Factors Influencing the Choice for Electric Vehicles in Bangladesh: A Study of Market Penetration and Consumer Preferences

by

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The thesis/project titled “Factors Influencing the Choice for Electric Vehicles in Bangladesh: A Study of Market Penetration and Consumer Preferences” submitted by S.M. Abdullah Al Jobair Raihan, Student No.: 1904145, has been accepted as satisfactory in partial fulfillment of the requirement for the degree of Bachelor of Science in Civil Engineering on March 17, 2025.

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DECLARATION

I hereby declare that this thesis/project is my own work and to the best of my knowledge it contains no materials previously published or written by another person, or have been accepted for the award of any other degree or diploma at Bangladesh University of Engineering and Technology (BUET) or any other educational institution, except where due acknowledgement is made. I also declare that the intellectual content of this thesis is the product of my own work and any contribution made to the research by others, with whom I have worked at BUET or elsewhere, is explicitly acknowledged.

S.M. Abdullah Al Jobair Raihan

Dedicated

to

“My father”

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ABSTRACT

The transportation sector in Bangladesh remains heavily reliant on internal combustion engine (ICE) vehicles, contributing significantly to greenhouse gas emissions and urban air pollution. To address these environmental concerns, the Bangladesh government has set an ambitious goal of achieving 30% electric vehicle (EV) adoption by 2030. However, the transition to EVs faces substantial challenges, including high purchase costs, limited charging infrastructure, and a lack of consumer awareness. This study evaluates the current state of EV adoption in Bangladesh and examines the factors influencing consumer preferences between EVs and ICE vehicles. Data were collected through field visits, interviews, and a Stated Preference (SP) survey involving 173 participants, including students, university teachers, and job holders. Using a binomial logistic regression model, the study analyzes the impact of socioeconomic variables, vehicle attributes, and consumer perceptions on vehicle choice. The findings reveal that purchase cost, operating cost, driving range, and charging infrastructure availability are the most influential factors affecting consumer decisions. Additionally, the study identifies policy gaps and emphasizes the need for targeted financial incentives and infrastructure development to accelerate EV adoption. This research provides critical insights for policymakers, industry stakeholders, and researchers to design effective strategies for promoting sustainable transportation in Bangladesh and achieving the 2030 EV adoption target.

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CHAPTER 1: INTRODUCTION

1.1 Background and Motivation

The transportation sector is one of the largest contributors to global greenhouse gas emissions, primarily due to the extensive use of internal combustion engine (ICE) vehicles. These vehicles burn fossil fuels, releasing significant amounts of carbon dioxide (CO_2) and other harmful pollutants that exacerbate climate change and air quality issues. Road transport alone accounts for approximately 25% of fossil fuel-related CO_2 emissions worldwide, highlighting the urgent need for cleaner alternatives [1]. While electric vehicles (EVs) offer the potential to mitigate these environmental impacts, their effectiveness depends on factors such as electricity generation sources, vehicle lifecycle emissions, and policy support [2].

The global shift toward EV adoption has been largely driven by government policies, financial incentives, and improvements in charging infrastructure. Countries such as China, Norway, and Germany have successfully promoted EVs through tax exemptions, subsidies, and stringent emissions regulations [1]. However, despite these efforts, challenges such as high upfront costs, limited charging infrastructure, and range anxiety continue to slow down mass adoption. These challenges are even more pronounced in developing economies, where EV adoption remains in its early stages. In Bangladesh, the government has set an ambitious goal of achieving 30% EV adoption by 2030, aiming to reduce fossil fuel dependency and urban air pollution [3]. However, key challenges persist, including inadequate charging networks, high import duties, and a lack of clear policy frameworks to support large-scale adoption. Additionally, since Bangladesh’s electricity generation still relies heavily on fossil fuels, the net environmental benefits of EV adoption remain uncertain.

Assessing the current state of EV adoption in Bangladesh is crucial to understanding whether the country is on track to meet its 2030 target. Analyzing data on EV sales, the number of charging stations, and government initiatives can help identify gaps and potential areas for policy intervention. Without a clear assessment of these factors, policymakers may struggle to implement effective strategies that facilitate EV adoption and ensure environmental benefits. Furthermore, understanding consumer preferences is equally important, as public perception and willingness to transition from ICE vehicles to EVs play a decisive role in market growth. Research indicates that factors such as vehicle affordability, charging convenience, and long-term maintenance costs significantly influence consumer choices [2]. Addressing these concerns through targeted policies and market incentives will be essential for ensuring a smooth transition to sustainable transportation.

This research is significant because it provides a comprehensive analysis of the market readiness for EVs in Bangladesh and the factors influencing consumer decisions, offering insights for policymakers, stakeholders, and consumers. As global markets shift toward electrification, Bangladesh must address its unique challenges for a successful and environmentally beneficial transition.

1.2 Problem Statement

Despite global advancements in electric vehicle (EV) technology, Bangladesh's transportation sector continues to rely heavily on internal combustion engine (ICE) vehicles, leading to escalating greenhouse gas emissions and urban air pollution. The country's commitment to environmental sustainability is hindered by the slow adoption of EVs, attributed to challenges such as limited charging infrastructure, high initial costs, a lack of financial incentives, and range anxiety among consumers. Unlike many developed countries where government policies have accelerated EV uptake, Bangladesh still lacks a well-defined roadmap for EV integration, creating uncertainty for both consumers and investors. Addressing these issues is crucial for reducing the transportation sector's carbon footprint and aligning with global sustainability goals. If these barriers persist, the country may struggle to meet its 30% EV adoption target by 2030, further delaying its transition toward a cleaner, more energy-efficient transportation system.

Furthermore, the absence of comprehensive and reliable data on EV adoption rates, charging station availability, and consumer attitudes hinders the development of targeted policies and investment strategies. Without clear insights into the current market landscape, decision-makers cannot accurately assess the feasibility of large-scale EV deployment or design regulatory frameworks that encourage adoption.

Understanding the key factors that influence consumer preferences and purchasing decisions is also critical. While EVs offer long-term benefits such as lower operational costs and reduced emissions, many potential buyers remain concerned about battery life, resale value, and the practicality of EVs in a country with limited charging stations. Social perceptions and lack of awareness regarding EV performance, maintenance, and cost-effectiveness further contribute to consumer reluctance. Without targeted efforts to address these concerns, Bangladesh risks failing to create a conducive environment for EV adoption, ultimately missing opportunities to enhance energy security, improve air quality, and contribute to global climate change mitigation efforts.

1.3 Research Objectives and Overview

The primary objective of this research is to assess the current state of electric vehicle (EV) adoption in Bangladesh and evaluate whether the country is on track to meet its 30% EV adoption target by 2030. Additionally, the research seeks to understand consumer preferences and the key factors influencing purchasing decisions between EVs and internal combustion engine (ICE) vehicles. By identifying these factors, the study will provide insights into the challenges and opportunities associated with EV adoption in Bangladesh.

This research aims to present a comprehensive overview of electric vehicle (EV) adoption in Bangladesh by examining the number of EVs sold, the brands currently available in the market, and the comparative tax structures between conventional internal combustion engine (ICE) vehicles and EVs. Additionally, it explores the price differences between these two vehicle types, the availability of charging stations, and the charging practices of EV owners in the country. The research also covers surveying a limited number of EV users to gain insights into their usage patterns and experiences.

Furthermore, this research seeks to develop a car choice model using discrete choice modeling to identify the optimal parameters for accurate vehicle selection predictions in Bangladesh. It examines factors such as purchase, operating, and maintenance costs, driving range, infrastructure availability, and environmental considerations. The study also explores the influence of socioeconomic variables, including gender, age, and education, on consumer preferences.

1.4 Scope of Study

This study focuses exclusively on passenger cars, excluding two-wheelers, three-wheelers, and commercial vehicles such as buses and trucks. The research primarily aims to assess the current state of EV adoption in Bangladesh by analyzing sales figures, market trends, charging infrastructure, and tax structures in comparison to conventional internal combustion engine (ICE) vehicles.

The study is based on both primary and secondary data sources. Primary data will be collected through field visits to car showrooms and service centers, as well as a stated preference (SP) survey to evaluate consumer preferences regarding EVs and ICE vehicles. Secondary data will be gathered from existing literature, news articles and government policies to support the analysis.

The scope of this research does not extend to battery disposal, recycling processes, or the environmental impact of battery production, as the focus remains on the economic, infrastructural, and consumer preference aspects of EV adoption in Bangladesh. Additionally, heavy-duty vehicles and public transport electrification are outside the study's scope, ensuring a concentrated analysis on private car ownership trends.

1.5 Organization of the Thesis

The study has been subdivided into the following six chapters:

Chapter 1: Introduction and Objective. This chapter provides the background and motivations of the research. The overall objectives and scope have also been described in this chapter.

Chapter 2: Literature Review. This chapter reviews global literature on EV adoption and consumer preferences, focusing on Bangladesh's unique challenges in promoting EVs. It explores factors influencing EV preferences through discrete choice models and discusses transportation survey methodologies and software tools used in developing these models.

Chapter 3: Methodology. This chapter details the data collection methods, including in-person surveys, interviews, and a web-based Stated Preference (SP) survey to assess EV adoption and consumer preferences in Bangladesh. It also describes the data processing, key variables, and discrete choice modeling techniques used for car choice modeling, along with the software employed for analysis.

Chapter 4: Current EV Scenario. This chapter presents an analysis of the current electric vehicle (EV) market in Bangladesh, discussing the challenges and conditions surrounding EV adoption. It highlights factors such as market penetration, charging infrastructure, and consumer behavior based on interviews and surveys.

Chapter 5: Choice Modelling. This chapter focuses on the factors influencing consumer preferences between EVs and internal combustion engine (ICE) vehicles, with an emphasis on purchase cost, operating cost, environmental impact, and sustainability beliefs. The chapter also presents utility functions based on a Stated Preference (SP) survey, which provides insights into the key drivers of vehicle choice in Bangladesh.

Chapter 6: Conclusion and Future Works. This chapter summarizes the key findings of the study and their implications for EV adoption and consumer preferences. It also provides recommendations for future research to explore further challenges and opportunities in promoting EV adoption.

CHAPTER 2: LITERATURE REVIEW

2.1 Introduction

The transition to electric vehicles (EVs) has gained global attention as a sustainable alternative to internal combustion engine (ICE) vehicles. Research has explored various aspects of EV adoption, including economic feasibility, environmental impact, government policies, and consumer preferences. However, the factors influencing EV adoption vary across regions based on infrastructure, incentives, and market conditions. This literature review examines studies on EV market trends, cost comparisons with ICE vehicles, charging infrastructure, and consumer choice factors. By reviewing these aspects, this section highlights key findings and gaps relevant to Bangladesh's EV landscape.

2.2 Global Trends in EV Adoption

EV adoption has grown significantly in recent years, driven by technological advancements, government incentives, and environmental concerns. Around 14 million electric vehicles were sold worldwide in 2023 [4]. While developed countries lead in growth, developing nations are gradually embracing EVs amidst several challenges.

In the United States, adoption of electric vehicles (EVs) notably increased between 2003 to 2011 due to better awareness and acceptance of new technology among consumers. Moreover, external factors such as, electricity prices (negative correlation), government incentives and urban road infrastructure (positive correlation) significantly influenced the adoption rates [5]. A study by researchers indicates that the presence of normal public charging stations hinders the adoption of Battery Electric Vehicles (BEVs), whereas fast public charging stations encourage greater adoption [6]. At present, many states provide additional benefits such as rebates, tax credits, reduced registration fees, and exemptions from sales taxes to promote the use of EVs [7]. However, in certain years, such as 2005 and 2006 due to the impact of Hurricane Katrina, and in 2008 amid the economic recession, the adoption of EVs by commuters declined [5].

In 2023, China dominated electric vehicle sales, exceeding 8.1 million units sold [4]. In a recent study, the authors employed a Difference-in-Difference (DID) approach, revealing that the implementation of the EV subsidy policy led to an average annual increase in EV sales by approximately 180% [8].

Europe has emerged as a leader in EV adoption, with Norway, Iceland, and the Netherlands leading in demand and Germany dominating industry supply. In 2019, EV sales grew by 44%, increasing Europe's global market share to 26%. To accelerate adoption, the EU imposed stricter CO_2 targets, requiring automakers to keep fleet emissions below 95 g/km or face fines, driving greater EV production. Many governments expanded subsidies, offering tax cuts, purchase incentives, and congestion charge exemptions, making EVs more competitive, especially in Germany and France. Additionally, Norway and the Netherlands led in charging infrastructure, reducing range anxiety and supporting market growth [9].

India has aimed for 30% EV sales penetration by 2030, driven by research, innovation, and infrastructure development [10]. However, the current market share stands at only 2% [11], with projections suggesting an increase to 4% by 2025 [12]. To accelerate adoption, the government has introduced subsidies of ₹150,000 for electric cars and promotes vehicle-grid integration, shared mobility, and policy incentives. India’s three-phase strategy focuses on expanding charging infrastructure, encouraging private sector participation, and integrating EVs with the power grid [13]. Despite efforts, the country still faces a significant infrastructure gap, with public EV charging stations increasing from 6,586 in March 2023 to 12,146 in February 2024, far below the estimated requirement of 3.9 million stations to meet the 1:20 vehicle-to-charger ratio by 2030 [14].

Electric four-wheelers (E4Ws) in developing countries face barriers such as high purchase price (USD 30,000 to USD 47,000), inadequate range, slow charging, and new production adoption anxiety. Unlike developed nations, which benefit from strong incentives and infrastructure, developing countries face weak policy support, limited affordability, and a lack of charging facilities [15].

2.3 EV Adoption Scenario in Bangladesh

Bangladesh's transition to electric vehicles (EVs) is still in its early stages compared to other countries. The government has set an ambitious goal of ensuring that 30% of all vehicles in the country are EVs by 2030 [3]. To support this transition, new policies have been introduced, including the Charging Station Installation Policy, to promote the adoption and use of EVs. Between September 2022 and January 17, 2024, a total of 70 global automotive brands, including Tesla and Porsche, have been registered with the Bangladesh Road Transport Authority (BRTA) [16]. Leading manufacturers such as Mercedes-Benz, Audi, and BYD have already started selling EVs in Bangladesh, while Toyota and Tata are offering both hybrid and electric models. Additionally, according to the Bangladesh Energy Regulatory Commission (BERC), 14 charging stations have received government approval. The commission also recommends setting electricity prices for charging stations at the consumer level [17].

According to a study published in December 2023, the adoption of electric four-wheelers (EVs) in Bangladesh faces several challenges. Despite growing interest, the market for passenger EVs is still underdeveloped, with very few vehicles on the road, mainly in urban areas like Dhaka. Key obstacles include high initial costs, limited charging infrastructure, and range anxiety. Additionally, charging EVs in residential areas presents a challenge as it places additional strain on the national grid, which is already under pressure. The country has started exploring solutions, including solar-powered charging stations, to alleviate the energy burden, but significant investment in infrastructure and policy development is required to support widespread adoption [18].

Another research published in June 2024 reveals that the four-wheeler electric vehicle (EV) market in Bangladesh remains virtually non-existent, with fewer than 10 passenger EVs in Dhaka. Despite this, there is potential for market growth, as the country anticipates substantial investments in the sector. However, several barriers hinder widespread adoption, including high upfront costs, limited charging infrastructure, and concerns about battery range and performance [19].

M. R. Ahmed and A. K. Karmaker also identified key challenges to EV adoption in Bangladesh, including inadequate charging infrastructure, high battery costs, and policy gaps. Limited public charging stations force users to rely on residential electricity, causing system losses. The national grid struggles with increased demand, while unclear registration policies and high investment costs further hinder adoption. Additionally, range limitations and long charging times remain concerns. Although renewable energy-based charging solutions have been proposed, implementation is still in the early stages [20].

2.4 Comparison between EVs and ICEs

M. Palinski demonstrated that electric vehicles (EVs) and internal combustion engine (ICE) vehicles differ significantly in total cost of ownership (TCO), maintenance, and fuel consumption. EVs generally have a higher purchase price, primarily due to battery costs, with battery electric vehicles (BEVs) being the most expensive upfront. However, their lower maintenance and service costs stem from fewer moving parts and the absence of oil, coolant, and spark plug replacements. In contrast, plug-in hybrid electric vehicles (PHEVs) incur the highest maintenance expenses due to their complex dual propulsion system. Fuel costs also favor EVs, as electricity is generally cheaper than gasoline, leading to lower long-term expenditures. However, factors such as regional energy prices, government incentives, and tax structures influence the financial feasibility of EVs compared to ICE vehicles.

Beyond cost considerations, EVs and ICE vehicles also differ in driving experience and practicality. EVs offer a quieter ride and instant torque, ensuring smoother acceleration, whereas ICE vehicles retain an advantage in long-distance travel due to their greater range and faster refueling times. Charging infrastructure remains a significant limitation, as most EV users rely on home charging, while public charging stations are still relatively scarce. While BEVs produce zero tailpipe emissions, reducing urban pollution, their overall environmental impact depends on the energy mix used for electricity generation [2].

Another study examines the economic and environmental impact of EVs, hybrid electric vehicles (HEVs), PHEVs, and ICE vehicles in the transition toward net-zero emissions by 2050. The findings indicate that EVs have the lowest CO and CO_2 emissions, reducing greenhouse gas emissions by approximately 20% compared to

ICE vehicles. However, their reliance on fossil fuel-based electricity generation leads to increased NO_x and N_2O emissions (over 70%). Additionally, air quality-related pollutants such as SO_x and PM_{10} are 90% and 85% higher in EVs, respectively, emphasizing the need for cleaner energy sources and advanced emission control technologies. Despite higher upfront costs, EVs offer the lowest maintenance expenses (0.00419 USD/km) due to fewer mechanical components. The study underscores the importance of expanding charging infrastructure, transitioning to renewable energy, and implementing stronger policy incentives to enhance the sustainability of EVs [21].

Similarly, another study highlights the significant differences in cost structure and emissions between EVs and ICE vehicles over their lifetime, influencing long-term sustainability. While EVs have a higher initial purchase cost, they compensate through lower operational expenses, primarily due to reduced fuel and maintenance costs. However, their economic breakeven point compared to ICE vehicles is only achieved after extensive mileage, estimated at approximately 203,000 km. The feasibility of EV adoption largely depends on reductions in battery costs, electricity pricing, and improved charging infrastructure, making policy interventions crucial for their widespread adoption.

From an environmental perspective, EVs offer substantial reductions in lifetime CO_2 emissions, particularly in regions that rely on renewable energy for electricity generation. In contrast, ICE vehicles continuously emit high levels of CO_2 and pollutants throughout their use, contributing significantly to urban air pollution [22].

2.5 Transportation Data Collection and Methods of Survey

A transportation data collection survey involves gathering information from a specific group of people about their travel behavior and other transport-related aspects. These surveys help researchers analyze travel patterns and preferences. Some of the commonly used data collection methods include: interviews, surveys and questionnaires, observations, records and documents, focus groups, oral histories etc.

These methods can be classified into two categories: quantitative and qualitative. Quantitative methods focus on numerical data and measurable trends, while qualitative methods emphasize contextual understanding, emotions, and perceptions.

- Qualitative approaches include interviews, focus groups, observations, and oral histories.
- Quantitative approaches involve surveys, questionnaires, and records.

Researchers may also integrate multiple methodologies to gain a more comprehensive understanding of transportation behaviors.

Data collection techniques' descriptions are as follows:

- **Interviews:** This method, also known as a face-to-face survey, is used when targeting a specific group of people. The purpose is to gather detailed insights by directly engaging with participants.
- **Questionnaires and Surveys**: A questionnaire consists of a set of questions, whereas a survey includes both the questions and the strategy used to collect, process, and interpret responses.
- **Observations:** This method involves carefully watching and interpreting behaviors in real-world settings. Researchers immerse themselves in a specific environment to draw meaningful conclusions.
- **Documents and Records:** Past records and official documents serve as valuable sources of data and can be used to analyze historical trends.
- **Focus Groups:** In this approach, a discussion is led by a surveyor who encourages participants to share their opinions and experiences on a predetermined topic. Since focus groups are qualitative, the findings are descriptive rather than numerical.
- **Oral Histories:** This method captures individuals' first-hand accounts and recollections of past events. Oral histories allow people to share their perspectives in their own words, contributing to a richer understanding of transportation behavior.

A combination of qualitative and quantitative methods can be applied to study the current progress of any initiative and to understand the choice behavior of people. For this, data might be gathered through in-person interviews with questionnaires and online surveys.

The main objectives of transportation surveys are:

- Assessing the current state of transportation patterns.
- Identifying underlying causes behind observed trends.
- Developing predictive models to forecast future conditions.

Before-and-after surveys are often used to track long-term changes in transportation behavior [23].

The two primary survey methods for mode choice modeling are:

1. Stated Preference (SP) Surveys
2. Revealed Preference (RP) Surveys

SP surveys capture individuals' decision-making in simulated scenarios, whereas RP surveys analyze choices made in real-world situations, providing insights into actual behavior.

Table 2.1: SP and RP Comparison

SP Data	RP Data
Control between attributes that allows for the mapping of utility functions with tools other than those now in use.	Possess fundamental connections between qualities (technological constraints are fixed).
Provides generic alternative options that have been presented or are already in existence.	Uses only existing alternatives.

2.6 Discrete Choice Modelling

Discrete choice analysis is used to study decision-making in situations where options are distinct and separate rather than continuous. Unlike models that analyze "how much" of something is chosen, discrete choice modeling examines "which option" is selected. This approach is particularly useful in transportation research for studying travel mode preferences and decision-making behaviors.

2.6.1 Types of Discrete Choice Models

Several discrete choice models have been developed and used. Each model can be differentiated based on the explanatory variables used, the statistical distribution of the error terms, or its ability to address the independence of irrelevant alternatives (IIA) constraint. The main types of discrete choice models are:

a) Probit Model:

The probit model is used when the dependent variable has only two possible outcomes. Its primary objective is to determine the probability that a perception, based on a specific set of characteristics, belongs to a particular class. It is a binary classification model that categorizes perceptions based on their expected probabilities. The probit model is similar to logistic regression and can be interpreted using the same techniques. When viewed in the context of a generalized linear model, it uses a probit link function**.** The model is typically evaluated using the maximum likelihood method, known as probit regression.

b) Logit Model:

The logit model, also called logistic regression, is a type of binomial regression model. It links a vector of random variables to two binomial random variables through logistic regression. It is a rare application of a generalized linear model and is primarily used for situations where the dependent variable has two discrete outcomes.

c) Multinomial Logit Model:

The multinomial logit model applies logistic regression to multiclass problems, where there are more than two distinct discrete outcomes. This model predicts the probabilities of various possible outcomes based on a set of independent variables. It assumes case-specific data, meaning each independent variable has only one value per case. It is based on the assumption of independence of irrelevant alternatives (IIA)**,** which means that the choice probability between two alternatives is not affected by the presence of a third irrelevant alternative. For example, adding a bicycle as an option does not affect the choice probability between car and bus.

d) Conditional Logit:

The conditional logit model is primarily used in conjoint analysis and is useful for analyzing a particular type of data. Unlike the traditional logit model, where each individual has one row of data, the conditional logit model has one row for each class of the relevant variable per individual. The model is similar to logistic regression, but it focuses on the qualities of the various choices available to individuals rather than individual characteristics.

e) Mixed Logit:

The mixed logit model allows for random parameters that can vary from person to person, considering population heterogeneity. This model addresses the limitations of the conventional logit model by overcoming three key constraints. Unlike the probit model, which is restricted to the normal distribution, the mixed logit model can incorporate arbitrary distributions for the coefficients, allowing for more flexibility.

f) Nested Logit:

The nested logit model introduces the concept of nests, which are collections of related alternatives. Each alternative belongs to only one nest. The model accounts for the fact that individuals may choose alternatives within a related set (a nest), and the choices are correlated within nests.

