancy (the perceived ease of use) are critical predictors of user adoption (Venkatesh et al., 2003).

i. Performance Expectancy

Performance expectancy has consistently been shown to be one of the strongest predictors of EV adoption. Consumers are more likely to adopt EVs if they believe these vehicles perform well, offering benefits such as fuel efficiency, smooth driving experience, and convenience. According to Sierzchula et al. (2014), performance expectancy includes factors like driving range, reliability, and ease of use, all of which are highly correlated with the intention to purchase an EV. Koirala et al. (2020) also emphasized that consumer perceptions of EV performance (e.g., power, speed, and overall quality) play a pivotal role in influencing their purchasing behavior.

ii. Effort Expectancy

Effort expectancy, or the perceived ease of use, has been identified as a crucial factor in the adoption of EVs. Studies have shown that potential buyers are more likely to purchase an EV if they believe it will not require significant effort to use or maintain. Al-Alawi and Bradley (2013) highlight that ease of charging and the simplicity of vehicle operation are essential to encouraging EV adoption. Consumers are more likely to choose EVs over traditional cars if they perceive that the technology is not complex or difficult to operate.

iii. Social Influence

Social influence refers to the impact of societal norms, peer pressure, and media portrayal on individuals' attitudes and behaviors. Several studies have pointed out that people’s decisions to adopt new technologies, including EVs, are significantly influenced by social factors. Ziegler et al. (2012) and Jensen et al. (2018) found that the social desirability of owning an EV, especially as portrayed in media and social circles, can greatly affect consumers' attitudes towards EVs. In regions where social influence is strong, the adoption of EVs may be more rapid, as individuals tend to conform to group norms and expectations.

iv. Price Value

Price value is a critical determinant of EV adoption, particularly in developing countries where purchasing power is limited. Consumers often consider the total cost of ownership, including the initial purchase price, maintenance costs, and potential savings in fuel. Egbue and Long (2012) argue that the perceived affordability of EVs, combined with the availability of financial incentives, is essential for increasing adoption. As noted by Zhou et al. (2015), price sensitivity is heightened in emerging economies, where income levels are lower, and the initial high cost of EVs may deter potential buyers.

2.2. Challenges in Developing Countries: The Ethiopian Context

The majority of EV adoption studies have focused on developed countries, where infrastructure and government incentives for EVs are more advanced. In contrast, few studies have investigated the factors influencing EV adoption in developing countries, particularly in sub-Saharan Africa. The unique socio-economic and cultural characteristics of Ethiopian cities, such as Dire Dawa, are important to consider when exploring the potential for EV adoption.

In Ethiopia, the adoption of EVs is impeded by several challenges, including limited public awareness of electric vehicles, the high upfront costs, and the lack of a charging infrastructure (Tariq et al., 2020). Moreover, the role of environmental concerns in Ethiopia’s adoption of EVs may be less pronounced than in wealthier nations, where climate change awareness is more prevalent. Therefore, understanding how non-environmental factors, such as price value and social influence, contribute to EV adoption in Ethiopia is a gap in the current literature.

3. Materials and Methods

3.1. Research Design and sampling

This study employed a mixed-methods research design, combining both quantitative and qualitative approaches to provide a comprehensive understanding of the factors influencing EV adoption in Dire Dawa, Ethiopia. The quantitative component involved a survey of 247 respondents, while the qualitative component included semi-structured interviews with a subset of 20 participants to gain deeper insights into consumer perceptions.

$$Sample\ size\ (SS) = \frac{Z2(p)(1-p)}{C2}$$

$$SS = Sample\ Size$$

$$Z = Z - value \ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots 1.96 = 95\ percent\ confidence\ level$$

$$P = Percentage\ of\ population\ picking\ a\ choice \ldots\ldots\ldots..50\%$$

$$C = Confidence\ interval, expressed\ as\ decimal\ \ldots\ldots\ldots 5\%$$

$$Sample\ Size = \frac{(1.96)2\ (0.5)\ (1-0.5)}{(0.05)\ 2} = 300$$

3.2. Survey Instrument

The survey was designed to assess four key determinants of EV adoption: performance expectancy, effort expectancy, social influence, and price value. The items in the questionnaire were adapted from established scales in the technology acceptance literature (Venkatesh et al., 2003; Al-Alawi & Bradley, 2013). The questionnaire included both Likert-scale questions (ranging from 1 to 5) and demographic questions to capture respondents' background information, such as age, income, education, and prior exposure to electric vehicles.

