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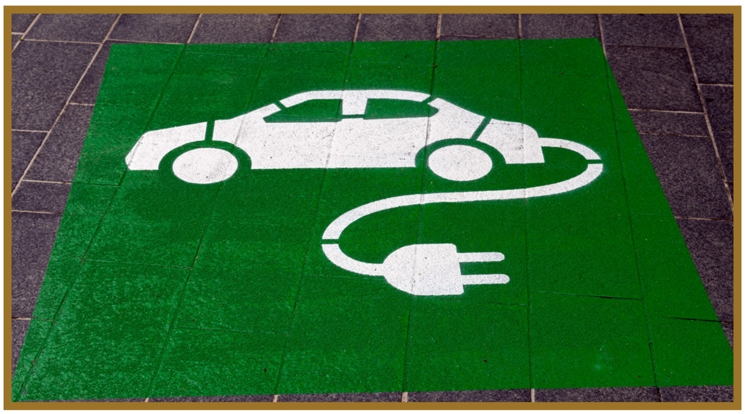
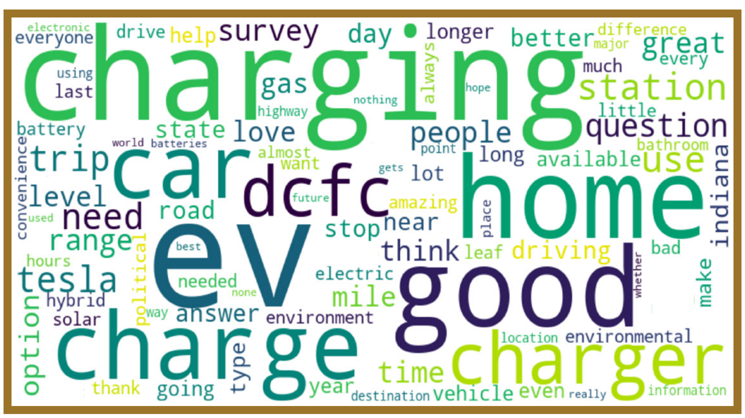
Electric Vehicles: Public Perceptions, Expectations, and Willingness-to-Pay





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NOTICE

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16. Abstract

The primary objective of this project was to understand Indiana resident's perspectives on electric vehicles (EVs), including adoption incentives and barriers, awareness of adoption incentives, charging preferences, and general travel patterns. A secondary objective was to establish a framework for identifying EV users, detailing their trips, and generating predictions for EV adoption and usage. To achieve these objectives, a stated preference survey was conducted with 1,217 Indiana residents. Two datasets containing travel behavior data were incorporated to generate synthetic data. The survey results revealed that Indiana EV users are typically middle-aged males living and working in urban areas. EV users tend to drive more frequently than non-EV users and prefer owning EVs over leasing them. They consider home charging as a vital component of EV usage. Non-EV users identified purchase price and charging issues as the main barriers to adoption and are generally unaware of charging incentives. They are also less inclined to use public charging facilities due to their perceived unreliability. EV trips are usually short distance. The generated synthetic dataset aligned with real-world data, predicting future EV demand for the next 8 years. Under an optimistic scenario, the number of EVs could increase by 18 times above the 2023 levels. Under a pessimistic scenario, it could double. This project supports INDOT, and other stakeholders prepare for the increased EV usage resulting from the deployment of charging stations. To foster EV adoption, it is recommended to better promote EV incentives, develop workforce programs focused on used EVs, and provide segmented education about public charging infrastructure.

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EXECUTIVE SUMMARY

Introduction

Indiana will receive approximately 100 million dollars from the federal government to build electric vehicle (EVs) charging stations by 2026. This investment is anticipated to accelerate EV adoption in the state, but the public perceptions of EVs for both EV users and non-EV users was unknown. The objective of this project aims was to inform INDOT on the following topics.

1. The adoption, incentives, and barriers to EV use in Indiana.
2. Public charging preferences among different groups and their willingness-to-pay (WTP) for different charging types.
3. Trip information for EV users and future EV demand predictions.

To achieve these goals, an online stated preference survey of Indiana adult residents was conducted, and a total of 1,217 valid responses were collected.

Findings

- Indiana EV users are predominantly male, middle age, high income, live and work in urban areas, and identify as Democrats. Generally, the EV is the most used car in their household, and EV users have a positive feeling about their vehicles. Tesla is the most common EV brand in Indiana, followed by Chevrolet, Kia, and Nissan. Most of the EV users own their vehicle instead of leasing it.
- Non-EV users are more likely to adopt an EV in the long term than in the short term. Their likelihood to purchase an EV increases over time, while the likelihood to lease one remains constant.
- Most survey respondents prefer used EVs due to their lower cost and are apprehensive about investing in a technology they are not familiar with. However, participants who prefer a new EV attribute it to the better performance of new EVs and their general inclination to buy new vehicles independent of the engine type.
- Incentives related to the purchase of EVs are more recognizable than the ones related to charging. Almost half of the sample agree that EV incentives would make them more willing to adopt an EV.
- The main barriers pointed out by non-EV users to not having an EV is the purchase price, access to home charging, and the inconvenience of charging.
- Non-EV users are less aware of charging technologies, prefer shorter driving distances to charge, and are less inclined to use public charging stations.
- Home charging is a vital component for EV users. Conversely, non-EV users appear to have more range anxiety, which greatly affects their willingness to use EVs for trips.
- EV users are more likely to choose direct current fast charging (DCFC), followed by DWPT and Level 2 charging. Non-EV users prefer Level 2, DCFC, and DWPT, in this order.
- EV users are willing to pay around \$9.44 (median) and \$2.93 (mean) per hour to reduce waiting times at Level 2 charging stations, while non-EV users are willing to pay approximately \$86.97 (median) and \$20.72 (mean) per hour to reduce it. For reducing charging time at DCFC stations, EV users' WTP is estimated at \$21.73 (median) and \$6.73 (mean) per hour, while non-EV users are willing to pay \$30.04 (median) and \$7.16 (mean) per hour. Finally, non-EV users expressed a WTP of an extra \$4.10 (median) and \$0.98 (mean) for amenities, such as restrooms, at DCFC stations.
- EV trips were found to be predominantly concentrated in urban areas or along highways. Of these trips, 50% were short distance and related to retail and catering.
- The generated synthetic dataset aligned with real-world data, predicting future EV demand for the next 8 years. In optimistic scenarios, the number of EVs increases by 18 times the 2023 levels, while in pessimistic scenarios, it doubled.

Implementation

This project prepares INDOT and other stakeholders for the increased EV adoption that will follow the deployment of charging stations across the state. The EV demand prediction provides several future scenarios of EV adoption in Indiana. To foster EV adoption, promotion of EV incentives, particularly those related to charging, are strongly recommended. Additionally, test drive and EV ride programs can address some barriers to EV adoption, such as lack of familiarity with the technology. Workforce programs focused on used EVs may become necessary due to the expected increase in demand for these vehicles in the future.

Charging stations should not be restricted to deployment; they should also focus on increasing the number of charger ports. This strategy has the potential to reduce range anxiety and queueing time. Furthermore, amenities at public charging stations can make them more appealing to drivers and their passengers. Segmented education about the different charging technologies is also recommended, especially if DWPT options emerge. Lastly, the synthetic dataset provides impact simulations of various policy adjustments or incentives on EV adoption rates. By understanding how changes in policies (such as increased subsidies, tax incentives, or expanded charging infrastructure) influence user behavior, INDOT, policymakers and EV stakeholders can make data-driven decisions to optimize the impact of these investments across Indiana.

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LIST OF ACRONYMS

ACS	American Community Survey
BEV	Battery Electric Vehicle
BMV	Bureau of Motor Vehicles
DC	Direct Current
DCFC	Direct Current Fast Charging
DWPT	Dynamic Wireless Power Transfer
EV	Electric Vehicle
GPS	Global Positioning System
GV	Gasoline Vehicle
HEV	Hybrid Electric Vehicle
ICEV	Internal Combustion Engine Vehicle
INDOT	Indiana Department of Transportation
NEVI	National Electric Vehicle Infrastructure
NHTS	National Household Travel Survey
PHEV	Plug-in Hybrid Electric Vehicle
POI	Point of Interest
SoC	State of Charge
U.S.	United States
VMT	Vehicle Miles Traveled
WTP	Willingness-to-Pay

1. INTRODUCTION

1.1 Study Overview

The United States (U.S.) government, through the Infrastructure Investment and Jobs Act, set the goal to have at least half of the new vehicles sold in 2030 being zero-emissions, which includes electric vehicles (EVs). The Indiana Department of Transportation (INDOT) plans to invest approximately $100 million to construct an EV charging infrastructure strategically positioned along Indiana's interstates and highways. This massive investment will increase EV utilization over the next years throughout the state. In this context, this study conducted a stated preference survey to better understand Indiana residents' public perception of EVs, the main incentives and barriers related to EV adoption, travel patterns and charging preferences. Additionally, cell phone data was analyzed to understand demand generation, visitation patterns, and charging needs. The study further assessed WTP for EV public charging technologies, which can offer valuable insights for marketing, resource allocation, infrastructure investment, and policy development.

1.2 Study Objective and Tasks

The objective of this study is twofold—understand the different public perspectives about EVs in Indiana and generate data about EV demand in the state. For this reason, a public opinion survey was designed and conducted to collect data about the perceptions and attitudes of Indiana's residents towards EVs. Also, a novel framework for data generation and fusion is designed to construct reliable synthetic datasets that reflect present and future EV utilization and assess the impact of EVs on the transportation network. Detailed descriptions about the different aspects of EV demand examined in this project are provided below.

1.2.1 EV Adoption: Determinants and Barriers

The survey asked questions related to the adoption of EVs at the time of the data collection and the likelihood of adoption in the future, as well as the respondents' opinions about the main barriers to the widespread utilization of EVs in the state. This information is important for gauging the current EV penetration and future scenarios related to EV use. Additionally, the level of knowledge about incentives was assessed as well as the main reasons for not having an EV.

1.2.2 Public Charging Preferences

The stated choice experiment was designed to investigate public charging preferences. The scenarios presented focused on key factors, including charging price, access time (time required to reach charging station from the current location), waiting time, charging duration (amount of time spent to charge EV), total trip time, initial state of charge (SoC) of the EV, and the availability of amenities.

In each scenario, participants were presented with three alternatives—AC Level 2, DCFC plug-in public charging, and the emerging DWPT charging technology.

1.2.3 Willingness-to-Pay (WTP)

The study also aimed to estimate the value consumers place on specific aspects of the charging experience, the so-called willingness-to-pay. This included factors such as waiting time reduction, charging time reduction, and the availability of amenities at charging stations. Understanding consumers' WTP for these attributes provides valuable insights into their priorities and informs strategic decisions for enhancing public charging infrastructure.

1.2.4 EV Trip Detection and Generation

This study establishes a framework for detecting EV users and their trip details from large-scale, unlabeled cellular data, as well as for generating synthetic sequential EV trips based on the outcomes of this detection process. Daily trip features, such as average trip distance, speed, and acceleration, are used in detection process. Then, the synthetic trip sequence data is constructed based on the detection results and Sequential Generative Adversarial Networks. This task is important for assessing the driving and charging behaviors of EV drivers and generating data for designing strategies to assist EV operations.

1.3 Background

1.3.1 EV Types

EVs are vehicles that use the Electricity stored in their batteries to improve their efficiency (AFDC, n.d.a). The following are the three main types.

Battery Electric Vehicles (BEVs) or Plug-in Electric Vehicles (PEVs): Their battery is charged by plugging the vehicle into the charging equipment, which is an external electrical power source. As these vehicles do not have internal combustion engines, their operation is totally based on the power from their battery packs. Most driving ranges vary between 150 to 400 miles.

Plug-in Hybrid Electric Vehicles (PHEVs): These vehicles have both electric motors, powered by batteries, and a conventional internal combustion engine, which uses gasoline. Usually, the electric power is the first supplier from PHEVs, that switch to the internal combustion engine when the battery is depleted. The batteries, as happens with the BEVs, are charged by an external electrical power source, and allow most PHEVs to travel approximately 20–40 miles operating in all-electric mode.

Hybrid Electric Vehicles (HEVs): Similar to PHEVs, HEVs are operated by an internal combustion engine and use the energy stored in the batteries to provide an additional power when it is needed, such as accelerating

TABLE 1.1
Comparison of EV types

	BEVs	PHEVs	HEVs
Fuel Type	Electricity	Electricity and gasoline	Electricity and gasoline
Electric Power Source	External source	External source	Regenerative braking and gasoline engine
Operation	By the electricity all the time	First by the electricity and, when the batteries are depleted, conventional engine	Mainly by combustion engine. The batteries provide additional power when it is needed (hybrid) or to propel the vehicle in low speed (full hybrid)
Electric Mileage	150−400 miles	20−40 miles	–

and passing (hybrid), or to propel the vehicle at low speed (full hybrid). Differently from PHEVs, their batteries are recharged by regenerative braking and the gasoline engine. Table 1.1 summarizes the provided information.

This project refers to EVs exclusively as the BEV type.

1.3.2 EV Charging Technologies

This section details the following charging methods: stationary plug-in charging, stationary wireless charging, DWPT, and battery swapping.

1.3.2.1 Stationary plug-in charging. The primary approach for charging EVs is stationary plug-in charging. In this process, vehicles are parked at charging stations and connected to an external electrical power source. The characteristics of the charging station, such as the voltage and current type, determine its category. The various categories of charging stations include (AFDC, n.d.b).

Alternating Current Level 1: "Level 1 charging is typically used when there is only a 120 V outlet available, such as while charging at home, but can easily provide charging for most of a driver's needs. For example, 8 hours of charging at 120 V can replenish about 40 miles of electric range for a mid-size EV. As of 2022, less than 1% of public EV charging ports in the U.S. were Level 1. Approximately 5 miles of range per 1 hour of charging assuming 1.9 kW power output."

Alternating Current Level 2: "AC Level 2 equipment (often referred to simply as Level 2) offers charging through 240 V (typical in residential applications) or 208 V (typical in commercial applications) electrical service. Level 2 is commonly used for public and workplace charging—approximately 25 miles of range per 1 hour of charging assuming 2.9 kW to 19.2 kW charging power."

Direct Current Fast Charging (DCFC): "DCFC charging equipment (typically a three-phase AC input) enables rapid charging along heavy traffic corridors at installed stations. As of 2022, more than 20% of public EV charging ports in the U.S. were DC fast chargers. DCFC enables rapid charging of approximately 100 to more than 200 miles of range within 30 minutes of charging assuming 25 kW to 250 kW power output."

1.3.2.2 Stationary wireless charging. Stationary wireless charging for EVs is a technology that enables the charging of EVs without the need for physical cables or plugs. Instead of connecting the vehicle to a charging station via a cable, stationary wireless charging systems use electromagnetic fields to transfer energy from a charging pad on the ground to a receiving pad on the vehicle, as detailed below.

Charging Pad: A charging pad is installed on the ground, typically in a parking spot or designated charging area. This pad is connected to a power source.

Receiving Pad: The electric vehicle is equipped with a receiving pad, usually mounted underneath the vehicle. This pad is designed to capture the electromagnetic energy transmitted by the charging pad.

Inductive Charging: The charging pad generates an alternating electromagnetic field, which induces an alternating current in the receiving pad on the vehicle. This current is then converted into direct current (DC) to charge the vehicle's battery.

Alignment and Efficiency: Proper alignment between the charging pad and receiving pad is crucial for efficient energy transfer. Some systems may include alignment guides or automated alignment mechanisms to ensure optimal positioning.

Safety and Standards: Stationary wireless charging systems adhere to safety standards to minimize electromagnetic interference and ensure safe operation. They may also include features such as automatic shut-off if foreign objects are detected on the charging pad.

In Los Angeles County, the Antelope Valley Transit Authority utilizes inductive systems from wave charging to power its electric bus fleet. The agency operates 15 wave wireless charging stations—one at its headquarters and 14 along its bus routes. Wave has installed over 50 charging pads across North America and received a DOE grant to develop a 500-kilowatt fast charger for trucks. Similarly, Indianapolis uses wireless charging for its electric buses, produced by Chinese EV manufacturer BYD Co. In 2019, the city collaborated with InductEV (formerly Momentum Dynamics Corp.), a Pennsylvania-based charging startup. Brooklyn-based startup Hevo Inc. is partnering with the DOE's Oak Ridge National Laboratory and Stellantis NV to test a 50-kilowatt wireless system on Chrysler Pacifica hybrids. Hevo is also working with Oak Ridge on developing a 300-kilowatt wireless fast charger (Alake, 2024). Additionally, WiTricity and Continental AG are few companies that have strong distribution network outside of U.S. including Europe and Asia (China, Japan, and South Korea).

1.3.2.3 Dynamic wireless power transfer. DWPT technologies enable EVs to be charged as they are driven at highway speeds. This capability will especially benefit medium- and heavy-duty applications. Also, it can address EV adoption barriers (Konstantinou et al., 2021). The deployment of DWPT can alleviate range anxiety, and can substantially reduce an EV's battery size, leading to lower EV purchase costs. Moreover, DWPT can increase productivity by eliminating the waiting period required by stationary charging (Bateman et al., 2018). Amid numerous potential benefits of DWPT, "lab developed, high-power DWPT technologies have not yet been tested under real-world road conditions to understand the practical installation, operation, performance, and maintenance challenges to deployment. In practice, a lack of practical and verified methods of integrating DWPT hardware into different types of roadways without compromising performance and safety and comprehensive data on performance impacts under rigorous operating conditions will need to be addressed to better understand key system and component-level challenges." (Energy.gov, n.d.). Additionally, according to Bateman et al. (2018), the cost of implementing the technology may vary from around the \$900k–\$11M/lane-mile and depend on multiple factors, such as the accessibility to the power network, the type of installation, and materials of the charging infrastructure.

1.3.2.4 Battery swapping. Battery swapping involves replacing depleted batteries in EVs with fully charged ones once they fall below a predetermined SoC level. This concept relies on the use of standardized, interchangeable batteries that can be quickly and easily swapped out at designated stations (Hussain et al., 2024). By doing so, it ensures the continuous operation of EVs without the downtime associated with conventional charging methods. Drivers can pull into a battery-swapping station, where the depleted battery is automatically removed and replaced with a fully charged one, allowing them to resume their journey within minutes. This approach not only extends the driving range of EVs but also addresses concerns related to long charging times, making electric vehicles more convenient and practical for daily use. Constructing battery swapping stations requires substantial investment. To scale these operations, it is essential to implement innovative financing strategies. These could include securitizing EV batteries and adopting flexible revenue-sharing models with investors (London Business School, 2024).

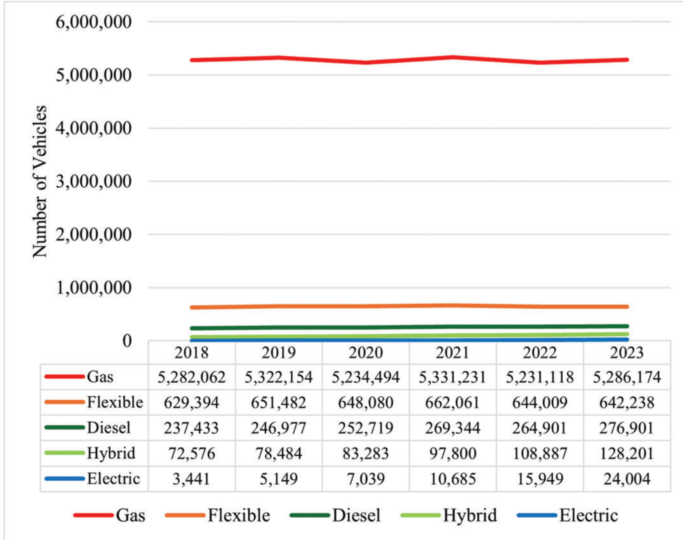
In 2007, Better Place launched one of the first battery-swapping services in California and later expanded to Israel, offering a network of automated stations for a monthly subscription fee. Despite its innovative approach, the company went bankrupt in 2013 after excessive spending with only gaining limited subscribers. Similarly, Tesla experimented with battery-swapping for its Model S in 2013, promising a 90-second swap, but abandoned the project in 2015 due to lukewarm customer interest (London Business School, 2024). In contrast, Chinese EV manufacturer NIO has successfully embraced battery-swapping, leveraging its position as a vehicle maker to ensure seamless integration. Operating under a Battery-as-a-Service (BaaS) model, NIO had 2,217 stations across six markets by November 2023, facilitating nearly 33 million swaps. Recognizing the potential of BaaS, CATL entered the market in 2022 with EVOGO, utilizing its expertise in modular battery design. Meanwhile, San Francisco-based Ample aims to revitalize battery-swapping with five stations launched in 2021 for Uber drivers, capable of swapping batteries for Nissan Leaf and some Kia Niro models in just five minutes (London Business School, 2024).

1.4 EV Trends in Indiana

According to publicly available data, most vehicles operating on Indiana's roadways are powered by gasoline. In the most recent year for which data are available, approximately 6.6 million vehicles were registered with the Bureau of Motor Vehicles (BMV). Of these, 80.6% were exclusively gasoline-powered vehicles, while hybrid electric-gasoline vehicles constituted 1.95% of the total vehicle registrations, while fully EVs comprised 0.37%. Despite representing a smaller fraction of the total vehicle registrations, alternative fuel vehicles have been experiencing a rising trend in popularity across Indiana since 2018, where hybrid vehicles made up 1.1% of all registrations and fully EVs accounted for 0.05% of the total, with 3,441 vehicles registered, as shown in Figure 1.1 (Indiana Office of Energy Development, n.d.).

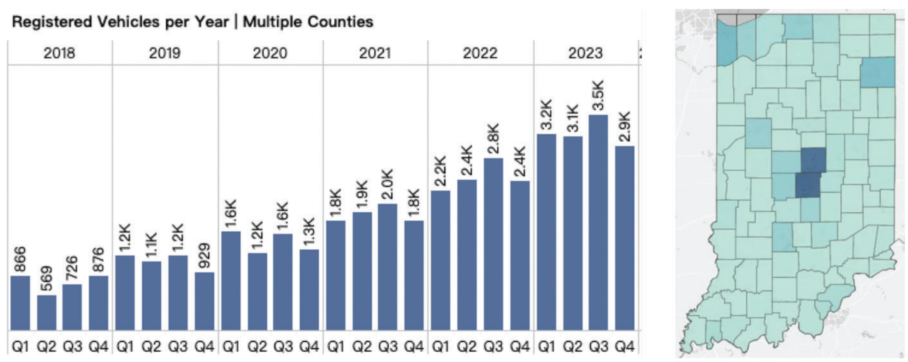
In the context of passenger vehicles specifically, the rate of market share increase has been more pronounced. Analysis indicates that the market share for EVs has grown from 0.1% in 2018 to 0.5% in 2023, a detail illustrated in Figure 1.2a. Concurrently, the spatial distribution of registered EVs is detailed in Figure 1.2b (Indiana Office of Energy Development, n.d.), highlighting the geographical spread across the state. Marion County emerges as a leading region, boasting the highest cumulative total of EV registrations over the last 5 years, and has 2,445 units in 2023. Significant contributions are also observed from Hamilton County with 2,291 registrations, followed by Lake County with 836, and Allen County with 736. The accelerating adoption rate indicates a robust and growing interest in sustainable transportation options among Indiana's residents.

To enhance EV adoption and adequately meet the growing demand for EV charging infrastructure, Indiana has embarked on a comprehensive strategy to develop a network of EV charging stations across the state. This initiative is part of the broader National Electric Vehicle Infrastructure (NEVI) Program, which aims to establish a convenient, reliable, and equitable charging network to facilitate long-distance travel and EV adoption nationwide.



	2018	2019	2020	2021	2022	2023
Gas	5,282,062	5,322,154	5,234,494	5,331,231	5,231,118	5,286,174
Flexible	629,394	651,482	648,080	662,061	644,009	642,238
Diesel	237,433	246,977	252,719	269,344	264,901	276,901
Hybrid	72,576	78,484	83,283	97,800	108,887	128,201
Electric	3,441	5,149	7,039	10,685	15,949	24,004

Figure 1.1 Indiana vehicle registrations from 2018 to 2023.



(a) (b)

Figure 1.2 Indiana EV registrations: (a) from 2018 to 2023, and (b) spatial distribution in 2023.