2.6.2 Softwares Used for Discrete Choice Modelling

a) Excel: Excel is a widely used spreadsheet application. The findings from discrete choice models can be transformed into a maximum likelihood problem (log-likelihood), which can be solved using Excel's built-in solver, provided the user understands the choice model structure. However, simulating random draws in Excel is time-consuming, making it unsuitable for logit models with random coefficients.

b) SAS/MDC: SAS is a powerful programming environment for statistical analysis. The MDC (Multinomial Discrete Choice) module allows for the estimation of various discrete models, including conditional logit, heteroscedastic extreme value, mixed logit, nested logit, and multinomial probit models. Beginners may find it time-consuming to learn the interface before creating scripts.

c) Stata: Stata is a statistical software offering a wide range of tools for data management, analysis, and visualization. It supports logit model regression and is suitable for various statistical tasks.

d) SPSS: SPSS is a versatile platform for statistical analysis, featuring machine learning methods, text analysis, and big data integration. It is user-friendly, adaptable, and scalable, allowing users of varying expertise to apply it to tasks of any size and complexity.

e) LIMDEP/LOGIT: LIMDEP, a popular statistical tool, includes the NLOGIT add-on package, which extends the functionality to estimate, simulate, and analyze data with multiple numeric variables. The latest version of NLOGIT can handle heterogeneity with varying utility functions and mixed logit models.

f) Sawtooth: Sawtooth is a specialized software for discrete choice modeling and conjoint analysis. It has an intuitive user interface for creating online or printed conjoint survey questionnaires and is used to assess market demand, forecast product acceptability, and evaluate the perceived value of product features.

g) R: bayesm: The Bayesm package in R, developed by Peter Rossi and Rob McCulloch, supports the estimation of various models such as Multinomial Probit (MNP), Multinomial Logit (MNL), and Hierarchical Multinomial Logit (HML), among others. It employs Bayesian MCMC methods for estimation, and users need to be familiar with Bayesian MCMC approaches for analyzing the posterior draws.

h) R: mlogit: The mlogit package in R simplifies the estimation of Multinomial Logit models with individual alternative variables. It supports extensions like heteroscedastic, nested, and random parameter multinomial models, as well as heterogeneity in mixed logit models using mixing distributions.

i) Kenneth Train's MATLAB code: Professor Kenneth Train recommends using Maximum Likelihood Estimation (MLE) and Bayesian methods for mixed logit models. He has also included outdated Gauss programs for mixed logit estimation, which have been adapted by Professor Glasgaw Garrett for use in multiparty election studies.

j) Peter Lenk's code: Professor Peter Lenk's Gauss code applies Bayesian techniques to estimate discrete choice models and is available for use in various studies.

k) DCM package: The Discrete Choice Model (DCM) package, created in the Ox programming language (now replaced by OxMetrics with a trial version available), provides software for discrete choice modeling. The package, last updated in August 2005, was developed by Melvyn Weeks and Matias Eklof from the University of Cambridge and the University of Uppsala, respectively.

l) BIOGEME: BIOGEME is an open-source software designed for maximum likelihood estimation of parametric models, particularly in discrete choice analysis. It offers two versions:

Pythonbiogeme: A Python-based program for general parametric models with pre-coded discrete choice models for ease of use.

Bisonbiogeme: Designed to assess parameters for a variety of discrete choice models, including heteroscedastic models, multivariate extreme value models, and various logit models, using a formal and straightforward language for model specification.

2.6.3 Types of Statistical Tests

Types of Variables: Before selecting a statistical test, it's important to understand the types of variables in the data. There are two main categories of variables: quantitative and categorical.

Quantitative variables describe the amount of something and can be further divided into two types. Continuous or ratio variables can be divided into smaller units, such as weight or height, while discrete or integer variables cannot be divided into smaller units, such as the number of people.

Categorical variables, on the other hand, are used to represent categories or groups. These include ordinal variables, which show the order or ranking of data, such as rankings; nominal variables, which represent the names of different groups, like colors or types; and binary variables, which have only two possible outcomes, such as yes/no or 1/0.

Parametric and Non-Parametric Tests: When conducting statistical analysis, understanding the difference between parametric and non-parametric tests is essential. Parametric tests assume that the data follows a specific distribution, often a normal distribution, and tend to have stricter assumptions, which allow them to draw more accurate conclusions. Examples of parametric tests include regression tests, correlation tests etc. In contrast, non-parametric tests do not rely on specific distribution assumptions and are typically used when the data doesn’t meet the conditions for parametric testing.

Regression Tests: Regression tests are commonly used to assess the relationship between variables. They can help determine how one or more continuous variables may affect another variable. The most common types of regression tests include logistic regression, multiple linear regression, and simple linear regression. These tests allow researchers to model and analyze relationships between variables, making them essential tools in statistical analysis.

Correlation Tests: These tests assess whether two variables are connected without assuming cause-and-effect linkages.

2.7 Review of Related Studies to Car Choice Modelling

The decision to purchase an electric vehicle (EV) or an internal combustion engine (ICE) vehicle is influenced by multiple factors, including economic considerations, technological advancements, environmental awareness, policy incentives, and behavioral attributes. Researchers have applied various discrete choice modeling techniques, such as the Multinomial Logit (MNL) model, latent class models, structural equation modeling (SEM), and bivariate ordered probit models, to understand how these factors shape consumer preferences.

Cecere et al. [24] employed a probabilistic choice model to examine EV adoption across six European countries, identifying purchase price, financial incentives, and driving range as the most critical determinants. Their findings suggested that financial support, such as subsidies and tax reductions, significantly boosts EV adoption. Zhuge and Shao [25] applied an MNL model with spatial analysis (Moran's I test) to study EV adoption in Beijing, reinforcing that vehicle price and driving behavior are primary factors influencing consumer choice.

Zhang et al. [26] used logistic regression models to investigate how government incentives, fuel prices, and tax policies affect EV adoption in China. Their findings highlighted that financial incentives, tax reductions, and fuel cost savings play a significant role in making EVs more attractive, particularly for high-income consumers. Additionally, they noted that higher education levels are associated with early EV adoption, a trend also observed by Peters et al. [27], who applied an Integrated Choice and Latent Variable (ICLV) model to explore the impact of sustainability awareness and environmental identity on EV preference.

Hasan [28] used Structural Equation Modeling (SEM) to analyze EV repurchase intentions in Norway, focusing on long-term behavioral factors rather than one-time adoption. The study found that charging infrastructure reliability, maintenance cost savings, and environmental consciousness were significant in sustaining EV ownership. Jabbari et al. [29] employed an MNL model to assess EV rejection and satisfaction factors, identifying range anxiety, charging duration, and high initial costs as primary barriers, while performance, cost savings, and environmental considerations motivated consumers toward EVs.

Abotalebi [30] applied a latent class model to examine EV adoption in Canada, showing that prior exposure to EVs, income level, and charging infrastructure availability were key determinants of adoption. Their study aligns with Zhang et al. [26] in suggesting that higher-income consumers are more likely to adopt EVs due to greater financial flexibility.

Mandys [31] used a discrete choice model to explore consumer preferences for EVs in the UK, highlighting driving range, charging speed, and fuel cost savings as significant factors. Their study emphasized that consumers often consider long-term cost benefits when deciding between EVs and ICE vehicles. Shin et al. [32] applied a bivariate ordered probit model in Maryland, concluding that multi-vehicle households and high-mileage drivers are more inclined to purchase EVs, as they can better compensate for range limitations

.

2.8 Car Choice Modeling in the Context of Bangladesh

The transition from internal combustion engine (ICE) vehicles to electric vehicles (EVs) in Bangladesh is shaped by multiple factors, including economic viability, technological advancements, policy interventions, and consumer awareness. As EV adoption gains momentum, researchers have applied various quantitative modeling techniques, such as Principal Component Analysis (PCA), Interpretive Structural Modeling (ISM), Bayesian Best-Worst Method (BWM), and Binary Logistic Regression, to analyze consumer preferences and key decision-making factors influencing this shift.

Palit et al. [33] employed PCA and ISM to identify and rank seventeen critical drivers affecting EV adoption in Bangladesh. Their study highlighted vehicle performance, availability of charging infrastructure, and government policies as the most influential determinants. The use of MICMAC analysis further revealed that policy initiatives and infrastructure development must progress concurrently to facilitate a smooth transition to EVs.

Similarly, Limon et al. [34] utilized the Bayesian Best-Worst Method (BWM) to assess the factors driving hybrid electric vehicle (HEV) adoption in Bangladesh. The study found that the lack of dependence on charging stations, financial incentives, and improved fuel efficiency were the most significant motivators. Their findings underscored the necessity of strong policy support and targeted financial incentives to encourage consumers to shift away from ICE vehicles.

To further explore consumer perceptions, Nath et al. [35] conducted a binary logistic regression analysis based on responses from 427 survey participants. The study revealed that while more than 80% of respondents recognized the energy efficiency and environmental benefits of EVs, 90% expressed concerns over high purchase costs, limited charging infrastructure, and low resale value. Additionally, their findings indicated that higher-income individuals with greater awareness of EV technology were more likely to adopt EVs, reinforcing the need for consumer education programs and financial assistance mechanisms to bridge the affordability gap.

A perception-based study by Munir et al. [36] focused on the attitudes of young consumers toward EV adoption. The study found that awareness and education levels play a pivotal role in shaping consumer attitudes, with younger generations demonstrating greater openness to adopting EVs. The authors recommended that targeted awareness campaigns and educational initiatives be incorporated into national policies to cultivate long-term demand for EVs.

2.9 Gaps in Existing Research

Existing research on Electric Vehicle (EV) adoption in Bangladesh has provided some insights, but several gaps remain in understanding the local dynamics and challenges. The EV market in Bangladesh is still in its early stages, and much of the research has either been conducted in developed countries or lacks sufficient data on the specific conditions within Bangladesh. The following are the key gaps identified based on the available literature:

1. There is a lack of comprehensive data on the current state of EV adoption, including sales and user demographics.

2. Much of the research focuses on developed countries, with limited attention to Bangladesh's unique market conditions, such as high import duties and limited infrastructure.
3. There is a lack of studies on consumer preferences specific to Bangladesh and the factors influencing vehicle choices.
4. Government policies and incentives have not been sufficiently analyzed for their impact on EV adoption in Bangladesh.
5. Discrete Choice Modeling (DCM), which can assess key factors influencing vehicle choices, has been underutilized in the context of Bangladesh's EV market.
6. Research on the role of charging infrastructure and its impact on EV adoption in Bangladesh remains inadequate.

These gaps highlight the need for more targeted research to understand the barriers and opportunities for EV adoption in Bangladesh.

2.10 Summary

This chapter reviewed global and Bangladesh-specific studies on EV adoption trends and car choice modeling. Globally, government incentives, charging infrastructure, and environmental concerns drive EV adoption, whereas developing nations face policy gaps, affordability issues, and inadequate infrastructure. In Bangladesh, EV adoption remains low due to high upfront costs, limited charging stations, and lack of clear regulations despite growing interest from consumers. Various models, including PCA, ISM, BWM, logistic regression, and MNL, have been used to analyze EV adoption determinants, highlighting the need for stronger policy support and infrastructure development.

CHAPTER 3: METHODOLOGY

3.1 Introduction

This chapter outlines the methodology used in the study, covering data collection, analysis, and modeling approaches. It includes a market penetration assessment through observations and interviews and a survey among EV users, though responses were limited. A Stated Preference (SP) survey was also conducted to analyze consumer preferences for EVs over ICE vehicles. The collected data was processed and analyzed using statistical modeling techniques to identify key adoption factors. Finally, the chapter discusses methods used to assess the model's accuracy and significance.

3.2 Methodology Overview

The first stage of the study assessed EV market penetration through observations and interviews in Tejgaon, which was identified as the most suitable location due to the concentration of car showrooms and service centers. EV-selling brands were documented, and showroom representatives were interviewed regarding sales trends and taxation policies. Additionally, charging stations were visited to evaluate the existing infrastructure. A questionnaire survey was also conducted among EV users to gather insights on their experiences. The detailed process is illustrated in the flowchart on the next page.

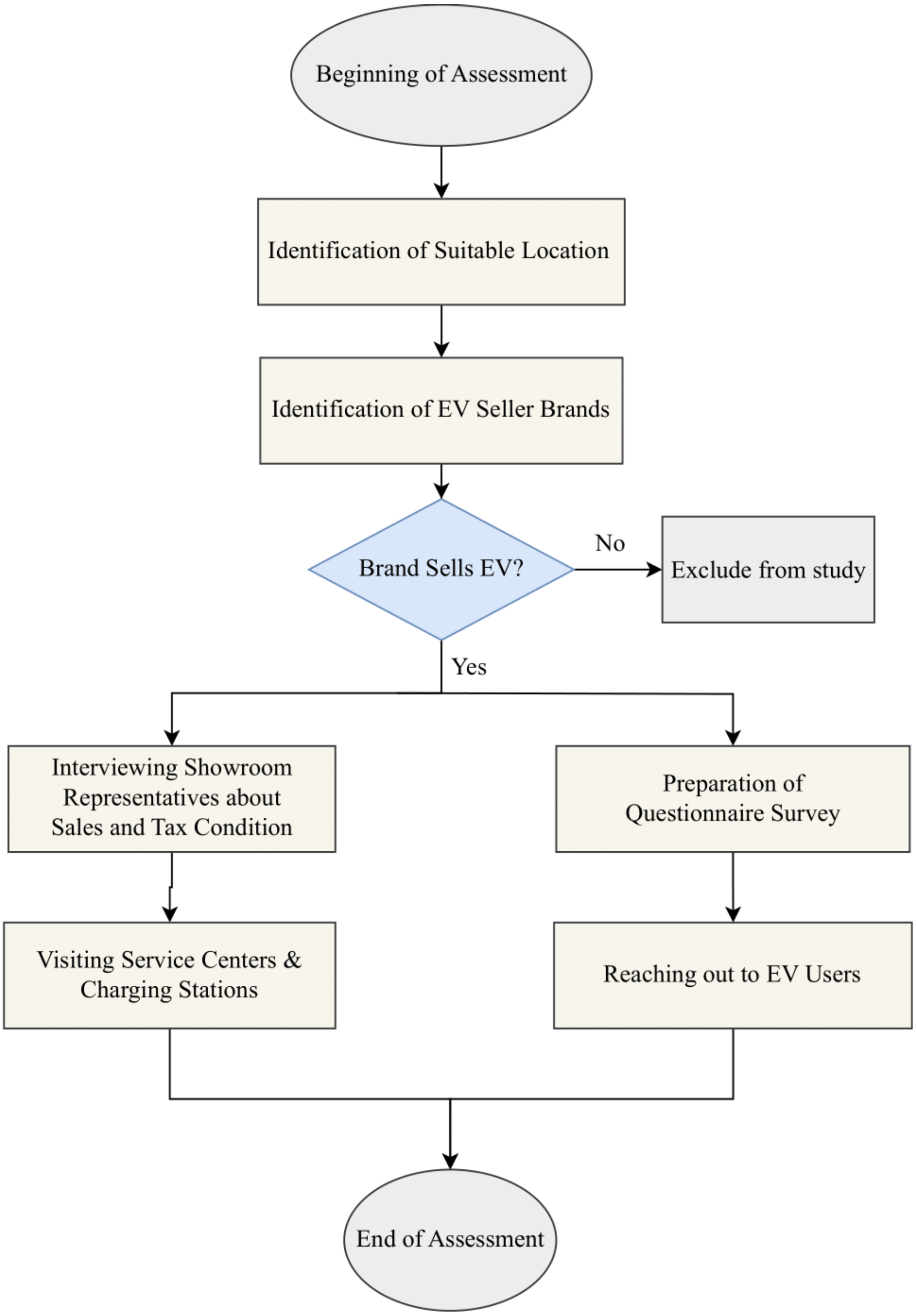


Figure 3-1: Overview of the Methodology of the First Stage of the Study

The second stage of the study involved a Stated Preference (SP) survey conducted among students, teachers, and job holders to analyze consumer preferences between EVs and ICE vehicles. The survey was designed based on identified influencing factors such as purchase cost, operating cost, charging infrastructure, driving range etc. The collected data was then used to develop a Binomial Logit Model, estimated using a statistical software package. For model calibration, 70% of the dataset was allocated for training, while 30% was used for testing to evaluate the model's predictive performance. Finally, the model’s prediction results were validated against the survey data. The flowchart below summarizes the process.

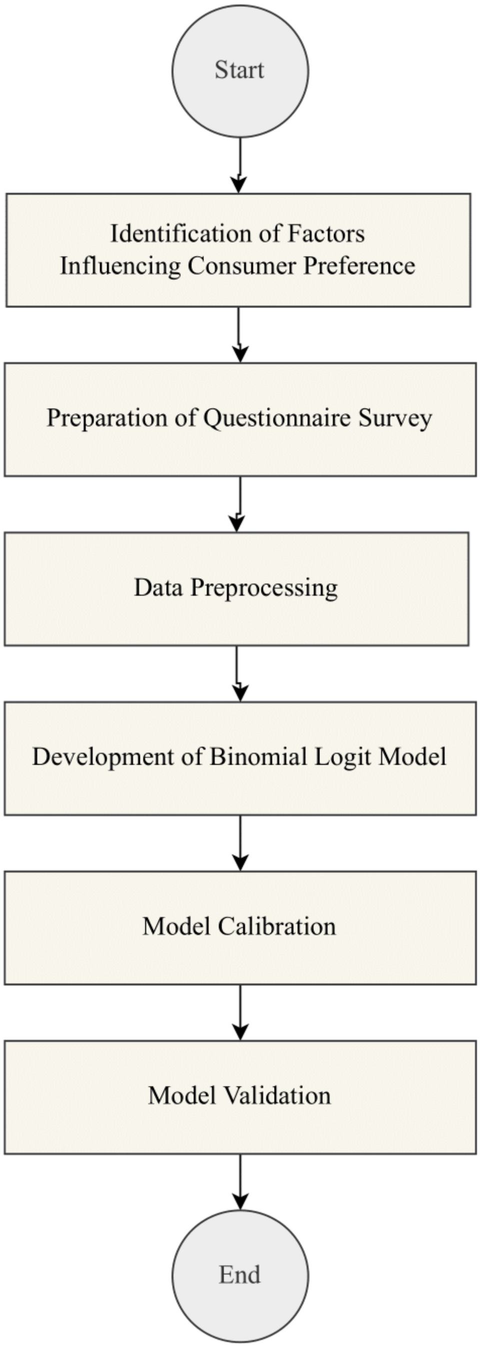


Figure 3-2: Overview of the Methodology of the Second Stage of the Study

3.3 Data Collection and Survey Design

Data collection was carried out in two stages. The first stage involved observations, interviews, and a questionnaire survey to assess the current EV market penetration. The second stage focused on the development and administration of a Stated Preference (SP) survey to analyze consumer preferences between EVs and ICE vehicles.

3.3.1 Identification of Suitable Location

Tejgaon was chosen for the data collection related to EV's current market condition in Bangladesh. Tejgaon has evolved into a pivotal area for automotive research in Dhaka, Bangladesh, due to its strategic transformation from an industrial zone to a commercial hub. Established in the 1950s as Dhaka's primary industrial area, Tejgaon has undergone significant changes over the decades, transitioning from traditional industrial uses to a more diverse commercial landscape. This evolution has attracted numerous automobile dealerships and service centers, making it a focal point for the automotive industry in Dhaka [38].

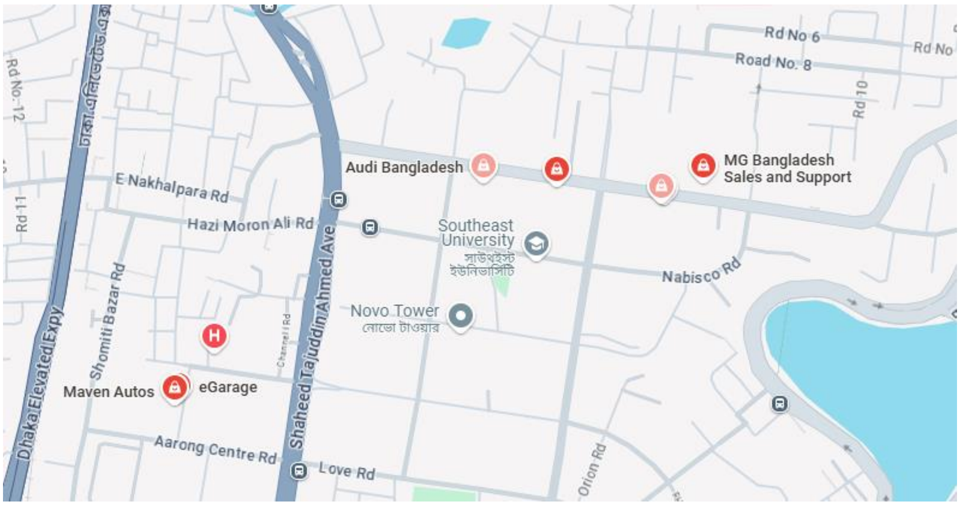


Figure 3-3: Map Showing Location of Study for Current EV Market Condition

The concentration of these and other automotive establishments in Tejgaon provides a comprehensive landscape for studying the dynamics of car showrooms and service centers. The area's strategic location, coupled with its historical significance and ongoing commercial development, makes it an ideal setting for such research endeavors.

3.3.2 Data Collection from Automotive Showrooms and Service Centers

To assess the market presence of EVs in Bangladesh, an initial identification of brands selling EVs was conducted. Visits to car showrooms were carried out to inquire about purchase prices and tax structures. However, showroom representatives were often reluctant to share details and advised contacting service center personnel for further information.

Following this, service centers of Audi and Mercedes were visited, where the same set of questions regarding pricing and taxation was asked. These interactions provided valuable insights into EV sales trends and available service infrastructure. Additionally, the Audi service center had a nearby charging station, offering further information on the existing charging network in Bangladesh.