3.3. Data Collection

Data were collected through face-to-face surveys conducted in public spaces, such as shopping centers and transportation hubs in Dire Dawa. Respondents were selected using a convenience sampling method, ensuring that they were potential EV buyers (i.e., individuals who owned vehicles or were likely to purchase a vehicle within the next five years). The surveys were distributed in both Amharic and English to ensure accessibility to all participants.

3.4. Data Analysis

The quantitative data were analyzed using statistical software, SPSS. Descriptive statistics were first calculated to assess the basic characteristics of the sample. Correlation analysis was then performed to identify relationships between the key determinants and EV purchase intention. A regression model was developed to determine the strength of each predictor variable in explaining purchase intention.

3.5. Ethical Considerations

The study adhered to ethical research guidelines, ensuring informed consent, confidentiality, and voluntary participation. Respondents were provided with detailed information about the study's purpose, and their participation was completely voluntary.

4. Analysis and discussion

4.1. Demographic analysis

The demographic analysis of the study sample provides a comprehensive understanding of the characteristics of respondents, which is important for contextualizing the study's findings on electric vehicle (EV) adoption. The sample consisted of 247 participants, with 62.3% male and 37.7% female, indicating a gender imbalance. This discrepancy suggests that the male perspective may be more strongly represented in the study, which could influence the findings, as gender differences in preferences and priorities for EV adoption may exist. Regarding age, the majority of respondents (90.3%) were between the ages of 25 and 34, a group likely to be more familiar with and open to adopting new technologies such as electric vehicles. However, the relatively small representation of younger (18-24) and older (35-44) age groups limits the ability to draw conclusions about these age cohorts' perceptions of EV adoption.

In terms of educational background, the data shows a diverse distribution, with 29.6% of respondents having less than a high school education, which may suggest that a significant portion of the sample could face challenges such as limited exposure to technology or financial constraints that might hinder EV adoption. In contrast, respondents with higher educational qualifications, including bachelor's degrees (13.8%) and above (2.0%), are likely to have a better understanding of the technological and environmental benefits of EVs, potentially making them more inclined toward adopting such technologies. The sample's employment status varied, with 33.2% unemployed, 34.8% part-time employed, and 21.9% self-employed. This diversity suggests that economic factors, such as income and job security, might have a substantial influence on an individual's ability to consider purchasing an EV, with full-time employed individuals likely having greater financial resources to do so.

The sample also represented both urban (52.2%) and suburban (47.8%) residents, reflecting a balance in geographical location. Urban areas typically offer better infrastructure, such as charging stations, which could facilitate EV adoption, while suburban areas may face challenges related to infrastructure access. Additionally, vehicle ownership data revealed that 47.6% of respondents did not own any vehicle, which could indicate that the adoption of EVs may not be immediately relevant to them. Among those who did own vehicles, the majority (85.4%) owned just one vehicle, suggesting that potential EV adoption may involve replacing an existing vehicle rather than purchasing a second one. This demographic profile provides valuable insights into the socio-economic and geographical factors influencing attitudes towards EV adoption in Dire Dawa, Ethiopia.

Table 1: Demographic Information

Demographic Variable	Frequency	Percent	Cumulative Percent
Sex			
Male	154	62.3%	62.3%
Female	93	37.7%	100.0%
Age Group			
18-24	7	2.8%	2.8%
25-34	223	90.3%	93.1%
35-44	17	6.9%	100.0%
Educational Qualification			
Master and Above	5	2.0%	2.0%
Bachelor Degree	34	13.8%	15.8%
Diploma/TVET	74	30.0%	45.7%
High School Completed	61	24.7%	70.4%
Less Than High School Completed	73	29.6%	100.0%
Employment Status			
Employed Full-time	22	8.9%	8.9%
Employed Part-time	86	34.8%	43.7%
Self-employed	54	21.9%	65.6%
Unemployed	82	33.2%	98.8%
Retired	3	1.2%	100.0%
Place of Residence			
Urban	129	52.2%	52.2%
Suburban	118	47.8%	100.0%
Number of Vehicles Owned			
None	117	47.6%	
1	94	85.4%	
2	36	100.0%	
Total	247	100.0%	

Source: Own Survey, 2024

4.2. Descriptive Statistics for major variables

The descriptive statistics for the major variables in this study provide an insightful overview of respondents' attitudes towards electric vehicle (EV) adoption. For Performance Expectancy, the findings indicate a generally moderate view on the benefits of EVs. The highest mean score of 3.07 for "The battery range of EVs is sufficient for my daily travel needs" suggests that respondents have a relatively positive outlook on the range of EVs. However, there is skepticism about their efficiency, as shown by a lower mean score of 1.93 for "I expect that driving an EV will be more efficient than driving a traditional vehicle." The variability in responses is also evident in the high standard deviation (1.214) for battery range, indicating diverse opinions on EV performance.

