Journal of Climate Change and Space Science (JCCaSS) 2(2) (2026): 2
https://doi.org/10.17576/jccass.0202.2026.02

Influence of Smart Pricing Tool on Electric Vehicle Adoption and Carbon Reduction in Kota Kinabalu, Sabah: Regression-based Assessment

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Received: 19 Nov 2025; Accepted: 7 April 2026; Published: 31 July 2026

ABSTRACT

The transition to electric vehicles (EVs) is a critical step toward achieving low-carbon urban mobility and meeting global climate targets. This study investigates the influence of EV charging cost on adoption rates in Kota Kinabalu, Sabah, Malaysia, using a linear regression model derived from a structured survey of 376 respondents. The model predicts the percentage of potential EV users based on varying charging price levels per 100 km, yielding a strong correlation with an R^2 value of 0.9517. Results indicate that lower charging costs significantly increase the likelihood of EV adoption; for instance, reducing the cost from RM8.50 to RM5.50 could increase the adoption rate from 10.3% to 19.7%. To assess the broader sustainability implications, the study incorporates a carbon emission reduction analysis based on predicted EV usage, estimating that each EV user saves approximately 13.03 kg of CO_2 emissions weekly for 100 km compared to internal combustion engine (ICE) vehicles. Under optimal pricing scenarios, potential savings could exceed 20,000 kg of CO_2 annually per 15,000 drivers. Scenario forecasting from 2025 to 2030 further illustrates that strategic price reductions can meaningfully influence adoption trends and environmental outcomes. The study highlights the role of charging cost as a key policy lever and introduces a conceptual decision-support tool to guide climate-responsive transport planning, in alignment with Malaysia's Low Carbon Mobility Blueprint and similar global sustainability initiatives.

Keywords: electric vehicle adoption; charging pricing strategy; regression modelling; carbon reduction; sustainable mobility

1. INTRODUCTION

The global transition from internal combustion engine (ICE) vehicles to electric vehicles (EVs) has emerged as a crucial pathway toward mitigating greenhouse gas (GHG) emissions and addressing the climate crisis. Traditional ICE vehicles, which convert thermal energy from fossil fuel combustion into mechanical energy, are known to emit significant amounts of carbon dioxide (CO_2), a key contributor to global warming (Tan et al., 2023; Molaeimanesh & Torabi; 2022). As a solution, EVs have gained attention as a cleaner, more sustainable mode of transportation. These vehicles are powered either entirely by electricity or through hybrid systems and produce little to no tailpipe emissions (Zhao & Yang, 2011). EVs are also associated with reduced noise pollution, higher energy efficiency, and lower operational and maintenance costs, making them increasingly attractive for both environmental and economic reasons (Herninda et al., 2022; Ayog, n.d.; Kasprzyk, 2017; Spanoudakis et al., 2020).

Globally, many countries have established ambitious EV adoption targets. Norway aims to eliminate ICE vehicle sales entirely by 2025 (Dow, 2021), while China mandates that EVs account for 40% of new vehicle sales by 2030 (Nancy, 2020). Singapore plans to transition all vehicles to clean energy by 2040, and Thailand targets 50% local EV production by 2030, with full conversion by 2035 ("Scaling EV for Future Mobility in SEA," 2022). Malaysia, keeping pace with these global megatrends, has outlined national strategies such as the National Energy Policy (NEP) 2040 and the Long-Term Low Emission Development Strategy (LT-LEDS) 2050, both aiming to achieve net-zero emissions by 2050 (Songkin & Jaafar, 2023).

Despite the government's commitment and incentives, EV adoption in Malaysia remains limited. According to the Malaysia Automotive Association, only 274 EVs were sold in 2021, with a significant increase to 2,631 units in 2022 (Chan, 2023). Projections suggest the number of EVs on Malaysian roads will reach 125,000 by 2030. Government efforts such as the Battery Electric Vehicle Global Leaders Incentive (BEV GLI) and the Low Carbon Mobility Blueprint which targets 10,000 charging stations by 2024 are intended to accelerate this transition ("Malaysia Electric Vehicles," 2023). Nevertheless, significant challenges persist, particularly the lack of charging infrastructure. A 2023 Deloitte study revealed that limited access to public chargers remains a primary barrier to EV ownership in Malaysia (Bernama, 2023), especially in states like Pahang, Terengganu, and Kelantan, which have sparse EV charging coverage.