3.3.3 Electric Vehicle Owners' Survey

A questionnaire survey was designed to evaluate uses and features of electric vehicles (EVs) and assess user satisfaction based on their driving experience. The survey was designed based on another study where the questionnaire survey was structured into six sections, each focusing on different aspects of EV ownership and user experience. The first section collected socio-demographic information such as gender, age, education, household size, and income. The second section assessed driving experience, including the total kilometers driven. The third section examined consumer attitudes toward EV attributes, such as charging convenience, range, economic benefits, battery life, emissions, noise levels, and performance, using a Likert scale. The fourth section measured user satisfaction, while the fifth section evaluated recommendation intentions, determining whether users would suggest EVs to others. The sixth section analyzed repurchase intentions, assessing consumers' willingness to buy another EV in the future. [38]

Similarly, the survey for assessing the aspects of EV owners in Bangladesh included a series of questions designed to capture demographic characteristics, vehicle ownership details, driving behavior, user satisfaction, and future adoption intentions. The demographic section collected information on age, gender, occupation, monthly household income, household size, and total vehicle ownership, including the number of EVs owned. Additionally, participants were asked about the specific EV model they use, its purchase price, and whether it was bought locally or imported.

To understand driving and charging behavior, the survey inquired about daily travel distances, battery capacity, average mileage, and charging patterns, including charging frequency, battery state at the time of charging, and the percentage of charging done at home versus public stations. Respondents were also asked about their perception of the public charging network and the challenges faced in EV adoption in Bangladesh, along with suggestions for improving public awareness and adoption strategies.

User satisfaction was measured using a Likert scale (1 to 5) based on factors such as:

- Charging Convenience
- Cruising Range
- Economic Benefits
- Battery Life
- Emissions
- Noise Levels and
- Overall Performance.

Finally, respondents were asked about their repurchase intention and likelihood of recommending an EV to others, also rated on a Likert scale. By incorporating these sections, the survey effectively captured both the existing EV user experience and the broader market barriers, providing insights into the factors influencing EV adoption in Bangladesh.

3.3.4 Stated Preference Survey

The Stated Preference (SP) method was chosen for this study because it allows for the analysis of consumer preferences in a market where EV adoption is still in its early stages in Bangladesh, and the number of EV users is very limited. Given that revealed preference (RP) surveys were not feasible due to the very small number of EV owners, there was insufficient real-world data to understand how consumers are currently making decisions between electric vehicles (EVs) and internal combustion engine (ICE) vehicles. The SP method offers a valuable alternative by providing insight into how consumers would hypothetically choose between EVs and ICE vehicles based on factors such as purchase price, fuel costs, range, charging infrastructure, and environmental impact.

This approach enables researchers to create hypothetical scenarios that simulate potential future conditions and assess consumer behavior in a context where actual market conditions are still evolving. By using the SP method, the study can explore consumer decision-making processes and predict future adoption patterns despite the lack of sufficient RP data. Additionally, the SP method helps evaluate how various incentives or policies—such as subsidies, tax reductions, or infrastructure improvements—could impact EV adoption rates moving forward. This makes the SP method particularly useful for understanding potential demand for EVs in a developing market like Bangladesh, where actual purchasing decisions are still limited due to the early stage of EV adoption.

3.3.5 Target Group for SP Survey

The primary aim of the Stated Preference (SP) Survey was to investigate the factors that influence consumers' decisions when choosing between electric vehicles (EVs) and internal combustion engine (ICE) vehicles. The survey targeted two main groups: undergraduate students, university teachers, and a small number of job holders and pre-university students. The undergraduate students were selected from various universities across Bangladesh, with a significant portion from BUET. The university teachers were drawn from prominent institutions, including BUET, CUET, KUET, RUET, and IUT.

A total of 173 responses were collected, with more than half coming from university teachers. These groups were chosen based on their potential connection to purchasing a private vehicle in the near future. Undergraduate students, after completing their education and securing a job, may have the financial ability to purchase a car, or it may be a decision made by their families, particularly if they are financially capable. Similarly, university teachers, assumed to have the means to buy a private vehicle, were included. A few job holders were also surveyed, as they too may have the financial capacity to make such a purchase.

The survey adhered to ethical principles, ensuring informed consent from participants, maintaining anonymity and confidentiality, and minimizing any potential harm to participants during the survey process.

3.3.6 SP Survey Design

For the Stated Preference (SP) survey, a showcard was designed to create a hypothetical scenario for respondents, presenting a comparison between an electric vehicle (EV) and an internal combustion engine (ICE) vehicle. The vehicles selected for comparison were the MG ZS EV MCE Long Range (EV) and the Toyota FL Award 2019 Silver (ICE). The choice of these two models was deliberate, as their characteristics provided a balanced and realistic comparison between EVs and ICE vehicles in Bangladesh.

While there are ICE vehicles available in the market that are way less expensive than the Toyota Premio, the decision was made to compare it to the MG ZS EV, which is a model with moderate pricing within the current EV market in Bangladesh. The goal was to avoid extreme comparisons, such as comparing a low-cost ICE vehicle with a high-end luxury EV that could skew consumer perceptions. By selecting the MG ZS EV—a more affordable EV in the context of the Bangladeshi market—the study ensured that the comparison was realistic and that respondents could relate to the prices and features presented, making the decision process more grounded in reality.

This approach was intended to create a realistic decision-making context, where respondents were asked to weigh attributes such as purchase price, fuel cost, and vehicle features without the influence of extreme pricing or unrealistic trade-offs. By presenting two vehicles with comparable levels of attractiveness and functionality, the survey allowed respondents to make sensible choices, ensuring the findings reflected the practical considerations of potential car buyers in Bangladesh. This strategy enhances the validity of the survey results by grounding the hypothetical scenario in real-world market conditions, making the study more relevant for understanding consumer preferences between EVs and ICE vehicles.

Table 3-1: Showcard showing comparison between a EV and an ICE Model

		
	MG ZS EV MCE Long Range 2023	**Toyota Premio FL 2019 Silver**
Type	Fully Electric	Fully fuel-based
Purchase Cost	59,18,000/- [39]	38,00,000/- [40]
Operating Cost (per 100 km)	214 Tk [41, 42]	807 Tk [43, 44]
Maintenance Cost	4.53 Tk/km [45] + Battery Replacement Cost: 8,80,000 to 13,20,000 Tk (8 years warranty) [46]	7.5 Tk/km [45]
Resale Value (after 3 years)	48% [47]	60.9% [47]
Driving Range	440 km [41]	900 km [48]
Emissions	0 g/km [49]	95 g/km CO_2 [49]
Charging/Fueling Station	Only 3 (total) at Dhaka, Chittagong and Cox's Bazar at present, more will be available in the future.	Available everywhere in the country

Along this showcard, some other benefits of EVs such as, quicker acceleration, smoother riding, more interior space, less noise and environmentally friendly were also mentioned.

The survey form considered obtaining the following parameters to form a discrete choice model:

Socio-economic Variables

1. Age
2. Gender
3. Income
4. No. of people in family
5. Educational Qualification
6. Occupation
7. Vehicle owned or not

Vehicle Attributes (Using a 1 to 5 scale)

1. Purchase Cost
2. Operating Cost
3. Maintenance Cost
4. Resale Value
5. Driving Range
6. Availability of charging or fueling
7. Quick Acceleration
8. Smooth Riding Experience
9. Interior Space
10. Noise Level
11. Environmental Protection

Behavioral and Perception Variables (Using a 1 to 5 scale)

1. Hearing about EV
2. Knowledge about EV
3. Cost awareness about EV
4. Belief in sustainability about EV

Beyond developing the discrete choice model, the online questionnaire survey also included two additional vehicle options: Hybrid Electric Vehicle (HEV) and Plug-in Hybrid Electric Vehicle (PHEV). This allowed respondents to switch from a fully electric vehicle (EV) or a fully internal combustion engine (ICE) vehicle and provided insights into whether consumers prioritize environmental benefits despite higher costs or prefer a less expensive but less environmentally friendly alternative. To facilitate this comparison, the survey presented key differences between EVs, PHEVs, HEVs, and ICE vehicles across multiple attributes, including purchase cost, operating cost, maintenance cost, driving range, emissions, and resale value.

Additionally, the survey collected consumer opinions on potential barriers to EV adoption, following a similar approach as in the EV Owners' Survey, to gain a broader perspective on the challenges and perceptions surrounding EV adoption in Bangladesh.

3.4 Data Preprocessing

Data processing is an essential step in preparing raw data for analysis. It involves organizing, cleaning, and transforming the data to ensure that it is suitable for statistical modeling. The quality of the data directly impacts the accuracy and reliability of the results, especially when developing a discrete choice model like Multinomial Logistic Regression (MNL). Proper data processing ensures that the model can effectively estimate the relationships between the dependent and independent variables while addressing potential issues such as missing data, inconsistent formatting, and outliers.

In the context of developing a discrete choice model, data processing becomes even more crucial because the choice modeling process requires the data to be structured in a way that reflects the hypothetical choices faced by individuals. For instance, in the Stated Preference (SP) survey used in this research, respondents were asked to choose between various vehicle options (EV, ICE, PHEV, HEV). Each of these vehicle choices had attributes such as purchase price, fuel cost, range, emissions, and maintenance costs, and the data needed to be organized in a way that these attributes could be quantified and modeled.

Data processing steps such as cleaning, normalization, and categorical variable handling ensure that the data is consistent, complete, and interpretable for the modeling software. For instance, categorical variables such as vehicle type (EV, ICE, HEV) or consumer demographics (age, income) need to be transformed into numeric or dummy variables to be used in the MNL model. Handling these variables appropriately ensures that the model is capable of estimating how changes in these attributes influence consumer decisions.

In essence, data processing is necessary to prepare the dataset in a way that the discrete choice model can be correctly estimated. It ensures that the model operates on a clean, consistent, and well-structured dataset, ultimately leading to more accurate predictions and insights into the factors driving consumer choice between EVs and ICE vehicles.

3.4.1 Data Cleaning

The data cleaning process involved several steps to ensure the dataset was accurate and reliable. These steps include identifying missing data, outlier detection, and removing irrelevant or incorrect data.

1. **Data Preparation:** The first step in the cleaning process was importing the raw data into a statistical software program such as Python or Microsoft Excel, where it was reviewed for completeness and accuracy.
2. **Identifying Missing Data:** Missing data was handled by identifying the instances where values were absent due to errors in data collection or entry mistakes. Missing data was addressed either by exclusion or imputation, depending on the extent and type of missingness.
3. **Outlier Detection:** Outliers, or extreme values that were significantly different from the majority of the data, were identified. These extreme values can skew the results of the analysis, so they were removed to ensure the integrity of the model.
4. **Removing Arbitrary Data:** After dealing with missing data and outliers, the remaining irrelevant or unnecessary data were identified and removed. This process ensures that only relevant and useful data is retained for the analysis.

The primary objectives of data cleaning include:

1. **Improving Data Quality:** Errors, inconsistencies, and missing values are corrected to enhance data reliability.
2. **Eliminating Duplicate Data:** Duplicate records, which may arise due to errors in data collection or entry, are identified and removed to prevent bias.
3. **Enhancing Data Consistency:** Variations in units or formats are standardized to ensure consistency across the dataset.
4. **Improving Data Analysis:** Accurate and consistent data facilitate more precise statistical modeling and interpretation.
5. **Facilitating Data Interpretation:** Cleaned data simplify the process of drawing meaningful and valid conclusions.

3.4.2 Data Normalization

Normalization refers to the process of scaling data so that all features are within a similar range. This prevents any single feature from having a disproportionate influence on the model and ensures that each feature is treated equally.

Input variables may be measured in different units (e.g., meters, taka, minutes), resulting in varying scales. Differences in these scales can complicate the modeling process. For instance, large input values (such as those ranging in the hundreds or thousands) can lead to a model with large weight values. Such models are often unstable, making them prone to poor performance during the learning phase and increasing sensitivity to input variations, which can cause higher generalization errors. To address these issues, it is necessary to standardize and normalize the data.

3.4.3 Data Binning (Midpoint Approximation)

Data binning is a technique used to group continuous data into discrete categories, which simplifies analysis by reducing noise. In midpoint approximation, each bin is represented by its central value. This approach is useful for converting survey responses or continuous variables into a structured form.

Example:

If survey responses are collected in intervals (e.g., 0–10, 11–20), midpoint approximation assigns the midpoint of each range as a representative value:

- 0–10 becomes 5
- 11–20 becomes 15

This transformation converts categorical ranges into numerical values, facilitating statistical analysis.

In this research, midpoint approximation has been applied to the age and income variables for model development.

3.4.4 Categorical Variable Handling

Handling categorical variables is a crucial aspect of statistical analysis, particularly in multinomial logistic regression. In the analysis, these variables were managed through several important steps:

1. **Recoding:** Categorical variables often appear as text or numerical codes that may not be directly interpretable by statistical software. To make these variables usable in the analysis, they were most likely recoded into numerical formats that could easily be interpreted by Python package BIOGEME.
2. **Dummy Coding:** For multinomial logistic regression, it is essential that dummy variables be created for categorical data. This involves generating a new binary variable for each category of the original variable. For instance, if the variable is "gender", with categories of male and female, two separate variables, such as "gender male" and "gender female", would be created, with the value being 1 for the relevant category and 0 otherwise.
3. **Collapsing Categories:** In some cases, categorical variables may contain numerous categories, making the analysis more complex and difficult to interpret. To simplify this, the categories were grouped into broader, more manageable categories. For instance, the variable "educational qualification", which originally included several specific options, was consolidated into two broader categories: "not graduate", which encompassed high school and undergraduate qualifications, and "graduate", which included master's and

PhD degrees. This categorization helped to reduce complexity while still capturing the essential distinctions needed for analysis, improving the clarity and interpretability of the results.

4. **Handling Missing Data:** Missing data is common in categorical variables, which can present challenges for analysis. In these instances, observations with missing values were either excluded or imputed using techniques such as mean imputation or multiple imputation.
5. **Checking for Multicollinearity:** Categorical variables can sometimes exhibit multicollinearity, where two or more variables are highly correlated, which can make it difficult to interpret individual effects. To address this, correlation matrices were used to identify and manage any multicollinearity issues.

3.5 Binomial Logistic Regression

3.5.1 General Expression

Multinomial logistic regression is a statistical technique used to examine the relationships between a categorical dependent variable with more than two categories and multiple independent variables [50]. This method is suitable when the dependent variable has three or more unordered categories. In cases where there are only two categories, the technique is called binomial logistic regression. A binomial logistic regression (or logistic regression for short) is used when the outcome variable being predicted is dichotomous (i.e. yes/no, pass/fail). This model can be used with any number of independent variables that are categorical or continuous. For this study, binomial logistic regression is applied to model the decision-making process of consumers when choosing between electric vehicles (EVs) and internal combustion engine (ICE) vehicles.

The basic equation for multinomial logistic regression can be expressed as follows:

$$\ln\left(\frac{P_{il}}{P_{ik}}\right) = \beta_1 X_{1_i} + \beta_2 X_{2_i} + \cdots + \beta_{k-1} X_{k-1_i}$$

Where $\ln\left(\frac{P_{il}}{P_{ik}}\right)$ is the log of the odds of choosing category 1 (e.g., EV) versus category k (e.g., ICE). β_1, β_2, ..., β_{k-1} are the coefficients associated with each independent variable X_1, X_2, ..., X_{k-1}, and i represents the individual consumer or observation. The dependent variable can be expressed in terms of k-1 log-odds equations, with one category as the reference category. In other words, we can compare the log-odds of choosing each category relative to the reference category.

3.5.2 Utility Function

To write the utility function of the two choices (EV and ICE) based on the factors we listed, we can use the following general form of the binomial logistic regression model:

$$U_i = \beta_0 + \beta_1 X_{1i} + \beta_2 X_{2i} + \cdots + \beta_k X_{ki} + \epsilon_i$$

Where U_i is the utility of alternative i (i.e., EV or ICE) for an individual, β_0 is the intercept, β_k is the coefficient of the kth independent variable, X_{ki} is the value of the kth independent variable for individual i, and ϵ_i is the error term.

Based on the factors we listed, we can specify the following utility functions for the two choices:

EV Utility Function:

$$U_{EV} = \beta_0 + \beta_{AGE_{EV}} * AGE + \beta_{GENDER_{EV}} * GENDER + \beta_{INCOME_{EV}} * INCOME + \beta_{PEOPLE_{EV}} * PEOPLE + \beta_{EQ_{EV}} * EQ + \beta_{OCCUP\sim STU_{EV}} * OCCUP\sim STU + \beta_{OCCUP\sim JOB_{EV}} * OCCUP\sim JOB + \beta_{V\sim OWN_{EV}} * V\sim OWN + \beta_{PURCHASE\sim COST_{EV}} * PURCHASE\sim COST + \beta_{OPERATING\sim COST_{EV}} * OPERATING\sim COST + \beta_{MAINTENANCE\sim COST_{EV}} * MAINTENANCE\sim COST + \beta_{RESALE\sim VALUE_{EV}} * RESALE\sim VALUE + \beta_{DRIVING\sim RANGE_{EV}} * DRIVING\sim RANGE + \beta_{AVAIL\sim CHARGE\sim FUEL_{EV}} * AVAIL\sim CHARGE\sim FUEL + \beta_{QUICK\sim ACCELERATION_{EV}} * QUICK\sim ACCELERATION + \beta_{SMOOTH\sim RIDING\sim EXPERIENCE_{EV}} * SMOOTH\sim RIDING\sim EXPERIENCE + \beta_{INTERIOIR\sim SPACE_{EV}} * INTERIOR\sim SPACE + \beta_{NOISE\sim LEVEL_{EV}} * NOISE\sim LEVEL + \beta_{ENVIRONMENTAL\sim PROTECTION_{EV}} * ENVIRONMENTAL\sim PROTECTION + \beta_{HEAR\sim EV_{EV}} * HEAR\sim EV + \beta_{KNOW\sim EV_{EV}} * KNOW\sim EV + \beta_{COST\sim AWARE\sim EV_{EV}} * COST\sim AWARE\sim EV + \beta_{SUSTAIN\sim EV_{EV}} * SUSTAIN\sim EV$$

ICE Utility Function:

$$
\begin{aligned}
U_{ICE} = \ & \beta_0 + \beta_{AGE_{ICE}} * \ AGE + \ \beta_{GENDER_{ICE}} * \ GENDER + \beta_{INCOME_{ICE}} * \ INCOME \\
& + \beta_{PEOPLE_{ICE}} * PEOPLE + \beta_{EQ_{ICE}} * EQ + \beta_{OCCUP\sim STU_{ICE}} \\
& * OCCUP\sim STU + \beta_{OCCUP\sim JOB_{ICE}} * OCCUP\sim JOB + \beta_{V\sim OWN_{ICE}} \\
& * V\sim OWN + \beta_{PURCHASE\sim COST_{ICE}} * PURCHASE\sim COST \\
& + \beta_{OPERATING\sim COST_{ICE}} * OPERATING\sim COST \\
& + \beta_{MAINTENANCE\sim COST_{ICE}} * MAINTENANCE\sim COST \\
& + \beta_{RESALE\sim VALUE_{ICE}} * RESALE\sim VALUE + \beta_{DRIVING\sim RANGE_{ICE}} \\
& * \ DRIVING\sim RANGE + \beta_{AVAIL\sim CHARGE\sim FUEL_{ICE}} \\
& * AVAIL\sim CHARGE\sim FUEL + \beta_{QUICK\sim ACCELERATION_{ICE}} \\
& * QUICK\sim ACCELERATION + \beta_{SMOOTH\sim RIDING\sim EXPERIENCE_{ICE}} \\
& * SMOOTH\sim RIDING\sim EXPERIENCE + \beta_{INTERIOIR\sim SPACE_{ICE}} \\
& * INTERIOR\sim SPACE + \beta_{NOISE\sim LEVEL_{ICE}} * NOISE\sim LEVEL \\
& + \beta_{ENVIRONMENTAL\sim PROTECTION_{ICE}} \\
& * ENVIRONMENTAL\sim PROTECTION + \beta_{HEAR\sim EV_{ICE}} * HEAR\sim EV \\
& + \beta_{KNOW\sim EV_{ICE}} * KNOW\sim EV + \beta_{COST\sim AWARE\sim EV_{ICE}} \\
& * \ COST\sim AWARE\sim EV + \beta_{SUSTAIN\sim EV_{ICE}} * SUSTAIN\sim EV
\end{aligned}
$$

In each of these utility functions, the independent variables (factors) have been included with their respective coefficients β_k. These coefficients reflect the extent to which each factor influences the utility of the corresponding mode. To estimate the coefficients in these utility functions, we can use the binomial logistic regression model. The coefficients can be interpreted as the marginal effects of each factor on the choice of vehicle type over the other, holding all other factors constant [51].

3.5.3 Probability Prediction

The logistic function is then applied to the log-odds to convert them into probabilities:

$$P_{ik} = \frac{e^{ln\left(\frac{P_{il}}{P_{ik}}\right)}}{1 + \sum_{j=1}^{k-1} e^{ln\left(\frac{P_{il}}{P_{ik}}\right)}}$$

The independent variables can be either categorical or continuous, and the coefficients represent the change in the log-odds of the dependent variable associated with a one-unit increase in the independent variable, holding all other variables constant [52]. Binomial logistic regression allows us to estimate the probability of choosing each category given a set of independent variables, which can be used to examine the factors influencing vehicle choice. By using binomial logistic regression, researchers can gain insights into the relative importance of various factors in the decision-making process of consumers, which can inform transportation planning and policy-making decisions.

To predict the probability of choosing each of the choices (EV and ICE) based on the estimated utility functions, we can use the following equation:

$$P_{iEV} = \frac{e^{U_{EV}}}{e^{U_{EV}} + e^{U_{ICE}}}$$

$$P_{iICE} = \frac{e^{U_{ICE}}}{e^{U_{EV}} + e^{U_{ICE}}}$$

Where P_{iEV} is the predicted probability of choosing EV for individual I and P_{iICE} is the predicted probability of choosing ICE for individual i.

To calculate the predicted probability for an individual, we need to substitute the estimated coefficients from the binomial logistic regression model into the utility function for each mode and then calculate the exponentials of the resulting values. Then, we divide each exponential value by the sum of the exponential values for all three modes to get the predicted probability for each mode.

For example, let’s say we have estimated the coefficients for the utility functions for the two choices using the binomial logistic regression model. Now, suppose we want to predict the probability of an individual choosing EV or ICE given their values for the independent variables (factors) included in the model.

The steps can be summarized as follows:

1. **Utility function calculation:** The utility function for each vehicle type is calculated using the estimated coefficients and the corresponding values of the independent variables for the individual.
2. **Exponential calculation:** The exponentials of the utility functions are calculated.
3. **Probability calculation:** Each exponential value is divided by the sum of the exponential values for both vehicle types to obtain the predicted probability for each choice.
4. **Vehicle type selection:** The vehicle type with the highest predicted probability is identified, representing the most likely choice for the individual.

3.6 Model Framework

BIOGEME is an open-source Python package designed for the maximum likelihood estimation of parametric models, with a particular focus on discrete choice models. Its implementation requires the use of the Python Data Analysis Library, commonly known as Pandas.

The software was initially developed and is currently maintained by Professor Michel Bierlaire from the Transport and Mobility Laboratory at the École Polytechnique Fédérale de Lausanne (EPFL) in Switzerland. For the estimation process, BIOGEME relies on two essential input files:

A model specification file with the extension .mod that defines the model structure.