For Effort Expectancy, respondents perceive EVs as somewhat easy to operate, but there are moderate concerns about the learning curve. The mean score for "I find electric vehicles easy to operate" was 2.12, indicating a mild perception of ease, while "I expect minimal difficulty in learning to drive an EV" had a slightly higher mean score of 2.26, suggesting some apprehension. The standard deviations for these variables were moderate, particularly the highest one for "I expect minimal difficulty in learning to drive an EV" (0.697), indicating varying levels of perceived difficulty.

Regarding Social Influence, the data reveals a moderate level of support for EV adoption from respondents' social circles. The mean score of 2.09 for "My friends and family support the idea of me buying an EV" suggests that social influence is present but not overwhelming, while the lower score of 1.96 for "I feel pressured by others to choose an EV over a traditional car" highlights that social pressure is not a significant driver of EV adoption. The relatively low standard deviations reflect consistent perceptions of social influence, with respondents generally agreeing on the role social factors play in shaping their attitudes towards EVs.

Table 2. Descriptive Statistics

Variable	Min	Max	Mean	Std. Dev.
Performance Expectancy				
1. I believe an electric vehicle will improve my driving experience.	1	3	2.02	0.604
2. I expect that driving an EV will be more efficient than driving a traditional vehicle.	1	3	1.93	0.517
3. An electric vehicle meets my needs for long road trips effectively.	1	3	2.07	0.662
4. EVs provide better performance in terms of acceleration and handling compared to traditional cars.	1	3	1.98	0.628
5. I think an EV will enhance my driving capabilities.	1	3	1.98	0.510
6. The battery range of EVs is sufficient for my daily travel needs.	1	4	3.07	1.214
Effort Expectancy				
1. I find electric vehicles easy to operate.	1	3	2.12	0.610
2. Learning how to use an EV is straightforward.	1	3	2.14	0.625
3. I believe that driving an EV requires less effort than a traditional vehicle.	1	3	2.16	0.601
4. Operating an EV is simple and uncomplicated.	1	3	2.15	0.542
5. The transition from a traditional vehicle to an EV is easy.	1	3	2.09	0.502
6. I expect minimal difficulty in learning to drive an EV.	1	3	2.26	0.697
Social Influence				
1. My friends and family support the idea of me buying an EV.	1	3	2.09	0.595
2. People whose opinions I value think I should buy an EV.	1	3	2.09	0.560
3. Social trends encourage the purchase of EVs.	1	3	1.98	0.566
4. I feel pressured by others to choose an EV over a traditional car.	1	3	1.96	0.646
5. Advertisements and media influence my decision to buy an EV.	1	3	2.00	0.628
Price Value				
1. The price of an EV is justified by its value.	1	3	2.08	0.603
2. I believe that EVs offer good value for their price.	1	3	1.98	0.533
3. Compared to traditional vehicles, EVs offer better value for the money.	1	3	2.09	0.663
4. The cost of owning an EV is reasonable given its benefits.	1	3	2.04	0.626
5. I would be willing to pay a premium for an EV if it provides significant savings in the long term.	1	4	2.04	0.583
6. The total cost of ownership of an EV is acceptable.	1	3	2.03	0.517
EV Purchase Intention				
1. I intend to purchase an EV within the next year.	1	3	1.85	0.589
2. I am seriously considering buying an EV for my next vehicle.	1	3	1.95	0.542
3. Given the choice, I would prefer to buy an EV over a traditional car.	1	3	1.88	0.643
4. I plan to make an EV my next vehicle purchase.	1	3	1.93	0.463
5. I am likely to choose an EV for my next vehicle purchase.	1	3	1.98	0.510
6. If I were to buy a new vehicle, an EV would be a top choice.	0	3	1.94	0.582

Source: Own Survey, 2024

When it comes to Price Value, the descriptive statistics reveal moderate perceptions of the value offered by EVs. The mean score of 2.09 for "Compared to traditional vehicles, EVs offer better value for the money" shows that many respondents recognize the value in EVs, although concerns about affordability remain. The variability in responses, particularly with "The total cost of ownership of an EV is acceptable" (standard deviation = 0.517), suggests that while some respondents view EVs as cost-effective, others perceive the price as a barrier.