This study focuses on Kota Kinabalu, the capital city of Sabah, as a case study for understanding urban EV adoption in Malaysia. With an estimated population of 589,000 in 2022, the city offers a growing urban environment ripe for transportation innovation (Kota Kinabalu, Malaysia Metro Area Population 1950-2023, United Nations-World Population Prospects, 2010). The research targets residents aged 20–69, representing approximately 328,000 potential drivers (Kota Kinabalu Population, 2022). A structured survey was conducted to assess public perceptions, key adoption drivers, and existing barriers. Using this data, a logistic regression model was developed to estimate EV adoption rates based on charging cost levels. The study also introduces an interactive Excel-based forecasting tool designed to simulate various pricing scenarios and estimate their impact on carbon emissions. This decision-support tool aims to aid local policymakers in evaluating the environmental benefits of EV-related policies and contribute toward Malaysia's low-carbon transportation goals.

2. METHODOLOGY

This study employs a quantitative approach to assess the impact of EV charging costs on adoption rates and corresponding carbon dioxide (CO_2) emission reductions. The methodology comprises three core components: (1) survey-based data collection, (2) logistic regression modelling, and (3) the development of a scenario-based Excel decision-support tool for policy simulation.

2.1 Data Collection

Primary data was collected through a structured online survey targeting private vehicle owners in Kota Kinabalu, Sabah. The survey included 376 valid responses and covered demographic information, perceptions of EVs, willingness to adopt under varying cost charging, and travel behavior. Respondents were asked to indicate their likelihood of switching to an EV at multiple cost levels per 100 km, which formed the basis for the modelling dataset.

The data is analyzed on age distribution, focusing on Kota Kinabalu residents aged 20 up to 69 years old. The reason in selecting the following age range is due to driving age and eligibility. According to Jabatan Pengangkutan Jalan (JPJ) Malaysia, the legal driving age starts at 18 (Driving License, 2017). Including respondents below this age would be irrelevant as they are not legally eligible to drive or purchase vehicles. Meanwhile, for people age above 69, this age can still drive, but the number of active drivers tends to decrease significantly due to health and mobility issues. Therefore, following age group is selected where the groups are classified into five group consist of age between 20-29, 30-39, 40-49, 50-59 and 60-69.

A broad range of income levels, providing a comprehensive view of the economic diversity among respondents. This diversity is crucial for understanding the impact of income on perceptions and behaviors related to the survey topic. The income level had been divided into three groups which are below RM4850 (B40), between RM4850 to RM10959 (M40) and above RM10960 (T20) ("T20, M40, B40 Household Income Update 2023," 2023). The education level data provides a detailed view of the educational backgrounds of survey respondents, with significant representation across all levels of education from pre-university to doctoral degrees. Data is categorized into five levels which Sijil Pelajaran Malaysia (SPM), Diploma or STPM, Degree, Master and Phd. The classification of respondents was based on the highest attained educational qualification.

2.2 EV Adoption Modelling

Researchers have employed various methods to predict the adoption of electric vehicles (EVs), including machine learning-based techniques and linear regression models. De Cauwer et al. utilized a neural network to predict the speed profiles of EVs. Subsequently, they employed a multiple linear regression (MLR) model to forecast energy consumption rates (Zhao et al., 2020). Similarly, linear regression analysis is used to model the relationship between vehicle weight and energy consumption in domestic electric vehicles (Li et al., 2019). These studies demonstrate the applicability of linear regression in understanding and predicting energy consumption in the context of EV adoption.