A text file with the extension .txt containing the dataset used for estimation.

In this study, Microsoft Excel was used to create these input files. The data was imported using the Pandas command “pd.read_excel('File_name')”. The model specification file is divided into several key sections:

[Choice]: Identifies the data field in the data file that contains information about the selected option for each observation.

[Beta]: Defines the parameters, including alternative-specific constants for each mode and variables such as BETA_PURCHASE_COST_EV. Upper and lower bounds for each parameter are established, and the estimation status is set, with zero indicating that the parameter is estimated from the model.

[Utilities]: Specifies the utility equation for each vehicle type separately.

Data collection was carried out using Google Forms, and the responses were later transferred to Microsoft Excel. A text file was then created by saving the Excel file in the appropriate format.

The subsequent results derived from the model generated by BIOGEME are of significant importance:

1. The study presents the estimated values of the parameters, along with their corresponding standard errors and t-statistics.
2. Additionally, the log-likelihood value is reported.
3. The present study reports on several measures of model fit, including rho-square, adjusted rho-square, and other relevant indicators.
4. The sample size utilized in the analysis is also specified, along with the number of parameters estimated.
5. Additionally, the number of iterations required to achieve convergence is reported.

3.7 Statistical Tests

These are intended to assess the rationality of the implications derived from the estimated parameters.

The estimated parameters' sign is indicative of the relationship between the vehicle type's utility and the parameter. For example, in case of EV, the negative sign denotes an inverse relationship commonly observed for parameters like driving range. In such cases, consumers are less inclined to choose EV if they consider driving range to be very important.

In binary logistic regression, alternative-specific constants (ASCs) represent the baseline preference or inherent utility of each alternative, independent of the explanatory variables. These constants capture the effects of unobserved factors that influence decision-making, such as personal attitudes, brand perception, or other qualitative aspects not directly measured by the model.

The magnitude and sign of each constant indicate the relative attractiveness of the corresponding alternative. A positive constant suggests a higher baseline preference for that alternative, while a negative constant indicates a lower baseline preference. Larger absolute values reflect stronger inherent preferences, either positive or negative, for a particular option.

In this study, the estimated constants reflect the underlying inclination of respondents toward electric vehicles (EVs) and internal combustion engine (ICE) vehicles. A higher positive value suggests a stronger inherent preference for the associated vehicle type, while a negative value implies a lower preference. These constants provide valuable insights into the intrinsic appeal of each vehicle type, beyond the direct effects of attributes like cost, driving range, or other measurable factors.

3.7.1 Test of Individual Parameters

The model parameters are subject to sampling error or standard error, as the model is derived from a limited sample of the pertinent population. The standard error reflects the variability of the parameter estimates—a higher standard error indicates a lower level of precision in the estimation of parameters, meaning the estimate is less reliable.

The t-statistic is used to determine whether a parameter significantly influences the model. Rejection of the null hypothesis occurs when the t-statistic reaches a sufficiently significant value, indicating that the corresponding parameter has a substantial effect on the model's explanatory power and should be retained. At a 95% confidence level, a parameter is considered statistically significant if the absolute value of the t-statistic exceeds 1.960. This corresponds to a p-value less than 0.05, meaning there is less than a 5% probability that the observed relationship is due to random chance.

In this study, an 85% confidence interval was used to evaluate the significance of parameters. This relaxed threshold allows for the inclusion of variables that exhibit a moderate but meaningful influence on the dependent variable. This approach is particularly useful when working with datasets where only a few parameters meet the stricter 95% confidence level, ensuring that important but less pronounced effects are still captured. For the 85% confidence interval, a parameter is considered significant if the absolute value of the t-statistic exceeds 1.44.

When the absolute value of a parameter is comparatively low, it implies that the parameter does not substantially influence the model's explanatory variables. Parameters with low t-statistics generally provide minimal informative value and can be safely removed from the model without significantly affecting its accuracy.

3.7.2 Overall Goodness of Fit Measures

The log-likelihood is a metric used to evaluate the degree of appropriateness of a given model. Models with higher values are considered superior. Multiple models are compared by means of comparing the log-likelihood values. The maximum estimator of a parameter is typically derived using this method. There exist four distinct categories of log-likelihood values:

- **Log-likelihood for zero coefficients, LL(0):** The log-likelihood value for a model where all parameters (coefficients) are set to zero, meaning the model assumes no relationship between the independent variables and the outcome.
- **Log-likelihood for the constants-only model, LL(C):** The logarithmic likelihood of the model that includes only constants, denoted as LL(C).
- **Log-likelihood for the estimated model, LL(β):** The log-likelihood of the estimated model can be denoted as LL(β) in academic writing.
- **Log-likelihood for the perfect prediction model, LL(*):** The log-likelihood of the ideal prediction model is denoted as LL(*).

The model that includes estimated parameters is consistently superior to the model with only constants, as it accounts for additional explanatory variables and better reflects the observed data.

The determination of the rho-squared (ρ^2) metric is predicated on the interdependence between the log-likelihood values. The range of values for rho-squared is bounded by 0 and 1. A score of zero indicates that the model's predictive performance is equivalent to random guessing, while a score of one represents a perfect model in which all choices are predicted with complete accuracy.

There are several limitations associated with the utilization of the rho-squared statistic. Initially, it is noteworthy that no established criterion exists for a favourable rho-squared value. A low value of rho-squared suggests that the independent variables have limited explanatory power in accounting for the variance observed in the dependent variable. However, in research, outcomes with low rho-squared values ranging from 25% to 30% can still be considered valid as they accurately reflect the obtained results.

Irrespective of the value of rho-squared, the coefficients that are statistically significant continue to denote the average alteration in the response variable for every unit of modification in the predictor variable, while keeping all other predictor variables constant in the model. Undoubtedly, this category of data holds significant value.

Another issue pertains to the rho-squared metric, which exhibits improvement irrespective of the variable added to the model. The resolution of this issue can be attained through the utilization of a modified rho-squared metric. This adapted variant of the rho-squared metric has been suitably calibrated to account for the number of predictors present in the model.

The increment in the model's performance is contingent upon the extent to which the new term surpasses the expected improvement by random chance. The decrement in performance occurs when a predictor enhances the model's efficacy to a degree that is lower than what would be anticipated by chance. The coefficient in question experiences a reduction in value in instances where the term fails to yield a significant enhancement in the model's goodness of fit.

The addition of extraneous variables to a model has the potential to decrease its efficacy, while the inclusion of useful variables is likely to result in an increase.

The rho-squared matrix is a fundamental tool for determining the amount of variance that is accounted for by a given model. In multivariate linear regression, the addition of new variables results in an increase in the rho-squared value, regardless of the significance of the added variables. The adjusted rho-squared statistic computes rho-square solely based on the variables that exhibit statistical significance upon their inclusion in the model.

When performing a binomial logit model, it is possible to utilize adjusted rho-square as an alternative to rho-square. The inclusion of additional variables in a model may result in an increase in the coefficient of determination, rho-squared. However, the adjusted rho-squared may not necessarily increase unless the added variable is deemed statistically significant. The present study employs adjusted rho-squared values as a metric to evaluate the overall goodness of fit of the models under consideration.

3.7.3 Test of Entire Model

The t-statistic is employed to examine the hypothesis that a particular parameter is equivalent to a predetermined value or that there exists a correlation between parameters. At times, researchers may conduct simultaneous testing of multiple hypotheses. The process involves generating a test statistic that facilitates the comparison of two models, where one model is a constrained version of the other. Specifically, the constrained model can be derived by imposing limitations on the parameters of the unconstrained model.

Assuming the validity of all restrictions that differentiate between the restricted and unrestricted models, a negligible discrepancy in log-likelihood values (upon reaching convergence) between the two models would be anticipated. If certain or all limitations are deemed invalid, the contrast in log-likelihood measures between the models with and without restrictions will be significant enough to warrant the rejection of the hypotheses. The fundamental reasoning behind this is the foundation for the likelihood ratio test.

This examination evaluates the adequacy of two models in terms of their suitability. The hypothesis of insignificance posits that the model with a smaller number of variables is the optimal model. If the null hypothesis is refuted, it can be inferred that the expanded model exhibits a statistically significant enhancement in comparison to the more restricted model.

When the likelihood ratio test value exceeds ten, it is indicative of rejecting the null hypothesis. This implies that the variable in question has a significant impact on modal utilities and should be retained in the model.

3.8 Model Calibration and Validation

- **Data Preparation:** The dataset was prepared by first cleaning and organizing the variables required for analysis. This involved ensuring that the data was in the correct format and addressing any issues such as missing data or outliers. In order to avoid any sequential patterns that could bias the model, the rows of the dataset were randomized in Excel before proceeding to the next steps.
- **Model Specification:** The model specifications, including the dependent variable (choice behavior) and independent variables (e.g., socioeconomic factors, vehicle attributes), were determined. The functional form of the model was decided upon, and relevant interaction terms were included where necessary to capture potential relationships between variables.
- **Training Set Selection:** The dataset was divided into a training set and a testing set. The training set comprised 70% of the data, which was used to estimate the model parameters. The testing set comprised the remaining 30%, which was reserved for validating the model's performance. The split was done after the dataset had been randomized to ensure no bias from sequential data.

3.9 Summary

This chapter outlined the methodology employed in the study, focusing on data collection, survey design, and model development. The first phase involved assessing the market penetration of electric vehicles (EVs) in Bangladesh through direct observations, showroom visits, and interviews with the representatives. Additionally, a small-scale survey was conducted among EV users to gather insights into their experiences, though responses were limited. The second phase included a Stated Preference (SP) survey to analyze consumer preferences between EVs and internal combustion engine (ICE) vehicles. The collected data was then processed and analyzed using a Binomial Logit Model, allowing for an evaluation of the key factors influencing vehicle choice in Bangladesh.

CHAPTER 4: CURRENT EV SCENARIO

4.1 Introduction

This chapter presents the results of the market observation and interviews conducted to assess the current state of electric vehicle (EV) adoption in Bangladesh. It covers key aspects such as the number of EVs currently on the market, purchase prices, and the availability of charging stations across the country. Additionally, the chapter delves into the findings from the EV users' survey, focusing on aspects like user satisfaction, driving behavior, and challenges faced by EV owners. Through this comprehensive analysis, the chapter aims to provide an understanding of the early-stage market dynamics and consumer behavior towards EVs in Bangladesh, shedding light on the factors influencing adoption and areas that require improvement.

4.2 State of EV Adoption in Bangladesh

4.2.1 Electric Vehicle Sales Overview

Electric vehicles (EVs) are a relatively new concept in Bangladesh, with their introduction marking a significant shift in the automotive industry. According to interviews conducted with showroom representatives in January 2024, EV sales in the country began around 1.5 years ago, starting in the middle of 2022. Despite the global presence of over 400 car brands manufacturing EVs, the EV market in Bangladesh remains in its early stages, with only 5 brands currently offering EVs. These brands include Audi, BMW, MG, Mercedes, and BYD.

Among these, Audi, BMW, and MG have been the pioneering sellers of EVs in the Bangladeshi market, establishing their presence before others. BYD began its operations in March 2024, marking a relatively recent entry into the market, while Mercedes also started selling EVs around the same time. This limited number of brands highlights the initial steps towards the growth of the EV market in Bangladesh, but it also underscores the challenges related to the low penetration of EVs and the need for expanded options and infrastructure to support this emerging sector. The following chart represents the no. of EVs sold by each brand in Bangladesh.

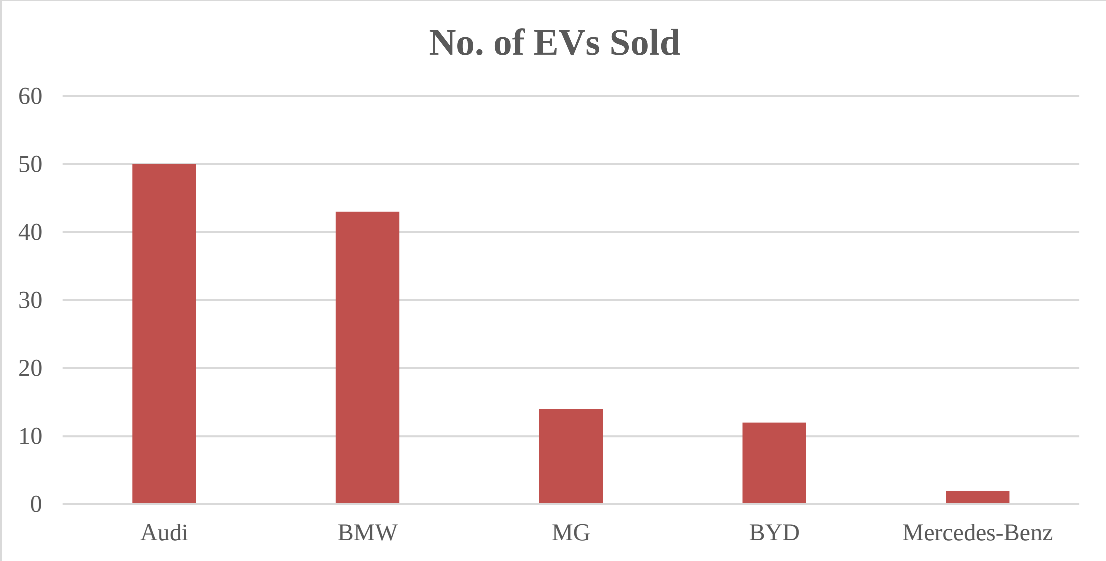


Figure 4-1: Comparison of no. of EV Sold by Different Brands in Bangladesh

4.2.1.1 Audi

Audi currently offers two electric vehicle (EV) models in the Bangladeshi market: the Audi e-tron and the Audi Q7. The Audi e-tron is a fully electric vehicle, while the Audi Q7 is a mild hybrid. The Audi e-tron is equipped with an electric motor that delivers a power output of 313 horsepower (HP), whereas the Audi Q7 has a slightly higher power output of 340 HP. Despite these power differences, the two models have significantly varying purchase prices.

As part of Bangladesh's efforts to promote EV adoption and meet the goal of achieving 30% EV penetration by 2030, the government has introduced several measures, including reducing the import duties on EVs. The Audi e-tron, being a fully electric vehicle, benefits from an 89% import duty, while the Audi Q7, classified as a mild hybrid, faces a much higher import duty of 312%. Additionally, hybrid models in the country are subject to an import duty of 212%.

In terms of pricing, the Audi e-tron costs approximately €70,000 (around 83,24,000 BDT), with added costs for shipping charges and the 89% import duty. On the other hand, the Audi Q7 is priced at €65,000 (around 77,30,000 BDT), also with shipping charges and the 312% import duty.

As of February 2024, Audi has sold approximately 50 units of its vehicles in Bangladesh, with 40 units of the Audi e-tron sold across Dhaka alone. This growing presence of Audi's EVs highlights the initial steps towards increasing EV adoption in the country, although challenges related to pricing and infrastructure still remain.

4.2.1.2 BMW

As of 2025, BMW's electric vehicle (EV) models in Bangladesh continue to cater to the high-end market, with prices ranging from 1.5 crore BDT to 4 crore BDT. Currently, BMW offers two fully electric models: the BMW i7 and BMW iX3, both of which are fully electric. These models maintain their position in the luxury EV segment, and approximately 40 to 45 units have been sold across the country.

BMW has also been selling Plug-in Hybrid Electric Vehicles (PHEVs) since 2016. Besides, BMW received 700 to 800 orders annually for their PHEV models. The import duty for EVs remains at 89%, while the duties on PHEVs range between 157% to 212%, depending on the specific model. These duties continue to impact the overall price of the vehicles, limiting accessibility and adoption among potential customers in Bangladesh.

4.2.1.3 MG

MG offers two fully electric vehicle (EV) models in the Bangladeshi market: the MG ZS EV and the MG 4, both of which provide affordable options for consumers seeking eco-friendly alternatives. By early 2024, a total of 14 EVs had been sold, but these models were out of stock in February 2024, with reselling expected to resume in March 2024. In addition to their EV offerings, MG also provides a Plug-in Hybrid Electric Vehicle (PHEV), the MG HS, which was unavailable in the market as of February 2024.

4.2.1.4 BYD

Since March 2024, the Chinese brand BYD has entered the Bangladeshi market, offering a range of fully electric vehicles. All the cars available in their showrooms are 100% electric, reflecting the brand's commitment to promoting sustainable mobility. By July 2024, BYD was expected to deliver 10 to 12 EVs across the country, marking the early stages of their expansion in Bangladesh.

4.2.1.5 Mercedes-Benz

As of March 2024, Mercedes-Benz has sold only 1 to 2 electric vehicle (EV) models in Bangladesh, indicating that the brand's presence in the EV market is still in its early stages.

4.2.2 Market Penetration of EV

According to the Bangladesh Road Transport Authority (BRTA) report, the total number of registered private passenger cars in Bangladesh from January 2023 to January 2024 is 11,847 (calculated as 10,784 + 1,068). Based on our data, the total number of EVs sold up to March 2024 is 123 (calculated as 50 + 45 + 14 + 12 + 2). Since the difference in the total number of registered cars between January 2024 and March 2024 is minimal, we can assume that the number of private passenger cars registered as of March 2024 is approximately the same as that reported for January 2024.

Using this assumption, the market penetration of EVs can be calculated as:

$$\text{Market penetration of EV} = \frac{\text{Number of EVs Sold in a Period}}{\text{Total Private Passenger Cars Sold in the Same Period}} \times 100\%$$

$$= \frac{123}{11{,}847} \times 100\%$$

$$= 1.04\%$$

This indicates that, as of March 2024, EVs account for about 1.04% of the total registered private passenger cars in Bangladesh.

4.3 Charging Stations in Bangladesh

The number of electric vehicles (EVs) sold in Bangladesh is still limited, and as a result, the number of charging stations across the country remains relatively few. One of the pioneering initiatives in this regard is Ekhon Charge, which is working to establish a comprehensive EV charging infrastructure in Bangladesh. Their mission is to support the growing adoption of electric vehicles by offering accessible and efficient charging solutions nationwide. Currently, Ekhon Charge operates four charging stations in the country, with the first station located in Tejgaon, Dhaka, within the premises of the Audi service center. On average, only three cars visit this station each week for charging, reflecting the limited number of EVs in the region.

In addition to the Tejgaon station, Ekhon Charge has established three other stations in Comilla, Chittagong, and Cox’s Bazar. Among the four charging stations, the stations except the one in Cox’s Bazar have DC (Direct Current) chargers, which are known for their faster charging speeds. The station in Cox’s Bazar, however, is equipped with an AC (Alternating Current) charger, which, although slower, is preferred for long-range driving due to its compatibility with more standard EV models.

Furthermore, BMW has plans to expand the charging infrastructure in Bangladesh, with future installations in areas like Jessore, Rajshahi, and Bagura. Meanwhile, BYD, a newly launched EV brand in Bangladesh, also has intentions to add more charging stations to support its growing customer base.

Although public charging stations are limited in number, a substantial share of EV users in Bangladesh depend on home charging for their daily needs. However, the country's charging infrastructure still faces challenges related to accessibility and availability, which must be addressed as EV adoption increases.

4.4 EV Owners' Survey Results

The survey aimed at understanding EV owners' experiences in Bangladesh yielded only two responses, which makes it insufficient for conducting any statistical analysis. Reaching out to EV owners proved challenging, as they tend to be affluent individuals who often have drivers to operate their vehicles. Additionally, as noted earlier, only three EVs were observed weekly at the Tejgaon charging station, typically visiting at night when outsiders were not permitted, further limiting access to these users.

Although the small sample size limits the statistical significance, the responses provide valuable insights into the perspective of EV owners in Bangladesh. One respondent drove an MG 4, a locally available model, while the other used an imported Toyota RAV4 PHEV. The purchase prices of these vehicles were 4,800,000 BDT and 9,000,000 BDT, respectively. Both respondents reported a monthly income exceeding 100,000 BDT, indicating that EV ownership is currently concentrated among the wealthier population. This may explain the limited popularity of EVs in the country, largely due to their high initial purchase costs. Both owners had home chargers and agreed that there are insufficient public charging points in Bangladesh, highlighting a key barrier to the broader adoption of EVs.

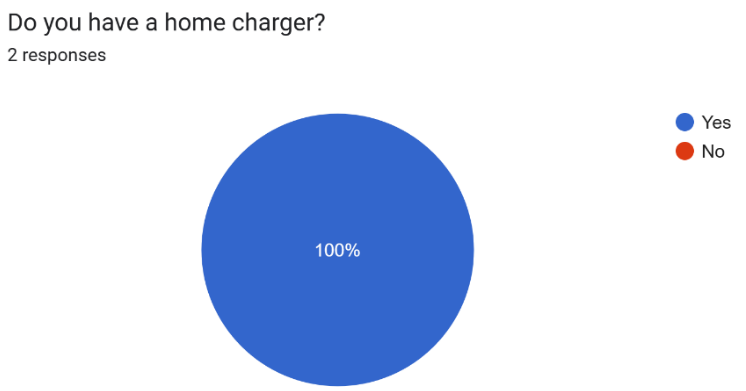


Figure 4-2: EV Users' Opinion about Having a Home Charger

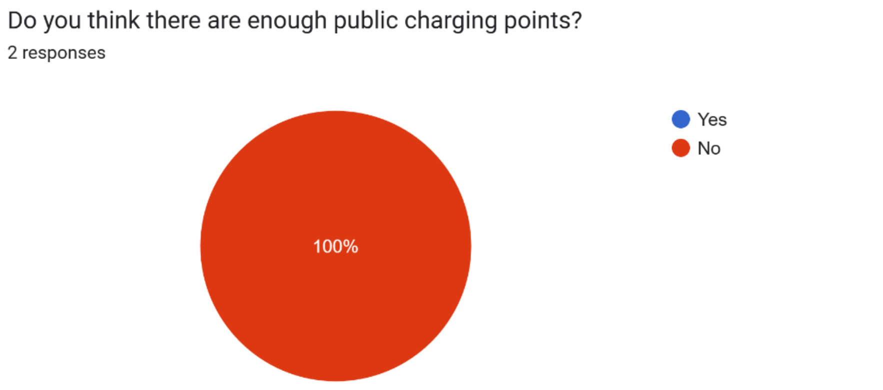


Figure 4-3: EV Users' Opinions about Charging Points

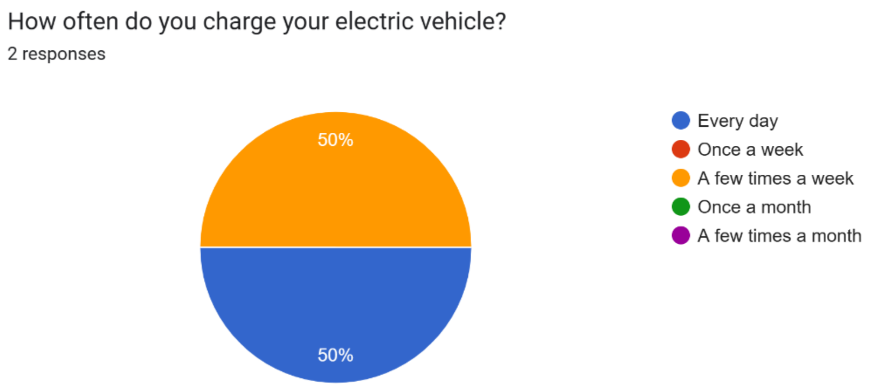


Figure 4-4: EV Users' Opinions about Frequency of Charging

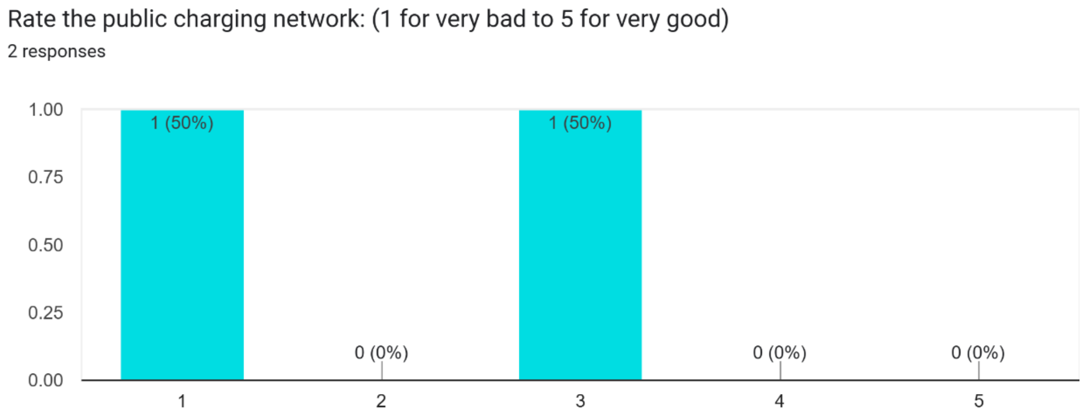


Figure 4-5: EV Users' Opinions about Public Charging Network

The users reported using their EVs regularly for various types of trips. The primary reasons they preferred EVs over conventional fuel-based vehicles include the lower operating costs and the environmental benefits associated with electric mobility. Both respondents rated the key characteristics of EVs, such as operating cost efficiency and environmental impact, between 4 and 5 on a scale of 1 to 5, indicating high satisfaction with these aspects of their EVs.