The deployment strategy for EV charging infrastructure within Indiana is meticulously planned to ensure both urban and rural areas benefit from accessible charging solutions. Furthermore, Figure 1.3 illustrates the current placement of Level 2 and DCFC stations (Joint Office of Energy and Transportation, 2024). Most of these charging stations are situated in urban centers to cater to daily EV charging needs, promoting the use of EVs for routine commutes and city driving. To complement urban charging infrastructure and support EV use for longer journeys, a significant number of charging stations have been strategically positioned along major highways and interstates. This ensures that EV drivers can undertake long-distance travel with confidence, knowing that charging support is readily available along key travel corridors.

1.5 Organization of the Report

The report of this project is structured as follows.

Chapter 2 reviews literature on EV adoption, focusing on determinants that influence the intention to buy EVs and barriers to adoption. It also covers literature on WTP for public charging attributes and datasets related to EV operations.

Chapter 3 describes the survey design and data collection. It outlines all sections of the survey and describes the data collection process, concluding with a description of the survey sample.

Chapter 4 presents the survey findings, including socio-economic profiles, travel patterns, EV perceptions, adoption factors, charging preferences, WTP, and responses to open-ended questions.

Chapter 5 addresses EV trip detection, detailing data preparation, evaluation metrics, and detection results. This chapter highlights the methodologies used to identify and assess EV trips.

Chapter 6 examines EV demand generation, providing an overview of the framework used and discussing its implementation results.

Chapter 7 summarizes the key findings and implications of this study, outlines its limitations, and offers recommendations for future work.

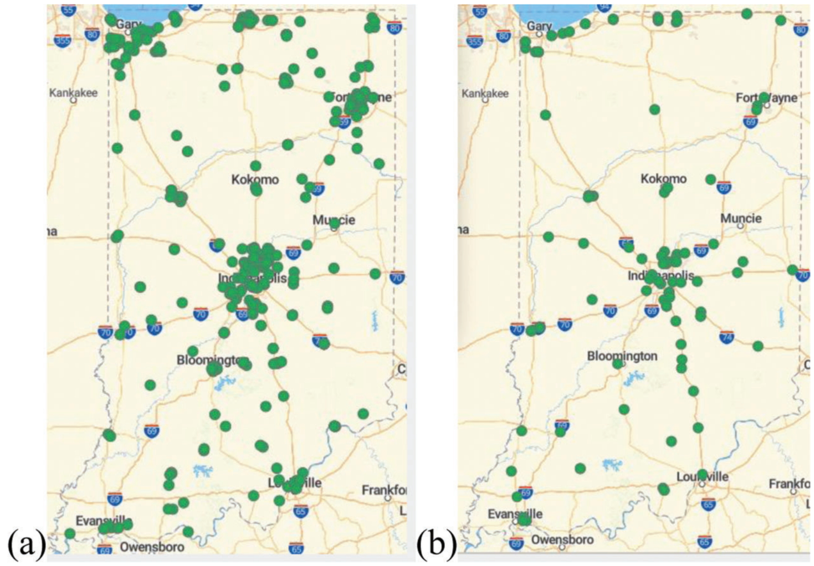


Figure 1.3 Indiana charging station distribution in 2023 of (a) Level 2, and (b) DCFC.

2. LITERATURE REVIEW

This chapter presents a review of the factors that affect the EV adoption and the main barriers for this adoption (Section 2.1); WTP to charging types (Section 2.2); and datasets about EV operations (Section 2.3).

2.1 EV Adoption: Determinants and Barriers

Studies point out socio-demographic, technological and economic factors as determinants of EV adoption. Regarding socio-demographic elements, age is an important factor. Studies point out that younger people are more attracted to EVs (Chen et al., 2020) because of characteristics such as greener and innovative attitudes (Konstantinou et al., 2021), although some previous work found the opposite—older people are more likely to adopt an EV (Buhmann & Criado, 2023). Individuals with higher level of education are more inclined to adopt EVs in comparison to those with lower level of education (Javid & Nejat, 2017; Sovacool et al., 2018), although this adoption will not necessarily happen in the short term. In a study involving participants from driving schools, findings suggested that university students are not inclined to adopt alternative fuel vehicles, such as EVs, soon due to the high purchase cost. Nevertheless, in the long run, there is a higher probability that they will eventually buy one (Zhang et al., 2011). Moreover, higher income is also related to a higher likelihood of purchasing an EV (Brückmann et al, 2021; Javid & Nejat, 2017; Soltani-Sobh et al., 2017). Regarding gender, men demonstrate a higher inclination to have prior experiences with EVs and embrace them (Visaria et al., 2022). This tendency is associated with characteristics such as personal innovativeness, perceived financial benefits, and perceived symbolism (Ling et al., 2021; Sovacool et al., 2018). Conversely, women are more prone to adopt these vehicles due to their environmental concerns (He et al., 2018).

The charging infrastructure is identified as a technological barrier to the widespread adoption of EVs, since insufficient availability of public charging stations adversely impacts the acceptance of EVs (Berkeley et al., 2018). Conversely, a higher number of chargers demonstrates a positive and statistically significant impact on promoting EV usage (Buhmann & Criado, 2023; Chandra, 2022), being acknowledged as one of the most crucial factors in EV adoption (Patil, 2020; Sierzchula et al., 2014). Beyond availability, the charging duration presents a challenge, given that the time needed to charge an EV significantly differs from the time required to refuel a gasoline-powered vehicle (Chen et al., 2020). Fear of limited driving range, known in the literature as range anxiety, is identified as a barrier to the widespread adoption of EVs (Szumska & Jurecki, 2021; Tanwir & Hamzah, 2020). It is noteworthy that EV drivers tend to be less concerned about the range of their vehicles. Besides the infrastructure itself, the perceived accessibility to charging stations, referring to how individuals assess the ease of reaching a charging station, is posited as a crucial factor influencing EV adoption (He et al., 2022). For drivers, the performance of their vehicle is a key consideration, and EVs are noted for their attributes such as low noise, smooth driving, and eco-friendly operation. By contrast, studies indicated that users of internal combustion engine vehicles (ICEVs) were reluctant to adopt EVs due to their unwillingness to compromise on traditional features, such as refueling time and range levels (Ewing & Sarigöllü, 2000).

Turning to financial aspects, it is notable that EV prices tend to be higher than ICEVs for equivalent models (Quak et al., 2016). This increased cost is influenced by factors such as a reduced number of vehicles produced, variations in battery sizes and prices, and the incorporation of new vehicle technologies. Financial incentives designed to promote EV adoption have shown a positive impact on EV acceptance in the U.S. (Soltani-Sobh et al., 2017; Tanaka et al., 2014), as well as on a global scale (Sierzchula et al., 2014; Kim et al, 2017). However, the presence of financial incentives, while influential, is not enough on their own. Their promotion is also important since only a segment of the public is informed about them (Singh et al., 2021).

Residents in Indiana can receive incentives at the federal and state level for different actions, such as purchase of new or used EVs and installing charging equipment. In the federal level, new EVs buyers are eligible to receive up to $7,500 as tax credits. For this, the vehicle's battery capacity must be at least 7 kilowatt hours and gross weight must be less than 14.000 pounds (U.S. EPA, n.d.). Buyers of used EVs are also eligible to tax credits. In this case, the amount is 30% of the cost up to $4,000 as tax credits. Besides the requirements for battery and gross weight, this incentive also requires the sale price to be less than $25,000 without taxes or registration fees. The model year of the EV should be at least 2 years earlier than the calendar year in which the purchase happens (IRS, 2023). Regarding charging equipment, EV users can apply for 30% of tax credit in the installation of charging equipment up to the maximum of $1,000. In the state level, utility companies offer rebates to customers installing charging stations at home, such as Indiana Michigan Power, rebate up to $250 per Level 2 charging station, or special rates to customer who charge their EVs during off-peak hours, commonly defined from 11pm to 6am. On the other hand, BEVs owners are mandated to pay an additional registration fee of $221, and PHEVs owners are obliged to pay an extra registration fee of $74 (BMV, n.d.) to compensate the fuel tax revenue that it is not collected from these vehicles.

2.2 Willingness-to-Pay (WTP)

This section is primarily inspired by and builds on the review of public charging choices provided in (Potoglou et al., 2023).

In general, few studies have analyzed the relative value of attributes such as WTP. Table 2.1 which was inspired from paper above illustrates this point, revealing that only eight studies, which focused exclusively on EV users, along with three studies involving both current and potential EV users, attempted to estimate the WTP for various attributes linked to public charging choices. Despite the inclusion of cost-related attributes (such as charging cost) in stated choice experiments, the scope of WTP estimation has been relatively limited.

The WTP estimations from Table 2.1 are the result of studies that were conducted various countries (Denmark, USA, China, Norway, Swiss, and Germany). The analysis delves into factors, such as charging location, cost in relation to detour time duration number of chargers, amenities, state of charge and excess range, waiting, access time (time required to reach charging station from the current location), renewable energy, inductive charging technology, deviation from planned route, and time of day.

2.3 Datasets About EV Operations

The exploration of EV operations and the strategic development of their supporting infrastructures heavily rely on diverse datasets and advanced analytical methodologies. This comprehensive understanding is crucial for addressing the multi-faceted challenges of EV integration into the current transportation networks.

Existing studies mainly use three categories of datasets to facilitate EV operations. The first one is transportation data, such as Global Positioning System (GPS) coordinates. GPS coordinates record drivers' trajectories, which can be utilized to explore their travel patterns (Yang et al., 2022) and further identify proper distribution for public charging (Yi et al., 2022). Secondly, point of interest (POI) information is used to infer users' charging desirability by trip purposes (Pagany et al., 2019). For example, establishing fast chargers in parking lots near shopping centers and restaurants can provide convenience to EV users while reducing placement costs. The third one is the power distribution network, such as charging loads and bus line data (Lin et al., 2019). In addition, different operation strategies have been designed to promote EV development. For example, energy prediction methods (Basso et al., 2019; Zhang et al., 2020), energy-efficient route models (Chen, Lei, et al., 2022) and charging schedule algorithms (Zhou et al., 2020) have been designed to alleviate EV drivers' range anxiety. Additionally, strategies for power management (Quddus et al., 2019) and electricity pricing (Lee & Choi, 2021; Moradipari et al., 2020) are proposed to ensure the efficiency of charging stations.

However, the reliance on transportation data derived from gasoline vehicles poses significant challenges in accurately capturing EV-specific operational dynamics (Cai et al., 2014; Lakshminarayanan et al., 2018). First, EV trip information is hard to collect. Although various policies encourage the development of electric transportation, the penetration is still very low, and only limited data can be collected. Next, the data related to EV ownership and other information are statistical information, which cannot be used to analyze driver behaviors. Third, not all EVs are equipped with telematics systems that connect online and upload information to servers. Some of the charging stations collect drivers' recharging activities, but the daily trip events are still missing. Finally, most of the trajectory analysis tools are used to distinguish transportation modes for driving trips, which cannot be directly applied to differentiate EV trip users (Dabiri & Heaslip, 2018; Zhang, Zhou, et al., 2019). These bring

TABLE 2.1
WTP-related studies (adapted from Potoglou et al., 2023)

WTP Factor	WTP	Study Location	Charging Type
Cost-Savings	Each dollar saving equal to 5.59 minutes willingness to detour	Denmark	Fast charging
Higher Charging Power	0.28 minutes of detour or $0.066 for an additional km/minute	Denmark	Fast charging
	Additional charge $1.91/hour for Level 2 vs. Level 1	USA	Not mentioned
	Additional $0.05 per extra mile	USA	Slow and fast charging
Charging Units	A detour of 7.87 minutes or a fee of $1.86 is the WTP for an available charger, whereas an occupied charger involves a detour of only 0.53 minutes or a fee of $0.13	Denmark	Fast charging
Amenities	A 1.23-minute detour or a cost of $0.29 is the WTP for access to toilets compared to having no toilets, while a 9.55-minute detour or a fee of $2.27 for the availability of toilets, restaurants, and a supermarket compared to having none of these amenities	Denmark	Fast charging
	$10.97 for amenities including shop, coffee place, small lawn area with park bench, and toilet	Swiss	Not mentioned
	An additional $21 for chargers that include access to toilets, dining facilities, and Wi-Fi compared to chargers with none of these amenities	USA	Slow and fast charging
Increase SOC	$0.1 for each additional kWh	China	Not mentioned
Increase of Excess Range	An extra $0.052 for each kWh	China	Not mentioned
Shorter Charging Duration Time (Min)	An additional $0.4 for each minute of reduction	USA	Slow and fast charging
	An additional $0.18 per month for each minute of reduction	Germany	Slow and fast charging
Shorter Waiting Time (Min)	$0.92/month	Germany	Slow and fast charging
	$0.486/minute	Norway	Slow and fast charging
Shorter Access Time (Min)	$2.5/minute	USA	Slow and fast charging
Higher Share of Renewable Energy (%)	An additional $0.61/hour for Level 2. For DCFC, WTP of an additional $1.82 per hour	USA	Slow and fast charging
	$0.47/month	Germany	Fast charging
Energy Source	BEV users: $21.6 (hydro), $25.77 (solar), $21.93 (wind) Non-BEV users: $19.19 (hydro), $20.73 (solar), $18.42 (wind)	Swiss	Not mentioned
Inductive Charging or Wireless Charging Technology vs. Cable Charging	$9.42/month	Germany	Fast charging
Charging Locations	WTP for chargers with grocery access is $2.81 WTP for chargers that located in a mall is $1.65 WTP for quick charging near home is $1.38 WTP for quick charging by the freeway is $1.26 WTP for chargers with transit access is $0.01 WTP for chargers near a gym is -$0.95 WTP for chargers near a school is $1.23	USA	Not mentioned
	$51.99 per month for at-home-charging compared to en route, and charging at work is $25.08 per month compared to at-home charging	Germany	Fast charging
Stay on the Original Route and Avoid Detours	$244/trip	USA	Slow and fast charging
Time of Day	Workday: $0.24 for 10:00–17:00; $0.31 for 17:00–22:00; $0.18 for 22:00–10:00+1; weekend: $0.23 for 10:00–17:00; $0.28 for 17:00–22:00; $0.36 for 22:00–10:00+1	China	Slow and fast charging

difficulties in collecting information about EV trips and users to design corresponding strategic planning for EV infrastructures and operations. Moreover, some studies (Chen, Lei, et al., 2022; Habla et al., 2021; Weldon et al., 2016; Zhang, Zhou, et al., 2019) investigate EV usage patterns and driver behaviors using small datasets, which lead to issues of representation and potentially skewed results.

2.4 Chapter Summary

This chapter examined the determinants that affect EV adoption, WTP for different charging attributes, and reviewed available datasets about EV operations.

The determinants of EV adoption are divided into three main categories: socio-demographic, technological and economic factors. Individuals who are male, have higher education and income, and young, are more likely to adopt EVs. Additionally, the literature points out charging infrastructure, perceived charging accessibility, EV performance, purchase price and incentives as key determinants of EV adoption. Regarding WTP for public charging attributes, there is a limited number of studies in the U.S. and internationally. Studies describe that consumers are willing to pay for various aspects of charging, including cost savings, higher charging power, more charging units, amenities, increased SoC, extended range, shorter charging durations, reduced waiting and access times, higher renewable energy share, inductive charging, charging locations, detour avoidance, and time of day. The exploration of EV operations and the strategic development of supporting infrastructure rely on diverse datasets and advanced analytical methodologies. Key data categories include travel data, POI information, and power distribution network data. However, the limited availability of EV-specific data poses significant challenges in accurately capturing EV operational dynamics. Existing studies often use small datasets, which may lead to issues of representation and skewed results, highlighting the need for more comprehensive data collection and analysis methods.

3. SURVEY DESIGN AND DATA COLLECTION

This chapter describes the survey design (Section 3.1), data collection (Section 3.2), and survey sample (Section 3.3).

A stated preference survey was designed to assess Hoosier's perceptions about EVs and to gather data concerning the demand for EVs in the state. The choice of a survey as a data collection instrument is related to the capability of the questionnaire to collect the plurality view of the Indiana residents in a format that allows statistical analysis by the researchers. The survey participants were informed in the beginning of the questionnaire that in the questions "EVs" refers exclusively to BEVs.

3.1 Survey Design

3.1.1 Survey Sections

The survey instrument was structured into eleven sections, which are outlined below and further discussed in detail.

1. Screening questions
2. EV knowledge and experience
3. Current travel patterns
4. Public perceptions about EVs
5. EV incentives and barriers
6. EV adoption curves
7. Charging knowledge and experience
8. Charging perceptions
9. Experimental design—willingness-to-pay
10. Socio-demographic questions
11. Final section

The full survey is added to this document in Appendix A.

The survey was designed with the consideration that participants may fall into three different groups depending on their actual situation: current EV users (i.e., those who had an EV at the time of the survey), past EV users (i.e., individuals who previously owned or leased an EV but did not have one at the time of the survey), and non-EV users (i.e., respondents who had never owned an EV). Some questions were addressed specifically to a group. This approach facilitated a targeted collection of data from a specific group of respondents, avoiding any inconvenience for participants outside that group, as they were exempt to respond to questions that were not relevant to their individual circumstances.

Survey questions were formulated based on various guiding principles. Commonly, multiple-choice and three or five-point Likert scales were used, as these formats are not only easier for respondents to navigate but also simplify the subsequent analysis. The questions were designed to be easily comprehensible, free from wording ambiguity, and formulated to address specific concerns. Questions related to travel behavior and socio-demographics were carefully phrased to harmonize with established data sources, including the National Household Travel Survey (NHTS) and the U.S. Census Bureau.

3.1.1.1 Screening questions. The first section of the survey aimed to ensure that the participants were adult residents of Indiana. For this purpose, it included two questions soliciting the age and state of residence. If the participant was younger than 18 years old or not an Indiana resident, this participant would not be allowed to proceed to the next section.

3.1.1.2 EV knowledge and experience. This section's main purpose was to collect the current situation of respondents regarding EVs. Participants were divided into three groups according to their situation as current

EV users, past EV users, or non-EV users. Besides this question, the participants were also asked about their experience using, driving, or taking a ride in EVs.

3.1.1.3 Current travel patterns. This section collected data on the travel patterns of the respondents, such as the frequency of trips for specific purposes (i.e., work, shopping, personal, social, and recreational), most used modes for specific purposes and weekly distance traveled for these purposes. Also, participants were asked about the number of non-EVs in their household. Finally, the current EV users were asked about the number of EVs that they own. These questions were used to create the travel behavior pattern of the respondents.

3.1.1.4 Public perceptions about EVs. The fourth section aimed to gather public opinion about some characteristics of EVs when compared with ICEVs. These characteristics, such as purchase price, maintenance cost, fuel cost, registration fees, life cycle cost, depreciation, refueling convenience, trip planning convenience, noise, driving comfort, driving range, reliability, and safety, were compared using a 5 Likert-scale from major disadvantage to major advantage (Likert, 1932). Additionally, questions on pro-environmental behavior related to vehicles and preferences for new or used EVs were included.

3.1.1.5 EV incentives and barriers. The questions presented in this section solicited the knowledge of the participants regarding any available incentives that EV users may be eligible for in Indiana and, if these incentives could influence their intention to adopt an EV. Additionally, non-EV users were asked about the reasons for not owning/leasing an EV. The main purpose of the section was to assess the level of awareness of the public regarding EV incentives and, also, understand the main reasons why people are not taking advantage of these incentives.

3.1.1.6 EV adoption curves. This section included questions on the possibility of the participants to purchase or lease an EV. Additionally, the respondents were asked about the likelihood to purchase or lease an EV in different timeframes of 1, 2, 3, 5, and 8 years. These questions were designed to develop adoption curves in different scenarios for the Indiana population, which was one of the main objectives of this project.

3.1.1.7 Charging knowledge and experience. Respondents were asked about the types of charging technologies that they had read or heard about (i.e., Level 1, Level 2, DCFC, DWPT and battery swapping). Also, they were asked about the types of charging (i.e., Level 1, Level 2, DCFC) that they use or would use. Finally, a question collected data about the preferred places where the participants would like to have public charging stations available.

3.1.1.8 Charging perceptions. This section assesses respondents' perceptions of public charging infrastructure. It includes one 5-point Likert scale question on the reliability of public charging, one question concerning drivers' tolerance for distances between charging stations, and six questions on the accessibility of public charging, also presented on a 5-point Likert scale.

3.1.1.9 Experimental design: willingness-to-pay (WTP). This section is designed to assess public charging preferences for EVs. Respondents will choose their preferred public charging station for each given scenario, assuming they are on a long journey and need to recharge. Each charging station option varied in terms of travel cost, charging time, access time (the time it takes to reach the station from the highway), waiting time (the time spent waiting to charge), initial state of charge (SoC) of the EV, and amenities (such as restrooms, restaurants, and shopping). By analyzing these preferences, we can model the sample population's choices and estimate their willingness-to-pay for public charging technologies.

In each scenario, participants were presented with three alternatives: AC Level 2, DCFC plug-in public charging, and the DWPT charging technology. A total of nine attributes with multiple levels were utilized to design the experiments and develop the scenarios, as detailed in Table 3.1. One of these attributes was scenario-specific, namely the SoC or battery level, while the remaining eight (charger type, trip cost, access time, waiting time, charging time, total travel time, and availability of amenities such as restroom, restaurant, retail, and shopping) pertained to the charging options. A fractional factorial design was used to enumerate the scenarios using *NLOGIT* with an objective of minimizing the D-error, which resulted in 24 total scenarios. Those 24 scenarios were divided into 4 blocks; each respondent was randomly assigned one block and was asked to answer six questions, each question asking what charging technology the participant would choose given a different scenario. An example of a scenario can be found in Appendix A.

To provide a clear delineation between attributes related to the scenario and those associated with the three charging alternatives, the narrative and variables were outlined as follows.

> *Assume that you are driving an EV with a range of 200 miles and a battery capacity of 60 kWh. It means that this EV can travel 200 miles when the battery is at 100% charge. The destination is 100 miles from your house with a speed limit of 70 miles/hour.*

3.1.1.10 Socio-demographic questions. The questions in this section collected information about gender, race, ethnicity, education, occupation, home area, work area, income, number of people living in the household, and political preferences of the participants.

TABLE 3.1
Choice task attributes and levels

	Level 2	DCFC	DWPT
SoC (%): Battery Level Percentage	(30, 50, 80)	(30, 50, 80)	(30, 50, 80)
Access Time (Minutes): Time Required to Reach Charging Station	(3, 6, 9)	(5, 10, 15)	NA
Waiting Time (Minutes): Time Spent in Queue	(0, 3, 6)	(5, 15, 30)	NA
Charging Time (Minutes): Time Required to Charge EV	(60, 90, 120, 240)	(4, 6, 10, 14)	NA
Total Travel Time (Minutes)	Travel time + access time + waiting time + charging time	85	
Trip Cost ($): Total Cost of Charging Per Trip	(3, 4, 5, 15)	(8, 11, 21, 27)	(16, 19, 22, 28, 35, 40)
Restroom	(available, unavailable)	NA	
Retail, Restaurant, and Shopping	(available, unavailable)	NA	

3.1.1.11 Final section. The last section of the survey consisted of a single open question allowing the participants to provide additional comments about EVs.

3.2 Survey Data Collection

3.2.1 Survey Dissemination

Approval by the Purdue University Institutional Review Board (IRB) was required since the project involves human subject research. On May 11, 2023, the project received approval to proceed (IRB-2023-158). The survey was then administered through a contract with Dynata, a market research company that collected participants. These participants were sourced from their pool of adult residents in Indiana and compensated by Dynata for their time. A second sample was also formed by adult residents in Indiana who were EV enthusiasts to enrich the Dynata sample that did not include as many EV users in Indiana as desired. These participants accessed the survey via a link posted in EV Facebook groups or on websites related to alternative fuel vehicles (see Figure 3.1). The survey was administered using Qualtrics.

3.2.2 Pilot Testing

On 29th of June 2023, a pilot test of the survey was initiated for the Dynata sample with approximately 10% of this sample. A total of 182 responses were collected and, from these, 102 passed the criteria to be considered valid. No adjustments to the survey design needed to be implemented.

3.2.3 Full Launch

The Dynata sample data collection began on June 29, 2023, and was completed on July 23, 2023. The full data collection from EV users or EV enthusiasts ran from June 14 through October 27, 2023.