Linear regression analysis is employed to forecast the value of one variable by considering the value of another variable. The variable to be predicted is termed the dependent variable, while the variable utilized for predicting the value of the former is referred to as the independent variable (What Is Linear Regression? 2023). The linear regression method can be performed in several programs such as R linear regression, MATLAB linear regression, Sklearn linear regression, linear regression Phyton and Excel linear regression.

Logistics functions that are commonly used in transport modelling are as follows;

$$P = \frac{1}{1+De^{ax}} \quad (1)$$

Where,
P = probability
D = constant
a = coefficient to be calibrated
x = independent value

Building on this foundation, the present study employs a logistic regression model to shift focus from energy performance to behavioral adoption, specifically examining the relationship between EV charging cost and the probability of user adoption. This approach enables a scenario-based assessment of how pricing strategies can influence adoption rates and, consequently, carbon emissions in an urban Malaysian context.

2.3 Sustainability Impact Estimation

To quantify the environmental benefits of electric vehicle (EV) adoption, this study calculates the difference in carbon dioxide (CO_2) emissions between internal combustion engine (ICE) vehicles and EVs. Emission factors were sourced from authoritative databases: 0.17726 kg CO_2/km for petrol vehicles and 0.047 kg CO_2/km for electric vehicles (UK Government GHG Conversion Factors, 2024; Ritchie & Roser, 2024). Based on an assumed average travel distance of 100 km per week, the weekly CO_2 savings per EV user were computed using Equation (2). These individual savings were then annualized and multiplied by the predicted number of EV adopters, derived from the logistic regression model, to estimate the total annual CO_2 reductions at the city scale for each charging cost scenario.

$$Total\ CO_2\ Savings\ (kgCO2) = EF\ (ICE - EV) \times Distance\ Travlled\ (km) \quad (2)$$

2.4 Excel-Based Decision Support Tool Development

An interactive Excel-based decision-support tool was developed to operationalize the adoption model for policy evaluation and urban planning applications. The tool allows users to input key parameters such as population size, average weekly travel distance, and EV charging cost (RM per 100 km). Based on these inputs, the tool dynamically calculates the predicted EV adoption rate using the logistic regression equation, estimates the corresponding number of EV users, and computes the annual CO_2 savings both in kilograms and metric tons. To enhance usability and accessibility, the tool incorporates color-coded input fields, protected formula cells, and integrated charts for real-time visual feedback. Additionally, a multi-year forecasting module was embedded to project cumulative CO_2 reductions over a defined period, enabling users to simulate long-term environmental impacts under different pricing strategies.

3. RESULTS AND DISCUSSION

This study employs a quantitative approach to analyze the influence of electric vehicle (EV) charging cost on user adoption in Kota Kinabalu, Sabah. The methodology consists of three main components: data collection, statistical modeling, and sustainability impact estimation.

3.1 Respondents Demographic

Table 1. Summarize respondents.

		Frequency Respondent	Respondent (%)
Age	20-29	120	31.9
	30-39	88	23.4
	40-49	91	24.2
	50-59	50	13.3
	60-69	27	7.2
Income Level	Above RM 10960	77	20.5
	Below RM 4850	185	49.2
	RM 4850 - RM 10959	114	30.3
Highest Education Level	Degree	124	33.0
	Diploma / STPM	95	25.3
	Master	35	9.3
	Phd	44	11.7
	SPM	78	20.7
Gender	Female	180	47.9
	Male	196	52.1

Table 1 summarizes the demographic characteristics of the respondents. Most respondents are aged between 20–29 years (31.9%), followed by those aged 40–49 (24.2%) and 30–39 (23.4%). Almost half of the respondents (49.2%) earn below RM4,850, while 30.3% fall within the middle-income group and 20.5% earn above RM10,960. In terms of education, the majority hold a degree (33.0%), followed by Diploma/STPM (25.3%) and SPM (20.7%). A smaller proportion have postgraduate qualifications. The gender distribution is nearly balanced, with 52.1% male and 47.9% female respondents.