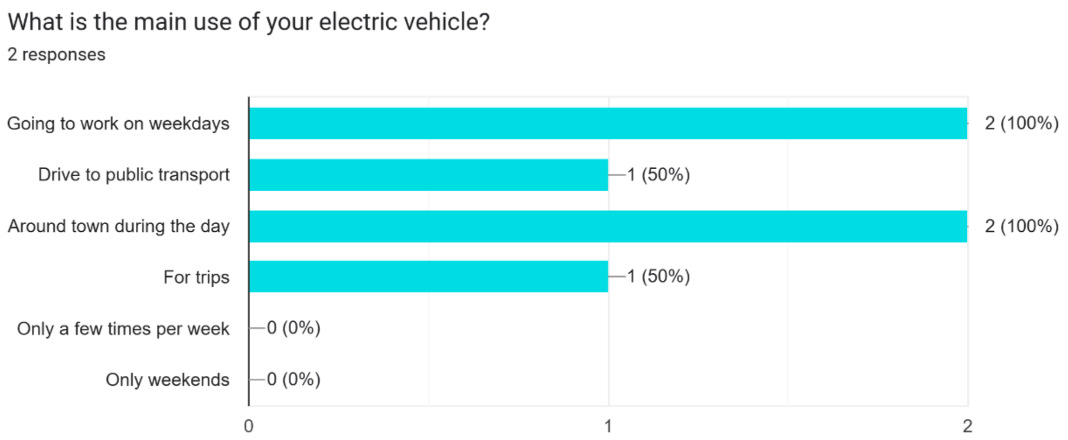


Figure 4-6: EV Users' Opinions about Use of EVs

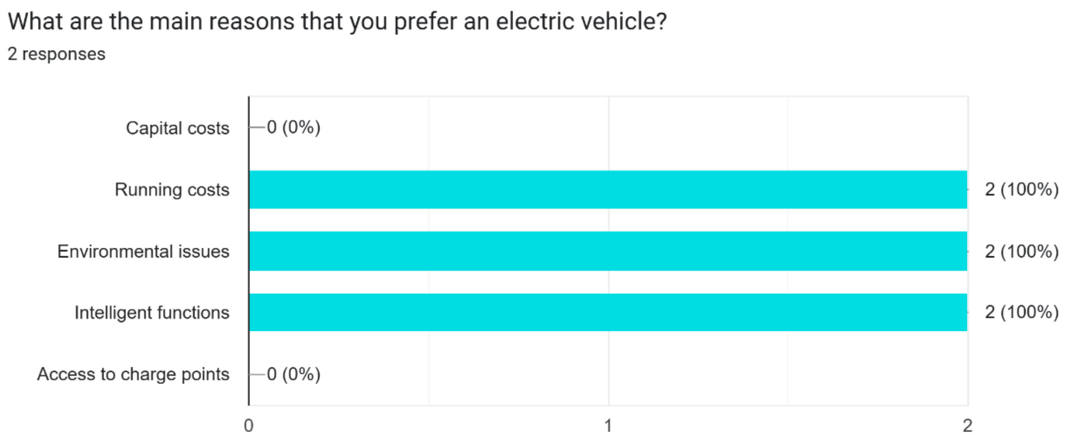


Figure 4-7: EV Users' Opinions Regarding Reasons for Preference for EV

Figure 4-8: EV Users' Ratings on Different Aspects of EV on a Scale of 1 to 5

However, both users agreed that there are still significant barriers to the widespread adoption of EVs in Bangladesh. Despite these challenges, they both acknowledged that EVs are being well promoted to the public, suggesting that efforts to raise awareness and encourage adoption are making progress.

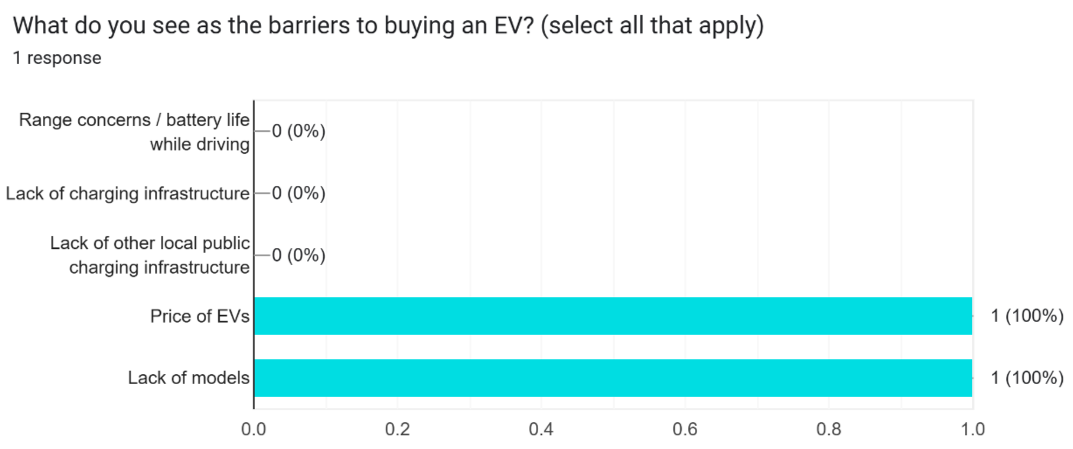


Figure 4-9: EV Users' Opinions on Barriers to Adoption of EV

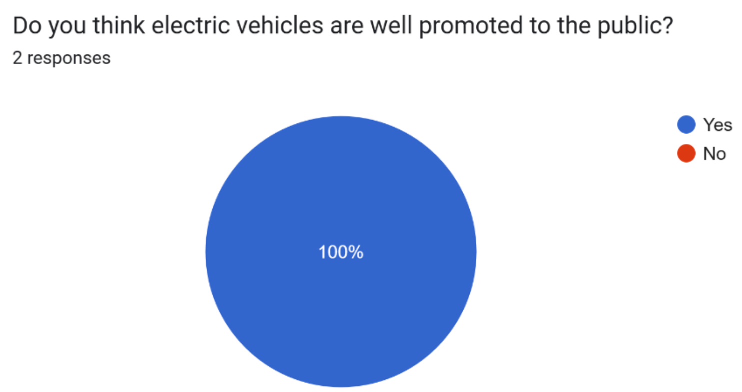


Figure 4-10: EV Users' Opinions about Promotion of EV to the Public

In general, both users had a positive experience with their EVs, which aligns with the expected benefits of electric vehicles. As a result, both expressed a willingness to repurchase EVs and indicated they would recommend them to others, reflecting their satisfaction with the overall EV ownership experience.

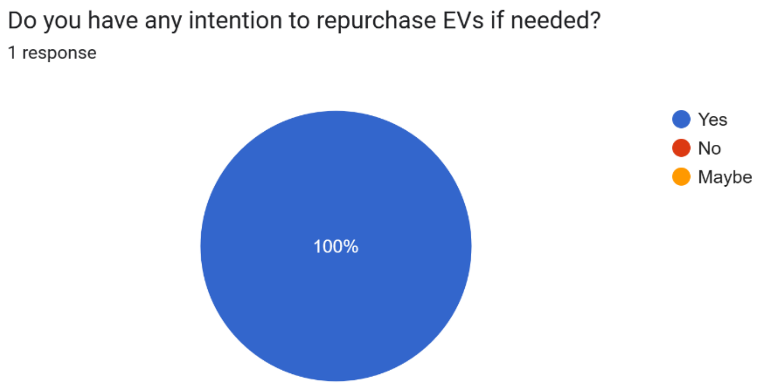


Figure 4-11: EV Users' Opinions about Repurchase Intention

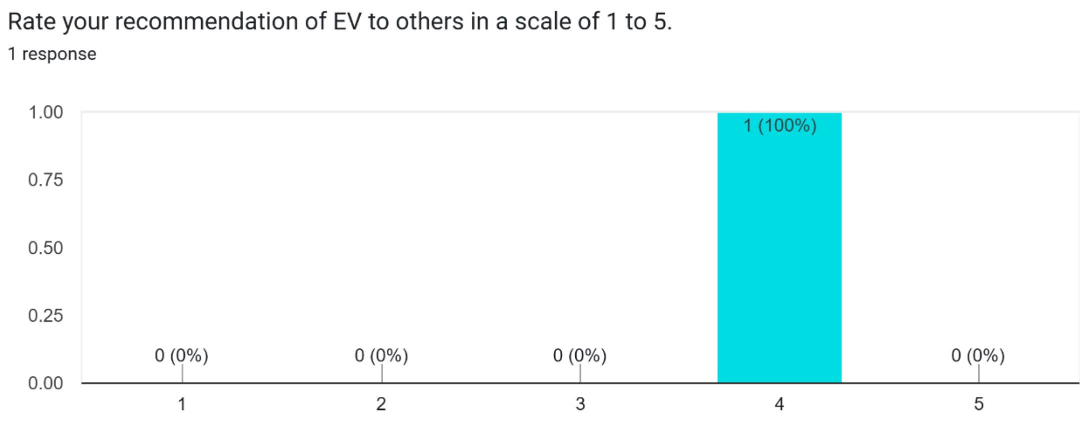


Figure 4-12: EV Users' Recommendation to the Public on a Scale of 1 to 5

4.5 Issues Related to EV Adoption in Bangladesh

While the Bangladesh government has set an ambitious goal to achieve 30% EV adoption by 2030, the current market penetration remains at only 1%, indicating that electric vehicles are still in their early stages of adoption in the country. After assessing the current EV conditions in Bangladesh, several significant issues have emerged as barriers to wider EV adoption. These challenges are hindering the growth of the electric vehicle market and need to be addressed in order to facilitate a smoother transition to electric mobility.

1. **High Purchase Cost:** One of the primary obstacles to EV adoption in Bangladesh is the high purchase cost of electric vehicles. Compared to traditional internal combustion engine (ICE) vehicles, EVs are considerably more expensive. For example, BMW's EV models start at approximately 1.5 crore BDT, which is prohibitively expensive for the majority of the population. This premium pricing limits access to EVs, as many consumers are unable or unwilling to invest such a large amount in a vehicle, especially when more affordable ICE vehicles are available.

2. **Limited Availability of EV Models:** The availability of electric vehicle models in Bangladesh is currently quite limited. There are only a few EV models available in the market, making it difficult for consumers to choose from a diverse range of options. The lack of variety means that consumers are forced to choose from a small selection, and most available models come with a high price tag. More affordable, alternative models with lower prices could encourage greater EV adoption by catering to a wider range of potential buyers.

3. **Insufficient Public Charging Infrastructure:** Another significant barrier is the limited number of public charging stations. As of 2024, there are only 4 operational public charging stations across the country, with only 1 station located in Dhaka. This lack of accessible charging infrastructure poses a significant challenge for potential EV owners, as it increases range anxiety and makes long-distance travel less feasible. Expanding the charging network is

essential to ensuring that EVs are more convenient and practical for everyday use.

4. **Lack of Public Awareness**: While the use of electric vehicles is being promoted, the efforts have been insufficient to reach the broader population. Many people in Bangladesh are unaware that EV sales have already started in the country. This lack of awareness is a key barrier to adoption, as potential buyers are not fully informed about the benefits of EVs, the availability of models, or the financial incentives that may exist. Comprehensive awareness campaigns are needed to educate the public about the advantages of switching to electric mobility.

5. **High Import Duty:** Although the import duty on EVs has been reduced compared to hybrid and mild hybrid vehicles, it remains significantly high, contributing to the overall high purchase price of electric vehicles. The 89% import duty on EVs increases the cost of acquisition considerably, making them less affordable for the average consumer. The high import duties EVs create an additional financial barrier that limits the adoption of electric vehicles for the people.

6. **Lack of Service Centers:** The availability of service centers for EVs is another challenge in Bangladesh. As only 5 brands have begun selling EVs in the country, the number of dedicated EV service centers is still very low. This lack of after-sales service infrastructure raises concerns among potential buyers about the long-term reliability and maintenance of EVs. Without sufficient service and repair options, consumers may be hesitant to purchase EVs, fearing difficulties in maintaining and repairing the vehicles.

In addition to these challenges, the Bangladesh Road Transport Authority (BRTA) website does not provide dedicated data on registered EVs. The records are still maintained in handwritten files and have not been digitized, making it difficult to effectively track the progress of EV adoption in the country.

4.6 Summary

This section summarizes the key findings regarding the current state of electric vehicle (EV) adoption in Bangladesh. The analysis highlights major challenges such as high purchase costs, limited charging infrastructure, and a lack of public awareness, all of which hinder widespread adoption. Despite these barriers, there is growing consumer interest in EVs, and users express satisfaction with the lower operating costs and environmental benefits. The findings suggest that addressing infrastructure gaps and promoting public awareness campaigns are crucial for achieving Bangladesh's 30% EV adoption target by 2030.

CHAPTER 5: CHOICE MODELLING

5.1 Introduction

This chapter explores the factors that influence consumer choice between electric vehicles (EVs) and internal combustion engine (ICE) vehicles. It examines the impact of various factors on consumer decisions and presents utility functions for each vehicle type using binary logistic regression. Additionally, the chapter discusses the results of model calibration and validation. It also provides insights into public perceptions of EVs and ICEs, including consumers' willingness to switch to Plug-in Hybrid Electric Vehicles (PHEVs) or Hybrid Electric Vehicles (HEVs). Finally, this chapter highlights the key findings from the analysis, offering a deeper understanding of the factors shaping vehicle preferences in the context of Bangladesh's automotive market.

5.2 Stated Preference (SP) Survey

The SP survey got a total of 173 response. Among these 173 responses, 87 people (50.3%) preferred the EV model and 86 people (49.7%) preferred the ICE model.

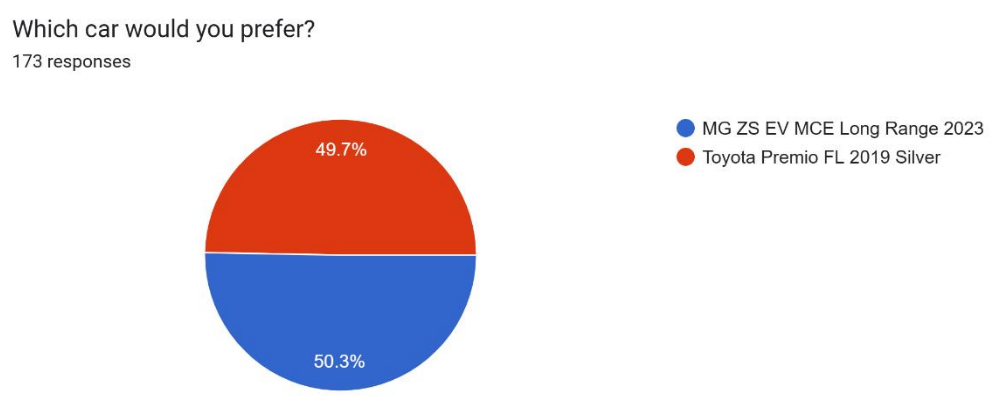


Figure 5-1: Percentage of Preference between EV Model and ICE Model

Among the 173 respondents, 141 respondents (81.5%) were men and 32 respondents (18.5%) were women.

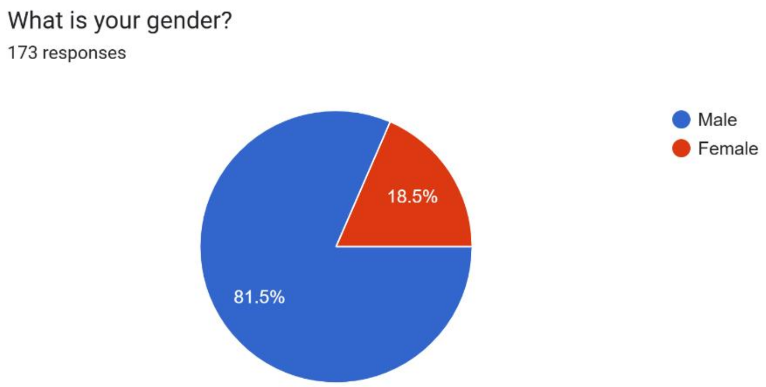


Figure 5-2: Pie Chart of Gender Distribution

5.3 Development of Utility Functions

A binomial logit model has been developed using BIOGEME package in Python. The model estimated the coefficients associated with each factors for both utility equations. The positive coefficient represents that an increase in the independent variable will increase the utility of the respective vehicle option. Oppositely, the negative coefficient represents that an increase in the independent variable will decrease the utility of the respective vehicle option.

After running the model with all variables included, an HTML file is generated showing the estimated report, estimated parameters and correlation matrix.

The estimated report has been shown in the following figure.

Number of estimated parameters:	48
Sample size:	173
Excluded observations:	0
Init log likelihood:	-70.77282
Final log likelihood:	-70.50207
Likelihood ratio test for the init. model:	0.5415083
Rho-square for the init. model:	0.00383
Rho-square-bar for the init. model:	-0.674
Akaike Information Criterion:	237.0041
Bayesian Information Criterion:	388.3621
Final gradient norm:	1.0143E-02
Nbr of threads:	4
Relative gradient:	9.945936900646008e-05
Cause of termination:	Relative gradient = 9.9e-05 <= 0.00012
Number of function evaluations:	3
Number of gradient evaluations:	3
Number of hessian evaluations:	2
Algorithm:	Newton with trust region for simple bound constraints
Number of iterations:	2
Proportion of Hessian calculation:	2/2 = 100.0%
Optimization time:	0:00:01.516101

Figure 5-3: Estimation Report of the Developed Binary Logit Model Including All Parameters

The rho-square value of the model is close to zero, indicating that the estimated model does not perform much better than the null model, and the explanatory variables have limited predictive power. This suggests that the independent variables included in the model do not significantly explain the dependent variable (the choice or decision being modeled). It is possible that the model is misspecified, meaning it may either lack important explanatory variables or include irrelevant ones. Additionally, the model includes a large number of parameters. To improve its fit, variables with insignificant p-values (greater than 0.15) were excluded from the model, and at the same time ensuring that the relevant variables were retained, based on an 85% confidence interval.

Table 5-1: Robust p-value of Estimated Parameters of the Model Including All Parameters

Name	Rob. p-value	Retained?
ASC_EV	0.0305	Yes (Constant)
ASC_ICE	0.0305	Yes (Constant)
B_AGE_EV	0.335	No
B_AGE_ICE	0.335	No
B_AVAIL_CHAGE_FUEL_EV	0.0132	Yes
B_AVAIL_CHAGE_FUEL_ICE	0.0132	Yes
B_COST_AWARE_EV_EV	0.406	No
B_COST_AWARE_EV_ICE	0.406	No
B_DRIVING_RANGE_EV	0.266	No
B_DRIVING_RANGE_ICE	0.266	No
B_ENVIRONMENTAL_PROTECTION_EV	0.0174	Yes
B_ENVIRONMENTAL_PROTECTION_ICE	0.0174	Yes
B_EQ_EV	0.083	Yes
B_EQ_ICE	0.083	Yes
B_GENDER_EV	0.342	No
B_GENDER_ICE	0.342	No
B_HEAR_EV_EV	0.729	No
B_HEAR_EV_ICE	0.729	No
B_INCOME_EV	0.207	No
B_INCOME_ICE	0.207	No

Name	Rob. p-value	Retained?
B_INTERIOR_SPACE_EV	0.529	No
B_INTERIOR_SPACE_ICE	0.529	No
B_KNOW_EV_EV	0.236	No
B_KNOW_EV_ICE	0.236	No
B_MAINTENANCE_COST_EV	0.622	Yes (Important parameter although p>0.15)
B_MAINTENANCE_COST_ICE	0.622	Yes (Important parameter although p>0.15)
B_NOISE_LEVEL_EV	0.433	No
B_NOISE_LEVEL_ICE	0.433	No
B_OCCUP_JOB_EV	0.232	Yes (Since the other dummy variable satisfies)
B_OCCUP_JOB_ICE	0.232	Yes (Since the other dummy variable satisfies)
B_OCCUP_STU_EV	0.115	Yes
B_OCCUP_STU_ICE	0.115	Yes
B_OPERATING_COST_EV	0.927	Yes (Important parameter although p>0.15)
B_OPERATING_COST_ICE	0.927	Yes (Important parameter although p>0.15)
B_PEOPLE_EV	0.632	No

Name	Rob. p-value	Retained?
B_PEOPLE_ICE	0.632	No
B_PURCHASE_COST_EV	0.619	Yes (Important parameter although p>0.15)
B_PURCHASE_COST_ICE	0.619	Yes (Important parameter although p>0.15)
B_QUICK_ACCELERATION_EV	0.499	No
B_QUICK_ACCELERATION_ICE	0.499	No
B_RESALE_VALUE_EV	0.0849	Yes
B_RESALE_VALUE_ICE	0.0849	Yes
B_SMOOTH_RIDING_EXPERIENCE_EV	0.811	No
B_SMOOTH_RIDING_EXPERIENCE_ICE	0.811	No
B_SUSTAIN_EV_EV	0.00459	Yes
B_SUSTAIN_EV_ICE	0.00459	Yes
B_V_OWN_EV	0.273	No
B_V_OWN_ICE	0.273	No

The model was then redeveloped using only the selected parameters. As a result, the new model showed an improved rho-square value, indicating a better fit and enhanced explanatory power.