3.3 Sample Description

A minimum sample size of 1,000 Indiana residents was required to achieve a margin of error of 3% and a confidence level of 95%. Quotas related to age, gender, and income were established to avoid selection bias based on the American Community Survey (ACS). Moreover, a minimum number of 335 participants living in rural areas was desirable.

Two screening questions were added at the beginning of the survey to ensure that the participants were Indiana adult residents. Additionally, three verification questions were added to ensure that the respondents read the survey and answered the questions carefully. These questions asked the participants to select a specific option or compare the answers to two equal questions.

The median time of the respondents who completed the survey was calculated and the respondents who finished in less than 1/3 of this time were excluded from the final sample. Also, participants who answered more than 80% of the Likert-Scale questions with the same answer were excluded, as well as duplicated participants.

In view of these criteria, 1,069 valid responses were collected via Dynata. Additionally, 148 participants from the EV enthusiasts' group were added to the total sample, which resulted in a sample size total of 1,217 participants.

3.3.1 Socio-Demographic Information

Table 3.2 shows the age and gender composition of the survey sample. The total number of females is slightly smaller than number of males.

Regarding household income, the survey sample is representative of the Indiana population. Table 3.3 displays the survey sample and the values for the same categories from the 5-year 2022 American Community Survey. Incomes below $75,000 are slightly overrepresented, while incomes over this value are underrepresented. There were 21 individuals who chose not to report their income in the survey.

Figure 3.1 Webpage informing about the survey.

TABLE 3.2
Age and gender distribution

	Male	Female	Non-Binary/Third Gender	Prefer Not to Say
18–24 Years Old	33 (2.7%)	47 (3.9%)	1 (0.1%)	0 (0%)
25–34 Years Old	89 (7.3%)	167 (13.7%)	4 (0.3%)	2 (0.2%)
35–44 Years Old	141 (11.6%)	120 (9.9%)	3 (0.2%)	2 (0.2%)
45–54 Years Old	101 (8.3%)	71 (5.8%)	0 (0%)	1 (0.1%)
55–64 Years Old	80 (6.6%)	84 (6.9%)	0 (0%)	4 (0.3%)
Over 65 Years Old	173 (14.2%)	94 (7.7%)	0 (0%)	0 (0%)
Total	*617 (50.7%)*	*583 (47.9%)*	*8 (0.7%)*	*9 (0.7%)*

TABLE 3.3
Income distribution

	Sample Distribution (%)	2022 5-Year ACS Estimate (%)
Under $25,000	17.1	16.4
$25,000−$49,999	25.7	20.9
$50,000−$74,999	19.4	18.0
$75,000−$99,999	13.1	14.0
$100,000−$149,999	14.8	16.8
$150,000 or More	9.9	13.9

The survey sample has a relatively more educated level than the Indiana population in general, when both groups are compared using the data of individuals aged 25 or older from the 5-year 2022 American Community Survey. Individuals with higher educational achievement, some college education or higher, are overrepresented while the ones with lower levels, high school graduates and lower, are underrepresented. For this analysis, both associate degrees and bachelor's degrees were considered to be "college degrees." Table 3.4 shows the educational level distributions.

3.3.2 Home Location

Respondents supplied their home ZIP codes for geographic classification. Since additional geographic identifiers were not gathered, respondents are assumed to reside at the geographic centroid of their ZIP code region. To classify the home location of the participants in rural or urban home location, the rural-urban commuting area (RUCA) codes were used. They were obtained thought the zip codes provided by the participants. Figure 3.2 reveals the frequency of survey responses according to zip code and county distribution.

3.3.3 Vehicle Ownership

In the beginning of the survey, it was defined that the EVs mentioned in the survey were exclusively the BEVs. The participants were asked about their current situation related to EVs. Table 3.5 shows the results. Current EV users, participants who currently have access to an EV, represent 15% of the total sample. As mentioned in Section 1.4, this number is overrepresented to facilitate the statistical analysis for the themes that involve exclusively

TABLE 3.4
Educational attainment distribution

	Sample Distribution (%)	2022 5-Year ACS Estimate (%)
Grade School or Less	0.5	3.5
Some High School	2.3	6.5
High School Graduate and Technical Training Beyond High School	30.2	33.0
Some College	23.7	19.7
College Graduate	27.9	27.0
Graduate or Professional School	15.4	10.2

TABLE 3.5
Survey sample related to the EV situation distribution

	Number of Participants	Percentage	Situation
I Currently Lease an EV	14	1.2	Current EV users 15.0%
I Currently Own an EV	153	12.6	
I Leased an EV in the Past and Now I Own One	4	0.3	
I Owned an EV in the Past and Now I Lease One	12	1.0	
I Leased an EV in the Past, but I Don't Have Access to an EV Anymore	14	1.2	Past EV users 2.0%
I Owned an EV in the Past, but I Don't Have Access to an EV Anymore	10	0.8	
I Have Never Owned or Leased an EV	1,010	83.0	Non-EV users 83.0%
Total	*1,217*	*100.0*	*100.0%*

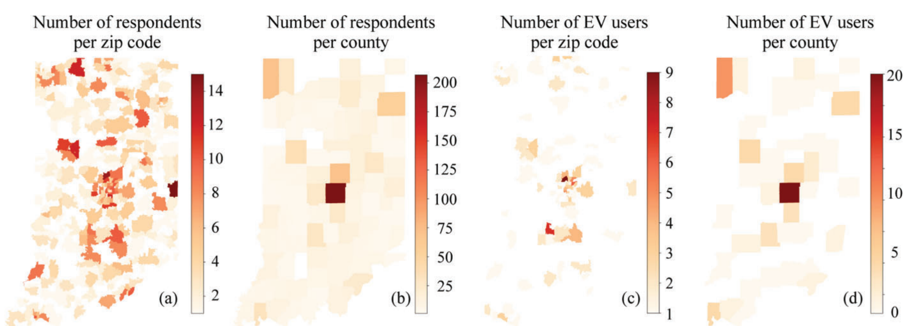


Figure 3.2 Frequency of survey responses by (a) zip code, and (b) county. Frequency of EV users survey responses by (c) zip code and (d) county.

current EV users. Additionally, 2% of the sample consists of respondents who had an EV in the past but do not have access to one any longer.

Current EV users were asked about the number of EVs in their household. Most of the group has only one EV, likely because it is a new technology. The distribution is shown in Figure 3.3, where the percentages are calculated based on the current EV users' group (total of 183 participants). The most common EV brand in Indiana is Tesla (42.1%), followed by Chevrolet (12.6%), Kia (8.7%) and Nissan (8.7%).

Participants were also asked about the number of non-EVs that they have in their households. With this information, summing up the number of EVs for the participants who have at least one, it is possible to calculate the total number of vehicles in their household. This distribution is shown in Table 3.6, where the percentage from the 5-year 2022 ACS is also displayed. Generally, the survey sample has a lower number of vehicles, EVs and ICEVs, per household when compared to the Indiana population.

Figure 3.4 shows the type of the most used household vehicle for EV users. As can be seen, EVs seem to replace ICEVs in contrast to being largely a second vehicle in the household.

3.4 Chapter Summary

A stated preference survey was designed and gathered data from Indiana adult residents on various aspects of EV usage, including EV knowledge, experience, current travel patterns, public perceptions about EVs, EV incentives and barriers, EV adoption curves, charging knowledge and experience, charging perceptions, and socio-demographic data. Screening and verification questions were added to ensure the high-

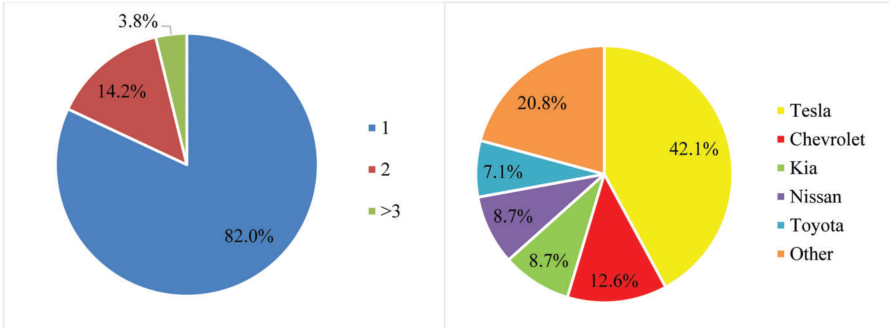


Figure 3.3 Number of EVs in the household of EV users and EV brands in Indiana.

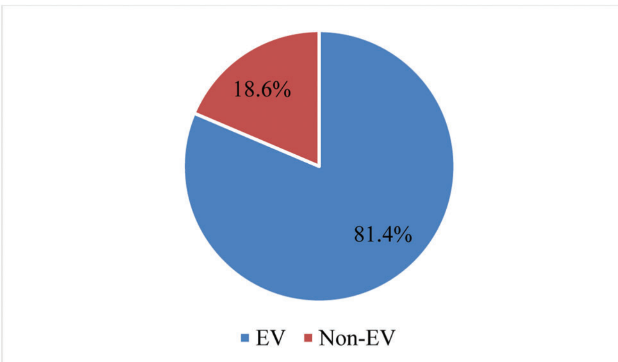


Figure 3.4 Most frequently used vehicle in the household of EV users.

TABLE 3.6
Survey sample number of vehicles per household distribution

	Sample Distribution (%)	2022 5-Year ACS Estimate (%)
0	27.7	6.2
1	23.2	31.7
2	32.0	38.3
>3	17.1	23.8

quality of the responses. Participants were recruited through Dynata, a market research company, and via links posted in EV Facebook groups and websites related to alternative fuel vehicles. A total of 1,217 participants were considered in the analysis, with 15% classified as current EV users (i.e., participants who owned or leased an EV at the time of the survey), 2% as past EV users (i.e., participants who owned or leased an EV in the past but did not have one at the time of the survey), and 83% classified as non-EV users (i.e., participants who had never owned or leased an EV).

4. SURVEY DATA ANALYSIS

This section aims to provide a statistical analysis of the survey data on the perspectives of the Indiana public regarding EVs. It includes the socio-economic profile of EV users (Section 4.1), their travel patterns (Section 4.2), and the perceptions of EVs by both EV users and non-EV users (Section 4.3). Also, it describes the charging preferences, WTP (Section 4.4) and respondents' comments to an open-ended question (Section 4.5).

All the mentions for the "EV" acronym are related exclusively to the BEV type. The results are presented separately for participants who are (or were) EV users "EV users" and participants who have never been an EV user "non-EV users." Figure 4.1 presents how these two groups were created.

4.1 Socio-Economic Profile

Table 4.1 shows the distribution of EV users and non-EV users by gender, age, and political preference. EV users in Indiana are predominantly men, aged between 25 and 44 years old, and Democrats. The results are in accordance with past findings (Sovacool et al., 2018). Middle-aged groups are more open to new technologies while having better financial conditions, which can explain their higher acceptance of EVs. People who are related to the Democrat party tend to show greener behavior (Sintov et al., 2020). Most of the EV users are employed full-time (74.9%) and have high educational levels since 70.6% of them are college graduates or higher.

EV users have a higher income than non-EV users, as shown in Figure 4.2, especially in the range above $100,000 annually. The higher prices of EVs when compared to ICEVs are a possible reason for the higher income profile of EV users.

The percentage of EV users who live and work in urban areas is greater than that of non-EV users. Regarding the type of residence, the groups do not show differences since most respondents in both groups live in single-family homes. The fact that most EV users live in this type of residence might be an opportunity for home charging installation programs. New condos are offering charging stations as incentives for potential buyers, but people who live in single-family homes must take the initiative to install the charging by themselves if interested. As the literature points out (Zoepf et al., 2013), home charging usually happens at night, and the electricity grid supports this usage better. This tendency is supported by the results of the survey since 69.1% of EV users with home charging are used to charging their EVs

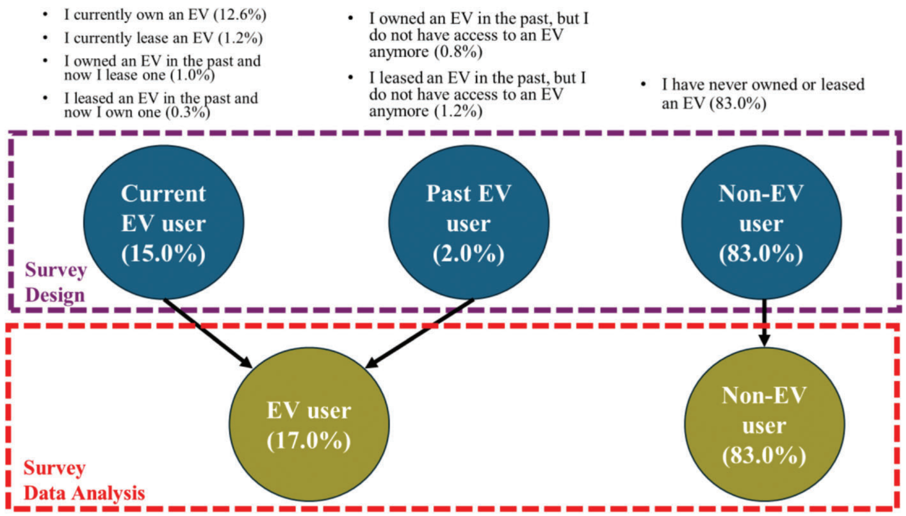


Figure 4.1 Different sample groups.

TABLE 4.1
Distribution by gender, age, and political preference

	EV User (%)	Non-EV User (%)
Gender		
Male	61.80	44.90
Female	36.20	53.90
Non-Binary/Third Gender	0.00	0.80
Other	0.00	0.00
Prefer Not to Say	1.90	0.50
Age		
18–24 Years Old	8.70	6.20
25–34 Years Old	26.60	20.50
35–44 Years Old	27.50	20.70
45–54 Years Old	15.90	13.90
55–64 Years Old	12.10	14.20
Over 65 Years Old	9.20	24.60
Preferential Party		
Democrat	51.7	28.3
Republican	19.3	33.7
Independent	22.2	27.7
Other	6.8	10.3

between 9 PM and 7 AM. Table 4.2 presents the results related to the households of the participants.

4.2 Travel Patterns

Regarding the frequency of trips, a higher percentage of EV users than non-EV users tend to travel daily, as shown in Figure 4.3. The higher percentage of daily trips to work highlights the importance of charging stations in offices, enabling EV users to charge their vehicles while working.

Moreover, the purpose of the trip might determine the type of vehicle used, as shown in Figure 4.4. The analysis of transportation modes for EV users shows that EVs are mostly used for shopping and personal trips, although EV usage rates higher than 70% are observed for work and social trips. Regarding recreational trips, while EVs remain the most used mode of transportation, nearly a third of EV users prefer to use ICEVs.

Additionally, another finding highlighting the specificity of recreational trips for EV usage relates to the percentage of participants who travel more than 100 miles weekly for each purpose. Figure 4.5 indicates that EV users tend to take long trips more often compared to non-EV users for all trip purposes, except for recreational trips.

This different pattern for recreational trips might be related to concerns related to charging and driving range. Recreational trips are the least frequent for EV users, as already shown in Figure 4.4. Making an unfamiliar trip might concern the EV users about being able to charge their vehicle, if needed, in a public charging station. The concern of EV users in unfamiliar trips is also addressed in Section 4.4.2.2.

4.3 EV Perceptions for Users and Non-EV Users

The overall feeling about EVs is encouraging since more than 95% of the users selected “positive” or “very positive” to describe their general experience, as shown in Figure 4.6.

This high usage of EVs as the main vehicle in households, as shown in Section 4.2, aligned to the fact that users report a positive experience with the vehicles points out that, after the adoption, the resistance against EVs disappears as the driver becomes more familiar with the vehicles.

The participants were also asked about how some EV characteristics were advantages or disadvantages when compared to ICEV characteristics. Figure 4.7 shows the results. EV users reported that most of the EV characteristics were major advantages or advantages, especially regarding the fuel cost and the noise of the vehicle. The opinions about driving range and trip

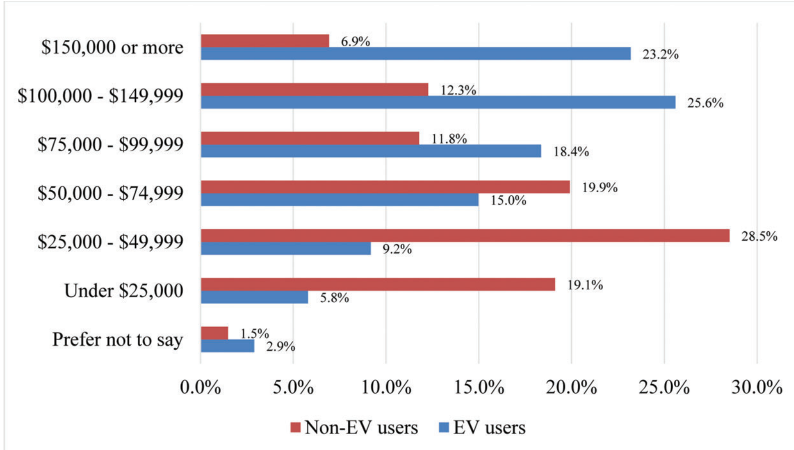


Figure 4.2 Income distribution for EV and non-EV users.

TABLE 4.2
Household profile for EV and non-EV users

	EV User (%)	Non-EV User (%)
Living Area		
Urban	87.4	68.4
Rural	12.6	31.2
Not Specified	0.0	0.4
Working Area		
Urban	81.6	63.6
Rural	9.2	28.3
Not Specified	9.2	8.1
Type of Residence		
Single Family Home	78.3	76.0
Apartment Complex	15.0	14.6
Other	6.8	9.4
People Living in the Household		
Up to 2	39.1	57.6
3 or 4	49.8	32.0
More than 5	11.1	10.4
Years Living in Indiana		
0 to 2 Years	3.9	4.8
2 to 5 Years	5.8	6.2
5 to 10 Years	14.5	6.3
More than 10 Years	75.8	82.8

planning convenience were split. The purchase price and registration fee were the only attributes for EVs that had more negative than positive perceptions when compared to ICEVs. The purchase price for EVs is generally recognized as higher, as stated in Section 2.1. On the other hand, it is interesting that even identifying this upfront cost as expensive, more than 65% of EV users recognized the life cycle cost of an EV as an advantage. Regarding the negative opinions about the EV registration fee, the reason behind this result is, most likely, the additional registration fee that EV owners must pay in Indiana, as also stated in Section 2.1. More EV users reported not having a specific opinion about vehicle depreciation over the years (compared to other characteristics), most likely because most of them may have had their first experience with an EV at the time of the survey and have never sold one.

Non-EV users showed a high level of uncertainty regarding the attributes; almost half of the characteristics have more than a third of answers as "don't know/ not sure." This result highlights that non-EV users are unaware of EV characteristics, as shown in Figure 4.8. Non-EV users also recognize the fuel cost and the noise as the greatest advantages of EVs. On the other hand, the purchase price, trip planning convenience, driving range, and refueling convenience, in that order, were considered the greatest disadvantages. Interesting to notice that this result is connected to the main barriers to not having an EV, as it is described in Section 4.3.4.

Chi-squared tests were performed in software R to investigate if the responses of the EV users and non-EV users differ statistically. For all 13 attributes, the p-values calculated were lower than 0.001. These results indicate there is an association between how people perceive the EV characteristics and their EV user status.

4.3.1 Likelihood to Purchase or Lease an EV

Non-EV users were asked about their likelihood to purchase and lease an EV in the next 1, 2, 3, 5, and 8 years (Figure 4.9). In the short term, most participants answered that they were unlikely to buy an EV. These perceptions, however, change over time. More interestingly, the number of respondents who are likely or extremely likely to purchase an EV in year 8 is more than 7 times the number of participants in year 1. This data indicates that Indiana can expect a high increase in EV use in the next years. Additionally, as the percentage of participants who are extremely unlikely to buy an EV decrease, the potential EV market for the state tends to increase since these participants are not totally averse to the idea of adopting an EV.

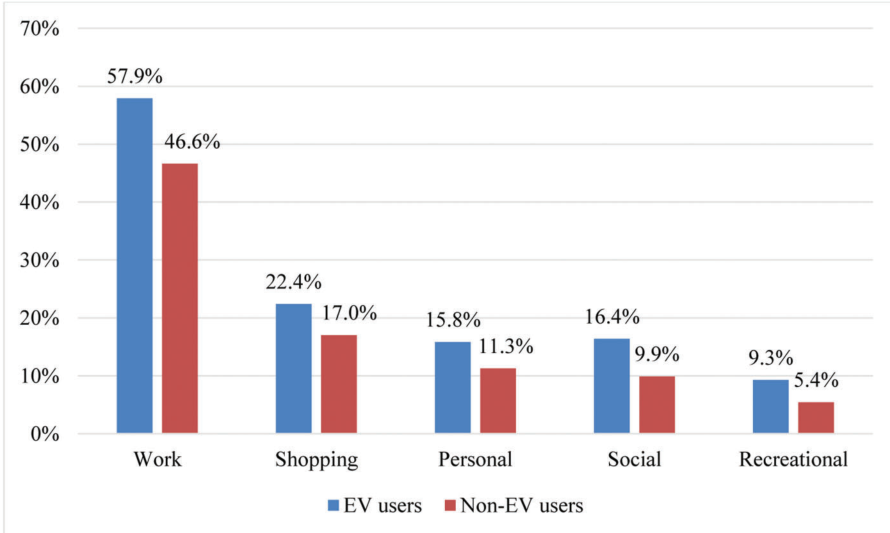


Figure 4.3 Percentage of EV users and non-EV users with daily trips.

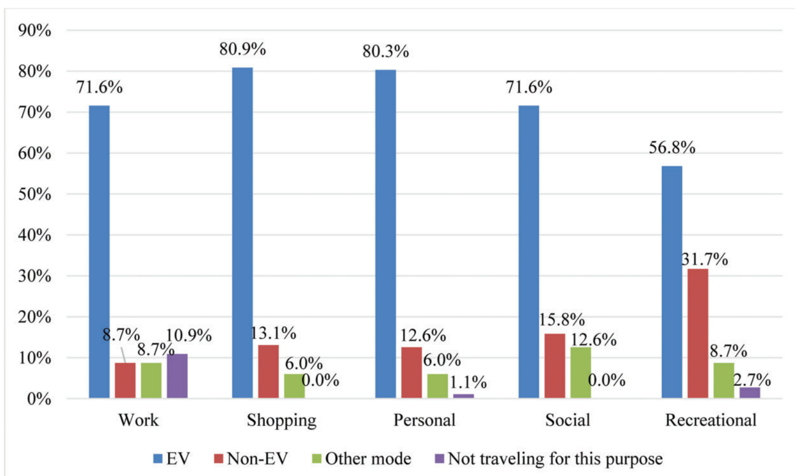


Figure 4.4 Preferred transportation modes of EV users for different purposes.

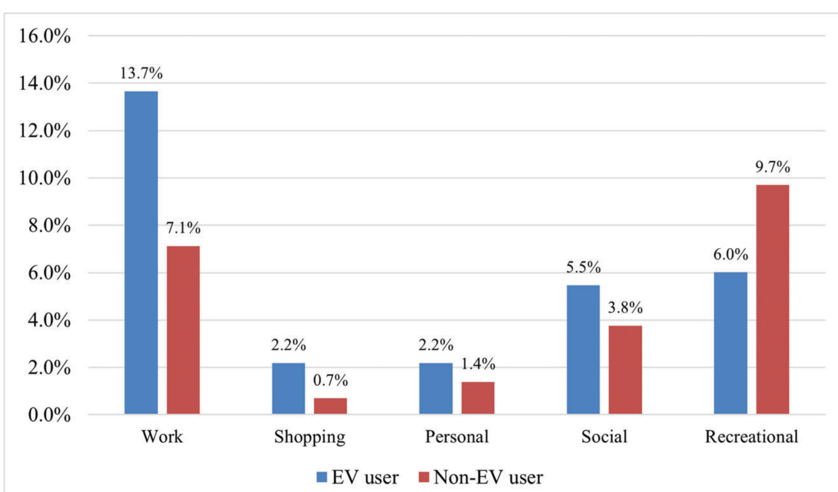


Figure 4.5 Percentage of EV users and non-EV users who travel more than 100 miles weekly.