3.2 Data Analysis

Primary data was gathered through a structured online survey distributed to residents of Kota Kinabalu. The survey included demographic information, factors influencing and challenges in EV adoptions, and perceptions of current EV charging costs. Respondents were also asked about their likelihood of adopting EVs at different charging price levels (per 100 km), which served as the key input for modeling. From the survey as shown in Figure 1, 52% of respondents were satisfied with the current charging cost, which is RM8.50 per 100km (*ChargEV - BMW REGAS PREMIUM SABAH (60kW DC)*, 2024). However, the margin is slim, as 48% are not satisfied, highlighting a significant majority that sees the cost as an issue.

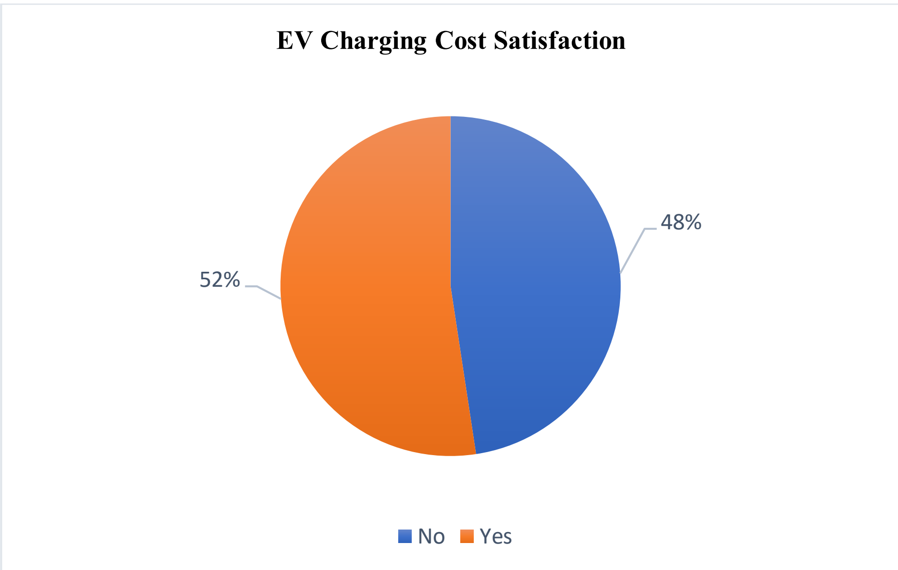

Figure 1. Satisfaction with EV Charging Cost.

3.3 Statistical Modelling

A linear regression model was used to predict the percentage of potential EV adopters based on varying EV charging costs. The independent variable was the charging cost (in RM/100 km), and the dependent variable was the proportion of respondents indicating willingness to adopt EVs. The data is tabulated and plotted as shown in Table 2 and Figure 2.

Table 2. Raw data collected from survey.

Price Reduction (RM)	Price*	Frequency	Percentage (%)
-	8.50**	99	0.08
0.50	8.00	144	0.11
1.00	7.50	167	0.13
1.50	7.00	182	0.14
2.00	6.50	195	0.16
2.50	6.00	209	0.17
3.00	5.50	262	0.21
Total		1258	1.00

* Price reduction for EV charging rate per 100km
** Current price for charging EV per 100km