Number of estimated parameters:	22
Sample size:	173
Excluded observations:	0
Init log likelihood:	-119.9145
Final log likelihood:	-78.12061
Likelihood ratio test for the init. model:	83.58771
Rho-square for the init. model:	0.349
Rho-square-bar for the init. model:	0.165
Akaike Information Criterion:	200.2412
Bayesian Information Criterion:	269.6136
Final gradient norm:	6.1734E-03
Nbr of threads:	4
Relative gradient:	2.0965471184311146e-05
Cause of termination:	Relative gradient = 2.1e-05 <= 0.00012
Number of function evaluations:	5
Number of gradient evaluations:	5
Number of hessian evaluations:	4
Algorithm:	Newton with trust region for simple bound constraints
Number of iterations:	4
Proportion of Hessian calculation:	4/4 = 100.0%
Optimization time:	0:00:01.287934

Figure 5-4: Estimation Report of the Developed Binary Logit Model Including Chosen Parameters Only

The initial log-likelihood of the model is -119.9145, which represents the likelihood of the observed data given the initial model parameters. The final log-likelihood value, after optimization, is -78.12061, showing an improvement in the model's ability to fit the data. The difference between the initial and final log-likelihood values is statistically significant, as indicated by the likelihood ratio test, which has a value of 83.58771. This suggests that the final model fits the data better than the initial one, rejecting the null hypothesis that the model is no better than the reference model. The rejection of the null hypothesis signifies that the independent variables included in the model are significant contributors to explaining the choice behavior between EVs and ICE vehicles.

The McFadden's rho-square (ρ^2) value of 0.349 suggests that the fitted model explains approximately 34.9% of the variance in the outcome variable. While this is a substantial proportion, it's important to note that pseudo R-squared values, such as McFadden's ρ^2, are not directly comparable to the traditional R-squared in linear regression. McFadden's ρ^2 is often lower, and a value between 0.2 and 0.4 generally indicates a good fit for a logistic regression model. The adjusted rho-square value (0.165), which accounts for the number of parameters in the model, is lower but still reasonable, reflecting the complexity added by the model's predictors. The adjusted rho-square is useful for preventing overfitting, and in this case, the value indicates that the model maintains a relatively good fit while adjusting for the added complexity.

When comparing this model with the previous model, where the rho-square value was only 0.00383, the improvement is quite evident. In the previous model, both the AIC (237.0041) and BIC (388.3621) were significantly higher, which indicates poorer model fit and less efficient use of the data. In contrast, the current model's AIC (200.2412) and BIC (269.6136) are notably lower, suggesting that the inclusion of more predictors has substantially improved the model's fit. These lower AIC and BIC values not only reflect a better explanatory power but also indicate that the current model achieves this improved fit with a more efficient number of parameters. Thus, the current model provides a much better fit, with a much improved rho-square, AIC, and BIC compared to the previous model.

Table 5-2: Estimation Results of the Binary Logit Model with Chosen Parameters Only

Name	Value	Rob. Std err	Rob. t-test	Rob. p-value
ASC_EV	-1.97	0.867	-2.27	0.0231
ASC_ICE	1.97	0.867	2.27	0.0231
B_AVAIL_CHAGE_FUEL_EV	-0.298	0.0996	-2.99	0.00276
B_AVAIL_CHAGE_FUEL_ICE	0.298	0.0996	2.99	0.00276
B_ENVIRONMENTAL_PROTECTION_EV	0.372	0.0818	4.54	5.52e-06
B_ENVIRONMENTAL_PROTECTION_ICE	-0.372	0.0818	-4.54	5.52e-06
B_EQ_EV	-0.361	0.232	-1.55	0.12

Name	Value	Rob. Std err	Rob. t-test	Rob. p-value
B_EQ_ICE	0.361	0.232	1.55	0.12
B_MAINTENANCE_COST_EV	0.135	0.182	0.743	0.457
B_MAINTENANCE_COST_ICE	-0.135	0.182	-0.743	0.457
B_OCCUP_JOB_EV	0.868	0.687	1.26	0.207
B_OCCUP_JOB_ICE	-0.868	0.687	-1.26	0.207
B_OCCUP_STU_EV	0.917	0.659	1.39	0.164
B_OCCUP_STU_ICE	-0.917	0.659	-1.39	0.164
B_OPERATING_COST_EV	0.0358	0.164	0.219	0.827
B_OPERATING_COST_ICE	-0.0358	0.164	-0.219	0.827
B_PURCHASE_COST_EV	0.0435	0.111	0.392	0.695
B_PURCHASE_COST_ICE	-0.0435	0.111	-0.392	0.695
B_RESALE_VALUE_EV	-0.23	0.108	-2.13	0.0331
B_RESALE_VALUE_ICE	0.23	0.108	2.13	0.0331
B_SUSTAIN_EV_EV	0.302	0.0975	3.1	0.00195
B_SUSTAIN_EV_ICE	-0.302	0.0975	-3.1	0.00195

Based on table 5-2, the utility functions for EV ad ICE can be written as below:

Utility function for EV:

$$U_{EV} = -1.97 - 0.361 * EQ + 0.917 * OCCUP\sim STU + 0.868 * OCCUP\sim JOB + 0.0435 * PURCHASE\sim COST + 0.0358 * OPERATING\sim COST + 0.135 * MAINTENANCE\sim COST - 0.23 * RESALE\sim VALUE - 0.298 * AVAIL\sim CHARGE\sim FUEL + 0.372 * ENVIRONMENTAL\sim PROTECTION + 0.302 * SUSTAIN\sim EV$$

Utility function for ICE:

$$U_{ICE} = 1.97 + 0.361 * EQ - 0.917 * OCCUP\sim STU - 0.868 * OCCUP\sim JOB - 0.0435 * PURCHASE\sim COST - 0.0358 * OPERATING\sim COST - 0.135 * MAINTENANCE\sim COST + 0.23 * RESALE\sim VALUE + 0.298 * AVAIL\sim CHARGE\sim FUEL - 0.372 * ENVIRONMENTAL\sim PROTECTION - 0.302 * SUSTAIN\sim EV$$

- **Constant:** The constant term in the EV utility function is -1.97, indicating that, in the absence of other factors, EVs are less attractive compared to ICE vehicles in Bangladesh. This negative value likely reflects the higher initial purchase costs, limited charging infrastructure, and lower consumer familiarity with EVs. In contrast, the constant term for the ICE utility function is 1.97, suggesting an inherent preference for ICE vehicles, which benefit from widespread availability of fuel stations, lower upfront costs, and consumer familiarity. These constants highlight the initial bias towards ICE vehicles in Bangladesh before considering other influencing factors like environmental concerns and long-term savings.

- **Educational Qualification:** The EQ variable, representing educational qualification, takes a value of 1 for graduates and 0 for non-graduates. In the EV utility function, the negative coefficient (-0.361) suggests that graduates are less likely to choose an EV compared to non-graduates. Conversely, in the ICE utility function, the positive coefficient (+0.361) indicates that graduates are more likely to prefer an ICE vehicle. This could reflect the idea that graduates might be influenced by factors such as financial considerations, familiarity with ICE vehicles, and higher purchase costs of EVs, which could make them lean more toward traditional vehicles despite other influencing factors.

- **Occupation:** The OCCUP_JOB and OCCUP_STU variables represent job holders and students, respectively, with others (unemployed, retired) serving as the reference category. In the EV utility function, both OCCUP_JOB and OCCUP_STU have positive coefficients, suggesting that individuals in these categories are more likely to choose an EV compared to others. However, the coefficient for OCCUP_STU (+0.917) is higher than that for OCCUP_JOB (+0.868), indicating that students have a slightly stronger preference for EVs than job holders. This could reflect a greater willingness among students to adopt new technologies, while job holders might be more influenced by financial considerations or practicality. In the ICE utility function, both coefficients are negative, indicating that students and job holders are less likely to choose an ICE vehicle compared to others.

- **Purchase Cost:** The purchase cost variable in the EV utility function has a positive coefficient (+0.0435) and in the ICE utility function has a negative coefficient (-0.0435), suggesting that as the purchase cost of EVs increases, their utility also increases. Although this might seem counterintuitive, in the context of Bangladesh, where EVs are still considered a luxury commodity, the higher price may not deter affluent buyers. According to economic theory, luxury goods often experience higher demand as their price increases, as they are perceived as symbols of status and wealth.

- **Operating Cost:** The operating cost variable has a positive coefficient (+0.0358) in the EV utility function and a negative coefficient (-0.0358) in the ICE utility function. EV users prioritize the lower operating costs of EVs compared to ICE vehicles, leading to higher ratings on a scale of 1 to 5. As a result, the utility of EVs increases, while the utility of ICE vehicles decreases, reflecting their higher operating costs.

- **Maintenance Cost:** Similar to operating cost, the maintenance cost variable has a positive coefficient (+0.135) in the EV utility function and a negative coefficient (-0.135) in the ICE utility function. EV users prioritize the lower maintenance costs of EVs compared to ICE vehicles, leading to higher ratings on a scale of 1 to 5. As a result, the utility of EVs increases, while the utility of ICE vehicles decreases, reflecting their higher maintenance costs.

- **Resale Value:** The coefficient in the EV utility function for resale value is negative (-0.23) and the coefficient in the ICE utility function for resale value is positive (+0.23). Since EV has lower resale value than ICE, the one who prioritizes high resale value tend to rate the factor high on a scale of 1 to 5, as a result the utility for ICE increases and the utility for EV decreases.

- **Availability of Charging and Fueling Stations:** The coefficient in the EV utility function for this attribute is negative (-0.298) and the coefficient in the ICE utility function for resale value is positive (+0.298). Since the number of charging stations in Bangladesh is only 4 and fueling stations are widely available, the one who prioritizes this availability in public tend to rate the factor high on a scale of 1 to 5, as a result the utility for ICE increases and the utility for EV decreases.

- **Environmental Protection:** Since EVs are considered more environmentally friendly, individuals who rate environmental protection higher on a scale of 1 to 5 are more likely to choose an EV, as reflected by the positive coefficient (+0.372) in the EV utility function. On the other hand, the negative coefficient (-0.372) in the ICE utility function indicates their reduced interest in choosing ICEs.

- **Belief in Sustainable Transportation by EVs:** Individuals who believe that EVs contribute to more sustainable transportation in Bangladesh are likely to give higher ratings on a scale of 1 to 5, making them more inclined to choose an EV, as reflected by the positive coefficient (+0.302) in the EV utility function. Conversely, the negative coefficient (-0.302) in the ICE utility function suggests that a higher rating for sustainability leads to a greater disutility for ICE vehicles, reducing the likelihood of choosing them.

5.4 Model Calibration and Validation Results

The whole dataset was randomized and then first 70% of the rows (122 rows) were taken for training. The estimation report of the trained model is as follows.

Number of estimated parameters:	22
Sample size:	121
Excluded observations:	0
Init log likelihood:	-83.87081
Final log likelihood:	-48.6944
Likelihood ratio test for the init. model:	70.35282
Rho-square for the init. model:	0.419
Rho-square-bar for the init. model:	0.157
Akaike Information Criterion:	141.3888
Bayesian Information Criterion:	202.8962
Final gradient norm:	1.4086E-02
Nbr of threads:	4
Relative gradient:	6.954418930984056e-05
Cause of termination:	Relative gradient = 7e-05 <= 0.00012
Number of function evaluations:	5
Number of gradient evaluations:	5
Number of hessian evaluations:	4
Algorithm:	Newton with trust region for simple bound constraints
Number of iterations:	4
Proportion of Hessian calculation:	4/4 = 100.0%
Optimization time:	0:00:00.285374

Figure 5-5: Estimation Report of Training Model

The 70% training model demonstrates a significant improvement over the original model across key performance metrics. Notably, the final log-likelihood value improves from -78.12061 in the original model to -48.6944 in the 70% training model, indicating a better fit to the data. The Rho-square value increases from 0.349 to 0.419, suggesting that the training model explains a larger proportion (41.9%) of the variance in the outcome variable. Additionally, the Akaike Information Criterion (AIC) and Bayesian Information Criterion (BIC) values are substantially lower in the training model (141.3888 and 202.8962, respectively, compared to 200.2412 and 269.6136 in the original model), reflecting a better balance between model fit and complexity. The following table shows the estimation results of the training model

Table 5-3: Estimation Results of the Training Model

Name	Value	Rob. Std err	Rob. t-test	Rob. p-value
ASC_EV	-1.54	0.776	-1.98	0.0472
ASC_ICE	1.54	0.776	1.98	0.0472
B_AVAIL_CHAGE_FUEL_EV	-0.31	0.119	-2.6	0.00941
B_AVAIL_CHAGE_FUEL_ICE	0.31	0.119	2.6	0.00941
B_ENVIRONMENTAL_PROTECTION_EV	0.498	0.126	3.96	7.48e-05
B_ENVIRONMENTAL_PROTECTION_ICE	-0.498	0.126	-3.96	7.48e-05
B_EQ_EV	-0.511	0.31	-1.65	0.0999
B_EQ_ICE	0.511	0.31	1.65	0.0999
B_MAINTENANCE_COST_EV	-0.0225	0.269	-0.084	0.933
B_MAINTENANCE_COST_ICE	0.0225	0.269	0.084	0.933
B_OCCUP_JOB_EV	0.483	0.63	0.768	0.443
B_OCCUP_JOB_ICE	-0.483	0.63	-0.768	0.443
B_OCCUP_STU_EV	0.572	0.569	1	0.315
B_OCCUP_STU_ICE	-0.572	0.569	-1	0.315
B_OPERATING_COST_EV	0.119	0.255	0.467	0.641
B_OPERATING_COST_ICE	-0.119	0.255	-0.467	0.641
B_PURCHASE_COST_EV	-0.0206	0.156	-0.132	0.895
B_PURCHASE_COST_ICE	0.0206	0.156	0.132	0.895

Name	Value	Rob. Std err	Rob. t-test	Rob. p-value
B_RESALE_VALUE_EV	-0.162	0.134	-1.21	0.227
B_RESALE_VALUE_ICE	0.162	0.134	1.21	0.227
B_SUSTAIN_EV_EV	0.261	0.108	2.41	0.0159
B_SUSTAIN_EV_ICE	-0.261	0.108	-2.41	0.0159

<u>Utility function for EV:</u>

$$\begin{aligned}U_{EV} = -1.54 - 0.511 * EQ + 0.572 * OCCUP{\sim}STU + 0.483 * OCCUP{\sim}JOB \\ - 0.0206 * PURCHASE{\sim}COST + 0.119 * OPERATING{\sim}COST \\ - 0.0225 * MAINTENANCE{\sim}COST - 0.162 * RESALE{\sim}VALUE \\ - 0.31 * AVAIL{\sim}CHARGE{\sim}FUEL + 0.498 \\ * ENVIRONMENTAL{\sim}PROTECTION + 0.261 * SUSTAIN{\sim}EV\end{aligned}$$

<u>Utility function for ICE:</u>

$$\begin{aligned}U_{ICE} = 1.54 + 0.511 * EQ - 0.572 * OCCUP{\sim}STU - 0.483 * OCCUP{\sim}JOB \\ + 0.0206 * PURCHASE{\sim}COST - 0.119 * OPERATING{\sim}COST \\ + 0.0225 * MAINTENANCE{\sim}COST + 0.162 * RESALE{\sim}VALUE \\ + 0.31 * AVAIL{\sim}CHARGE{\sim}FUEL - 0.498 \\ * ENVIRONMENTAL{\sim}PROTECTION - 0.261 * SUSTAIN{\sim}EV\end{aligned}$$

The coefficients except purchase cost and maintenance cost show similar behavior as the model made with 100% data. Here negative coefficient (-0.0206) for purchase price in the EV utility function and positive coefficient (+0.206) might predict that lowering the price of EV can help boost EV adoption in Bangladesh. On the contrary, the negative coefficient (-0.0225) for maintenance cost in the EV utility function and positive coefficient (+0.0225) might indicate anxiety about battery replacement cost

Then the model was tested on the rest 30% of the dataset.

SI No.	CHOICE	EV UTILITY	ICE UTILITY	HIGHEST UTILITY	COMPARISON
1	1	0.8245	-0.8245	1	MATCHED
2	1	0.7508	-0.7508	1	MATCHED
3	1	0.2313	-0.2313	1	MATCHED
4	1	0.5463	-0.5463	1	MATCHED
5	2	-1.385	1.385	2	MATCHED
6	1	1.1601	-1.1601	1	MATCHED
7	1	-0.8753	0.8753	2	NOT MATCHED
8	2	-0.1688	0.1688	2	MATCHED
9	2	0.9129	-0.9129	1	NOT MATCHED
10	1	0.1207	-0.1207	1	MATCHED
11	2	0.5928	-0.5928	1	NOT MATCHED
12	1	0.0931	-0.0931	1	MATCHED
13	2	-0.5124	0.5124	2	MATCHED
14	1	2.2459	-2.2459	1	MATCHED
15	1	1.8045	-1.8045	1	MATCHED
16	1	-0.4058	0.4058	2	NOT MATCHED
17	1	-0.6051	0.6051	2	NOT MATCHED
18	1	0.8336	-0.8336	1	MATCHED
19	2	-0.7835	0.7835	2	MATCHED
20	2	0.3077	-0.3077	1	NOT MATCHED
21	1	1.2905	-1.2905	1	MATCHED
22	1	0.5006	-0.5006	1	MATCHED
23	1	-1.3218	1.3218	2	NOT MATCHED
24	1	0.5515	-0.5515	1	MATCHED
25	2	-1.1545	1.1545	2	MATCHED
26	1	-0.5125	0.5125	2	NOT MATCHED
27	1	1.6666	-1.6666	1	MATCHED
28	1	0.9507	-0.9507	1	MATCHED
29	1	2.0873	-2.0873	1	MATCHED
30	1	1.4551	-1.4551	1	MATCHED
31	1	1.1327	-1.1327	1	MATCHED
32	1	-0.5125	0.5125	2	NOT MATCHED
33	1	1.6897	-1.6897	1	MATCHED
34	2	-1.0285	1.0285	2	MATCHED
35	2	-0.5909	0.5909	2	MATCHED
36	2	0.4277	-0.4277	1	NOT MATCHED
37	2	-1.192	1.192	2	MATCHED
38	1	-0.8017	0.8017	2	NOT MATCHED
39	2	0.1571	-0.1571	1	NOT MATCHED
40	2	-0.464	0.464	2	MATCHED
41	1	0.767	-0.767	1	MATCHED
42	2	0.1462	-0.1462	1	NOT MATCHED
43	2	0.6304	-0.6304	1	NOT MATCHED
44	2	-1.2035	1.2035	2	MATCHED
45	2	0.9353	-0.9353	1	NOT MATCHED
46	1	0.8465	-0.8465	1	MATCHED
47	2	-1.3025	1.3025	2	MATCHED
48	2	-0.0661	0.0661	2	MATCHED
49	1	-0.4105	0.4105	2	NOT MATCHED
50	2	-0.8383	0.8383	2	MATCHED
51	2	-0.5995	0.5995	2	MATCHED
52	1	-0.3437	0.3437	2	NOT MATCHED

Figure 5-6: Evaluation on The Test Set

70% accuracy was obtained in the validation process, which can be considered reasonable since the data was limited.

5.5 Switching Tendency to HEV and PHEV

Among the 87 respondents who initially preferred EVs, 48.3% (42 respondents) chose to remain with EVs, while 32.2% (28 respondents) opted to switch to PHEVs, and 19.5% (17 respondents) shifted their preference to HEVs, which are less environmentally friendly than EVs. Similarly, among the 86 respondents who initially preferred ICE vehicles, 38.4% (33 respondents) chose to stick with ICEs, while 34.9% (30 respondents) decided to switch to PHEVs, and 26.7% (23 respondents) switched to HEVs.

Aggregating all responses, 42 individuals ultimately preferred EVs, while 58 chose PHEVs, 34 chose HEVs, and 33 opted for ICE vehicles. These findings suggest that while a considerable portion of EV users remain committed to fully electric vehicles, a significant fraction has shifted toward PHEVs, likely due to concerns about charging infrastructure, driving range, or cost. On the other hand, a noteworthy percentage of ICE users showed willingness to transition to PHEVs and HEVs, indicating an openness to adopting more environmentally friendly alternatives. However, the fact that EV retention is lower than PHEV adoption suggests that barriers such as charging availability and affordability still hinder full EV adoption, even among those who initially preferred electric mobility.

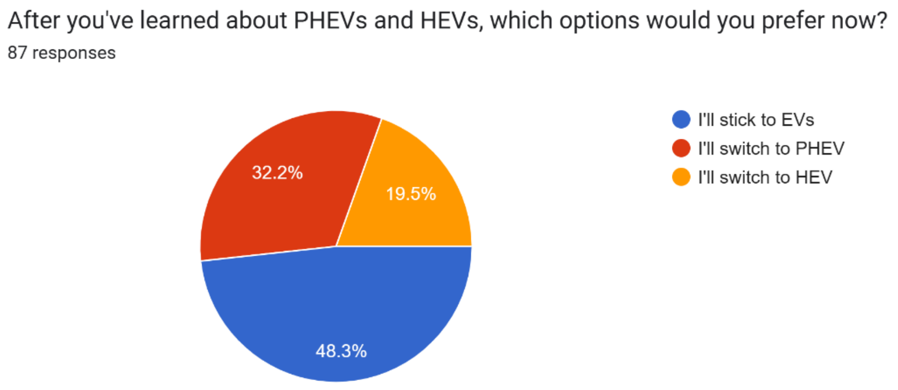


Figure 5-7: Respondents After Giving Option to Switch from EVs

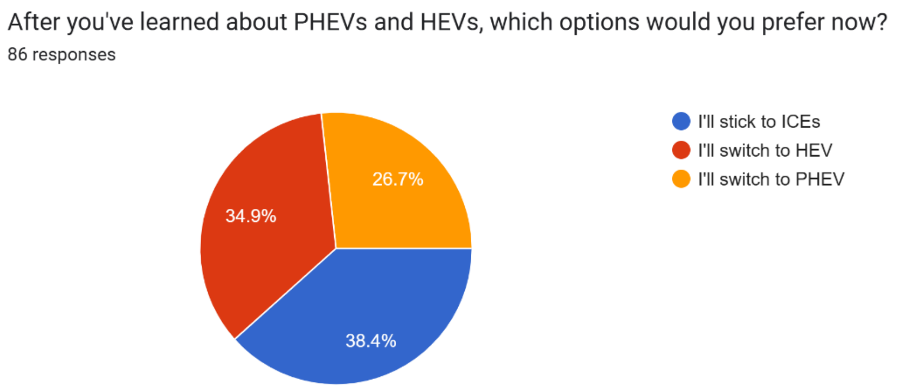


Figure 5-8: Respondents After Giving Option to Switch from ICEs

5.6 Summary

This chapter explores the factors influencing consumer choice between Electric Vehicles (EVs) and Internal Combustion Engine (ICE) vehicles in Bangladesh. It identifies key determinants such as purchase cost, operating cost, environmental protection, and sustainability beliefs, based on findings from a Stated Preference (SP) survey. The chapter also presents the utility functions for both EVs and ICE vehicles and interprets the significant variables affecting consumer preferences. Furthermore, the results highlight the willingness of consumers to switch to Hybrid Electric Vehicles (HEVs) and Plug-in Hybrid Electric Vehicles (PHEVs). This chapter emphasizes the importance of factors like cost and environmental concerns in shaping vehicle choice while also acknowledging the challenges in EV adoption.