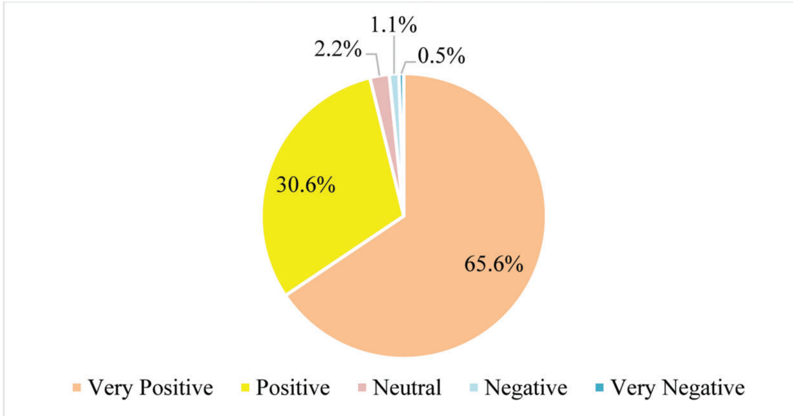


Figure 4.6 General feelings of EV users about the EV.

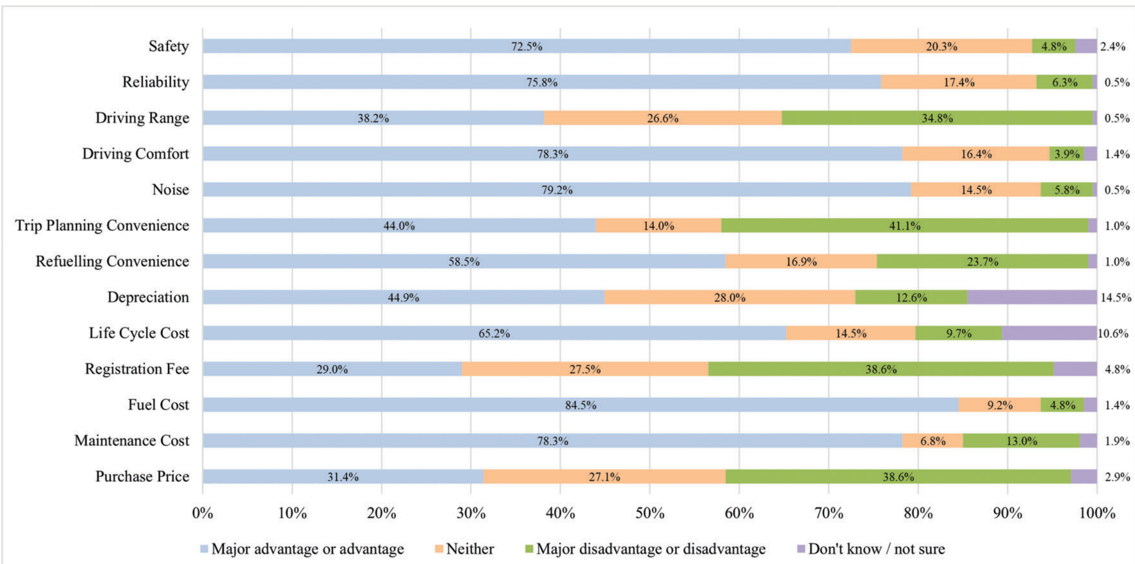


Figure 4.7 Perceptions of EV users about EV characteristics.

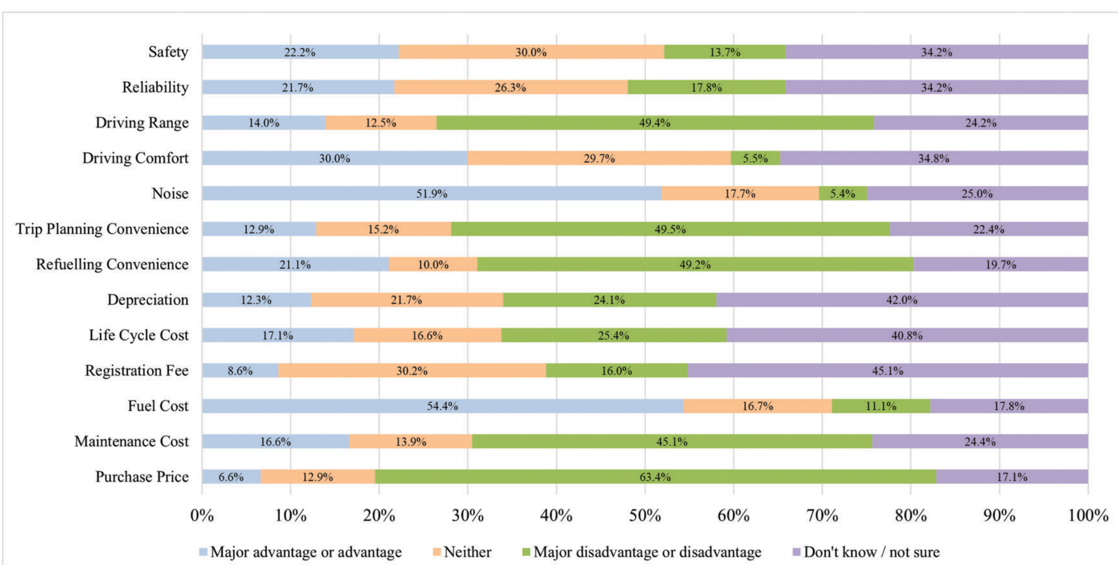


Figure 4.8 Perceptions of non-EV users about EV characteristics.

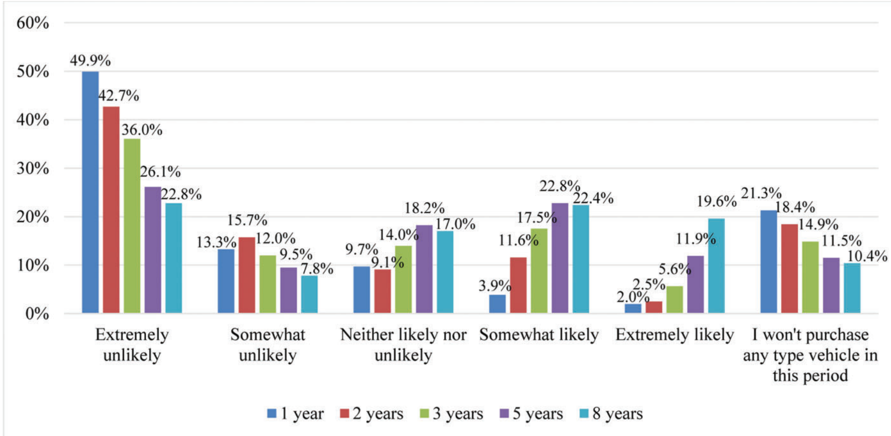


Figure 4.9 Non-EV users' stated likelihood of purchasing an EV in different timeframes.

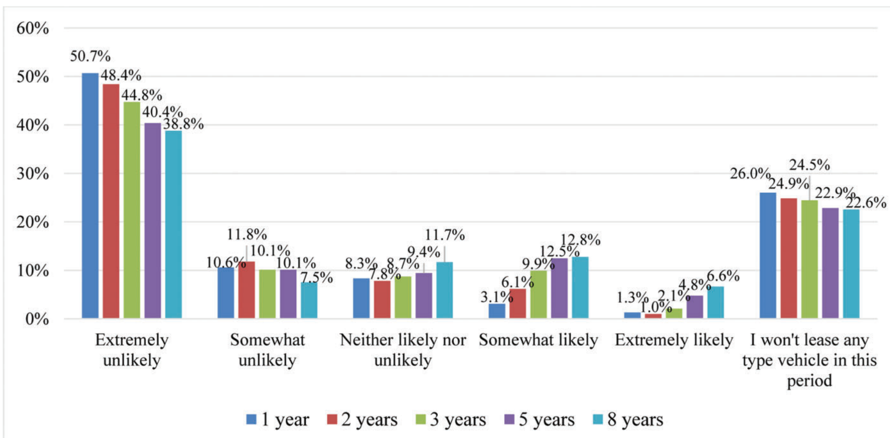


Figure 4.10 Non-EV users' stated likelihood of leasing an EV in different timeframes.

The same question asking about leasing was formulated for the non-EV users. In this scenario, the responses showed to be more constant over time. The sum of participants who are somehow likely to lease an EV is lower than 20% in all five different timeframes. Additionally, the percentage of non-EV users who were averse to the idea of leasing an EV in 1 year (61.3%) is like the percentage of non-EV users who are unlikely to purchase one (63.2%). This indicates that the idea of first leasing an EV to experiment on it and then purchasing a vehicle of the same type later is not a possibility for most of the participants. Figure 4.10 shows the graphic related to the likelihood of purchasing an EV.

These answers were used to create the adoption curves, as described in Section 6.3. More details about EV purchasing intentions in Indiana can be found in Moras et al., 2024.

4.3.2 Likelihood to Purchase a New or Used EV

Participants were asked if they would prefer to buy a new or used EV. The sample was divided but most of them preferred a used one, as shown in Figure 4.11.

The most selected reason to prefer a pre-owned EV is a financial one. Almost half of the participants considered that they would not be able to buy a new EV since the purchase price was higher. This reason was also the most mentioned one for the non-EV users to not have an EV of any type, as shown in Figure 4.16. This reinforces how affordability plays a crucial role in the decision to adopt an EV.

More than a third of the participants cited that buying a used EV would allow them to become used to the technology without investing much financial resources. This concern is generally common for new products. As vehicles are relatively expensive for a family, it is expected that some participants try to mitigate risks when buying one. Additionally, it is interesting to notice that although some participants prefer purchasing a used EV to test the vehicle, the option for leasing is not as attractive, as described in Section 4.3.1. Since leasing options may force individuals to make long-term commitments, the purchase of a used EV can be an easier gateway for EV adoption than the option for leasing one. Figure 4.12 shows all the reasons and the respective percentages for participants preferring to buy used EVs.

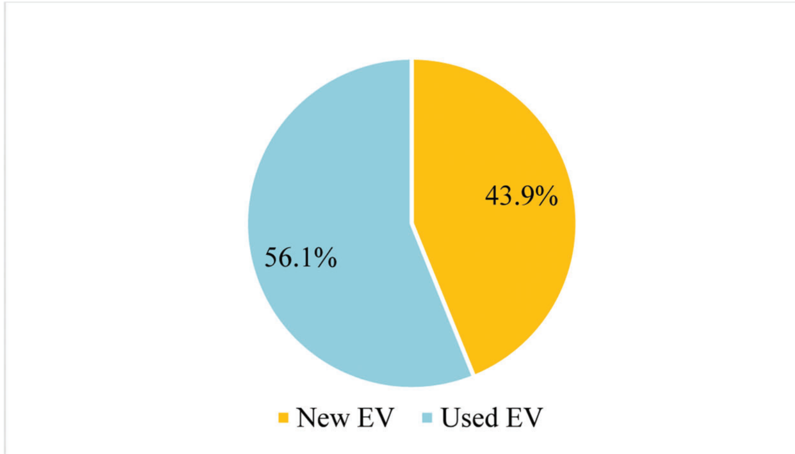


Figure 4.11 Non-EV users' preferences between a new and a used EVs.

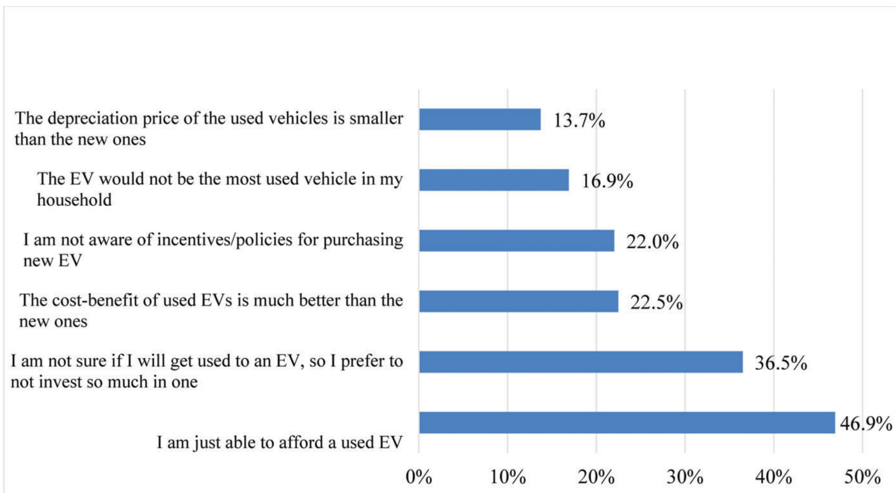


Figure 4.12 Reasons for buying a used EV.

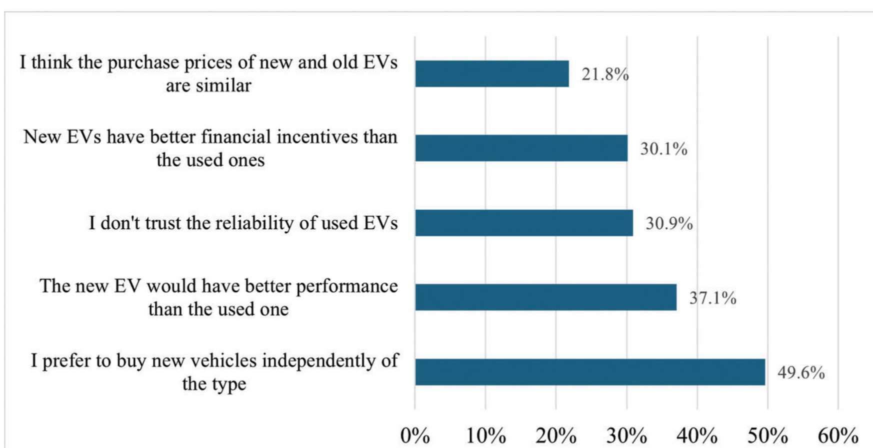


Figure 4.13 Reasons for buying a new EV.

Regarding the participants who selected the option for a new EV, almost half of them would buy a new vehicle independent of the type. This suggests that for some consumers, the appeal of owning a brand-new vehicle may outweigh other factors, such as cost or potential benefits of purchasing a used EV. The better performance of a new EV when compared to a used one is the second most mentioned reason, followed by concerns with the reliability of pre-owned EVs. These reasons may indicate a public perception that EVs are experiencing rapid evolution in a short time. Better financial incentives for new EVs, pointed out by approximately 30% of the respondents, suggest that the difference of up to $3,500 between the tax credits for both options is an important factor. Additionally, as will be described in Section 5.1.3, many participants are not aware of EV incentives. This information is especially relevant for the Federal tax credit incentive for used EVs, which started just a few months before the participants answered the questionnaire. Figure 4.13 shows the causes and the respective percentages for participants preferring to buy new EVs.

4.3.3 Awareness of Incentives

Figure 4.14 shows the percentage of participants who are familiar with all the incentives provided in the survey. The EV Federal Tax Credit is the incentive that most participants were familiar with. This result is expected because this incentive has been available since 2008. The next known incentives are installing home charging rebates and special rates for home charging in off-peak hours. For all the incentives, the EV users' group is more familiar with them than the non-EV users. The fact that less than 60% of EV users are familiar with the incentive to install home charging equipment shows that public policies can be driven to explore this gap. The availability of home charging is an important step towards the promotion of EVs. The fact that the special rates for home charging in off-peak hours are the less-known incentive for both groups indicates that incentives promoted by utility companies are more difficult to become recognized by the public. This data suggests that incentives are a long-term policy for EV adoption. Additionally, increasing EV use is important not just to create incentives but also to promote them.

Almost half of the participants stated that incentives could influence them to buy or lease an EV. When asked if they agree with a statement saying that awareness of incentives would make them more willing to adopt an EV, less than 20% somehow disagreed with that statement. The data shown in Figure 4.15 states that EV incentives play a crucial role in EV adoption.

4.3.4 Barriers to EV Adoption

Non-EV users were asked about the reasons why they do not have an EV. Multiple options could be selected, as shown in Figure 4.16. Among them, the purchase price being high is the most cited reason, with almost 70% of the sample reporting that. As mentioned in Section 2.1, studies around the world corroborate this perception. Since purchase prices tend to decrease over the years, this barrier might become less important in the future. The unavailability of home charging is the second most mentioned reason. This result is interesting since the Federal government offers incentives to promote the installation of home charging equipment. It is noteworthy that this incentive is familiar to just 21.5% of the non-EV users' group, as mentioned in the previous section.

The following most selected reasons are also related to charging. The inconvenience of charging the EV is pointed out as a barrier for 43.5% of non-EV users. The long-duration time that charging requires when compared to filling an ICEV with gas can be a reason for that as well. Additionally, non-EV users are less aware of the charging technologies, which makes them less confident to be able to charge an EV (refer to Section 4.4). The difficulty of finding reliable charging stations nearby was also pointed out by 43.5% of non-EV users as a reason for not having an EV. This statement highlights two concerns participants anticipate encountering—the challenge of locating nearby charging stations and the uncertainty of their operational reliability. Regarding the difficulty locating a charging station, this concern seems to decrease after a person started to use an EV. The current users are inclined to drive further to charging an EV as non-EV users (more details in Section 4.4). Additionally, the group without EVs in their household are less aware of the location of stations and, for this reason, can be more concerned about finding one.

The disturbance when planning trips also was selected by more than a third of the non-EV users. This reason is strongly related to range anxiety. In the next few years, this concern might change with the outcomes of the NEVI program in Indiana. The public charging stations located at a distance equal to or smaller than 50 miles in the interstates can facilitate trip planning. The vehicle itself does not look to be a barrier for non-EV users. Few respondents stated that they believe the vehicle is unreliable, while 27.9% of the respondents stated that the maintenance costs are too high.

4.4 EV Charging Preferences, Perceptions, and Willingness-to-Pay (WTP)

4.4.1 Charging Knowledge and Preferences

4.4.1.1 Charging technology awareness. Figure 4.17 shows the disparity in charging technology awareness between EV users and non-EV users. While EV users demonstrate an understanding of various charging technologies, nearly half of non-EV users were unaware of these technologies. This highlights the need for targeted efforts aimed at bridging this knowledge gap, particularly among segments of the population less exposed to EV charging technologies.

4.4.1.2 Home charging availability. The finding that approximately 75% of EV users have access to home charging facilities (Figure 4.18) underscores the significant role of home charging infrastructure in

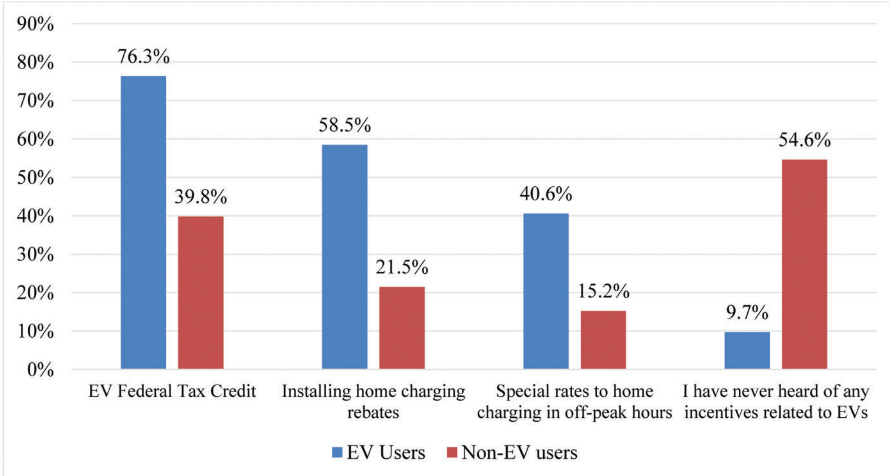


Figure 4.14 Incentive awareness of EV users and non-EV users.

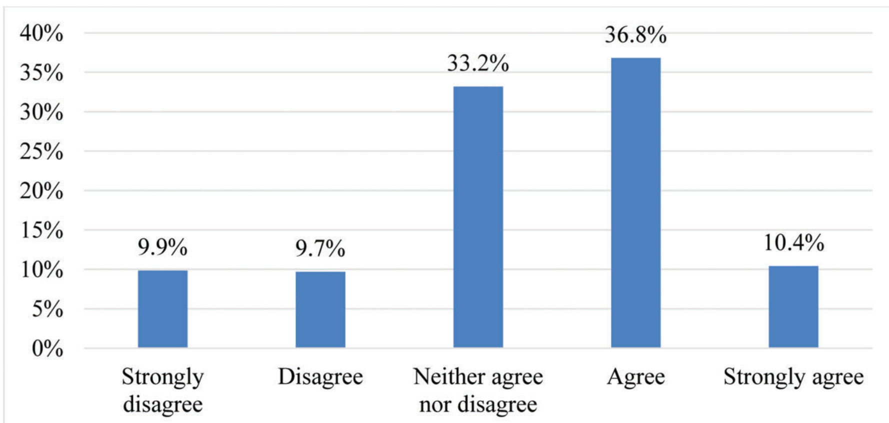


Figure 4.15 Awareness of incentives and likelihood to buy/lease an EV.

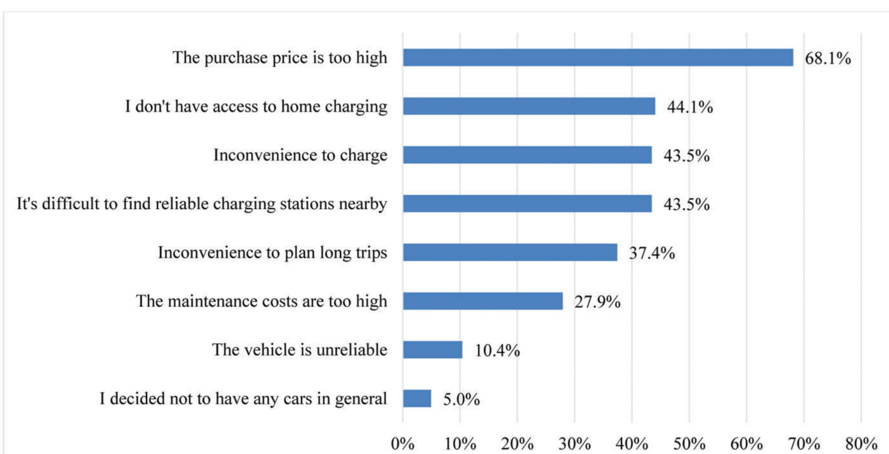


Figure 4.16 Non-EV users' stated reasons for not having an EV.

facilitating the adoption and usage of EVs. This high prevalence suggests that for a substantial portion of EV users, the convenience and reliability of home charging play a crucial role in their overall EV ownership experience. Moreover, it highlights the importance of ensuring widespread availability and accessibility of home charging solutions to support the continued growth of the EV market.

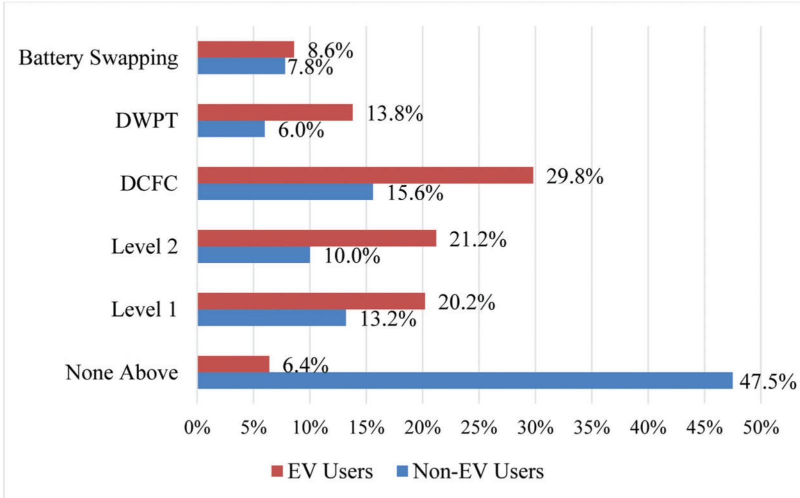


Figure 4.17 Charging technology awareness.