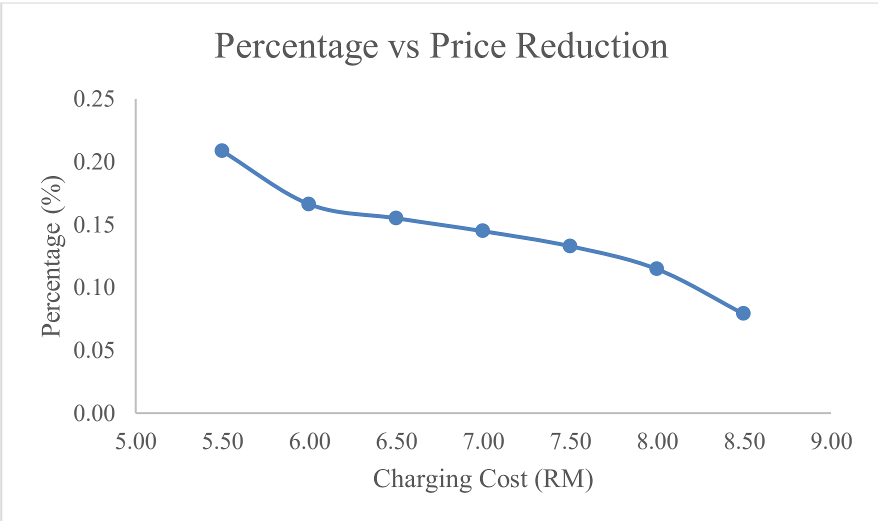

Figure 2. Percentage of people using EVs/week depending on the Charging Cost.

Table 3. Result from regression analysis from Excel.

R Square, R^2	0.9517
Standard Error	0.0596
Intercept of Y-axis	0.0175
The coefficient of X variable	0.2528

Table 3 shows the data obtained from the linear regression analysis by using Excel. R2 obtained is 0.9517, which means 95.17% of the variance in the percentage of people using EVs per week. A high R2 value, which is near to 1, indicates there is a strong relationship between the charging cost and EV usage. From the linear regression analysis, a linear regression equation is obtained as shown below, where y represents the percentage of people using EVs per week and x represents the charging cost;

$$y = 0.2528x + 0.0175 \qquad (3)$$

From the equation above, ln D equals 0.0175, which means D equals 1.0176 and α equal to 0.2528. Therefore, the final model equation is as (4), where P is the predicted EV adoption probability and x is the charging cost in RM per 100km.

$$P = \frac{1}{1+1.0176e^{(0.2528x)}} \quad (4)$$

Based on Equation 3, the prediction on frequency of EV usage in a week based on changing in the charging cost can be obtained as shown in Table 4 and Figure 3. From the table and graph below, the result shows as the price charging cost increases, the usage of EV decreases.

Table 4. Predicted P based on Charging Cost.

Charging Cost (RM), x	Predicted P
8.50	0.103
8.00	0.115
7.50	0.129
7.00	0.143
6.50	0.160
6.00	0.177
5.50	0.197

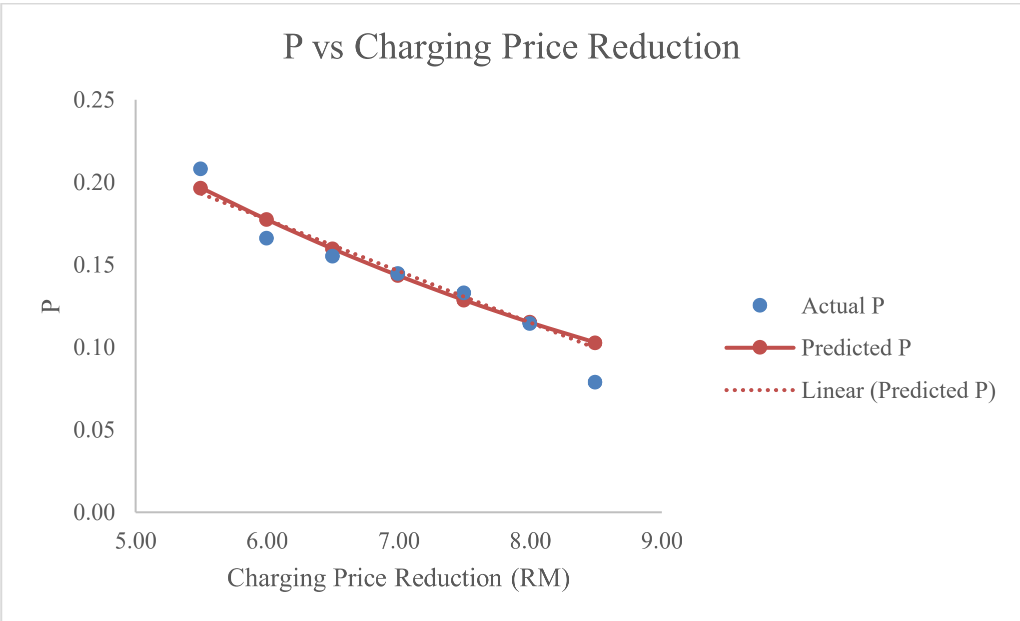

Figure 3. Actual P and Predicted P comparison against Charging Cost.