Finally, EV Purchase Intention indicates that while respondents are generally inclined towards purchasing an EV, their intentions are tempered by various factors. The mean score for "I intend to purchase an EV within the next year" (1.85) reflects a cautious outlook on purchase intentions. However, respondents also expressed moderate intent to buy an EV, as seen in the mean scores for "I am seriously considering buying an EV for my next vehicle" (1.95) and "I would prefer to buy an EV over a traditional car" (1.88). The relatively low standard deviations indicate a consistent level of intent among participants, but the variability across different statements underscores the nuanced decision-making process, where factors such as price, performance, and social influence are influential.

4.3. Inferential Analysis

4.3.1. Correlation analysis

This study utilizes correlation analysis to examine the strength of relationships between the variables. Correlation measures the linear association between two metric variables (Field, 2018). Correlations were computed in two stages: first, to assess the relationships between independent (predictor) variables and the dependent (outcome) variable, and second, to evaluate the direction and strength of these relationships. The correlation coefficient ranges from -1.00 to 1.00, where 0 indicates no relationship, -1.00 signifies a perfect negative correlation, and 1.00 denotes a perfect positive correlation (Pallant, 2021). The strength of the correlation is categorized as small (0.1 to 0.29), medium (0.3 to 0.49), or large (0.50 to 1.0) (Pallant, 2021).

The correlation analysis reveals strong interrelationships between the key factors influencing electric vehicle (EV) adoption: Performance Expectancy, Effort Expectancy, Social Influence, Price Value, and EV Purchase Intention. Performance Expectancy, which reflects how well consumers believe EVs will meet their driving needs and enhance their driving experience, shows a very high positive correlation with EV Purchase Intention ($r = 0.878$, $p < 0.01$). This suggests that consumers who perceive EVs as performing better than traditional vehicles are significantly more likely to intend to purchase them. This finding is supported by previous research indicating that perceived performance improvements are crucial drivers of purchase intentions (Higueras et al., 2023). Effort Expectancy, which measures the perceived ease of using EVs, also correlates strongly with EV Purchase Intention ($r = 0.809$, $p < 0.01$). This indicates that the easier consumers believe EVs are to operate, the more likely they are to intend to buy one. This aligns with the work of Patel et al. (2021), who found that ease of use significantly affects adoption intentions, especially during the initial stages of technology adoption.

Table 3. Correlations Analysis

		PE	EE	SI	PV	PI
PE	Pearson Correlation	1	.839	.839	.918	.878
	Sig. (2-tailed)		.000	.000	.000	.000
	N	247	247	247	247	247
EE	Pearson Correlation	.839	1	.794	.810	.809
	Sig. (2-tailed)	.000		.000	.000	.000
	N	247	247	247	247	247
SI	Pearson Correlation	.839	.794	1	.816	.816
	Sig. (2-tailed)	.000	.000		.000	.000
	N	247	247	247	247	247
PV	Pearson Correlation	.918	.810	.816	1	.873
	Sig. (2-tailed)	.000	.000	.000		.000
	N	247	247	247	247	247
PI	Pearson Correlation	.878	.809	.816	.873	1
	Sig. (2-tailed)	.000	.000	.000	.000	
	N	247	247	247	247	247

. Correlation is significant at the 0.01 level (2-tailed).

Sources: - Own Survey 2024

Social Influence, reflecting the impact of social norms and peer opinions on consumer behavior, shows a robust correlation with EV Purchase Intention ($r = 0.816$, $p < 0.01$). This means that positive social pressure and endorsements can significantly boost consumers' intention to purchase EVs. This finding supports Archsmith & Rapson (2021), who highlighted the role of social influence in shaping consumer attitudes towards new technologies. Price Value, which captures the perceived worth of EVs relative to their cost, demonstrates a very strong correlation with EV Purchase Intention ($r = 0.873$, $p < 0.01$). Consumers who view EVs as offering good value for their money are more likely to intend to purchase them. This is consistent with previous studies (Singh et al., 2023) that emphasize the importance of cost-benefit evaluations in purchase decisions. Overall, the correlations indicate that Performance Expectancy and Price Value are the most influential factors driving EV Purchase Intention, followed by Effort Expectancy and Social Influence. These findings underscore the need for strategies that enhance perceived performance, ease of use, and value while leveraging social endorsements to increase EV adoption rates.