CHAPTER 6: CONCLUSION AND FUTURE WORKS

6.1 Conclusions

This research aimed to explore the adoption of Electric Vehicles (EVs) in Bangladesh, focusing on consumer preferences and the barriers to EV adoption. Through Discrete Choice Modeling (DCM) and a Stated Preference (SP) survey, the study examined the factors influencing the decision between EVs and Internal Combustion Engine (ICE) vehicles, and provided valuable insights into the current state of the market. The study highlighted several significant findings regarding market penetration, consumer behavior, and the impact of government policies. One of the key contributions of this research is its application of DCM to assess consumer preferences in a developing country like Bangladesh, where EV adoption is still in its nascent stages. The findings show that, despite government initiatives and tax reductions, the high purchase cost and limited charging infrastructure remain the most significant barriers to EV adoption in the country. The study also provided utility functions for EVs and ICE vehicles, quantifying the influence of factors like purchase cost, operating cost, and environmental concerns on consumer choices. Moreover, this research emphasizes the importance of sustainability and environmental protection in driving EV adoption, particularly among higher-income and more educated individuals.

The novel contributions of this research include an in-depth analysis of EV adoption in the Bangladeshi context, which is relatively underexplored. By examining local factors such as income levels, charging infrastructure, and government incentives, this study fills a gap in understanding how Bangladeshi consumers make decisions about adopting EVs. Furthermore, it provides a foundation for future research on EV adoption in other developing countries, considering the socio-economic and infrastructural challenges unique to these regions.

6.2 Limitations and Recommendations for Future Works

While this research provides valuable insights into EV adoption in Bangladesh, it is important to acknowledge several limitations that may affect the generalizability of the findings. These limitations stem from factors such as sample size, data availability, and the scope of the study. By addressing these limitations in future research, a more comprehensive understanding of the factors influencing EV adoption can be achieved, contributing to the development of targeted policies and strategies.

6.2.1 Limitations

This research has the following limitations:

1. The Stated Preference (SP) survey had a relatively small sample size, which limits the ability to generalize findings to the broader population. The survey was mostly filled by higher-income individuals, leaving out insights from lower-income and rural populations, who may have different preferences and constraints regarding EV adoption.

2. There is a lack of publicly available data on EV sales, charging infrastructure, and consumer demographics in Bangladesh. This research relied on interviews and surveys, which might not fully capture the overall dynamics of the EV market in Bangladesh.

3. The study primarily focused on EVs and ICE vehicles, without considering Hybrid Electric Vehicles (HEVs) and Plug-in Hybrid Electric Vehicles (PHEVs). These vehicles are gaining popularity in many regions and can play a crucial role in the transition to sustainable transport.

4. The study highlighted the lack of public charging stations, but did not explore in-depth factors such as charging accessibility, cost, and consumer perceptions regarding charging convenience, which are critical for EV adoption.

5. While government policies and incentives were mentioned, the study did not evaluate the effectiveness of these policies in driving EV adoption in Bangladesh. This leaves a gap in understanding how additional measures might improve the EV market.

6.2.2 Recommendation for Future Works

To address the limitations identified in this research, several key recommendations for future studies are proposed below:

1. Future studies should include a larger and more diverse sample, particularly focusing on low-income and rural populations, to better understand their preferences and constraints related to EV adoption.

2. There is a need for better data on EV sales, charging infrastructure, and consumer demographics. Establishing a centralized database with real-time tracking of EV registrations and charging stations will improve the accuracy of the research.

3. Future research should investigate HEVs and PHEVs, which serve as an intermediary between ICE vehicles and full EVs. Understanding consumer interest in hybrid vehicles is essential for a comprehensive view of the EV adoption transition.

4. Further research is needed to explore how to enhance charging infrastructure, focusing on accessibility, cost, and consumer perceptions. This will help identify solutions to scale up the infrastructure and improve convenience for EV owners.

5. Future studies should assess the effectiveness of government incentives, such as tax reductions, import duty relief, and subsidies, to make EVs more affordable. The research should also explore how additional incentives,

financing options, and support for manufacturers can help lower production costs and increase the availability of EVs.

In conclusion, addressing these limitations and following the recommendations above will significantly improve the understanding of EV adoption in Bangladesh and contribute to the formulation of more effective policies for a sustainable transportation in future.

REFERENCES

[1] Veza, M. Z. Asy’ari, M. Idris, V. Epin, I. M. R. Fattah, and M. Spraggon, “Electric vehicle (EV) and driving towards sustainability: Comparison between EV, HEV, PHEV, and ICE vehicles to achieve net zero emissions by 2050 from EV,” *Alexandria Engineering Journal*, vol. 82, pp. 459–467, Oct. 2023, doi: 10.1016/j.aej.2023.10.020.

[2] M. Palinski, "A Comparison of Electric Vehicles and Conventional Automobiles: Costs and Quality Perspective," Bachelor's thesis, Degree Program in Business Administration, 2017. [Online]. Available: https://www.electric-vehicles.info/library/these/these061.pdf

[3] Bangladesh Road Transport Authority, "Regulations on Road Transport in Bangladesh," May 4, 2023. [Online]. Available: https://brta.gov.bd/sites/default/files/files/brta.portal.gov.bd/legislative_information/91dfffe3_0925_4772_a852_02caaf5f299e/2023-05-04-17-24-09bf15ec644bf3ed70795aa2552ef4e8.pdf. [Accessed: Mar. 16, 2025].

[4] RoadGenius, "EV Sales by Country," [Online]. Available: https://roadgenius.com/cars/ev/statistics/sales-by-country/#:~:text=Key%20EV%20Statistics%20Globally&text=95%25%20of%20EV%20sales%20were,to%20surpass%20Tesla%20in%20sales. [Accessed: Mar. 16, 2025].

[5] A.Soltani-Sobh, K. Heaslip, A. Stevanovic, R. Bosworth, and D. Radivojevic, "Analysis of the Electric Vehicles Adoption over the United States," *Transportation Research Procedia*, vol. 22, pp. 203-212, 2017, doi: 10.1016/j.trpro.2017.03.027.

[6] S. A. Neves and A. C. Marques, "What has driven the adoption of BEV and PHEV in the EU?," *Research in Transportation Business & Management*, vol. 60, p. 101331, 2025, doi: 10.1016/j.rtbm.2025.101331.

[7] TopSpeed, "Best EV Incentives in US States," [Online]. Available: https://www.topspeed.com/us-states-best-ev-incentives/. [Accessed: Mar. 16, 2025].

[8] X. Zheng, F. Menezes, X. Zheng, and C. Wu, "An empirical assessment of the impact of subsidies on EV adoption in China: A difference-in-differences approach," *Transportation Research Part A: Policy and Practice*, vol. 162, pp. 121-136, Aug. 2022, doi: 10.1016/j.tra.2022.05.020.

[9] T. Gersdorf, P. Hertzke, P. Schaufuss, and S. Schenk, "McKinsey Electric Vehicle Index: Europe cushions a global plunge in EV sales," *McKinsey & Company*, July 2020. Available: https://www.mckinsey.com. [Accessed: Mar. 16, 2025].

[10] "India targets 30% EV sales by 2030, pushes for infrastructure expansion," *The Economic Times*, [Online]. Available: https://energy.economictimes.indiatimes.com/news/power/india-targets-30-ev-sales-by-2030-pushes-for-infrastructure-expansion/115454418. [Accessed: Mar. 16, 2025].

[11] "Electric vehicle sales in Europe outpace global growth," *Financial Times*, [Online]. Available: https://www.ft.com/content/ff9a765a-fa28-4d2e-b9ff-17fa52139785. [Accessed: Mar. 16, 2025].

[12] "Electric vehicles in India: 2025 launches, market growth," *Business Standard*, [Online]. Available: http://business-standard.com/industry/auto/electric-vehicles-india-2025-launches-market-growth-125012400596_1.html. [Accessed: Mar. 16, 2025].

[13] R. Vidhi and P. Shrivastava, "A review of electric vehicle lifecycle emissions and policy recommendations to increase EV penetration in India," *Energies*, vol. 11, no. 3, p. 483, Feb. 2018, doi: 10.3390/en11030483.

[14] "India needs 39 lakh charging stations by 2030: Report," *The Hindu*, [Online]. Available: https://www.thehindu.com/news/cities/bangalore/india-needs-39-lakh-charging-stations-by-2030-report/article69187609.ece. [Accessed: Mar. 16, 2025].

[15] S. Z. Rajper and J. Albrecht, “Prospects of Electric Vehicles in the Developing Countries: A literature review,” *Sustainability*, vol. 12, no. 5, p. 1906, Mar. 2020, doi: 10.3390/su12051906.

[16] "Runner to build nationwide charging network to boost EV sales," *The Daily Star*, [Online]. Available: https://www.thedailystar.net/business/news/runner-build-nationwide-charging-network-boost-ev-sales-3520901. [Accessed: Mar. 16, 2025].

[17] "Electric vehicle boom stalls as charging infrastructure lags," *Dhaka Tribune*, [Online]. Available: https://www.dhakatribune.com/bangladesh/350558/electric-vehicle-boom-stalls-as-charging. [Accessed: Mar. 16, 2025].

[18] M. U. Salehin, I. A. Joarder, and S. W. Hasan, "Adoption of electric vehicles and renewable energy charging systems in Bangladesh: Opportunities and challenges," *Am. J. Innov. Res. Appl. Sci.*, vol. 17, no. 6, pp. 1-8, Dec. 2023, doi: 10.5281/zenodo.10231788.

[19] M. S. Islam, M. S. Sunny, J. H. Rabbi, N. U. Pritom, and M. W. Shaowkat, "Future assessment of low-cost EV automobile market in Bangladesh," *Int. J. Eng. Adv. Technol. Stud.*, vol. 12, no. 2, pp. 12-29, Jun. 2024, doi: 10.37745/ijeats.13/vol12n21229.

[20] M. R. Ahmed and A. K. Karmaker, "Challenges for Electric Vehicle Adoption in Bangladesh," *2019 International Conference on Electrical, Computer and Communication Engineering (ECCE)*, Cox's Bazar, Bangladesh, 2019, pp. 1-6, doi: 10.1109/ECACE.2019.8679288.

[21] U.S. Department of Energy. (2021, June 14). *FOTW #1190, June 14, 2021: Battery-Electric Vehicles Have Lower Scheduled Maintenance Costs than Other Light-Duty Vehicles*. Alternative Fuels Data Center. https://afdc.energy.gov/files/u/publication/ev-efficiency-maintenance-fotw.pdf

[22] E. Zammit, A. Convello, C. Leone, M. Longo, W. Yaici, and F. Foiadelli, "Cost and emission comparison of long-distance travel and life-cycle for EV and ICE vehicle: A case study," *2022 IEEE International Conference on Environment and Electrical Engineering and 2022 IEEE Industrial and Commercial Power Systems Europe (EEEIC / I&CPS Europe)*, Prague, Czech Republic, 2022, pp. 1-6, doi: 10.1109/EEEIC/ICPSEurope54979.2022.9854748.

[23] A.J. Richardson, E. S. Ampt, and A. H. Meyburg, *Survey Methods for Transport Planning*. Melbourne, Australia: Eucalyptus Press, 1995.

[24] G. Cecere, N. Corrocher, and M. Guerzoni, “Price or performance? A probabilistic choice analysis of the intention to buy electric vehicles in European countries,” *Energy Policy*, vol. 118, pp. 19–32, Mar. 2018, doi: 10.1016/j.enpol.2018.03.034.

[25] C.Zhuge and C. Shao, “Investigating the factors influencing the uptake of electric vehicles in Beijing, China: Statistical and spatial perspectives,” *Journal of Cleaner Production*, vol. 213, pp. 199–216, Dec. 2018, doi: 10.1016/j.jclepro.2018.12.099.

[26] Y. Zhang, Y. Yu, and B. Zou, “Analyzing public awareness and acceptance of alternative fuel vehicles in China: The case of EV,” *Energy Policy*, vol. 39, no. 11, pp. 7015–7024, Sep. 2011, doi: 10.1016/j.enpol.2011.07.055.

[27] A.M. Peters, E. Van Der Werff, and L. Steg, “Beyond purchasing: Electric vehicle adoption motivation and consistent sustainable energy behaviour in The Netherlands,” *Energy Research & Social Science*, vol. 39, pp. 234–247, Dec. 2017, doi: 10.1016/j.erss.2017.10.008.

[28] S. Hasan, “Assessment of electric vehicle repurchase intention: A survey-based study on the Norwegian EV market,” *Transportation Research Interdisciplinary Perspectives*, vol. 11, p. 100439, Sep. 2021, doi: 10.1016/j.trip.2021.100439.

[29] P. Jabbari, W. Chernicoff, and D. Mackenzie, "Analysis of Electric Vehicle Purchaser Satisfaction and Rejection Reasons," *Transportation Research Record: Journal of the Transportation Research Board*, vol. 2628, no. 12, pp. 1-6, Jan. 2017, doi: 10.3141/2628-12.

[30] E. Haj Abotalebi, "Understanding the preferences and suitability of consumers for electric vehicle adoption in Canada," PhD thesis, School of Geography and Earth Sciences, McMaster University, Hamilton, ON, Canada, 2018.

[31] F. Mandys, "Electric vehicles and consumer choices," *Renewable and Sustainable Energy Reviews*, vol. 135, p. 110874, May 2021, doi: 10.1016/j.rser.2021.110874.

[32] H. Shin, Z. A. Farkas, and A. Nickkar, "An analysis of attributes of electric vehicle owners’ travel and purchasing behavior: The case of Maryland," *2019 International Conference on Transportation and Development*, New Orleans, LA, USA, 2019, pp. 77-85, doi: 10.1061/9780784482582.008.

[33] T. Palit, A. B. M. M. Bari, and C. L. Karmaker, “An integrated Principal Component Analysis and Interpretive Structural Modeling approach for electric vehicle adoption decisions in sustainable transportation systems,” *Decision Analytics Journal*, vol. 4, p. 100119, Sep. 2022, doi: 10.1016/j.dajour.2022.100119.

[34] M. H. Limon, B. Debnath, and A. B. M. M. Bari, “Exploration of the drivers influencing the growth of hybrid electric vehicle adoption in the emerging economies: Implications towards sustainability and low-carbon economy,” *Sustainable Operations and Computers*, vol. 4, pp. 76–87, Jan. 2023, doi: 10.1016/j.susoc.2023.04.002.

[35] T. K. Nath, S. Nath, A. Paul, and T. K. Baul, “Factors affecting consumers’ preference for private electric vehicles in Bangladesh: Policy implications for adoption,” *Research Square (Research Square),* Jul. 2024, doi: 10.21203/rs.3.rs-4706474/v1.

[36] A.I. Munir, I. M. Chowdhury, and T. R. Khan, "Understanding the perception and attitude toward electric vehicles among young citizens of Bangladesh," *2024*. [Preprint]. Available: https://www.researchgate.net/publication/381407521.

[37] A.Das, S. A. Taher, and M. A. Salam, "A study on development trend of Tejgaon industrial area," B.Sc. thesis, Dept. of Urban and Regional Planning, Bangladesh Univ. of Eng. and Tech. (BUET), Dhaka, Bangladesh, Sep. 2015.

[38] L. C. Dinis, "Exploring electric vehicles attributes and users' satisfaction based on driving experience," Master's thesis, Católica Porto Business School, Porto, Portugal, Mar. 2021.

[39] "MG ZS EV car price in Bangladesh," *Car Price*, [Online]. Available: https://www.ccarprice.com/bd/mg-zs-ev-car-price-in-bangladesh-510. [Accessed: Sep. 27, 2024].

[40] "Toyota Premio FL Pearl 2019," *Toyota Bangladesh*, [Online]. Available: https://toyotabd.com/product/premio-fl-pearl-2019/. [Accessed: Sep. 27, 2024].

[41] "MG ZS EV," *MG UK*, [Online]. Available: https://www.mg.co.uk/new-cars/mg-zs-ev?fbclid=IwZXh0bgNhZW0CMTEAAR38Kie-5Fl7U7aBtQkRaj9HcSG3nOzxCoFhjanMf4i3A4cOgdzeWRI96GI_aem_yeudMnXMd52LJAn00NnS9w#:~:text=*%20Range%20applies%20to%20MG%20ZS,(17.8%20kWh%2F100km). [Accessed: Sep. 27, 2024].

[42] "DHAKA, Feb 29, 2024," *BSS News*, [Online]. Available: https://www.bssnews.net/news-flash/176172#:~:text=DHAKA%2C%20Feb%2029%2C%202024%. [Accessed: Sep. 27, 2024].

[43] "Toyota Mark X vs Premio Comparison," *Be Forward Blog*, [Online]. Available: https://blog.beforward.jp/car-comparison/toyota-mark-x-vs-premio-comparison.html?fbclid=IwZXh0bgNhZW0CMTEAAR0c0rZwgyMAaDt0tJNgTYakDqhTFT3HyKnsHeVLrGG5RjSevA5p-ctY7jI_aem_enksnnQpZRN5iWzDkLrroQ#:~:text=in%20your%20browser.-,Fuel%20Consumption,for%20the%202.0%2Dliter%20engine. [Accessed: Sep. 27, 2024].

[44] "Gasoline prices in Bangladesh," *Global Petrol Prices*, [Online]. Available: https://www.globalpetrolprices.com/Bangladesh/gasoline_prices/?fbclid=IwZXh0bgNhZW0CMTEAAR1WJX4OOwV_r6ds_oVJJLR-77qikq2IbmRo8010CMtY3t1n-_eYYuBbVZ0_aem_TARGTGO7QFOqF7u93XD63g. [Accessed: Sep. 27, 2024].

[45] "Battery electric vehicles have lower scheduled maintenance costs than other light-duty vehicles," *U.S. Department of Energy*, [Online]. Available: https://www.energy.gov/eere/vehicles/articles/fotw-1190-june-14-2021-battery-electric-vehicles-have-lower-scheduled?fbclid=IwZXh0bgNhZW0CMTEAAR2bSnoSm6UC17Ugg4Dv_UP7lpal7_qPo7rbA-fdOk2wKZ0iYdIFJrmo1fo_aem_9_9h4i7wCTDrXJYSZrRmpw. [Accessed: Sep. 27, 2024].

[46] "Electric car battery replacement cost in India," *E-Vehicle Info*, [Online]. Available: https://e-vehicleinfo.com/electric-car-battery-replacement-cost-in-india/. [Accessed: Sep. 27, 2024].

[47] "Do electric cars depreciate faster?" *EV-Lectron*, [Online]. Available: https://ev-lectron.com/blogs/blog/do-electric-cars-depreciate-faster?srsltid=AfmBOoqNLvEKH-lOeugjiSU8cUAM_Yrsr8O4h694ciFYVa2yKsu9t13k&fbclid=IwZXh0bgNhZW0CMTEAAR3bFNElPzgWimHF1v_TDY4-5ne0z5nqdNqmmwjeZVPFRRaVm-wdzvYJ8eg_aem_75hz1gxlatIDQwAKeCNg7g. [Accessed: Sep. 27, 2024].

[48] "Toyota Premio F.L Package 1.5," *PakWheels*, [Online]. Available: https://www.pakwheels.com/new-cars/toyota/premio/f-l-package-1-5/?fbclid=IwZXh0bgNhZW0CMTEAAR22Sd0FBUG_eSBjfBelJGsd7QrzGzjdhWBAMwcaL3EMylThX3ipe9BAgQ8_aem__fk6HGhMUAHnitDsBhm6aQ#:~:text=What%20is%20the%20Fuel%20Tank,tank%20capacity%20of%2060%20Liters. [Accessed: Sep. 27, 2024].

[49] B.Propfe, M. Redelbach, D. J. Santini, and H. Friedrich, "Cost analysis of Plug-in Hybrid Electric Vehicles including maintenance & repair costs and resale values," *EVS26 International Battery, Hybrid and Fuel Cell Electric Vehicle Symposium*, Los Angeles, CA, USA, May 6-9, 2012.

[50] Y. Gu, A. R. Hole, and S. Knox, “Fitting the generalized multinomial Logit model in Stata,” *The Stata Journal Promoting Communications on Statistics and Stata*, vol. 13, no. 2, pp. 382–397, Jul. 2013, doi: 10.1177/1536867x1301300213.

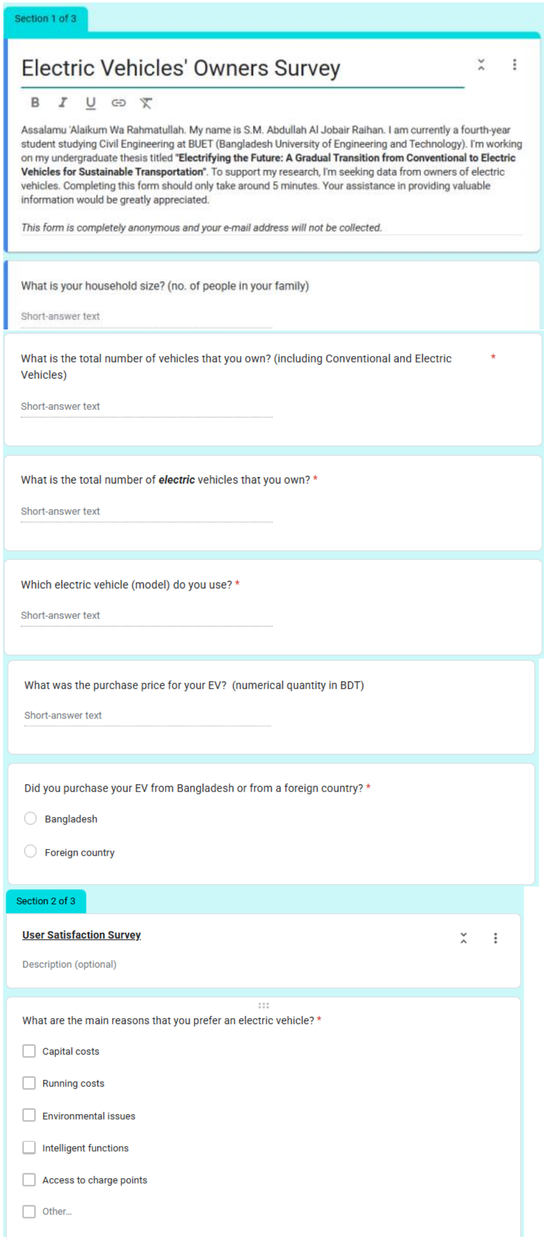
[51] M. G. Karlaftis and E. I. Vlahogianni, “Statistical methods versus neural networks in transportation research: Differences, similarities and some insights,” *Transportation Research Part C Emerging Technologies*, vol. 19, no. 3, pp. 387–399, Dec. 2010, doi: 10.1016/j.trc.2010.10.004.