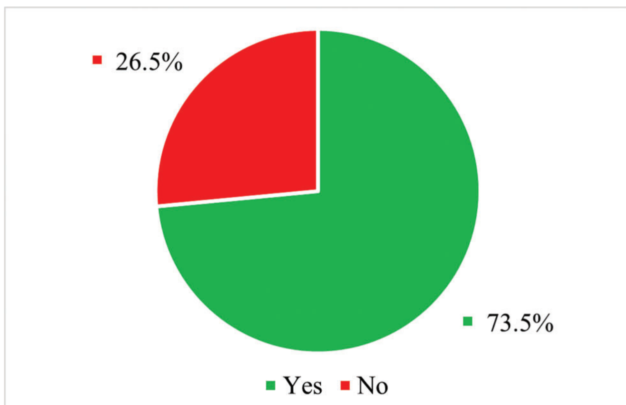


Figure 4.18 Home charging availability.

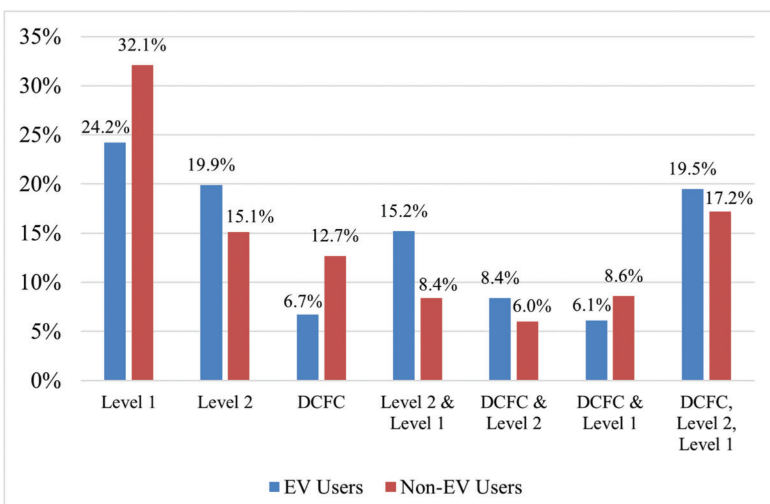


Figure 4.19 Charging technology preference.

4.4.1.3 Preference for EV charging technologies. As can be seen in Figure 4.19, the preference for home charging (Level 1) emerged as the dominant choice across both EV users and non-EV users. This trend underscores the convenience and reliability associated with home charging solutions, aligning with the notion that the ability to charge at home is a major factor driving EV adoption.

Furthermore, the notable finding that half of the respondents expressed a preference for more than one charging options suggests a growing recognition of the importance of various types of public charging infrastructure to accommodate varying needs and preferences. This inclination towards having access to multiple charging options reflects a desire for flexibility and convenience.

Moreover, a considerable proportion of both EV users and non-EV users expressed a preference for having all three charging options available—Level 1, Level 2, and Level 3/DCFC. Having multiple charging options might indicate reliability for EV itself.

4.4.1.4 Maximum distance to drive to charge EV. The survey highlights a clear contrast in the maximum distance non-EV users and EV users are willing to travel for EV charging. Non-EV users predominantly favored zero miles or solely relied on home charging, indicating a preference for convenience and familiarity, as shown in Figure 4.20. In contrast, EV users display a greater flexibility, with a higher percentage willing to travel varying distances beyond home charging. Addressing non-EV users' concerns, such as expanding home charging solutions, and catering to the diverse needs of EV users by enhancing public charging networks, are essential for broadening EV adoption and sustaining market growth.

4.4.1.5 Maximum distance to drive to charge in between charging stations. The disparity in tolerance for driving distances between non-EV users and EV users is evident, with 41% of non-EV users selecting 10 miles as the maximum distance they are willing to drive to reach a charging station, compared to only 15% of EV users (Figure 4.21). This discrepancy underscores a greater aversion among non-EV users to travel extended distances for charging, possibly reflecting concerns about range anxiety or limited familiarity with available charging infrastructure. In contrast, EV users demonstrate a higher threshold for driving distances, suggesting a more nuanced understanding of charging options and a greater willingness to adapt their charging behavior to accommodate longer journeys. Addressing the specific needs and apprehensions of non-EV users, such as by improving awareness of charging infrastructure and alleviating range anxiety through targeted education and infrastructure development, can play a crucial role in encouraging broader EV adoption and usage.

4.4.1.6 Willingness to walk to destination from nearby public charging station. More than 50% of non-EV users stated that they would be willing to walk 0−3 minutes to reach a destination from an EV public charging station, in contrast with approximately 20% of EV users stating the same (Figure 4.22). A majority of EV users are comfortable walking 3 minutes or more, with 38% of them willing to walk within 3−7 minutes. This suggests that placing charging stations close to major destinations and POIs would benefit both groups, but certainly improve the perceptions of non-EV users.

4.4.1.7 Willingness to charge at public settings. The willingness to charge at public settings reveals a trend where EV users consistently exhibit a higher percentage of willingness across all nine scenarios (including office, retail, public administration, medical, educational, leisure, transit, hotel, and restaurant) compared to non-EV users. This observation underscores the greater comfort and familiarity that EV users have with

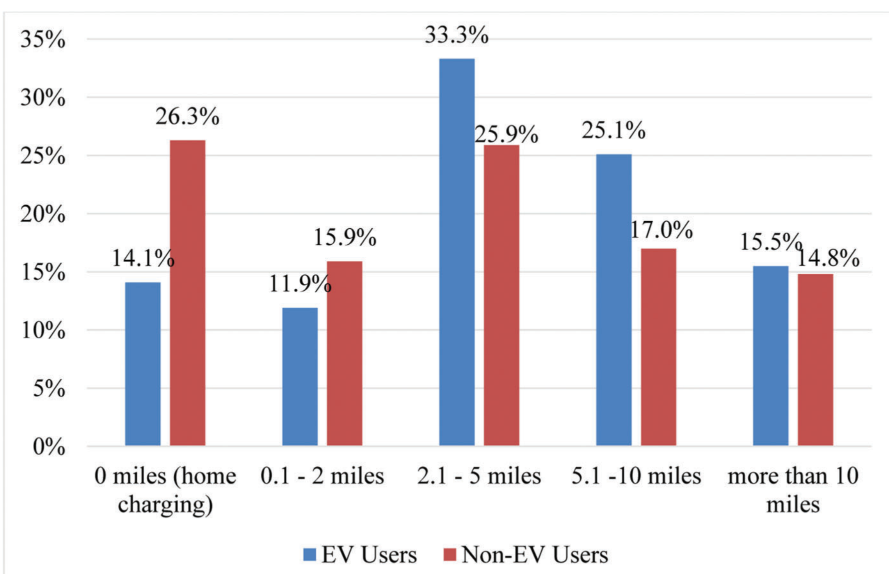


Figure 4.20 Maximum distance users are willing to drive to charge EVs.

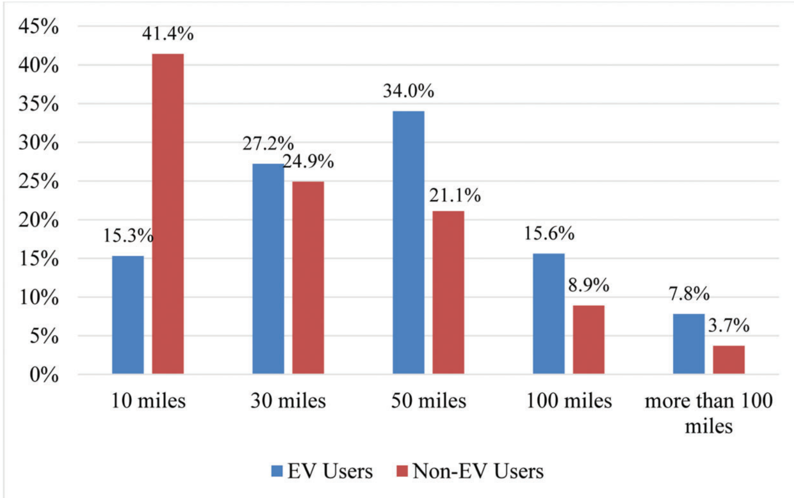


Figure 4.21 Maximum distance to charge between charging stations.

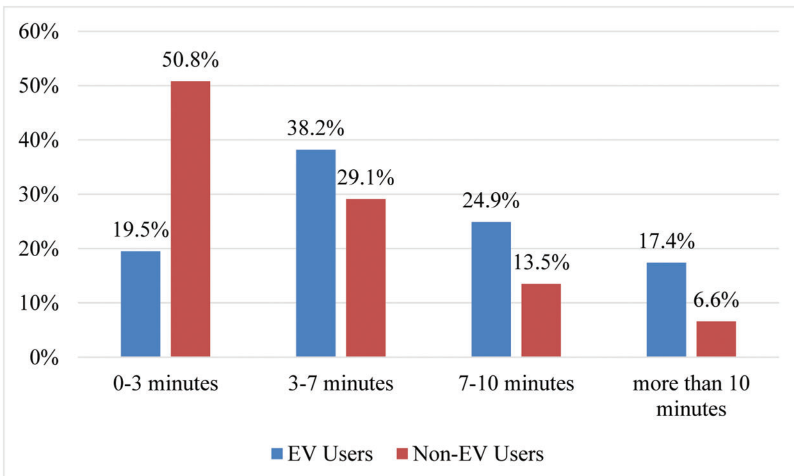


Figure 4.22 Willingness to walk to destination from nearby public charging station.

utilizing public charging infrastructure. Figure 4.23 and Figure 4.24 provide further statistics for EV users' and non-EVusers' willingness to charge at restaurants and retail shops, respectively. This highlights the importance of providing safe and convenient public charging location as part of strategies to attract new EV adopters.

4.4.1.8 Typical battery level when leaving home (first time of the day). Figure 4.25 shows that a small proportion of EV users depart with a battery level below 50%, suggesting a preference for starting their journeys with ample charge reserves. Instead, the majority opt to maintain their battery levels within the range of 70.0%–89.9%, indicating a deliberate effort to ensure a comfortable buffer for their daily activities.

Figure 4.26 further reveals a diverse range of battery levels among EV users when initiating the charging process. Interestingly, respondents demonstrate nearly proportional preferences across three distinct ranges: 20.0%−39.9%, 40.0%–59.9%, and 60.0%–100.0%. This distribution suggests that EV users exhibit flexibility in their charging behaviors, with no single range dominating their charging habits.

4.4.1.9 Typical charging duration. The analysis of typical charging durations (Figure 4.27) revealed a clear relationship between charging time and the power output of the charging technology. For Level 1 charging (typically at home), over 60% of users spend at least 1 hour charging, with 34% extending their charging sessions beyond 3 hours. This longer duration reflects the lower power output of Level 1 chargers, which are designed for overnight charging. Conversely, for Level 2 charging (commonly found at public charging stations), nearly half of the users spend between 30 minutes to 3 hours charging, indicating a moderate power output that balances charging speed with convenience. Finally, for Level 3/DCFC charging (rapid charging available at public stations), users predominantly spent between 15 minutes to almost an

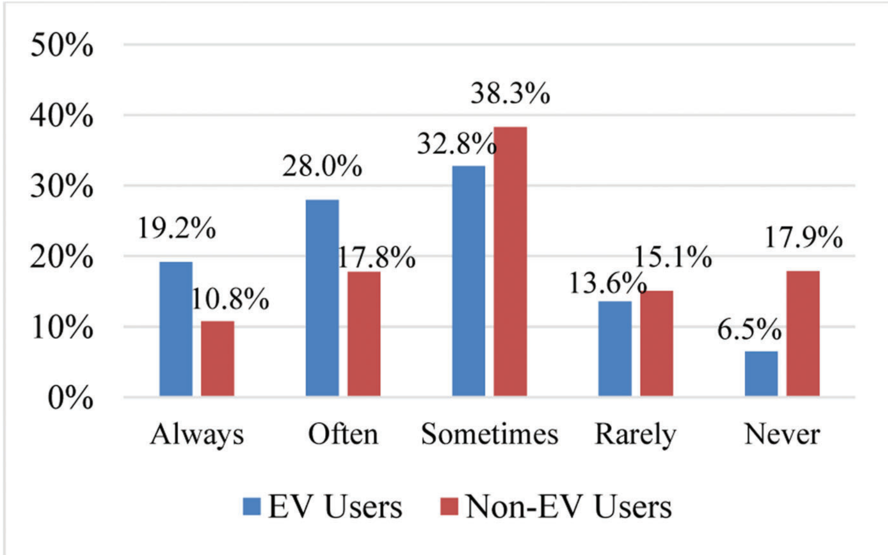


Figure 4.23 Willingness to charge at a restaurant setting.

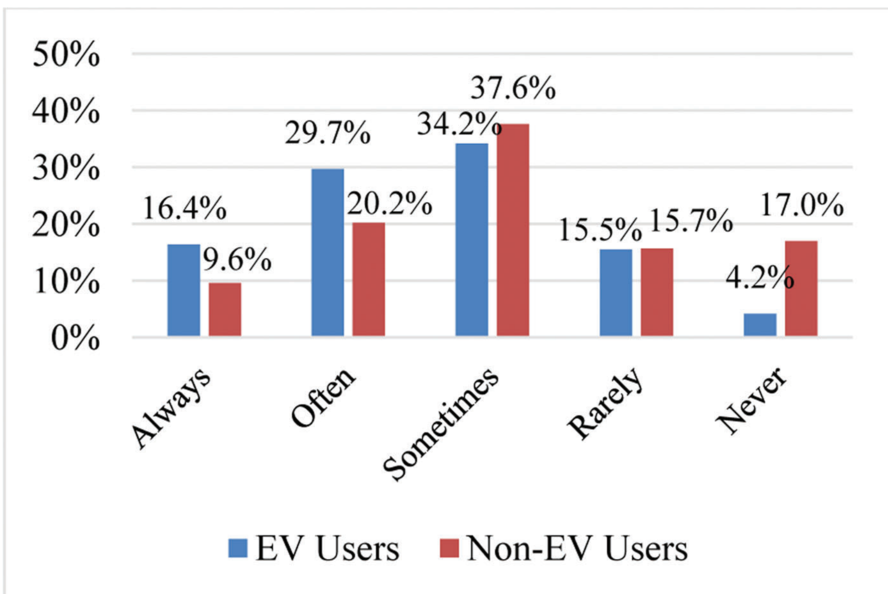


Figure 4.24 Willingness to charge at a retail setting.

hour charging, highlighting the high power output and rapid charging capabilities of these stations.

4.4.2 Charging Perceptions

4.4.2.1 Willingness to start a trip when battery level is equal to trip length. The analysis indicates a significant contrast in range anxiety between non-EV users and EV users when considering starting a trip with a battery level equal to the trip length (Figure 4.28). Among EV users, approximately 22% expressed a willingness to "always" embark on a trip under these conditions, while 11% indicated they would "never" do so. In contrast, non-EV users exhibit higher levels of range anxiety, with only 5% expressing a willingness to "always" start a trip with a matching battery level, and a substantial 27% stating they would "never" do so. This disparity underscores the greater apprehension among non-EV users regarding the range capabilities of EVs, potentially attributed to limited exposure or understanding of EV battery technology.

4.4.2.2 Willingness to start an unfamiliar trip when battery level is higher than trip length. The data presented in Figure 4.29 presents a surprising trend among non-EV users regarding their willingness to embark on an unfamiliar trip when their EV battery level exceeds the length of the journey. Despite the trip

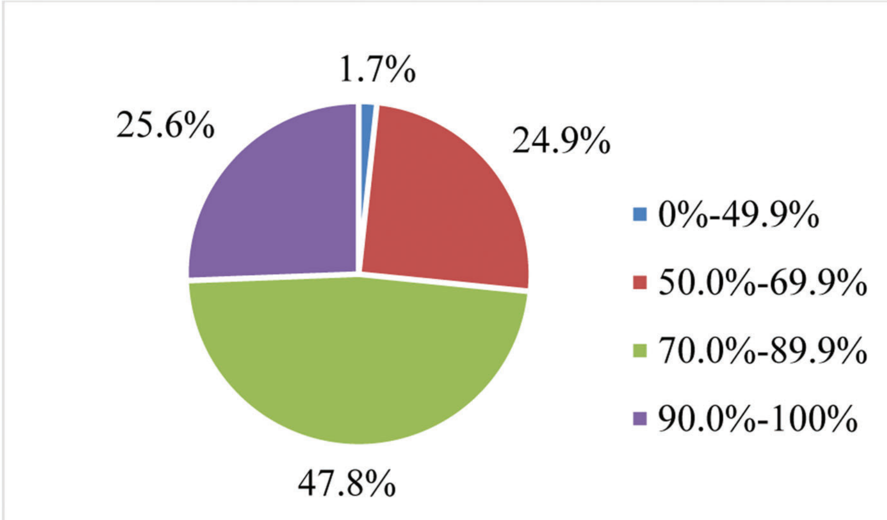


Figure 4.25 EV battery level when leaving home.

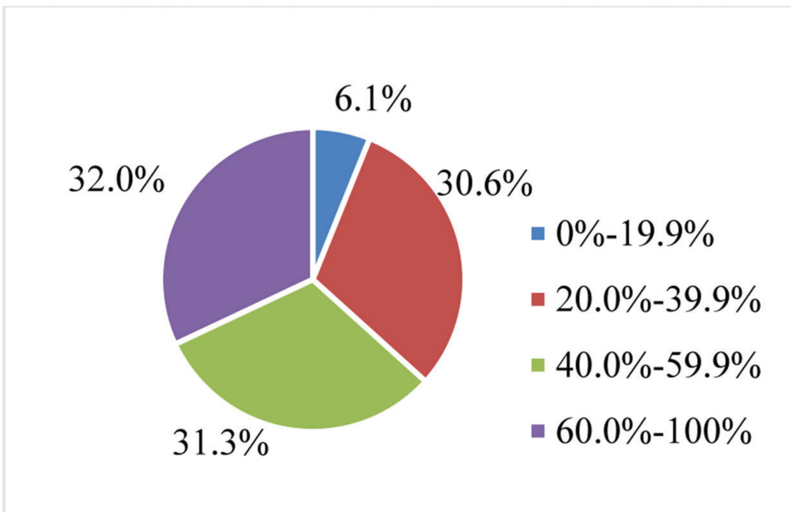


Figure 4.26 EV battery level when starting to charge.

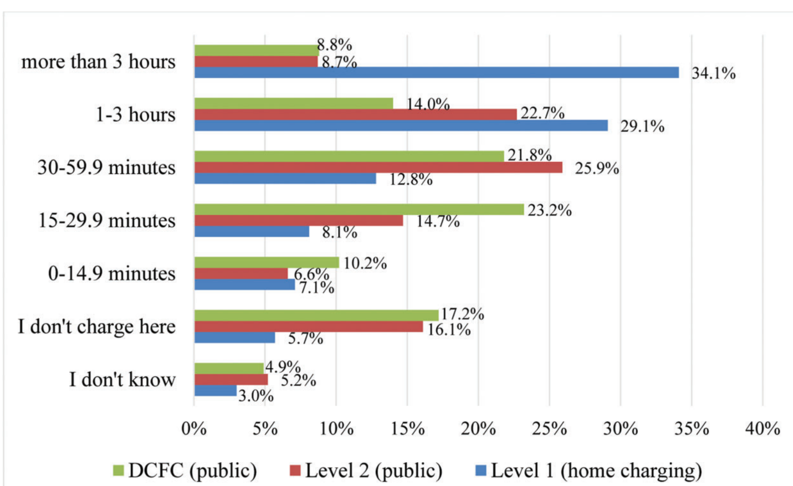


Figure 4.27 Typical charging duration.

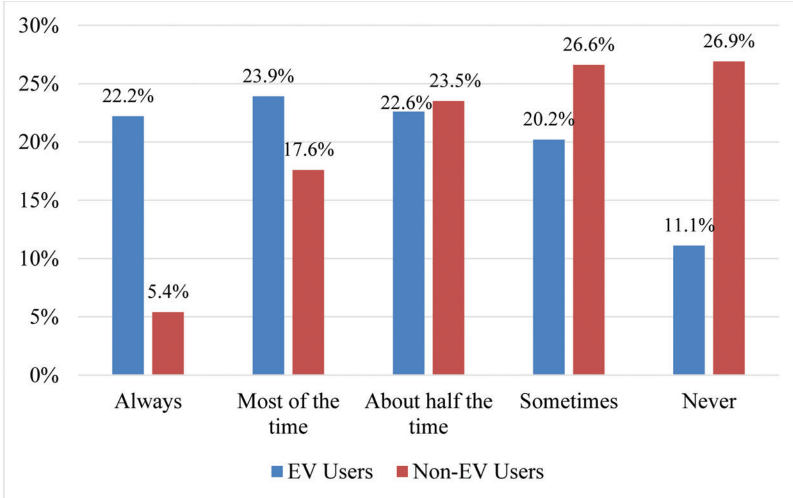


Figure 4.28 Willingness to start a trip when battery level is equal to trip length.

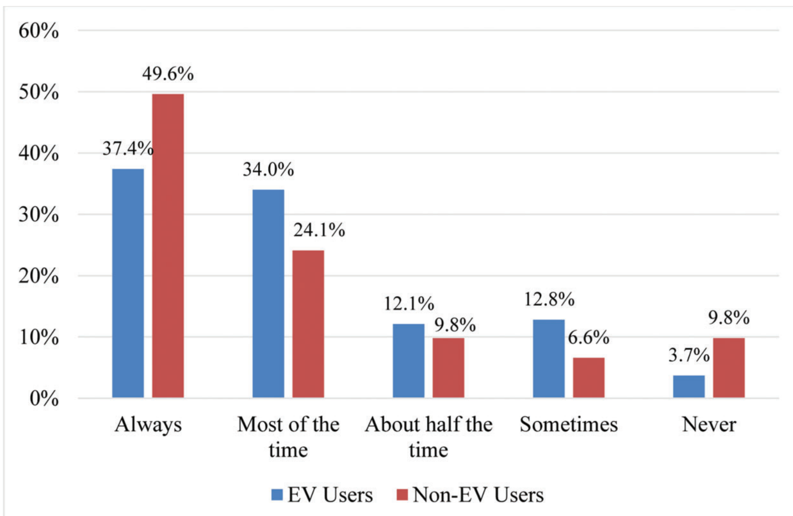


Figure 4.29 Willingness to start an unfamiliar trip when battery level is higher than trip length.

being unfamiliar, most non-EV users expressed a willingness to start the journey under these conditions. This finding suggests that for non-EV users, concerns related to the reliability of battery level or range anxiety may be significant barriers instead of the characteristics of the trip itself. A similar concern was raised in the open comment section of the survey (Section 4.5), which stated, *"If there was more infrastructure or better mileage range on EVs, they would be more popular."*

4.4.2.3 Perceptions about public charging availability. Figure 4.30 shows that, among EV users, a significant 30% stated that they would "always" find public charging when needed, with only a minimal 1.2% expressing doubt in availability. In contrast, non-EV users exhibit a more cautious outlook, with only 9.1% being confident that they would "always" find public charging, while a concerning 19% expressed a belief that they would "never" find any public charging when needed. This discrepancy underscores the varying levels of confidence and familiarity with public charging infrastructure between the two groups. Addressing the perceived barriers to public charging accessibility among non-EV users, such as through infrastructure expansion and awareness campaigns, is essential for fostering greater trust and acceptance of EVs among this demographic.

4.4.2.4 Opinions and expectations about public charging infrastructure. The results presented in Figure 4.31 revealed that about half of the EV respondents found that charging at public stations was cumbersome, whereas a small portion admitted they lacked the patience to wait for their car to charge. Similarly, almost half of the non-EV users also felt that using public charging stations could be cumbersome, with an even larger proportion expressing impatience with waiting times. Over half of the respondents in both

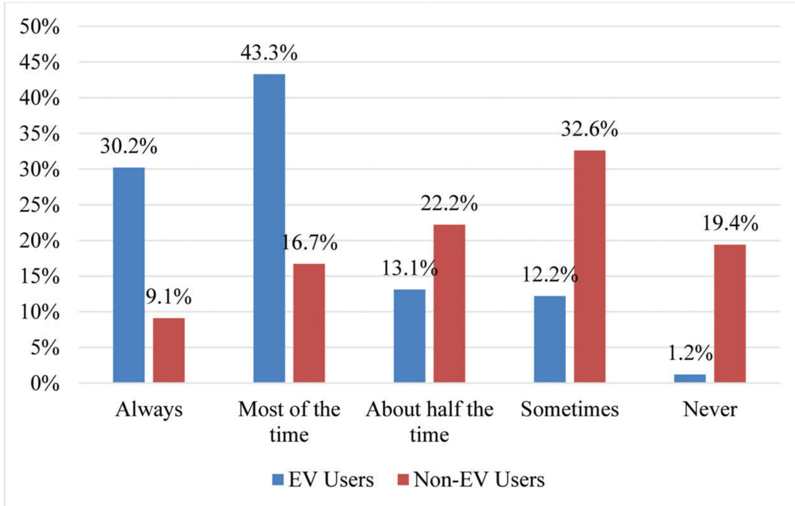


Figure 4.30 Perception of charging station availability when needed.