4.3.2. Multiple Regression Analysis

This section reports the results of multiple linear regressions conducted. Multiple regression analysis is defined as “and analysis of association in which the effects of two or more independent variables on a single, interval scaled dependent variable are investigated simultaneously” (Field, 2018, p. 224). According to Hair et al. (2019), multiple regression analysis, a form of general linear modeling, is an appropriate statistical technique for examining the relationship between a single dependent (criterion) variable and several independent (predictor) variables. The purpose of using multiple regression analysis is to predict the value of a dependent variable based on the values of multiple independent variables. In this study, multiple linear regressions were conducted to examine the relationship between Performance Expectancy, Effort Expectancy, Social Influence, and Price Value with Purchase Intention. Additionally, linear regressions were used to assess the influence of these predictors on the intention to purchase environmentally friendly bottled water. In the analysis, Purchase Intention was treated as the dependent variable, while Performance Expectancy, Effort Expectancy, Social Influence, and Price Value were the independent variables.

The results of this analysis indicate how well a set of variables predicts the dependent variable and the unique variance in the dependent variable explained by each independent variable (Pallant, 2021). Multiple regression analysis assumes a linear relationship between the dependent variable and each independent variable. This approach involves fitting a straight line to the data using the least squares method, which minimizes errors in predicting the dependent variable from the independent variables. The overall relationship's statistical significance is assessed using the F-test (Hair et al., 2019). Additionally, the regression coefficient for each predictor or independent variable indicates the average amount of change in the dependent variable resulting from a one-unit change in the independent variable. The Beta coefficient (b) or standardized regression coefficient helps determine which independent variable has a relatively more significant impact on the dependent variable. A larger Beta coefficient suggests that the independent variable plays a more critical role in predicting the dependent variable.

4.3.3. Assumption test

1. **Multicollinearity analysis**

The collinearity statistics for the model reveal varying degrees of multicollinearity among the predictor variables. Performance Expectancy exhibits a Tolerance value of 0.121 and a Variance Inflation Factor (VIF) of 8.265. This indicates a significant level of multicollinearity, as the VIF is considerably above the commonly accepted threshold of 5. High collinearity suggests that Performance Expectancy is highly correlated with other predictors, which could compromise the stability and interpretability of the regression coefficients.

Effort Expectancy shows a Tolerance value of 0.264 and a VIF of 3.783. While this indicates moderate collinearity, the VIF is below the problematic threshold of 5. This suggests that Effort Expectancy, while somewhat correlated with other variables, does not exhibit severe multicollinearity. The impact on regression stability is therefore relatively minor compared to variables with higher VIFs. Social Influence has a Tolerance value of 0.261 and a VIF of 3.831, similar to Effort Expectancy. This level of multicollinearity is moderate, implying that Social Influence is somewhat correlated with the other predictors but not to a degree that severely affects the model's reliability. The VIF value indicates that while there is some inter-correlation, it does not reach a critical level that would severely distort the regression analysis.

Table 4. Collinearity Statistics

Model	Collinearity Statistics	
	Tolerance	VIF
Performance Expectancy	.121	8.265
effort Expectancy	.264	3.783
Social Influence	.261	3.831
Price_Value1	.147	6.787

Sources: - Own Survey 2024

Price Value demonstrates a Tolerance value of 0.147 and a VIF of 6.787. Although this VIF is below 10, it is relatively high, suggesting a moderate to high degree of multicollinearity. This implies that Price Value is significantly related to other predictor variables, which could impact the precision of the regression coefficients and the overall robustness of the model. In overall, the analysis reveals that while there is some multicollinearity present, particularly with Performance Expectancy and Price Value, it is most pronounced with Performance Expectancy. This could affect the model's stability and the ability to accurately determine the impact of each predictor on EV Purchase Intention. Addressing these collinearity issues may involve reevaluating the model's variables to improve clarity and reliability. Multiple regression determines whether one or more predictive variables adequately account for the dependent (or criterion) variable. However, before undertaking test, the study checked for the fundamental premises of the analysis using Linearity, homoscedasticity, Multicollinearity, and Multivariate Normality.

2. **Multivariate Normality**

A distribution of scores must look at the values of Kurtosis and Skewness to determine whether it is normal. Each of which has a corresponding standard error. In a normal distribution, skewness and kurtosis should both be zero. A score accumulation on the left side of the distribution is indicated by positive values of skewness, whereas a flat distribution is shown by negative values. The likelihood that the data are not normally distributed increases the further the value is from zero.