A sensitivity test is conducted by randomly inserting the Charging Cost, and the calculated P shows a trend that when the charging cost decreases, the P obtained increases. This correlates with actual data, where, as the charging cost decreases, actual P increases as shown in Figure 2. Thus, this indicates that the model is suitable to describe the actual data in predicting EV adoption in the future based on charging cost.

3.4 Sustainability Impact Estimation

The ICE vehicle emits 17.726 $kgCO_2$ per week, while the EV emits 4.7 $kgCO_2$, and the transition from ICE to EV can save 13.03 $kgCO_2$, which is equivalent to a 73% reduction. Thus, by utilizing the linear regression model's predicted probability (P) at various charging costs, this paper estimates the number of potential EV users out of a hypothetical population of 15,000 vehicle owners in Kota Kinabalu, according to the report (2023 Malaysia Transportation Statistics, 2024). The results are summarized in Table 5, which outlines the estimated number of EV users per week and their corresponding weekly CO_2 emissions at different charging cost levels.

Table 5. Emissions from EV based on Charging Cost (RM).

Charging Cost (RM)	8.50	8.00	7.50	7.00	6.50	6.00	5.50
Predicted EV adoption	10.30%	11.50%	12.90%	14.30%	16.00%	17.70%	19.70%
Estimated Users Weekly	1545	1725	1935	2145	2400	2655	2955
Weekly CO_2 EV Emission Reduction (kg)	20,125	22,470	25,205	27,941	31,262	34,584	38,492

As shown in Table 5, reducing the EV charging cost leads to a clear increase in adoption: from 10.3% (1,545 users) at RM8.50 to 19.7% (2,955 users) at RM5.50. Correspondingly, weekly CO_2 savings increase significantly from 20,125 kg to 38,492 kg which equivalent to 92% increment. This reflects not only a growing user base but also the cumulative environmental benefit of transitioning more ICE vehicle users to EVs under favourable pricing conditions. The results highlight the effectiveness of strategic pricing as a policy tool for accelerating EV uptake and maximizing carbon emission reductions in urban settings.

3.5 Scenario Forecasting (2025-2030)

To evaluate the long-term influence of charging costs on EV adoption and emission reduction, a scenario forecasting analysis was conducted for the period of 2025 to 2030. Three pricing strategies were formulated to reflect possible policy and market trajectories: Status Quo (constant charging cost of RM8.50 per 100 km), Gradual Reduction (RM8.00 to RM5.50), and Aggressive Reduction (RM7.50 to RM5.00). These scenarios were integrated with the linear regression model derived from the survey, which predicts EV adoption probability (P) based on the charging cost using equation 1. In projecting the number of EV adopters, an assumption was made that the total number of private vehicle owners in Kota Kinabalu would increase by 1,000 annually, rising from 15,000 in 2025 to 19,000 in 2030. This allows the model to more accurately reflect adoption scale as population and vehicle ownership expand. The summary of the findings for each scenario are shown in Table 6,7 and 8.

Table 6. Summary for scenario 1 (Status Quo).

Year	**Charging Cost (RM)**	**Predicted EV Adoption (%)**	**EV Users**	**Annual CO2 Saved (tons/year)**
2025	8.50	10.28	1,542	1,045
2026			1,645	1,114
2027			1,748	1,184
2028			1.851	1,254
2029			1,954	1,323
2030			2,056	1,393

Table 7. Summary for scenario 2 (Gradual Reduction).