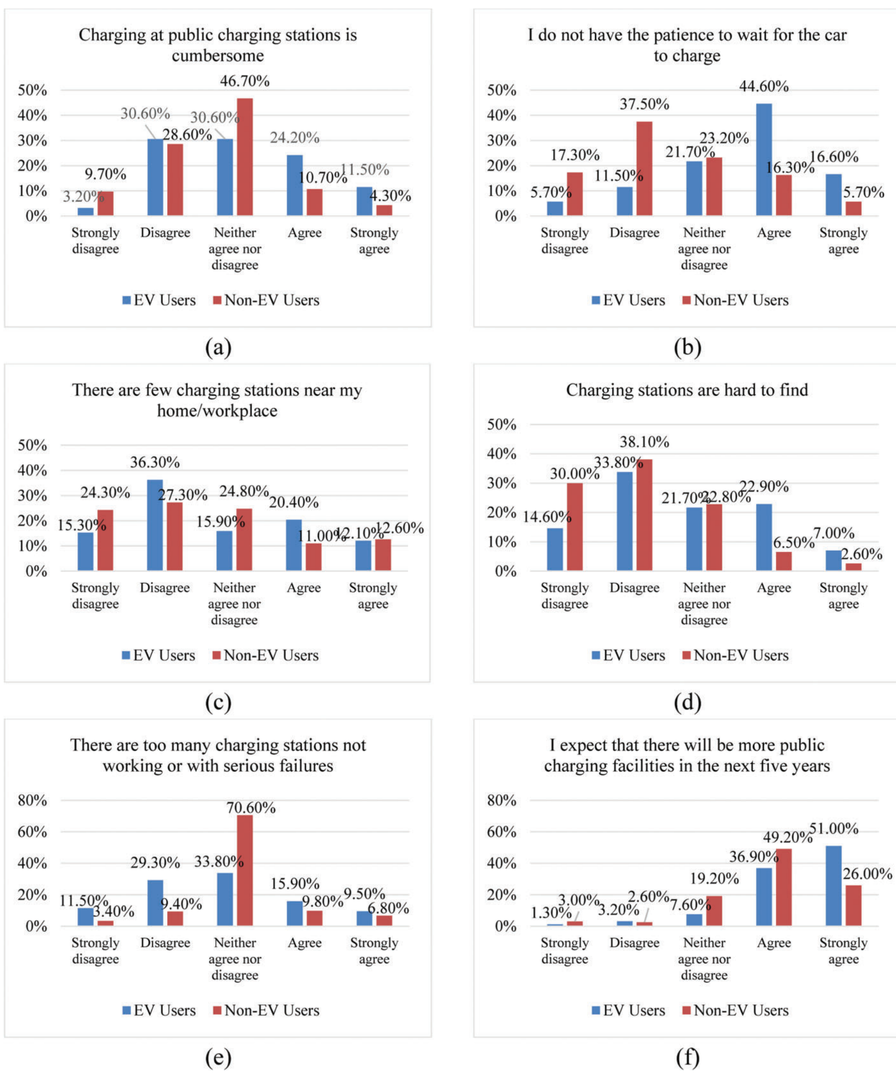


Figure 4.31 Opinion about public charging infrastructure.

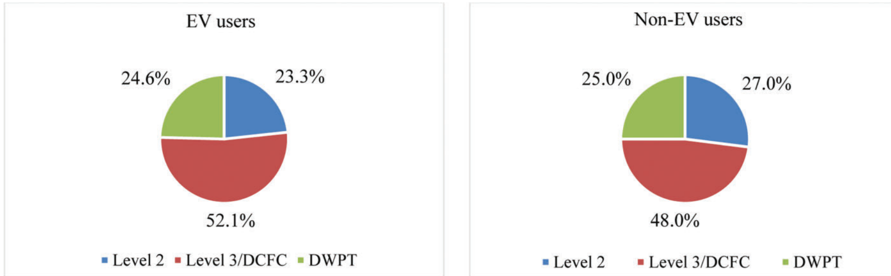


Figure 4.32 Charging preferences based on choice experiment.

groups reported having access to only a few charging stations near their homes or workplaces. Additionally, about half of the EV users found it hard to locate charging stations, with even more non-EV users facing this challenge. Moreover, nearly half of the EV users noted that many charging stations were out of order or had serious issues, while most non-EV users did not have a strong opinion on this matter. Lastly, most respondents from both groups stated that they expected more public charging stations in the following 5 years.

4.4.3 Choice Experiment and WTP

Based on the findings from the choice experiment, it was observed that respondents, including both EV and non-EV users, showed a clear preference for Level 3/DCFC, with approximately half of the respondents selecting this option. The remaining responses were evenly distributed between Level 2 charging and DWPT, each accounting for around 25% of the respondents' choices. This indicates a significant inclination towards fast-charging infrastructure among both groups of EV users. Both groups' reluctance in choosing DWPT could be attributed to lack of firsthand experience due to the absence of publicly available DWPT infrastructure in Indiana at the time of the survey.

It is also worth noting that nearly 50% of non-EV users are unaware of charging technologies, as depicted in Figure 4.17, this lack of awareness should be addressed with public education and awareness capaings around EV charging technologies. For EV users, it is crucial to educate them about DWPT since it is a relatively new technology and not widely available yet. Once DWPT becomes accessible and vehicles adapted to it, targeted advertisements may be necessary to encourage users to experience it firsthand. For non-EV users, the focus should be on providing comprehensive education about various charging technologies. As indicated in Section 4.4.1, there is a significant lack of knowledge about charging options among non-EV users, making general charging technology education a priority.

Table 4.3 summarize willingness-to-pay (WTP) estimation values related to charging station amenities and services (see Appendix C for the model details).

For EV users, the willingness-to-pay to reduce waiting time at Level 2 charging stations was estimated at approximately \$9.44 (median) and \$2.93 (mean) per hour. This is lower than findings from a study in Norway (Solvi Hoen et al., 2023), where EV users were willing to pay \$28.34 per hour of reduced waiting time. In contrast, non-EV users showed a higher willingness-to-pay, with estimates around \$86.97 (median) and \$20.72 (mean) per hour; a study in Germany (Wolff & Madlener, 2019) found WTP for waiting time was around \$53.40 per hour for non-EV users. The results highlights the difference in WTP between the two groups.

Regarding charging time at DC fast charging (DCFC) stations, EV users were willing to pay about \$21.73 (median) and \$6.73 (mean) per hour of reduced charging time. This is similar to another U.S. study (Ge & MacKenzie, 2022), which reported a WTP around \$24 per hour. Non-EV users' WTP was approximately \$30.04 (median) and \$7.16 (mean) per hour; similar study in Germany (Wolff & Madlener, 2019) found WTP for charging time approximately \$10.20 per hour for non-EV users.

In the literature on public charging, there is no consensus on the exact value of WTP estimates. However, our findings reinforce the literature that the characteristics between users and non-users are not similar. This phenomenon were also captured in various transportation studies involving different transportation mode, including EVs (He et al., 2022), e-scooters (Mesimäki & Lehtonen, 2023), public transport (Pedersen et al., 2011).

Additionally, non-EV users were willing to pay an extra \$4.10 (median) and \$0.98 (mean) for restroom availability at DCFC charging stations. A study in Denmark (Visaria et al., 2022), found the participants were willing to pay \$2.27 for access to restrooms, restaurants, and supermarkets. However, some findings differ; for instance, in Switzerland (Brückmann & Bernauer, 2023), the willingness-to-pay for amenities like toilets, shops, coffee places, and park benches was around \$10.97, while in the U.S. (Ge & MacKenzie, 2022), it was \$21 for facilities including toilets, dining options, and WiFi.

4.5 Analysis of Open Question/Comments About EVs

At the end of the survey, the participants were asked if they would like to provide comments about EVs that they thought would be relevant to the research team.

TABLE 4.3
WTP estimates

Attributes	EV Users	Non-EV Users
Waiting Time (Level 2): Median	$9.44/hour	$86.97/hour
Waiting Time (Level 2): Mean	$2.93/hour	$20.72/hour
Charging Time (Level 3/DCFC): Median	$21.73/hour	$30.04/hour
Charging Time (Level 3/DCFC): Mean	$6.73/hour	$7.16/hour
Restroom (Level 3/Dcfc): Median	–	$4.10/restroom availability
Restroom (Level 3/DCFC): Mean	–	$0.98/restroom availability

Figure 4.33 Word cloud for EV users.

The comments were topic free without length restrictions. Not all participants provided feedback as it was not mandatory. This section summarizes the feedback received along with some examples.

4.5.1 Comments by EV Users

Generally, EV users provided positive feedback about their vehicles.

- "*I love them.*"
- "*Excellent type of car.*"

Respondents also expressed comments related to the benefits of EVs to the environment.

- "*They are critical to decarbonizing our society.*"
- "*I mostly like EV because they're best for the environment.*"

On the other hand, they were vocal about the need for public charging infrastructure improvements, especially for DCFC/Level 3 stations on highways.

- "*We need more stations.*"
- "*To facilitate the needed transition to EVs, DC superchargers need to become essentially as available as gas stations are today along interstate highways or other major highways.*"
- "*I would love to see level 3 charging stations at major highway exits. I do not need charging stations near my home since I have a home charger.*"
- "*We love our EV and frequently take it on trips out of state. It is disappointing how few DCFC options there are in Indiana compared to other places we visit. Looking forward to seeing how the state will use the available federal dollars to improve DCFC options.*"

On the other hand, EV users expressed concerns about the registration fee and lack of POIs close to charging stations.

- "*I'm curious about this technology of charging while driving. I object strongly to paying $150 extra for my license plate every year.*"
- "*Registration fees are punitive.*"
- "*Having safe place near EV charging is important. Having shopping, restaurants, parks or walking trails near the charging stations help.*"

Figure 4.33 summarizes the comments received from EV users as a word cloud.

4.5.2 Comments by Non-EV Users

Barriers to EV adoption, such as the purchase price, were frequently mentioned.

- "*Cost of vehicle, cost of charging and range will influence decision to purchase.*"
- "*Currently, I think the price of EVs is beyond the reach of most households.*"
- "*I don't think EV's will be very popular. Not everyone is able to afford one.*"

Figure 4.34 Word cloud for non-EV users.

Many respondents reported interest in EVs but prefer to wait for the technology to mature before adopting one.

- *"I have driven one before and I was impressed. However, I like to see how everything pans out for a few years with new technology."*
- *"I'm waiting for the technology to improve, and/or the cost to go down."*
- *"I'm very interested in more information."*

Non-EV users expressed conflicting opinions about the environmental benefits of the vehicles.

- *"EVs are good for the environment."*
- *"EVs are possibly more destructive to the environment due to the mining of metals required, especially in undisturbed areas."*
- *"I think they are good in some ways but harmful in others such as the batteries that are harmful both to be made and when they are done being used."*

Additional comments confirmed the non-EV users' perceptions about range anxiety and the lack of public charging.

- *"I think they are good when they get more charging stations."*
- *"I am more likely to use an EV for short trips near home to eliminate waiting for public charging."*
- *"Currently I am traveling 250 miles/500 miles round trip frequently. I would worry that I could not find a place to charge my vehicle."*

Finally, non-EV users expressed additional concerns about the location, safety, and POIs at public charging stations.

- *"Another of my concerns is safety at public charging stations and feeling vulnerable as both a senior and also LGBTQ."*
- *"I believe EVs are an important step in the right direction for cleaning up our air quality, etc. However, my concerns lie with more rural areas not having access to charging for long distances as well as the set up cost for installation of a home charging station and the time needed to charge a vehicle for those without a home charging station that could be taking time away from family, work, or leisure."*

Figure 4.34 summarizes the comments received from EV users as a word cloud.

4.6 Chapter Summary

This chapter presented a descriptive analysis of the survey designed to gauge the Indiana public's perspective about EVs. The results of the questionnaire revealed that Indiana EV users are typically middled aged high-income males living and working in urban areas. EV users tend to drive more frequently than non-EV users and prefer owning EVs over leasing them. They considered home charging as a vital component for EV usage. Non-EV users stated a high level of uncertainty about the EV attributes, although they recognized the fuel cost and the noise as the greatest advantages of EVs. They also stated that they are more likely to purchase than lease an EV, especially in the long term, and identified purchase price and charging issues as the main barriers to adoption. Non-EV users are less aware of charging technologies, prefer shorter driving distances to charge, and are less inclined to use public charging stations. Most participants stated a preference for used EVs due to their lower cost and stated an apprehension about investing in a technology they are not familiar with. However, participants who stated a preference for a new EV attributed it to the better performance of new EVs and their general inclination to buy new vehicles independently of the engine type. Finally, respondents were more aware of incentives related to the purchase of EVs than the ones related to charging. Almost half of the sample agreed that EV incentives would make them more willing to adopt an EV.

5. EV TRIPS DETECTION

This chapter examines algorithms (Section 5.1), describes the data preparation (Section 5.2) and presents the results (Section 5.3) for EV trip detection.

Specifically, this work aims to collect EV samples from available datasets and provide reasonable synthetic sequential EV trip information, which can support the EV infrastructure investments. Figure 5.1 illustrates the framework of the EV trip detection and synthetic problem. Initially, vehicles are operating in the road network without specified fuel types, gasoline vehicles (GVs) or EVs (Figure 5.1), and their travel trajectories are collected by forms such as cellular data. However, given their distinct power sources, GVs and EVs might exhibit different movement characteristics, which can be leveraged to distinguish between the types of vehicles. For instance, upon evaluating various travel characteristics, such as velocity and acceleration on the sample dataset, vehicles A and B (green) are identified as EVs, and vehicles C and D (blue) are recognized as GVs. The identified EVs and their trip distribution can reflect the travel characteristics of EV users.

We extract some daily trip features, such as average trip distance, speed, and acceleration, which serve as input features to the detection algorithms. Eight algorithms are trained to classify if the vehicles are EVs or not on a labeled dataset, including ensemble models, such as Random Forest and XGBoost. We apply the algorithm with the highest accuracy (XGBoost) to detect EV users from an unlabeled cellular dataset.

5.1 EV Trip Detection

This subsection presents eight different algorithms aimed at detecting vehicle types by utilizing the generated vehicle trip features. These algorithms are trained and evaluated using the dataset containing vehicle type labels. The input matrix comprises the daily trip attributes of users, wherein the rows correspond to the users and the columns correspond to trip features. For users who have trip data spanning multiple days, the representations on multiple rows are possible. The outputs of algorithms are vectors with lengths equal to the user number (the number of rows of the feature matrix), with elements indicating the probabilities that the corresponding users are EV users. The algorithm with the highest accuracy is utilized to identify EV users from a large cellular dataset in the same area with vehicles without type information. The classification algorithms used in this section include.

- *Logistic Regression (LR)* utilizes the logistic function to estimate the probability of the vehicle type based on the input features. These features are linearly combined using coefficients or weights to predict the outcome's probability.
- *Decision Tree (DT)* represents decisions and their potential results in the form of nodes and branches. It operates by repeatedly partitioning the data into subsets based on feature values. After tuning, the longest path from the tree's root to a leaf is set to 10.
- *Random Forest (RF)* consolidates multiple decision trees to enhance prediction accuracy and robustness. It randomly samples data and features to mitigate overfitting. After tuning, the tree count is set to 100 and the maximum path length from the tree root to a leaf is set to 10.
- *K-Nearest Neighbor (KNN)* identifies the K nearest neighbors of a new data point in the training set using a distance metric such as Euclidean distance. In this section, the number of neighbors (K) is set to 5.
- *Support Vector Machine (SVM)* finds the optimal hyperplane that separates the data into different classes. It is adept at handling high-dimensional and nonlinear data and shows resilience to noise and outliers. In this section, the polynomial kernel degree is set to 5.
- *Naive Bayes (NB)* relies on the Bayes theorem and assumes that the features are conditionally independent given the class. It calculates the conditional probability of a class given the values of the features.
- *XGBoost* uses the gradient boosting framework and amalgamates multiple decision trees into a robust ensemble model. It applies gradient-based regularization to prevent overfitting and improve the model's generalization. We have configured XGBoost to randomly select 40% of the training data for tree growth and limited the maximum depth of each tree to 10.

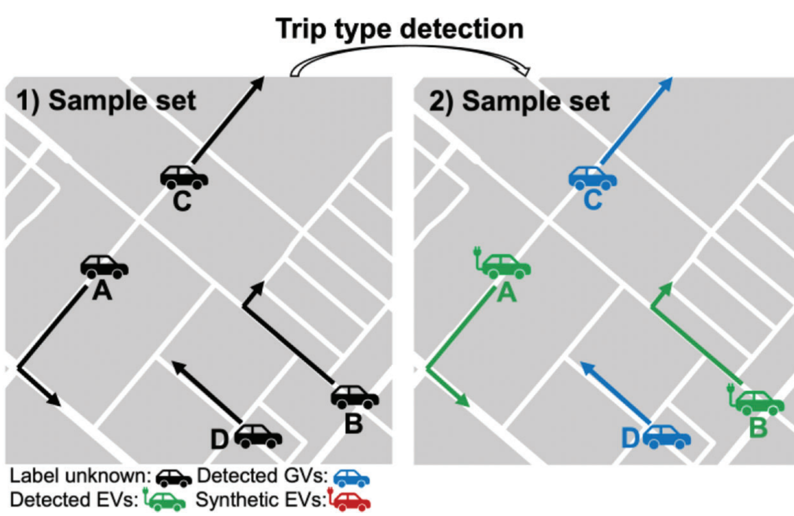


Figure 5.1 EV trip detection process.

- *Label Propagation Algorithm (LPA)* is a semi-supervised learning algorithm, which uses several labeled nodes and the network structure to detect groups of nodes with the same label at a very high speed. We tune the parameter as the KNN kernel, and the number of neighbors equals 25.

5.2 Data Preparation

Two datasets from Indiana were employed in this section. The initial dataset (Dataset 1) is provided by the Otonomo platform and contains the trajectories (latitude, longitude, and time) of 596 EVs along with 1,355,132 GVs. It records daily vehicle trajectories over a span of two weeks starting from 10/01/2022. The vehicle IDs are altered daily to maintain anonymity. The subsequent dataset (Dataset 2) is sourced from a private vendor, Quadrant. It is a cellular dataset for a month, delivering anonymous IDs, locations (latitude and longitude), and time indicators for device holders, devoid of travel modes or vehicle types. Commencing from 03/01/2021, this dataset incorporates 2,027,034 users, representing approximately one-third of Indiana's population. The cellular dataset has multiple advantages—first, it has good coverage of the population, which may contain a large sample size of EV users; second, it contains rich information about EV user activities outside of transportation infrastructure; this is a significant advantage when compared with data collected by charging stations or from vehicles; third, it has been applied in mobility research for many years, and the corresponding privacy issues are well-studied and amended.

Initially, we transition the sequential coordinates into features that can assist in discerning the types of vehicles. This process, known as trajectory pre-processing, is crucial for trajectory data mining tasks as it cleans raw trajectories and segments them into meaningful trips. Both datasets' coordinates and the corresponding geographic information files are gathered as inputs. Afterward, each user's sequential trajectories are processed into individual trips from start points to end points, and additional features, such as trip speed and accelerations are constructed based on these identified trips. It is important to note that various factors, such as city topographical characteristics (for example, inclines and declines in roads) and traffic conditions (such as average traffic speed and congestion levels) can influence the energy consumption of vehicles and driving patterns. However, this section operates under the assumption that a vehicle's energy consumption is primarily determined by the travel distance.

5.2.1 Stay Point Detection and Trip Segmentation

Raw trajectories may deviate from accurate information, leading to issues in identifying the precise locations of the vehicles within the urban network. Utilizing noise filtering methods can aid in eliminating this discrepancy based on predefined thresholds. Furthermore, the two fundamental states in trajectory data are moving and staying, which can be employed to partition raw trajectories into logical sub-trajectories or trips. The stay point represents the geographic location of the trip destination, and the time span indicates the user's activity duration at that specific location (Sun et al., 2021; Yu et al., 2019). For instance, in a round-trip scenario from a home to a supermarket by a driver, the supermarket would be identified as a stay point, with the time span indicating the duration of shopping. These stay points, along with their respective durations, depict users' interests in each POI category. As illustrated in Figure 5.2a, two types of stay points exist. The first one corresponds to a fixed location, where the user remains stationary, for instance, a shopping mall. The second kind refers to a virtual location, constituted by a cluster of points around which the user has a series of ongoing activities, such as in a park.

This section organized each user's trajectories, divided them into discrete trips, and created the trajectory using the following steps: noise filtering, trajectory compression, trajectory segmentation, and stay point detection. To circumvent the issue of coordinate deviation, we considered both types of stay points. Once this procedure was completed, we extracted the segments of each trip and the stay points for every user, as demonstrated in Figure 5.2b.

Several previous studies have employed varying time interval thresholds or speed values for segmentation (Bohte & Maat, 2009; Zheng et al., 2010). Despite their straightforward implementation, these methods are often imprecise due to their reliance on fixed, subjectively set

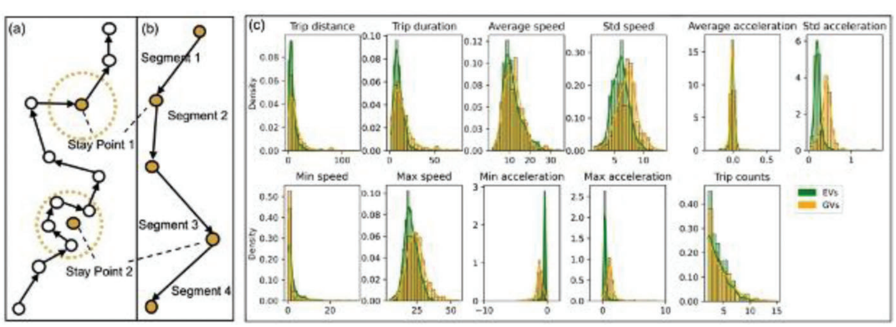


Figure 5.2 (a) Two kinds of stay points in a trajectory, (b) trip segment illustration, and (c) trip feature distribution of EVs and GVs.

thresholds. In our approach, we implement a basic heuristic filter to maintain sequential trajectories in the datasets with a maximum speed of 60 m·s. After noise elimination, we consider the refined trajectory as an input. If the distance between consecutive coordinates exceeds 100 meters and the duration between these two points is calculated; any duration longer than 5 minutes denotes the two coordinates as different trip segment cut-off points. It is worth noting that recommendations for the stop duration threshold fluctuate between 2 to 30 minutes in various studies (Hwang et al., 2018). Certain research also proposes that these thresholds be personalized for individual users (Bonavita et al., 2020, 2022). However, since our study's aim is to identify EV users and their trips, a stop duration of 5 minutes is deemed sufficient to distinguish between the fueling times of GVs and the recharging times of EVs.

5.2.2 Features Generation

After the trip segmentation process, we collected 1,678,667 driving segments from Dataset 1 and 29,062,569 from Dataset 2. To mitigate potential variations in feature values due to fluctuating traffic conditions, we computed average features by aggregating trip segments daily. Features such as distance, duration, speed, and acceleration were generated as outlined in Table 5.1. The feature distinctions between EVs and GVs are described both in Table 5.1 and Figure 5.2c. These show that EV trips tend to cover shorter distances and have shorter durations than GV trips. Average travel speed and acceleration are primarily constrained by the city network and show minimal variances. However, when comparing minimum and maximum accelerations, EV trips appear to be smoother, contradicting existing claims that EVs accelerate faster than GVs. This discrepancy may arise due to driver behaviors and differences between the ideal testing conditions of an experimental environment and the reality of road networks for evaluating EV driving performance.