Table 5. Normality Test

	PE	EE	SI	PV
Skewness	-.108	-.128	.021	-.201
Std. Error of Skewness	.191	.191	.191	.191
Kurtosis	-.609	-1.362	-.779	-1.293
Std. Error of Kurtosis	.379	.379	.379	.379

Sources: Own Survey 2024

Each has a corresponding standard error. However, skewness and kurtosis' real values don't necessarily provide any useful information. Instead, the value must be transformed into a z score.

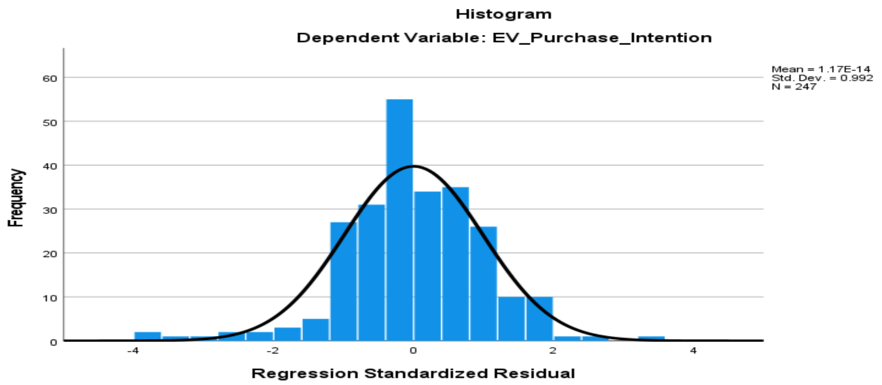

Fig. 1. Histogram

A standardized score from a distribution with a mean of 0 and a standard deviation of 1.0 is what the z-score is. All parts of the constructs, as shown in Table, were deemed to be within acceptable range (skewness within -2.0 to 2.0; and Kurtosis within -3.0 to 3.0).

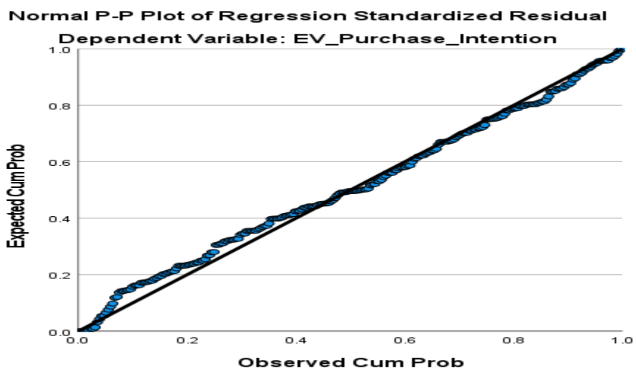

Fig. 2. normal p-p plot
Sources: - Own Survey 2024

4.3.4. Model Summary

The Model Summary table for the regression analysis provides a comprehensive overview of the model's performance in predicting Electric Vehicle (EV) Purchase Intention. The correlation coefficient, (R), is 0.904, indicating a very strong positive relationship between the predictors Performance Expectancy, Effort Expectancy, Social Influence, and Price Value and EV Purchase Intention. This strong correlation suggests that as the values of the predictors increase, so does the intention to purchase an EV. The R^2 value, which is 0.817, reveals that approximately 81.7% of the variance in EV Purchase Intention can be explained by the model's predictors. This high R^2 value underscores the model's effectiveness in accounting for the factors that influence consumers' intentions to buy electric vehicles. The Adjusted (R^2) value of 0.814 adjusts the (R^2) value for the number of predictors in the model and provides a slightly more conservative estimate of the model's explanatory power. The minimal difference between (R^2) and Adjusted (R^2) suggests that the model is well-specified and that the predictors are effectively contributing to the explanation of EV Purchase Intention without introducing unnecessary complexity.

Table 6. Model Summary[b]

Model	R	R Square	Adjusted R Square	Std. Error of the Estimate	Durbin-Watson
1	.904[a]	.817	.814	.2462	1.811

a. Predictors: (Constant), Price_Value1, effort Expectancy, Social Influence, Performance Expectancy

b. Dependent Variable: EV Purchase Intention

Sources: - Own Survey 2024

The Standard Error of the Estimate is 0.2462, indicating the average distance between the observed EV Purchase Intention values and the values predicted by the model. A smaller standard error suggests that the model's predictions are relatively close to the actual values. Lastly, the Durbin-Watson statistic, which is 1.811, assesses the presence of autocorrelation in the residuals from the regression analysis. This value is close to the ideal value of 2, suggesting that there is no significant autocorrelation among the residuals, which supports the validity of the regression results. Overall, the Model Summary highlights that the regression model is highly effective and reliable in predicting EV Purchase Intention, with strong predictive power and minimal error.