Year	**Charging Cost (RM)**	**Predicted EV Adoption (%)**	**EV Users**	**Annual CO2 Saved (tons/year)**
2025	8.50	10.28	1,542	1,045
2026	8.00	11.51	1,1841	1,247
2027	7.50	12.86	2,186	1,481
2028	7.00	14.34	2,582	1,749
2029	6.50	15.97	3,034	2,055
2030	6.00	17.74	3,547	2,403

Table 8. Summary for scenario 3 (Aggressive Reduction).

Year	Charging Cost (RM)	Predicted EV Adoption (%)	EV Users	Annual CO2 Saved (tons/year)
2025	8.50	10.28	1,542	1,045
2026	7.50	12.86	2,058	1,394
2027	6.50	15.97	2,714	1,839
2028	5.50	19.66	3,538	2,397
2029	4.50	23.96	4,552	3,083
2030	3.50	28.86	5,772	3,910

Scenario 1 (Status Quo) projects a constant EV adoption rate of 10.28%, resulting in an increase from 1,542 to 2,056 EV users, and annual carbon savings rising from 1,045 to 1,393 metric tons. Over six years, this represents a 33% increase in emission savings. Similarly, Scenario 2 (Gradual Reduction) shows a steady increase in adoption from 10.28% to 17.74%, translating into 3,547 EV users by 2030. CO_2 savings climb from 1,045 to 2,403 tons/year, with cumulative improvement of 130% relative to the baseline year. Lastly, Scenario 3 (Aggressive Reduction) yields the strongest outcomes, with adoption rising from 10.28% in 2025 to 28.86% by 2030. This results in 5,772 EV users and 3,910 tons of CO_2 saved annually with 274% increase from the baseline. These projections demonstrate that even moderate reductions in charging cost can significantly influence EV adoption and environmental outcomes. Furthermore, as the vehicle-owning population grows, the cumulative emissions reduction potential compounds, highlighting the importance of integrating cost-based policy levers into long-term transport and climate strategies.

3.6 Smart Pricing Tool

The Smart EV Pricing Tool is a Microsoft Excel–based scenario modeling tool developed to estimate electric vehicle (EV) adoption and the resulting CO_2 emission reductions under varying economic and policy conditions. It serves as a decision-support instrument for policymakers, urban planners, and sustainability researchers by simulating both fixed and dynamic adoption scenarios. The tool requires minimal user input, including the total vehicle-owning population, average weekly travel distance, EV charging cost, and anticipated annual growth in vehicle population. Based on these parameters, the model predicts EV adoption rates using a logistic regression function calibrated from survey data collected in Kota Kinabalu, Malaysia. Emission savings are then calculated by comparing EV and internal combustion engine (ICE) emission factors (0.047 kg CO_2/km for EVs and 0.177 kg CO_2/km for ICE vehicles).

This tool is intentionally designed with an editable input interface and a locked output dashboard to ensure ease of use while maintaining data consistency. Its transparency, adaptability, and local contextualization make it suitable for evaluating smart transport interventions and informing sustainable mobility policies in Malaysian urban contexts, especially in Kota Kinabalu, Sabah.