To prevent any potential bias in the detection results that might be induced by closely correlated features, we carried out a feature correlation test. The results from this analysis indicate that none of the generated features display a strong correlation, with all absolute values below 0.5. Additionally, we find no significant correlation between vehicle labels (i.e., EV or GV users) and the generated features, indicating that it is impractical to differentiate vehicle types based solely on any individual feature. Despite both datasets originating from the same state and undergoing identical pre-processing steps, normalization is still required due to the different sources of the datasets. The train and test sets, composed of 604 and 200 samples respectively, are derived from Dataset 1. In each set, half of the samples are EVs.

5.3 Evaluation Metrics and Results

This section first introduces the EV detection phase and employs the algorithm exhibiting the highest accuracy (XGBoost) to discern EV users and their corresponding trip data from the unlabeled cellular dataset. We evaluate the identified results against non-EV users using metrics such as trip distance and visit frequency to various POIs.

5.3.1 EV Detection Results

We utilize performance metrics—precision, recall, and F1 score to evaluate the algorithms' effectiveness—where higher values indicate better algorithm performance. Table 5.2 illustrates the basic concepts used in these metrics. Precision is calculated by TP/(TP+FP) and measures the accuracy of positive predictions. Recall measures the effectiveness of the model in identifying positive samples, it is obtained from TP/(TP+FN). The F1 score provides a single metric that

TABLE 5.1
Feature description and statistic of labeled dataset

Features	Definition	EVs	GVs
Average Trip Distance (Km)	The average daily trip distance of single users, which is obtained from converting the latitude and longitude information in trajectories.	8.77	9.15
Average Trip Duration (Mins)	The average daily trip duration of single users, which is derived by accumulating the time epochs in trajectories.	10.93	8.48
Minimum	The minimum/average/standard deviation/maximum trip acceleration of single users, which is calculated by trip speed divided by trip duration.	-0.42	-0.85
Average		0.00	-0.02
Standard Deviation		0.21	0.34
Maximum Trip Acceleration (M/S^2)		0.46	0.76
Minimum	The minimum/average/standard deviation/maximum trip speed of single users, which is calculated by trip distance divided by trip duration.	1.91	6.68
Average		11.51	17.21
Standard Deviation		6.00	5.77
Maximum Trip Speed (M/S^2)		20.60	25.87
Trip Counts	The total number of trip segments of single users.	3.13	1.66

Note: Negative acceleration is deceleration, and minimum acceleration is equivalent to maximum deceleration.

TABLE 5.2
Definition of true/false and positive/negative

Type	Prediction Type	True Type	Definition
True Positive (TP)	EV	EV	Correctly predicts the EV user
True Negative (TN)	Non-EV	Non-EV	Correctly predicts the non-EV user
False Positive (FP)	EV	Non-EV	Incorrectly predicts the EV user
False Negative (FN)	Non-EV	EV	Incorrectly predicts the non-EV user

TABLE 5.3
Algorithm performance on EV detection

Algorithm	Prob >0.5	Type	Precision	Recall	F1 Score	Prob >0.8	Type	Precision	Recall	F1 Score
LR	0.71	Non-EV	0.76	0.61	0.68	0.50	Non-EV	0.50	0.98	0.66
		EV	0.68	0.81	0.74		EV	0.50	0.02	0.04
DT	0.89	Non-EV	0.89	0.89	0.89	0.89	Non-EV	0.89	0.89	0.89
		EV	0.89	0.89	0.89		EV	0.89	0.89	0.89
RF	0.93	Non-EV	1.00	0.86	0.92	0.88	Non-EV	0.86	0.91	0.88
		EV	0.88	1.00	0.93		EV	0.90	0.85	0.88
LP	0.72	Non-EV	0.81	0.58	0.67	0.61	Non-EV	0.56	0.93	0.70
		EV	0.67	0.86	0.75		EV	0.80	0.28	0.41
SVM	0.88	Non-EV	0.97	0.77	0.86	0.74	Non-EV	0.67	0.96	0.79
		EV	0.81	0.98	0.89		EV	0.93	0.52	0.67
KNN	0.71	Non-EV	0.77	0.58	0.66	0.66	Non-EV	0.63	0.75	0.68
		EV	0.66	0.83	0.74		EV	0.69	0.56	0.62
NB	0.86	Non-EV	0.97	0.74	0.84	0.87	Non-EV	0.95	0.78	0.86
		EV	0.79	0.98	0.87		EV	0.95	0.78	0.86
XGBoost	0.94	Non-EV	1.00	0.88	0.94	0.92	Non-EV	0.91	0.90	0.90
		EV	0.89	1.00	0.94		EV	0.90	0.91	0.91

balances both precision and recall. It is the harmonic mean of precision and recall and is calculated as 2 * (Precision * Recall)/(Precision + Recall).

The algorithms' detection results on the test set are summarized in Table 5.3. The decimals, 0.5 and 0.8, represent distinct thresholds for determining the output probabilities that the sample is EV. For example, under the 0.8 threshold, an output of 0.7 is determined as a non-EV user. A greater threshold can filter potential EVs with higher probabilities. The results show that the generated eleven features are sufficient to distinguish between EV and non-EV users. Meanwhile, XGBoost has an accuracy greater than 90% on both thresholds. Its recall value reaches 1.0 under the 0.5 judgment threshold, which means that the XGBoost can identify all EVs from the test set correctly.

5.3.2 Driving Behavior Analysis of Detection Results on Cellular Dataset

The trained XGBoost algorithm is employed to detect EVs from daily trip segments in unlabeled cellular data. It should be noted that users may not have recorded trip data every day for the 30-day period. To mitigate any potential bias resulting from a low number of trip records and to increase the likelihood that the detected users are indeed EV users, we impose two constraints. Firstly, users must have at least 5 days of recorded trips. Secondly, the number of times a user is detected as an EV user must be at least half the total number of days recorded. Then, the trained XGBoost detects that 1,340 users are potential EVs, which is about 19% of the registered EV users in Indiana by the end of 2020 (6,990 EVs). It is worth mentioning that the reference to the year 2020 is because the cellular data used in this section is from March 2021. The discrepancy observed between detected EVs/EV registrations (19%) and users in dataset/Indiana population (30%) could be attributed to the stringent thresholds we established. Additionally, it is plausible that some EV users did not have trips recorded in March 2021.

We extracted the trips of detected EV users and analyzed their travel and behavioral characteristics with indexes. Trip distribution and home location in Figure 5.3a and Figure 5.3b and trip distance distribution under different area types in Figure 5.3c.

Trip distribution counts the trip origins of the detected EV users as displayed in Figure 5.3, where

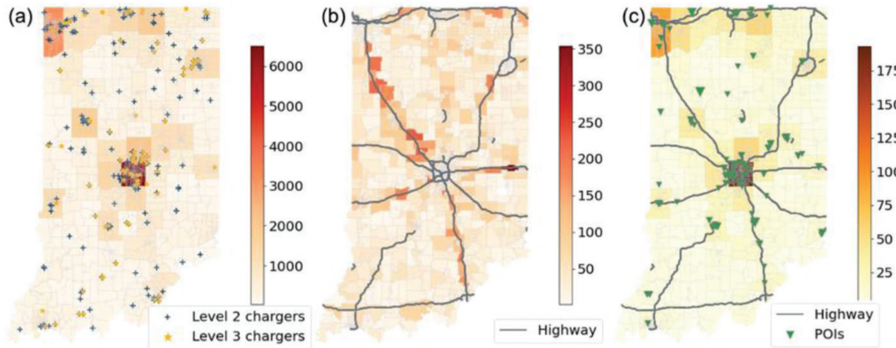


Figure 5.3 Trip distribution of detected EVs based on (a) counties, (b) census tracts, and (c) home location distribution based on counties and the top 100 most visited POIs.

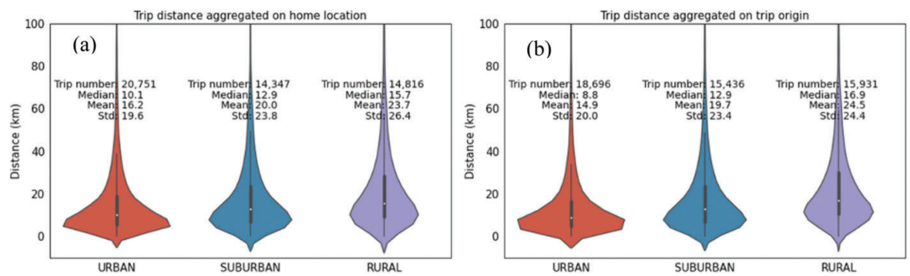


Figure 5.4 Trip distance aggregated based on different area types: (a) count on users' home location, and (b) count on users' trip origins.

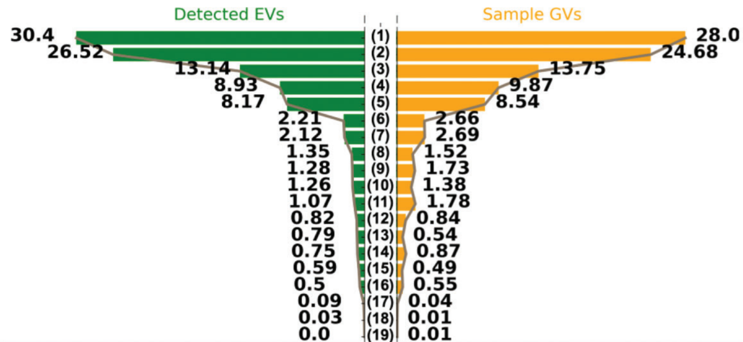
(a) and (b) show the trip numbers based on county and census tract levels, separately. By 2021, Indiana has constructed 3,183 gas stations and 323 charging stations, and their spatial distributions are illustrated in Figure 5.3a, where the blue and orange dots are the locations of Level-2 chargers (651 counts in total) and Level-3 chargers (389 counts in total). Compared to the accessibility of gasoline stations, we find that few charging stations are constructed near the suburbs and rural areas. We can observe that higher EV trips are generated in the counties with a higher number of charging stations, such as Marion or Lake counties. This is reasonable because adequate charging facilities, especially Level-3 chargers, will promote the adoption and utilization (Figure 5.3b). Areas along Interstate 65 (I-65) have higher EV trip numbers. This indicates that when considering the installation of charging stations on highways to support long-distance trips, priority can be given to those along the I-65.

The *home locations* of detected EV users are determined by aggregating the positions where they spend the most time between 10 PM and 6 AM. The location distribution is shown using a heat map (Figure 5.3c), where their homes are situated near well-developed regions with numerous charging stations. Almost 40% of identified EV users are in urban regions, even though urban areas make up just 4% of Indiana's total land. Marion County, where Indianapolis is located, is home to 14.6% of all detected users. The next is Lake County, which is home to 6.8% of the identified users. The home locations are distributed similarly to the EV trip by county, which indicates that users prefer short-distance trips within counties.

Trip distance offers insights into users' travel patterns, aiding policymakers in devising appropriate incentives, grants, or rebates to encourage EV adoption. Figure 5.4 displays the distribution of trip distances across various area categories, grouped by users' predefined home locations (Figure 5.4a) and by their trip origins (Figure 5.4b). We find that EV trips are primarily driven in urban areas, and occupy 42% and 37% in two subgraphs, respectively. As urbanization levels decrease, the travel distance of EVs continuously increases, and the kurtosis of the distribution consistently decreases. This demonstrates that EV trips generated farther away from urban areas generally cover longer distances. Comparing Figure 5.4a−b, the number of urban trips has decreased by 10%. This could suggest that EV users residing in areas away from urban may have concerns about their vehicle's range and the available locations of charging stations.

We also compared the trip characteristics of the detected EV and non-EV users, using visit frequency on various POIs in Figure 5.5, number of locations visited and number of trips in Figure 5.6, and average and total travel distance in Figure 5.7. Both EV and non-EV users' trips are from the dataset we introduced in Section 5.2, which is recorded during 10/01/2022–10/15/2022.

The differences between EVs and GVs in *visit frequency on various POIs* could reflect the driving behaviors. We accumulate the nearest POIs within a



No.	Category	No.	Category
1	Retail Trade	10	Information
2	Accommodation and Food Services	11	Educational Services
3	Other Services (except Public Administration)	12	Public Administration
4	Finance and Insurance	13	Wholesale Trade
5	Health Care and Social Assistance	14	Manufacturing
6	Arts, Entertainment, and Recreation	15	Construction
7	Real Estate and Rental and Leasing	16	Administrative and Support Services
8	Transportation and Warehousing	17	Management of Companies and Enterprises
9	Professional, Scientific, and Technical Services	18	Utilities
		19	Agriculture, Forestry, Fishing and Hunting

Figure 5.5 Trip destination POIs statistics of detected EVs and sample GVs.

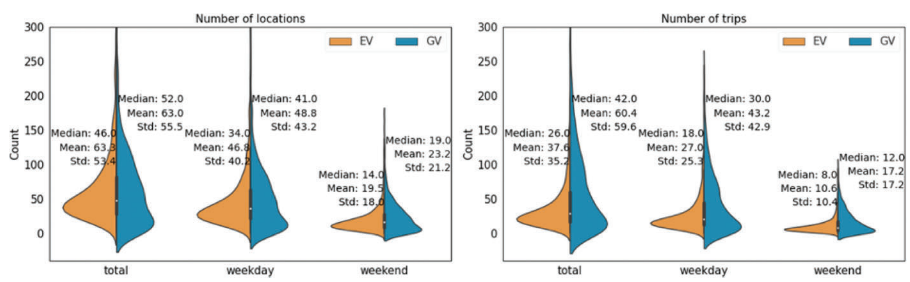


Figure 5.6 Distributions of (a) number of locations visited, and (b) trip numbers of EVs and GVs.

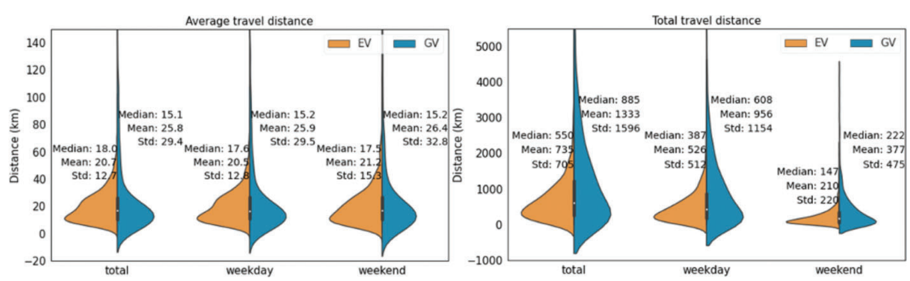


Figure 5.7 Distributions of (a) mean travel distance, and (b) sum travel distance of EVs and GVs.

50-meter radius of the trip destinations, and the visitation percentages on various North American Industry Classification System (NAICS) categories are shown in Figure 5.5. The results show that the percentage of short-distance trip purposes of EV users is higher than that of GV users. For example, retail trade and food services purposes occupy more than 50% with a total increase of 4.2% over GV trips. We also find that for long-distance trip purposes (agriculture and hunting), all the users drive GVs. This makes sense since even EVs equipped with a 70 kWh-capacity battery (Tesla Model Y) could drive for around 200 miles. In comparison, the median GV range (on one full tank) is around 413 miles, nearly double what the average EV would cover. Therefore, EV trips are mainly for short-distance purposes. We further find that the top 100 most visited POIs of the detected users (green triangles in Figure 5.5c) are clustered in areas with high user density and along highways. Based on the NAICS code, 42% of the POIs are under the retail trade category, and 29% of them are related to the food services.

The *number of locations visited* indicates the variety of activity locations they frequent during the observed time, which can reflect the extent that users engage in having activities at more diverse locations. Figure 5.6a shows the distribution of EV and GV users on entire month, weekday, and weekend. There are no marked differences between the two vehicle types, though EV users have a slight decline in the number of locations they visit compared to GV users. Yet, the number of locations drops significantly during weekends, and the disparity between vehicle types becomes slightly more pronounced. The Welch's t-test is conducted under the null hypothesis that the averages of the two groups (location numbers on weekends) are equal. Given a p-value of 1.77e*5, we can reject the null hypothesis and conclude that there is a statistically significant difference in the number of locations visited by EVs and GVs. We can infer that EVs are mainly used for weekday commuting, the mobility patterns on weekends might differ between EV and GV users due to varying usage purposes and charging infrastructure availability.

The *number of trips* describe the frequency of journeys taken by users during the recorded time. This can shed light on their mobility patterns, preferences, and the intensity of their daily activities. As depicted in Figure 5.6b, EV users typically have fewer trips, amounting to almost half when compared to GV users. For each comparison group of EVs and GVs, a Welch's t-test is executed with the null hypothesis that their means are identical. In all cases, the null hypothesis was rejected, as the p-values are close to zero, indicating significant differences between the groups. The reduced trip numbers could be attributed to the limited range of EVs and restricted charging opportunities. User occupation may also play a role in the variance in trip numbers. For example, professionals who require frequent travel for work, such as salespeople or consultants, may take more trips if they use GVs due to their longer range and quicker refueling times. Conversely, those in occupations that allow for more flexible work arrangements, or those who work from home, may find EVs more suitable as they have fewer requirements for long-distance travel and more time for charging.

Figure 5.7a presents the *average travel distance*. No significant differences are found in the average travel distance on weekdays and weekends. The disparity between the median and average for EVs suggests that EVs might be serving a wide variety of use cases. Some users might rely on them for daily commutes, while others might use them only for quick errands around town. The larger median of EVs suggests that a portion of EV users are still making longer trips, which means that at least half of the EV users are comfortable taking their vehicles for slightly longer distances. This makes sense since the presence of more charging stations might encourage longer median travel distances for EVs. However, the unevenly distributed charging stations cannot satisfy the charging needs of all EV users. The lower average distance for EVs indicates that factors such as range constraints or lack of charging facilities discourage some users from long journeys, leading them to use EVs primarily for short commutes. Additionally, while EVs have a larger median travel distance, they fall behind GVs in terms of average distance. This could mean that GVs exhibit a more uniform distribution of travel distances with fewer short journeys, thereby resulting in a higher average distance.

The *total travel distance* refers to the cumulative distance covered during the recorded month. EVs are traveling shorter distances than GVs, as shown in Figure 5.7b. The travel distance distribution for EVs exhibits a shorter tail and seems to cut off beyond a particular range, a trend also documented in Yang et al. (2022). Furthermore, p-values below 0.05 from Welch's t-test, based on the null hypothesis asserting identical average total travel distances for EVs and GVs, highlight their distinct differences. This suggests that EV users might be limiting their trips within a certain distance, possibly due to concerns about battery range, the availability of charging stations, or other factors affecting longer-distance travel with EVs (Sierzchula et al., 2014). The smaller total distances for EVs, both in average and median, might also reflect that while the adoption of EVs is growing, it has not reached the same penetration or usage intensity as GVs.

5.4 Chapter Summary

This section presented a comprehensive framework for detecting and generating synthetic EV trips. First, various trip features, such as trip speed and acceleration, were generated based on the Indiana vehicle trajectory dataset to reflect the user's driving behavior. Then, eight algorithms were trained to distinguish EVs and GVs. The one with the best prediction accuracy (XGBoost) was selected to detect EV users from an unlabeled cellular dataset, and 1,340 users were identified as EV users. Meanwhile, vehicle acceleration was identified as the most important factor in distinguishing between EV and non-EV users, while the daily trip count is of the lowest importance. By analyzing EV driving behaviors, we found that EV trips are concentrated in urban areas or along highways, and the trips are mainly for short-distance retailing and catering (more than 50%).

6. EV DEMAND GENERATION

This section proposes a novel framework for data generation and fusion (Section 6.1), designed to construct reliable synthetic datasets that reflect both present and future EV utilization (Section 6.2), as well as to assess the impact of EVs on various networks (Section 6.3).

As illustrated in Figure 6.1, the process begins with the collection of questionnaire survey and cellular data, which serve as the input/reference for training the Sequential-Generative Adversarial Networks (Seq-GANs) (Figure 6.1a), separately. The generated synthetic survey data is then spatially distributed according to home zip codes to align with the statistical distribution of households (Figure 6.1b). Simultaneously, the synthetic travel sequence data is transformed into

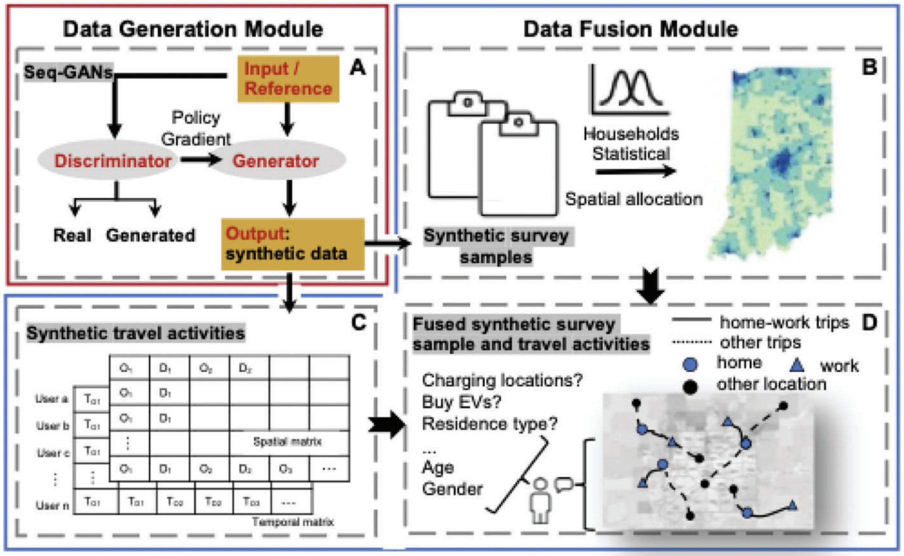


Figure 6.1 The framework of the sample synthetic and survey and travel activity pairing process.

sequences of origins and destinations, along with corresponding times, to depict users' travel patterns (Figure 6.1c). The subsequent fusion step pairs the synthetic survey and travel sequence datasets, offering a comprehensive view of users' social attributes and travel patterns (Figure 6.1d).

6.1 Framework Overview

The framework encompasses two primary modules: the data generation module and the data fusion module, as depicted in Figure 6.1a and 6.1b–d, respectively. This section begins by introducing the data generation process in Subsection II-A, where we delve into the components and architecture of the Seq-GANs. The synthetic datasets are then fused based on residential locations during the data fusion process elaborated in Subsection II-B. The final outputs of these modules are samples with both socio-demographic and travel diary information, that enable us to comprehensively depict the future EV demand and users' travel and charging activities in multiple dimensions.

6.1.1 Data Generation Module

Seq-GANs can learn the underlying distribution of the elements in the training data and master the sequence-based dependencies that influence element arrangement. They produce a variety of sequences that capture the diversity observed in the training dataset. These generative models excel not only in replicating frequently occurring patterns but also in constructing sequences that represent a broader range of possibilities, such as some rare samples in real-world examples. In this section, each user's survey and travel diary data are used to describe an individual's socio-demographic profile and travel activities and serve as separate sentences to train and test distinct models.

In the Seq-GANs framework, illustrated in Figure 6.1a, the Generator module and Discriminator module play pivotal roles. These modules engage in a dynamic competition, the Generator aims to create data indistinguishable from actual reference data, while the Discriminator strives to distinguish between the reference data and the generated data. The Generator specializes in generating synthetic data. It creates each subsequent element based on either an initial token or a sequence of historical elements, informed by the provided reference inputs. In contrast, the Discriminator functions as a binary classifier, tasked with identifying whether data is generated or genuine. This module evaluates the synthetic output and imparts rewards to the Generator, facilitating its training through policy gradient techniques. It is important to note that the Generator produces one element at a time, and the Discriminator evaluates it only after the completion of a full sequence. To calculate the reward for each element generated by the Generator, we employ a rollout policy (Yu et al., 2017). This approach is used as a Monte Carlo search strategy and allows the Discriminator to provide immediate feedback on each output from the Generator, enhancing the efficiency and effectiveness of the learning process.

The synthetic algorithm is shown in Algorithm 1, where G and D represent the Generator and the Discriminator, separately (Figure 6.2). The sequence is defined as $Sn = (s1, \ldots st \ldots sT)$. $i \in N$ is the generated sample number. $t \in T$ is the dimension to describe one single sample, such as the sequential responses in the survey or the ordered Origins (O) and Destinations (D) in the travel diary.