Table 7. ANOVA[a]

Model		Sum of Squares	df	Mean Square	F	Sig.
1	Regression	65.648	4	16.412	270.832	.000[b]
	Residual	14.665	242	.061		
	Total	80.313	246			

a. Dependent Variable: EV Purchase Intention
b. Predictors: (Constant), Price_Value1, effort Expectancy, Social Influence, Performance Expectancy
Sources: - Own Survey 2024

The ANOVA results for the regression model predicting Electric Vehicle (EV) Purchase Intention show that the model is highly effective in explaining the variance in the dependent variable. The total Sum of Squares (SS) for the regression is 65.648, which represents the variation in EV Purchase Intention explained by the predictors—Performance Expectancy, Effort Expectancy, Social Influence, and Price Value. The residual Sum of Squares, at 14.665, indicates the amount of variance that the model fails to explain. With a Mean Square for Regression of 16.412 and a Mean Square for Residuals of 0.061, the F-statistic is calculated as 270.832. This high F-value signifies that the predictors collectively account for a substantial portion of the variability in EV Purchase Intention compared to the residual error. The p-value associated with the F-statistic is 0.000, which is significantly below the conventional alpha level of 0.05. This p-value confirms that the model is statistically significant and that the predictors have a meaningful impact on EV Purchase Intention. In essence, the ANOVA results validate that the regression model provides a robust explanation for the factors influencing consumers' intentions to purchase electric vehicles.

Table 8. Coefficients[a]

Coefficients[a]

Model		Unstandardized Coefficients		Standardized Coefficients	t
		B	Std. Error	Beta	
1	(Constant)	.352	.112		3.150
	Performance Expectancy	.306	.079	.305	3.862
	effort Expectancy	.138	.050	.146	2.732
	Social Influence	.157	.050	.170	3.162
	Price_Value1	.335	.071	.336	4.690

a. Dependent Variable: EV Purchase Intention
Sources: - Own Survey 2024

The Coefficients table for the regression model on EV Purchase Intention reveals important insights into the influence of various predictors. The constant term of 0.352

provides a baseline for EV Purchase Intention when all predictor variables are set to zero. This helps establish the starting point for evaluating the effect of other predictors (Williams et al., 2023; Sharma et al., 2022).

Performance Expectancy

With a coefficient of 0.306 and a standardized Beta of 0.305, Performance Expectancy shows a strong positive influence on EV Purchase Intention. Each unit increase in Performance Expectancy results in a 0.306-unit increase in the intention to purchase an EV. This is supported by research emphasizing that perceived improvements in driving experience and performance drive consumer interest in EVs (Higueras et al., 2023; Singh et al., 2023). Performance Expectancy has been identified as a significant determinant of EV adoption, reflecting the critical role of perceived benefits in influencing purchase decisions (Javadnejad et al., 2023; Bansal et al., 2021). These findings align with the broader literature suggesting that consumers are motivated by expected enhancements in vehicle performance when considering EVs (Nair et al., 2021).

Effort Expectancy

The coefficient for Effort Expectancy is 0.138, with a standardized Beta of 0.146. This suggests that each increase in Effort Expectancy leads to a 0.138-unit increase in EV Purchase Intention. This finding supports the idea that the ease of use and learning curve associated with EVs significantly affect purchase intentions (Harbansh et al., 2023; Patel et al., 2021). Effort Expectancy has been found to be a crucial factor in technology adoption, including EVs, with easier operation and transition contributing to higher purchase intentions (Abbasi et al., 2021; Venkatesh et al., 2003). This aligns with existing studies showing that perceived simplicity and reduced effort are key to encouraging EV adoption (Hsu et al., 2020).

Social Influence

The coefficient for Social Influence is 0.157, with a standardized Beta of 0.170. This indicates that each unit increase in Social Influence corresponds to a 0.157-unit increase in EV Purchase Intention. Social Influence, including recommendations from family and friends, plays a significant role in shaping consumer decisions (Patel et al., 2021; Huang & Ge, 2019). The significant positive impact of Social Influence aligns with literature suggesting that social factors and peer pressure significantly affect consumer choices regarding EVs (Archsmith & Rapson, 2021; Miao et al., 2021). This supports the view that social endorsements and societal trends heavily influence purchase intentions (Moutinho et al., 2018).