[52] D. Hess, "The effects of free parking on commuter mode choice: Evidence from travel diary data," *The Ralph and Goldy Lewis Center for Regional Policy Studies*, UCLA, 2001.

[53] Bangladesh Road Transport Authority, "Transport regulation 2024," *Bangladesh Road Transport Authority*, Feb. 13, 2024. [Online]. Available: https://brta.gov.bd/sites/default/files/files/brta.portal.gov.bd/page/6d849ccb_09aa_4fbe_aef2_3d254a2a0cd1/2024-02-13-06-58-00a465ab52ef0d35a090ca0610ebb75f.pdf. [Accessed: Mar. 16, 2025].

APPENDIX

APPENDIX A: EV OWNERS' SURVEY FORM



Section 1 of 3

Electric Vehicles' Owners Survey

Assalamu 'Alaikum Wa Rahmatullah. My name is S.M. Abdullah Al Jobair Raihan. I am currently a fourth-year student studying Civil Engineering at BUET (Bangladesh University of Engineering and Technology). I'm working on my undergraduate thesis titled **"Electrifying the Future: A Gradual Transition from Conventional to Electric Vehicles for Sustainable Transportation"**. To support my research, I'm seeking data from owners of electric vehicles. Completing this form should only take around 5 minutes. Your assistance in providing valuable information would be greatly appreciated.

This form is completely anonymous and your e-mail address will not be collected.

What is your household size? (no. of people in your family)

Short-answer text

What is the total number of vehicles that you own? (including Conventional and Electric Vehicles) *

Short-answer text

What is the total number of ***electric*** vehicles that you own? *

Short-answer text

Which electric vehicle (model) do you use? *

Short-answer text

What was the purchase price for your EV? (numerical quantity in BDT)

Short-answer text

Did you purchase your EV from Bangladesh or from a foreign country? *

Bangladesh

Foreign country

Section 2 of 3

User Satisfaction Survey

Description (optional)

What are the main reasons that you prefer an electric vehicle? *

Capital costs

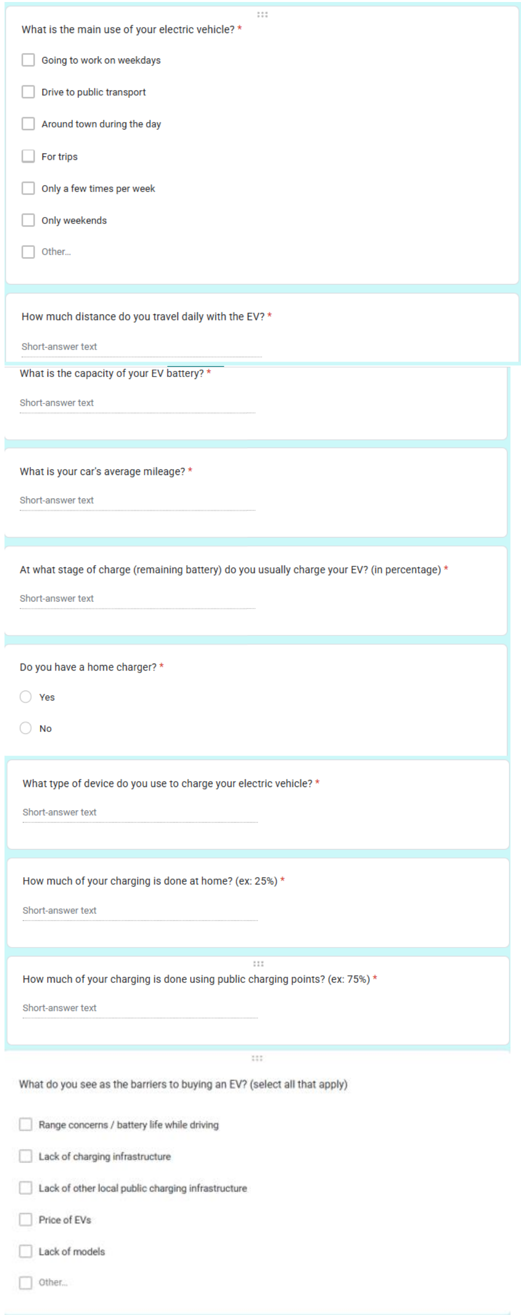
Running costs

Environmental issues

Intelligent functions

Access to charge points

Other...



What is the main use of your electric vehicle? *

Going to work on weekdays

Drive to public transport

Around town during the day

For trips

Only a few times per week

Only weekends

Other...

How much distance do you travel daily with the EV? *

Short-answer text

What is the capacity of your EV battery? *

Short-answer text

What is your car's average mileage? *

Short-answer text

At what stage of charge (remaining battery) do you usually charge your EV? (in percentage) *

Short-answer text

Do you have a home charger? *

Yes

No

What type of device do you use to charge your electric vehicle? *

Short-answer text

How much of your charging is done at home? (ex: 25%) *

Short-answer text

How much of your charging is done using public charging points? (ex: 75%) *

Short-answer text

What do you see as the barriers to buying an EV? (select all that apply)

Range concerns / battery life while driving

Lack of charging infrastructure

Lack of other local public charging infrastructure

Price of EVs

Lack of models

Other...

Do you think there are enough public charging points? *

- Yes
- No

Rate the public charging network: (1 for very bad to 5 for very good) *

1	2	3	4	5
○	○	○	○	○

How often do you charge your electric vehicle? *

- Every day
- Once a week
- A few times a week
- Once a month
- A few times a month

Rate you satisfaction based on the following factors with a score between 1 and 5. (Higher score will indicate greater satisfaction)

	1	2	3	4	5
Charging conv...	○	○	○	○	○
Cruising range	○	○	○	○	○
Economic bene...	○	○	○	○	○
Battery life	○	○	○	○	○
Low emission	○	○	○	○	○
Low noise	○	○	○	○	○
Performance	○	○	○	○	○

Do you think electric vehicles are well promoted to the public? *

- Yes
- No

How could it be improved? *

Long-answer text

Do you have any intention to repurchase EVs if needed?

- Yes
- No
- Maybe

Rate your recommendation of EV to others in a scale of 1 to 5.

	1	2	3	4	5	
Totally disagree	○	○	○	○	○	Totally agree

Section 3 of 3

Personal Information

Description (optional)

What is your age? *

Short-answer text

What is your gender? *

- Male
- Female

What is your current job? *

Short-answer text

What is your monthly household income? (numerical quantity in BDT)

Short-answer text

APPENDIX B: STATED PREFERENCE SURVEY FORM

You have chosen one of the two cars. *

Now please rate the importance of the following factors **you considered** when choosing between these two cars, from 1 (least important) to 5 (most important).

	1	2	3	4	5
Purchase Cost	○	○	○	○	○
Operating Cost	○	○	○	○	○
Maintenance ...	○	○	○	○	○
Resale Value	○	○	○	○	○
Driving Range	○	○	○	○	○
Availability of ...	○	○	○	○	○
Quick Acceler...	○	○	○	○	○
Smooth Ridin...	○	○	○	○	○
Interior Space	○	○	○	○	○
Noise Level	○	○	○	○	○
Environmenta...	○	○	○	○	○

Section 1 of 6

Stated Preference Survey for Vehicle Option Selection

আসসলামু আলাইকুম ওয়া রহমাতুল্লাহ। আমি *এস. এম. আব্দুল্লাহ আল জুবাইর রায়হান*, বাংলাদেশ প্রকৌশল বিশ্ববিদ্যালয়ের পুরকৌশল বিভাগের চতুর্থ বর্ষের শিক্ষার্থী। আমি বর্তমানে আমার Undergraduate Thesis এর কাজ করছি যার শিরোনাম হল: **Electrifying the Future: A Gradual Transition from Conventional to Electric Vehicles for Sustainable Transportation in Bangladesh.**

Thesis এর জন্য এই Survey form টি প্রস্তুত করা হয়েছে। এই ফর্মটি পূরণ করতে সর্বোচ্চ পাঁচ মিনিটের মতো সময়ের প্রয়োজন হতে পারে। আপনার মতামত প্রকাশের জন্য আপনাকে আন্তরিক ধন্যবাদ।

ফর্মে আপনার পরিচয় সম্পূর্ণ গোপনীয় থাকবে এবং আপনার ই-মেইল অ্যাড্রেস সংগ্রহ করা হবে না।

Section 2 of 6

Preference Survey

Description (optional)

নিচে দুইটি গাড়ির মডেল এবং সংশ্লিষ্ট তথ্যাদি উল্লেখ করা হয়েছে। পরবর্তী প্রশ্নগুলোর উত্তর দেয়ার পূর্বে একনজর চোখ বুলিয়ে নিন।

ছবি স্পষ্ট বোঝা না গেলে ব্রাউজার থেকে Zoom করুন।

	MG ZS EV MCE Long Range 2023	Toyota Premio FL 2019 Silver
Type	Fully electric	Fully fuel-based
Purchase Cost	59,18,000/-	38,00,000/-
Operating Cost (per 100 km)	2.14 Tk	807 Tk
Maintenance Cost	4.53 Tk/km + Battery replacement cost[1]: 8,80,000 to 13,20,000 BDT (8 years warranty)	7.5 Tk/km
Resale Value (after 3 years)	48%	60.9%
Driving Range[2]	440 km	900 km
Emissions	0 g/km	95 g/km CO_2
Charging/ Fueling Station	Only 3 (total) at Dhaka, Chittagong and Cox's Bazar at present, more will be available in the future	Available everywhere in the country

[1] *After 8 years, the battery of electric vehicle may need to be replaced with the cost shown in the table.*
[2] *The **driving range** refers to the maximum distance a vehicle can travel on a single full charge or a full tank of fuel.*

লক্ষণীয়

টেবিলে দেয়া তথ্য অনুযায়ী যদিও Electric গাড়ি (EV) এর Operating এবং Maintenance cost Fuel-based গাড়ি (ICE) এর চেয়ে কম, ১০ বছর চালানোর পর EV এর সর্বমোট খরচই বেশি হবে।

কিন্তু EV তে রয়েছে বেশকিছু গুরুত্বপূর্ণ ফিচার:

- দ্রুত accelerate করতে পারে
- Smooth riding
- গাড়ির অভ্যন্তরে জায়গা বেশি, তাই অধিক আরামদায়ক
- Noise খুবই কম
- সবচেয়ে গুরুত্বপূর্ণ পয়েন্ট: EV পরিবেশবান্ধব, এবং চলার সময় কোনো কার্বন বা বিষাক্ত গ্যাস নিঃসরণ হয় না।

Which car would you prefer? *

○ MG ZS EV MCE Long Range 2023

○ Toyota Premio FL 2019 Silver

Section 3 of 6

TWO MORE OPTIONS FOR YOU!

যেহেতু আপনি EV (Electric Vehicle) কে ICE (Internal Combustion Engine) বা ফুয়েল-চালিত গাড়ির উপর Choose করেছেন, ফর্মের এই সেকশনে খরচের দিক দিয়ে সাশ্রয়ী, তবে তুলনামূলক কম পরিবেশবান্ধব দুইটি অপশন আপনার সামনে উপস্থাপন করা হল।

Option 1:

PHEV (Plug-in Hybrid Electric Vehicle) হচ্ছে এমন গাড়ি যাকে ব্যাটারির চার্জ এবং ফুয়েল উভয় দিয়ে চালানো সম্ভব। এই গাড়িতে ব্যাটারিকে বাইরে থেকে আলাদাভাবে চার্জ করা যায়।

Option 2:

HEV (Hybrid Electric Vehicle) এ ফুয়েলের ট্যাংকের পাশাপাশি ব্যাটারি থাকে, কিন্তু তাকে বাইরে থেকে আলাদাভাবে চার্জ করা যায় না। গাড়ি ব্রেক করার সময় Kinetic energy কে Electrical energy তে রূপান্তর করে এবং পরবর্তীতে ব্যবহারের জন্য শক্তিকে ব্যাটারিতে সংরক্ষণ করে রাখে।

	Toyota Crown Sport PHEV 2024	2024 Lexus Ux 250h Hybrid
Type	Plug-in Hybrid	Hybrid
Purchase Cost	58,19,000/-	40,13,900/-

Cost and Other Factors Comparison:
(sometimes may vary from the list below because of difference in brands and models)

1. **Purchase Cost**: ICE < HEV < PHEV < EV
2. **Operating Cost**: EV < HEV < PHEV < ICE
3. **Maintenance Cost**: EV < HEV < PHEV < ICE
4. **Driving Range**: EV < PHEV < HEV < ICE
5. **Emissions**: EV < PHEV < HEV < ICE

Resale Value

In the article https://doi.org/10.3390/wevj5040886,

The hierarchy of resale values appears to be as follows:

- **ICE<HEV**
- **EV<PHEV**

However, **in future**, due to technological advancement, the sequence might be: **ICE < HEV < PHEV < EV.**

After you've learned about PHEVs and HEVs, which options would you prefer now? *

○ I'll stick to EVs

○ I'll switch to PHEV

○ I'll switch to HEV

Section 4 of 6

TWO MORE OPTIONS FOR YOU!

যেহেতু আপনি ICE (Internal Combustion Engine) বা ফুয়েল-চালিত গাড়িকে EV (Electric Vehicle) এর উপর Choose করেছেন, ফর্মের এই সেকশনে খরচের দিক দিয়ে অধিক পরিবেশবান্ধব, তবে তুলনামূলক/কিছুটা ব্যয়বহুল দুইটি অপশন আপনার সামনে উপস্থাপন করা হল।

Option 1:

PHEV (Plug-in Hybrid Electric Vehicle) হচ্ছে এমন গাড়ি যাকে ব্যাটারি চার্জ এবং ফুয়েল উভয় দিয়ে চালানো সম্ভব। এই গাড়িতে ব্যাটারিকে বাইরে থেকে আলাদাভাবে চার্জ করা যায়।

Option 2:

HEV (Hybrid Electric Vehicle) এ ফুয়েলের ট্যাংকের পাশাপাশি ব্যাটারি থাকে, কিন্তু তাকে বাইরে থেকে আলাদাভাবে চার্জ করা যায় না। গাড়ি ব্রেক করার সময় Kinetic energy কে Electrical energy তে রূপান্তর করে এবং পরবর্তীতে ব্যবহারের জন্য শক্তিকে ব্যাটারিতে সংরক্ষণ করে রাখে।

		
	2024 Lexus Ux 250h Hybrid	**Toyota Crown Sport PHEV 2024**
Type	Hybrid	Plug-in Hybrid
Purchase Cost	40,13,900/-	58,19,000/-

Cost and Other Factors Comparison:
(sometimes may vary from the list below because of difference in brands and models)

1. **Purchase Cost**: ICE < HEV < PHEV < EV
2. **Operating Cost**: EV < HEV < PHEV < ICE
3. **Maintenance Cost**: EV < HEV < PHEV < ICE
4. **Driving Range**: EV < PHEV < HEV < ICE
5. **Emissions**: EV < PHEV < HEV < ICE

Resale Value

In the article https://doi.org/10.3390/wevj5040886,

The hierarchy of resale values appears to be as follows:

- **ICE<HEV**
- **EV<PHEV**

However, **in future**, due to technological advancement, the sequence might be: **ICE < HEV < PHEV < EV.**

After you've learned about PHEVs and HEVs, which options would you prefer now? *

- I'll stick to ICEs
- I'll switch to HEV
- I'll switch to PHEV

Section 5 of 6

Your Opinion on EVs' current condition in Bangladesh

(সর্বশেষ সেকশন)

বাংলাদেশে EV এসেছে বছর দেড়-দুয়েক আগে। সবমিলিয়ে দেড়শ EV ও বাংলাদেশে বিক্রি হয়নি। অথচ বাংলাদেশ সরকারের লক্ষ্য ২০৩০ সালের মধ্যে EV Adoption যেন ৩০% হয়।

Rate the following statements. *

	Strongly Disgr...	Disgree	Neutral	Agree	Strongly Agree
I have been he...	○	○	○	○	○
I have sufficien...	○	○	○	○	○
I believe that E...	○	○	○	○	○
I believe EVs w...	○	○	○	○	○

What are the potential barriers to EV adoption in Bangladesh in your opinion? *

- Insufficient Charging Infrastructure
- High Price of EVs
- Relatively Lower Driving Range
- Inadequate Policy Framework
- Lack of Incentives (e.g. Reduction of Import Duty)
- Limited Awareness among the Public
- Other...

Section 6 of 6

Personal Information

Description (optional)

What is your age? *

- Under 18
- 18 - 30
- 31 - 45
- 46 - 60
- 60+

What is your gender? *

- Male
- Female

What is your family income per month? (Tk) *

- Up to 50,000
- 51,000 to 1,00,000
- 1,01,000 to 1,50,000
- 1,51,000 to 2,00,000
- >2,01,000

What is the number of people in your family? *

Short-answer text

What is your educational qualification? *

- High school
- Undergraduate (Bachelor's Degree)
- Master's Degree
- PhD
- Other...

What do you do? *

- I am a student
- I am not a student but unemployed
- I am currently in a job
- I am retired from my job

What type of vehicle do you currently own? *

- BEV (Battery Electric Vehicle)
- HEV (Hybrid Electric Vehicle)
- PHEV (Plug-in Hybrid Electric Vehicle)
- ICE (Internal Combustion Engine) Vehicle
- None

APPENDIX C: PYTHON CODE FOR TRAINING MODEL

Step 1: import the packages

```
import pandas as pd
import biogeme.database as db
import biogeme.biogeme as bio
import biogeme.models as models
import biogeme.version as ver
from biogeme.expressions import Beta
```

Check the version of Biogeme

```
ver.get_version()
```

Step 2: prepare the data

```
df = pd.read_csv('Final text file 70.txt', sep='\t'
df
```

```
df.describe()
```

```
database = db.Database("Final text file 70.txt", df)
```

Define the name of the variables as Python variables

```
globals().update(database.variables)
```

Model specification

Parameters to be estimated

```
ASC_EV = Beta('ASC_EV', 0, None, None, 0)
ASC_ICE = Beta('ASC_ICE', 0, None, None, 0)
B_EQ_EV = Beta('B_EQ_EV', 0, None, None, 0)
B_EQ_ICE = Beta('B_EQ_ICE', 0, None, None, 0)
B_OCCUP_STU_EV = Beta('B_OCCUP_STU_EV', 0, None, None, 0)
B_OCCUP_STU_ICE = Beta('B_OCCUP_STU_ICE', 0, None, None, 0)
B_OCCUP_JOB_EV = Beta('B_OCCUP_JOB_EV', 0, None, None, 0)
B_OCCUP_JOB_ICE = Beta('B_OCCUP_JOB_ICE', 0, None, None, 0)
B_PURCHASE_COST_EV = Beta('B_PURCHASE_COST_EV', 0, None, None, 0)
B_PURCHASE_COST_ICE = Beta('B_PURCHASE_COST_ICE', 0, None, None, 0)
B_OPERATING_COST_EV = Beta('B_OPERATING_COST_EV', 0, None, None, 0)
B_OPERATING_COST_ICE = Beta('B_OPERATING_COST_ICE', 0, None, None, 0)
B_MAINTENANCE_COST_EV = Beta('B_MAINTENANCE_COST_EV', 0, None, None, 0)
B_MAINTENANCE_COST_ICE = Beta('B_MAINTENANCE_COST_ICE', 0, None, None, 0
B_RESALE_VALUE_EV = Beta('B_RESALE_VALUE_EV', 0, None, None, 0)
B_RESALE_VALUE_ICE = Beta('B_RESALE_VALUE_ICE', 0, None, None, 0)
B_AVAIL_CHAGE_FUEL_EV = Beta('B_AVAIL_CHAGE_FUEL_EV', 0, None, None, 0)
B_AVAIL_CHAGE_FUEL_ICE = Beta('B_AVAIL_CHAGE_FUEL_ICE', 0, None, None, 0)
B_ENVIRONMENTAL_PROTECTION_EV = Beta('B_ENVIRONMENTAL_PROTECTION_EV', 0, None, None, 0)
B_ENVIRONMENTAL_PROTECTION_ICE = Beta('B_ENVIRONMENTAL_PROTECTION_ICE', 0, None, None, 0)
B_SUSTAIN_EV_EV = Beta('B_SUSTAIN_EV_EV', 0, None, None, 0)
B_SUSTAIN_EV_ICE = Beta('B_SUSTAIN_EV_ICE', 0, None, None, 0)
```

Specification of the utility functions

```
V1 = ASC_EV + \
     B_EQ_EV * EQ + \
     B_OCCUP_STU_EV * OCCUP_STU + \
     B_OCCUP_JOB_EV * OCCUP_JOB + \
     B_PURCHASE_COST_EV * PURCHASE_COST + \
     B_OPERATING_COST_EV * OPERATING_COST + \
     B_MAINTENANCE_COST_EV * MAINTENANCE_COST + \
     B_RESALE_VALUE_EV * RESALE_VALUE + \
     B_AVAIL_CHAGE_FUEL_EV * AVAIL_CHAGE_FUEL + \
     B_ENVIRONMENTAL_PROTECTION_EV * ENVIRONMENTAL_PROTECTION + \
     B_SUSTAIN_EV_EV * SUSTAIN_EV

V2 = ASC_ICE + \
     B_EQ_ICE * EQ + \
     B_OCCUP_STU_ICE * OCCUP_STU + \
     B_OCCUP_JOB_ICE * OCCUP_JOB + \
     B_PURCHASE_COST_ICE * PURCHASE_COST + \
     B_OPERATING_COST_ICE * OPERATING_COST + \
     B_MAINTENANCE_COST_ICE * MAINTENANCE_COST + \
     B_RESALE_VALUE_ICE * RESALE_VALUE + \
     B_AVAIL_CHAGE_FUEL_ICE * AVAIL_CHAGE_FUEL + \
     B_ENVIRONMENTAL_PROTECTION_ICE * ENVIRONMENTAL_PROTECTION + \
     B_SUSTAIN_EV_ICE * SUSTAIN_EV
```

Associate the utility functions with the numbering of the alternatives

```
V = {1: V1 ,
     2: V2}
```

Associate the availability conditions with the alternatives

```
av = {1: EV_AV ,
      2: ICE_AV}
```

The contribution to the log likelihood function is the logarithm of a logit model

```
logprob = models.loglogit (V, av, CHOICE)
```

Biogeme

```
biogeme = bio.BIOGEME(database, logprob)
biogeme.modelName = 'Thesis 17 Train'
```

Running the estimation

```
results = biogeme.estimate()
```

Read the results

```
pandasResults = results.get_estimated_parameters()
pandasResults
```

```
print(results)
```