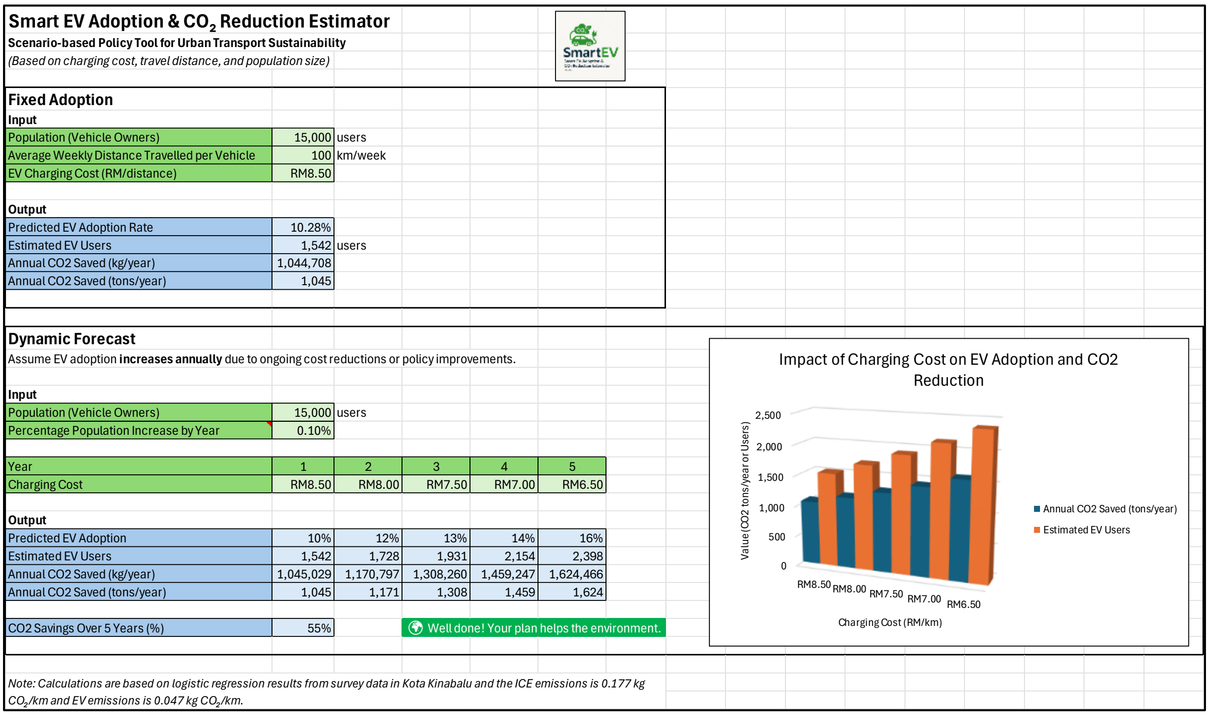

Figure 4. Interface of Smart EV Pricing Tools (https://shorturl.at/1fBnD).

4. CONCLUSION

This study demonstrates that charging cost plays a significant role in influencing electric vehicle (EV) adoption in urban Malaysia, specifically within Kota Kinabalu. From a policy perspective, the findings suggest that EV charging cost is a powerful and adjustable policy lever. Rather than relying solely on vehicle purchase incentives, policymakers may achieve higher adoption impacts through strategic charging price interventions, particularly in cities with growing but immature EV markets such as Kota Kinabalu.

Using a logistic regression model developed from survey data of 376 respondents, the research reveals a strong inverse relationship between charging price and the probability of EV adoption, with an R^2 value of 0.9517. A reduction in charging cost from RM8.50 to RM5.50, for example, could nearly double the adoption rate from 10.3% to 19.7%. To translate these findings into actionable insights, an interactive Excel-based decision-support tool was developed, allowing policymakers to simulate various price scenarios and evaluate their impact on both user adoption and carbon dioxide (CO_2) emissions.

The environmental implications are notable. At an average travel distance of 100 km per week, each EV user is estimated to reduce CO_2 emissions by 13.03 kg weekly. Under optimal pricing scenarios, projected annual savings could exceed 378 metric tons of CO_2 per 15,000 drivers. A multi-year forecasting module embedded within the tool further illustrates the potential for cumulative emission reductions from 2025 to 2030, reinforcing the role of strategic pricing in achieving national climate goals.

Looking forward, future work can expand the model by incorporating additional variables such as electricity tariffs, fuel prices, charging infrastructure availability, and user income levels to enhance prediction accuracy. Integration with Geographic Information Systems (GIS) could further support the spatial planning of EV infrastructure. Additionally, transforming the Excel tool into a web-based or mobile application would improve accessibility and usability for both policymakers and the general public. Ultimately, this research offers a practical, data-driven framework to inform climate-responsive transport planning and supports Malaysia's commitment to its Low Carbon Mobility Blueprint.

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