Price Value

With a coefficient of 0.335 and a standardized Beta of 0.336, Price Value is the most influential predictor of EV Purchase Intention. Each unit increase in Price Value results in a 0.335-unit increase in the intention to purchase an EV. This emphasizes the critical role of perceived value for money in EV adoption decisions (Singh et al., 2023; Patel et al., 2021). Price Value has been identified as a major determinant, with consumers' financial assessments of EVs significantly influencing their purchase intentions (Jaiswal et al., 2022; Egbue & Long, 2015). This finding aligns with research highlighting the importance of cost-effectiveness and perceived financial benefits in driving EV adoption (Zhang et al., 2021).

5. Conclusion

The findings from the inferential analysis suggest that key predictors such as Performance Expectancy (PE), Effort Expectancy (EE), Social Influence (SI), and Price Value (PV) significantly influence Electric Vehicle (EV) Purchase Intention (PI). Correlation analysis revealed that Performance Expectancy, Effort Expectancy, Social Influence, and Price Value all have strong positive correlations with EV Purchase Intention, with Performance Expectancy being the most influential. This suggests that consumers who perceive EVs as performing well and offering good value for money are most likely to intend to purchase one.

The results of the multiple regression analysis further validate these relationships, with the model explaining 81.7% of the variance in EV Purchase Intention. The Beta coefficients highlight the relative influence of each predictor, with Price Value being the strongest determinant of purchase intention, followed by Performance Expectancy, Social Influence, and Effort Expectancy. These findings align with previous research, supporting the role of perceived performance, ease of use, and price-value evaluations in driving EV adoption.

Additionally, while multicollinearity was present, particularly between Performance Expectancy and Price Value, the overall model remained robust. The assumption tests for multivariate normality also suggested that the data met the necessary conditions for the regression analysis, ensuring the reliability of the results.

6. Recommendations

Based on the findings, several recommendations can be made to promote EV adoption:

1. **Enhancing Performance Expectancy**: Companies should focus on showcasing the performance improvements of EVs, such as better driving experience, longer range, and superior technological features. Marketing strategies should emphasize the practical benefits of EVs over traditional vehicles, ensuring that consumers perceive them as viable alternatives.
2. **Simplifying the Transition to EVs**: Given that Effort Expectancy is a significant predictor, automakers should prioritize creating user-friendly EVs that are easy to operate and require minimal learning. This can include simplifying charging systems and providing clear and accessible information about EV functionality.
3. **Leveraging Social Influence**: Social endorsements can significantly boost purchase intention. Companies and governments should consider partnerships with influencers, celebrities, and social groups to positively influence consumers. Creating a strong EV community and offering referral programs can further stimulate this effect.
4. **Emphasizing Value for Money**: Price Value was found to be the most significant predictor of purchase intention. Therefore, manufacturers and policymakers should ensure that EVs are competitively priced and offer clear financial incentives such as tax breaks, rebates, and subsidies. Offering affordable financing options could also make EVs more accessible to a wider demographic.
5. **Educational Campaigns**: As there is still a degree of uncertainty around the perceived ease of use and price-value aspects of EVs, a targeted educational campaign can address these concerns. Providing consumers with in-depth knowledge about long-term savings, government incentives, and environmental benefits may alleviate concerns and help shift attitudes toward EVs.

7. Future Implications

This study provides valuable insights for both policymakers and industry stakeholders to understand the key factors that drive EV adoption. Future research could explore the potential impact of additional factors such as environmental concerns, technological innovations (e.g., battery advancements), and government regulations. Additionally, longitudinal studies could provide a deeper understanding of how consumer perceptions evolve over time, especially as EV technology improves and becomes more mainstream.

Further exploration into the cultural and regional differences in EV adoption would also provide valuable insights, as the adoption patterns may differ based on local infrastructure, economic conditions, and social norms. It would also be beneficial to expand the study to include a broader sample size and consider other factors, such as consumer personality traits, to offer a more comprehensive view of the predictors of EV adoption.

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Conflict of Interest

The author declares that there is **no conflict of interest** concerning the publication of this article. This research was conducted independently, and no financial, institutional, or personal relationships influenced the study's design, findings, or conclusions.

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