6.1.2 Data Fusion Module

The data fusion module, depicted in Figure 6.1b–d, aims to fuse the synthetic survey samples and travel

Algorithm 1 Data Generation Module

Require: Input data: collected survey data/ travel activity data;
Generator G; discriminator D

Initialize Generator G and Discriminator D
Pretrain G and D using maximum likelihood estimation
while not converged **do**
    for g steps **do**
        Generate a sequence $S_n = (s_1, \ldots s_t \ldots s_T)$ using G
        Initialize Roll-out Policy π to be G
        for each time step t in S_n **do**
            Execute roll-out policy π for M roll-outs from t to T;
            Compute average reward R_t across the M roll-outs for t;
        end for
        Update the parameters of G with policy gradient to maximize expected reward
    end for
    for d steps **do**
        Generate negative sequences using G;
        Sample positive sequences from M_{real};
        Train the Discriminator D to maximize $\log(D(\text{real})) + \log(1 - D(\text{generated}))$
    end for
    Update roll-out policy R to be a copy of G
end while

Figure 6.2 Algorithm 1.

sequences based on their home locations. While the survey data may not capture participants' visits to various POIs, the travel sequences can fill this gap, which are passively logged by mobile devices. This integration enriches the dataset with insights into the socio-demographic profiles of residents and their current travel behaviors. It is important to note that the objective of this process is to compile a broad and representative dataset that highlights overarching statistical trends and patterns, rather than precisely aligning each user's detailed information.

During the data collection process, problems are unavoidably encountered that result in missing data for certain areas. The data synthetic models are incapable of fabricating data from scratch for the areas lacking reference data. Besides, the collected datasets may not exactly follow the same statically distribution as reality, such as age and gender distribution. Therefore, it is necessary to fill in the missing data and adjust the proportion of data components according to authoritative statistics characteristics during the fusion process.

To address data gaps in certain areas, this section assumes that residents in geographically proximate and demographically similar areas exhibit comparable survey responses and travel behaviors. For instance, individuals residing in neighboring suburban areas but commuting to city centers for work purposes are likely to share similar mobility patterns. Therefore, additional samples are produced by the Data Generation module based on areas with available reference data. These additional samples have their home locations adjusted to areas with insufficient data. Subsequently, these synthetic survey samples are spatially distributed to align with the current statistical distributions, as illustrated in Figure 6.1b. Meanwhile, the outputs from the synthetic travel diaries include both spatial and temporal data, such as the sequence of spatial and temporal events depicted in Figure 6.1c. Each user's travel behavior is described through a sequence of Origins (O_t) and Destinations (D_t), where t denotes the order of the trip sequence, starting from 1. T_{Oi} and T_{Di} indicate the corresponding temporal information. These processed synthetic samples are then utilized as inputs for the data fusion model, represented as blue-shaded and green-shaded data in Figure 6.3.

Note that multiple statistical datasets are utilized as references for population characteristics throughout the fusion of two synthetic datasets. Datasets include population estimates by age and gender at the census tract level and household information from the Local Area Transportation Characteristics for Households Data (BTS, 2021). The survey provides detailed records on family size and vehicle ownership (0, 1, 2, or more) at census tracts, which is crucial for estimating mobility activity among household users.

The left side of Figure 6.3 illustrates the process of creating synthetic survey samples for various households. Initially, we evaluate whether the size of the synthetic sample is sufficiently representative of the population of the area, ensuring it covers, for example, 95% of the population. If it is insufficient, we incorporate additional synthetic samples from nearby areas as aforementioned. Subsequently, households are formed by grouping samples that share the same family size and number of vehicles indicated in their records. It is important to note that the survey samples are

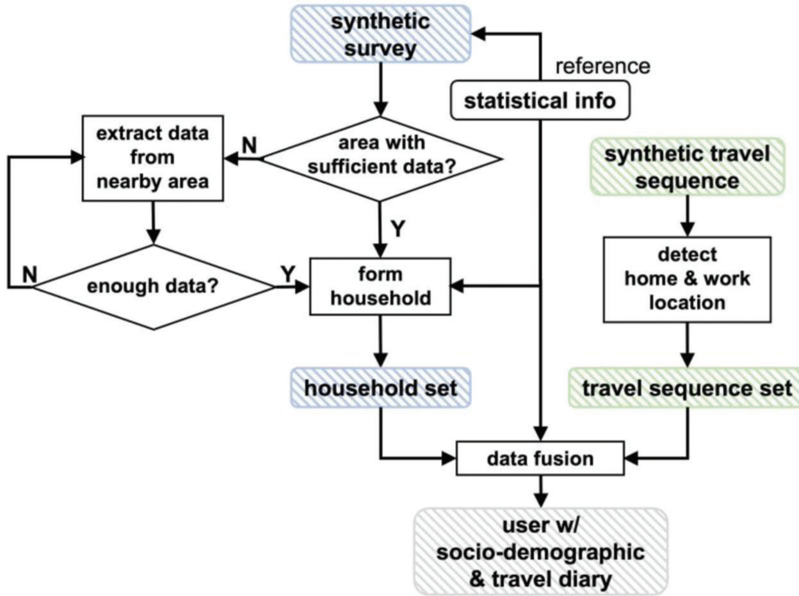


Figure 6.3 Data fusion process based on the synthetic survey and travel sequence datasets. The outputs are user samples with both socio-demographic and travel diary information.

collected from individuals aged 18 and above. Therefore, for each household, we randomly assign blank samples as children based on the family size and complete the family composition using the synthetic samples. This process results in a set of households prepared to be integrated with the travel diary data.

The synthetic travel diary data processing steps are depicted on the right side of Figure 6.3. We employ a specialized Python package, Scikit-mobility (Pappalardo et al., 2019), to identify the home and work locations for each sample. Subsequently, these two processed datasets are fused according to their respective home locations, while adhering to the statistical constraints of the areas involved. The resulting dataset comprises a collection of users approximately equivalent to the population size, featuring socio-demographic details, such as age and home locations, along with their sequential locations visited and the corresponding timestamps.

6.2 Results

To evaluate the effectiveness of our proposed framework, we incorporate two datasets from Indiana. The first dataset is a questionnaire survey collected in the project. The second dataset is a cellular dataset described in Section 5. The accuracy and reliability of the synthesized dataset are then assessed in Subsection III-B by comparing it with daily vehicle miles traveled (VMT) (INDOT, n.d.). This comparison demonstrates the framework's capability to produce realistic datasets for studying EV usage and planning infrastructure.

6.2.1 Synthesis of EV Trips

The aforementioned EV detection results, including the spatial and temporal trip information, are utilized as the reference for the synthesis process. A cumulative total of 12,712 day-based sequential trips are recorded, with the most active user contributing 12 trips per day. Two key measures are employed to evaluate the performance of the Generator and Discriminator, respectively, the Generator's performance is gauged through the Negative Log-likelihood, which provides a measure of the model's ability to predict the data; the Mean Cross-entropy Loss is used to assess the performance of the Discriminator, it serves as a suitable choice given that the task of the Discriminator is essentially a binary classification task. The convergence performance of the algorithm is visualized in Figure 6.4, where the blue lines correspond to the pre-training phase and the red lines depict the adversarial training phase. The Generator and the Discriminator work in an adversarial manner and improve their performances simultaneously over time. We find that Algorithm 1 converges well when we set the number of pre-training and adversarial training epochs to 50 iterations each. Moreover, when the adversarial training epoch is bigger than 75, the losses stabilize and no longer decrease significantly, it indicates that the networks are converged.

To ensure the synthesized trips maintain reasonable and consistent spatial and temporal behaviors, we utilize the trained generator to create equivalent EV day-based trips (12,712 samples). Then, various distributions are visualized to evaluate the similarity of the reference and generated trips, shown as the day-based trip numbers, the number of locations visited, and the trip duration in Figure 6.5, and the home location and number of locations visited (county level) in Figure 6.6.

Day-based trip numbers refer to the count of trips an EV user makes throughout a day, which provides insights into the travel patterns of EV users.

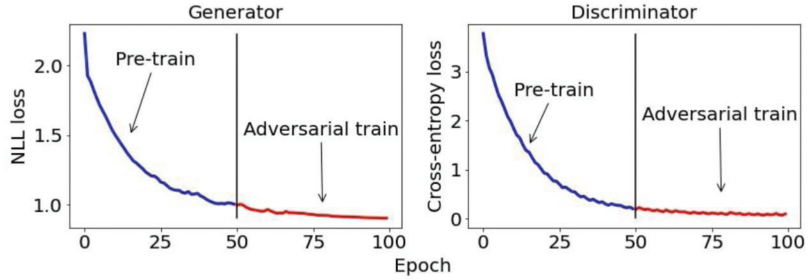


Figure 6.4 Convergence performance of the generator (negative log-likelihood loss) and the discriminator (mean cross-entropy loss).

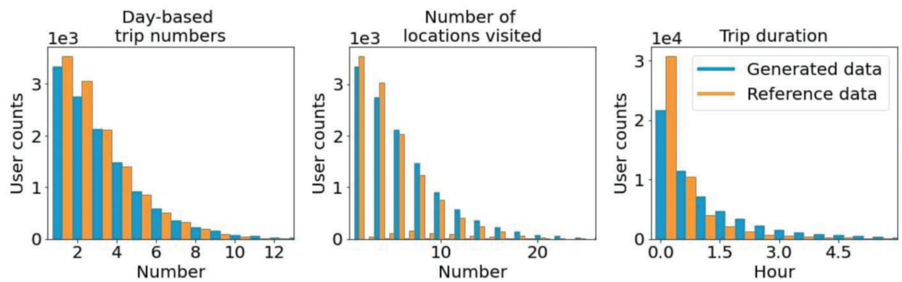


Figure 6.5 Comparison of reference data and synthetic data: histogram of day-based trip numbers, number of locations visited, and the trip duration.

The reference trip numbers adhere to a Poisson distribution, with over 90% of users taking no more than 5 trips per day. Notably, the distribution of the generated trip numbers closely resembles the distribution of the reference trip numbers, boasting a correlation coefficient of 99.62% between the two series of trip numbers. However, it is worth mentioning that the synthesized trip sequences might exhibit marginally higher day-based trip numbers, with approximately 87% of generated users taking no more than 5 daily trips.

Number of locations visited represents the total count of unique places an EV user visits within a day. It reveals how users utilize their vehicles, which could inform decisions about EV infrastructure deployment, such as charging stations. Of the reference users, 90.5% visit no more than 10 unique locations, and this percentage slightly drops to 86.6% for the synthetic trips. Nevertheless, the synthetic data correlates strongly with the reference data with a coefficient of 99%. Interestingly, in the reference data, the numbers of locations visited are predominantly even, with 94.6% of users demonstrating this pattern. The synthetic trips effectively capture this characteristic, showing lower counts on the columns representing odd numbers.

Trip duration indicates the length of time taken for a user to complete a single trip, which provides insights into the travel purposes and travel ranges of EV users. For example, shorter trips might indicate urban or local use for commercial purposes or shopping, and long-duration trips may require high-capacity batteries or access to fast-charging infrastructure. A significant number, around 45,142 real-world trips, are completed within 1 hour, which constitutes 83% of the total trips. The synthetic data successfully captures these real-world usage patterns of EVs, although it demonstrates a slightly elevated preference for longer trips. This could be an artifact of the data generation process or might indicate a trend toward more extended EV usage in the model's training data. The correlation coefficient between the synthetic and real-world trip duration is above 96.2%, indicating a high level of similarity.

Home location is defined as the location visited the most during nighttime. This can reflect the overnight-charging locations and the centers for short-distance trips, which can guide the installation of public charging infrastructure in those areas. Each row of the trip sequence is treated as a distinct user, and we calculate their home location. The scattered points illustrate the geographical distribution of different users' homes, and the heat maps provide a count of home locations at the county level. This gives us a visual representation of the density and distribution of EV users across different regions. Both reference and generated data predominantly display home locations concentrated in urban regions, particularly in the same counties. Notably, a significant concentration can be seen in Marion County, which includes Indianapolis. However, upon the comparison of the heat maps, it is evident that the synthetic data underestimates the number of users in Lake County and slightly overestimates the numbers in other counties, such as Monroe County and Clark County. These discrepancies might be due to the varying number of reference trips available in these counties. This indicates that while the synthetic data can capture general spatial trends, it may require further fine-tuning to accurately mimic the distribution in certain areas.

Number of locations visited shows the location visit frequencies within the counties, which can provide insights into areas that are of high interest or frequent use to EV users. Understanding the frequency distribution of location visits can inform infrastructure planning, such as the placement of charging stations. Although the detailed trip numbers are different, trips are primarily concentrated in similar counties both in the reference and the generated. Marion, Lake, and Hamilton counties are the top three most frequented areas, which implies that the synthetic data successfully replicates the spatial distribution of trips as observed in the real-world data, capturing the same high-activity regions.

In summary, the synthetic data generated in this section closely aligns with the real-world data in terms of various key metrics, including trip duration, day-based trip numbers, number of locations visited, and home location distributions. Despite slight discrepancies in specific areas, the synthetic data generally captures the spatial-temporal patterns and behaviors of EV users quite accurately. These findings underscore the efficacy of the synthetic data generation model. The closely matched synthetic data can serve as a valuable tool for EV-related policymaking and infrastructure planning topics, where access to large-scale real-world data is challenging or privacy concerns arise.

6.2.2 Synthetic Data Validation

Leveraging the datasets gathered, we generated and fused synthetic samples of surveys and travel activities based on the established framework. It is important to highlight that the gender and age distribution within the synthetic samples precisely mirrors official population statistics, as these were employed as benchmarks during the data fusion process. This section employs the VMT dataset, as released by INDOT, to ascertain the fidelity of the synthetic dataset. This VMT dataset encompasses historical VMT data across 92 counties in Indiana.

The analysis reveals a Pearson correlation coefficient of 0.9577, indicating a robust positive linear relationship between the synthetic and the Daily VMT datasets. Furthermore, the exceedingly small p-value of $1.7557 \times e{-50}$ significantly diminishes the likelihood that this strong correlation could have occurred by chance. Such statistical evidence underscores the synthetic dataset's exceptional representation of actual travel behaviors, thereby offering a solid foundation for subsequent research and analyses. Note that despite the high correlation, there may be discrepancies in the actual values between the synthetic and the Daily VMT datasets due to variations in the input data used for the Data Generation module. For instance, Marion County is recorded with the highest VMT in both datasets, yet the synthetic dataset exhibits a mileage number that is approximately 2.7 times greater than that observed in the Daily VMT dataset. To enhance the realism of the synthetic dataset, adjustments are made by using the Daily VMT dataset as a benchmark to recalibrate the number of synthetic trips.

6.3 Application on Future EV Demand Prediction

This section explores one prospective application, the future EV demand prediction, derived from the proposed framework and the synthetic dataset. These illustrative examples are intended to offer critical insights for policymakers and transportation planners who are navigating the complexities of transitioning toward electric mobility. The utility of these applications lies in their ability to inform strategic decision-making and facilitate effective planning, thereby supporting the broader goal of sustainable and efficient EV integration into transportation infrastructure systems.

Based on the survey results regarding likelihood of the participants to purchase or lease an EV in the next 1, 2, 3, 5, and 8 years, the likelihood of adopting an EV was categorized in "extremely likely," "somewhat likely," "neither likely nor unlikely," "somewhat unlikely," "extremely unlikely," and "not planning to purchase/lease." This section introduces scales for quantifying these responses under different methods. The gradations of probability scales are designed to reflect the propensity for EV adoption among individuals, potentially influenced by varying policy scenarios. For instance, additional EV incentives or the expansion of charging infrastructure could shift respondent responses from lower to higher probability scales, thereby signaling a greater propensity towards EV adoption. Note that the synthetic dataset can support applications under various probability scales. The primary objective of providing the proposed probability scales is to present a demo application, illustrating how such datasets can be leveraged to assess and predict EV demand changes under different policy interventions.

This application operates under several key assumptions. Firstly, it posits that EV adoption occurs at the household level, with each household limited to adopting a maximum of one EV, irrespective of family size. Secondly, it situates the current state of EV adoption in Indiana within the "innovators" phase (2.5%) of Roger's Diffusion of Innovations theory (Rogers, 2003). This is the initial stage in a five-phase model that includes "innovators" (2.5%), "early adopters" (13.5%), "early majority" (34%), "late majority" (34%), and "laggards" (16%). Being in the "innovators" phase suggests that Indiana is at the start of EV adoption, with an imminent increase in adoption rates expected as the state progresses through the subsequent phases. Besides, we employ the existing number of EVs as a benchmark to refine and adjust our estimation figures. This methodological approach ensures that our projections remain grounded in current adoption trends while anticipating future growth in EV adoption.

In this section, two distinct methods are employed to assess EV adoption likelihood; both consider respondents who indicated they were "extremely likely" to

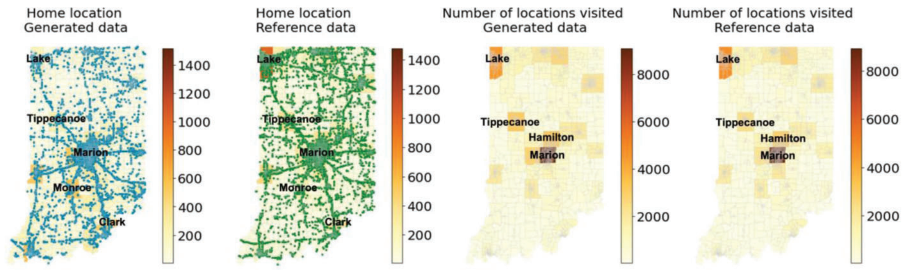


Figure 6.6 Comparison of reference data and synthetic data: county level heat-maps of home location and number of locations visited.

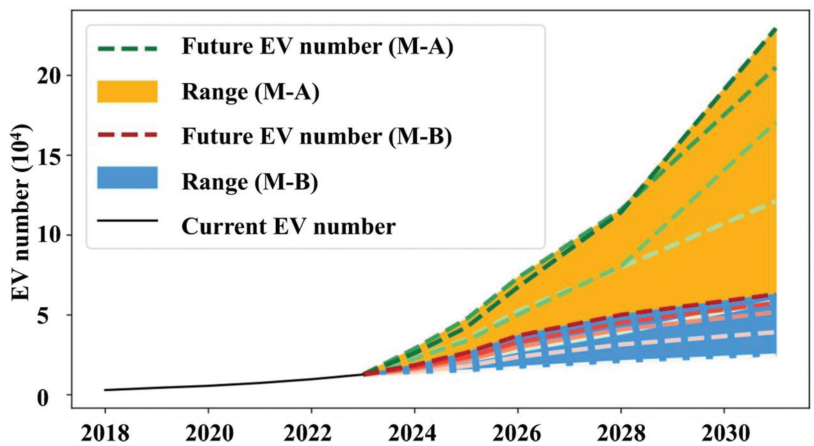


Figure 6.7 Future EV demand in different scenarios.

TABLE 6.1
Scale numbers for levels of likelihood

Scenario	Extremely Likely	Somewhat Likely	Neither Likely nor Unlikely	Somewhat Unlikely	Extremely Unlikely
Highly Optimistic	1 (0.9)	0.9	0.7	0.5	0.3
Optimistic	1 (0.9)	0.75	0.5	0.25	0.1
Moderate	1 (0.9)	1 (0.9)	1 (0.9)	0	0
Pessimistic	0.5	0.3	0.2	0	0
Highly Pessimistic	0.5	0	0	0	0

adopt yet may ultimately not proceed with that decision due to various inhibiting factors. In the first method (M-A), the chronological order of their stated preference for adoption years is considered. In the second method (M-B), adoption is contingent upon the occurrence of the year where the probability of adopting exceeds the predetermined threshold specific to that year. Table 6.1 presents five hypothetical scenarios, ranging from highly optimistic to highly pessimistic, created for each method. The scenarios depicted in the black text correspond to M-B. To derive M-A from these scenarios, numbers in designated positions are substituted with blue text.

Figure 6.7 graphically illustrates results on estimating numbers of EVs in the upcoming years, employing a gradient of colors to signify the transition from highly optimistic to highly pessimistic adoption scenarios across different scenarios. Additionally, shaded areas delineate the range of possible future EV numbers, offering a visual representation of the variability and uncertainty associated with these projections, including technological advancements, market dynamics, consumer preferences, and the evolving regulatory landscape. In the most highly optimistic scenario, the number of EVs is projected to increase to approximately 229,393 by 2031, which is about 18 times the number in 2023 (12,686). Conversely, under the most highly pessimistic scenario, the increase could be as modest as doubling the number of EVs. This contrast highlights the significant impact of different policy settings on EV adoption rates. Simultaneously, the scenario depicted by the darkest green curve suggests that aggressive incentive strategies may not immediately boost EV numbers in the short term, their influence becomes increasingly apparent over an extended period, suggesting a delayed but substantial impact on adoption rates.

6.4 Chapter Summary

This section presented a comprehensive data generation and fusion framework that mitigates the limitations associated with data scarcity in the context of EV-related problems. Specifically, the Generation module can simultaneously generate synthetic survey data and travel sequence data. Additionally, the Fusion module integrates these datasets and fills gaps in missing areas, thereby offering a comprehensive reconstruction of socio-demographic profiles and travel diaries. The synthesized data from the generation module closely mirrored the trip duration, day-based trip numbers, and home location distributions of detected EV users from Chapter 5. These evaluation metrics validate the high quality of the synthesized trips. Demonstrating the framework's practical relevance, we synthesize a representative dataset for Indiana's entire population, subsequently validating this dataset against the daily vehicle miles traveled dataset to affirm its accuracy and reliability. Finally, our exploration of future EV demand predictions under a range of optimistic to pessimistic scenarios showcases the real-world utility of the generated datasets. Overall, this framework enables the production of rich datasets that encapsulate detailed insights into users' social attributes and travel behavior, thus providing a solid foundation for further research and policy development.

7. CONCLUSIONS

7.1 Summary of Key Findings

This project examined the Indiana public perceptions about EVs. The results of a stated preference survey with 1,217 valid participants analyzed the main determinants and barriers of EV adoption, different perspectives about EV attributes, charging preferences and WTP. Additionally, the socio-economic profile of EV users and their travel patterns were studied. Finally, synthetic data was generated to predict EV trips and future EV demand.

7.1.1 EV User and Non-EV Users' Profile, Travel Patterns, Perceptions and Adoption

The survey data revealed that most of the Indiana EV users are males, middle aged, with higher income, living and working in urban areas, and identifying as Democrats. Tesla is the most common EV brand in Indiana, followed by Chevrolet, Kia, and Nissan. EV users tend to drive more frequently than non-EV users and prefer owning than leasing EVs. Generally, EV users seem to have replaced their ICEVs with EVs for different types of trips, except for long recreational trips. EV users stated the inconvenience to plan long trips as the biggest disadvantage of EVs when compared to ICEVs. On the other hand, the fact that the EV users effectively use these vehicles indicates a positive feeling about their experience, which was reported in the survey. Finally, EV users seem to be generally aware of EV incentives, especially for EV purchase, although almost 10% have never heard of any incentive for EVs.

The survey results also showed that acceptance of EVs for non-EV users changes over time. Non-EV users stated more likelihood to purchase than lease an EV, especially in the long term. The purchase price and issues with charging, such as the absence of home charging, inconvenience to charging, and the difficulty of finding reliable charging stations nearby, are pointed out as the main barriers to EV adoption. Non-EV users recognize the lower fuel costs and noise produced by EVs as their main advantages when compared to ICEVs. On the other hand, they seemed unaware about the registration fee, depreciation, and life cycle cost of EVs. Most non-EV users are also unaware of EV incentives, especially the ones related to charging, such as installing home charging rebates and special rates for home charging during off-peak hours. It is worth noting that some non-EV users stated in the open comments that they do not believe in the environmental benefits of EVs.

Lastly, amongst the whole sample, there seems to be a slight preference to purchase a used EV instead of a new one, mainly because of affordability and fear of not getting used to an expensive vehicle. The participants, who would choose a new EV, mainly reported that they usually buy new vehicles independently of the type and because of the better performance of new vehicles.

7.1.2 EV Charging Preferences, Perceptions, and Willingness-to-Pay (WTP)

Regarding charging behavior, EV users and non-EV users exhibit significant differences in their preferences, perceptions, and WTP for charging services. Non-EV users generally lack awareness of charging technologies compared to EV users, showing less tolerance for driving long distances to charge their vehicles and are more averse to walking from charging stations to their final destinations. Non-EV users seem more concerned about range anxiety, greatly affecting their willingness to use EVs for their trips. They are hesitant to start a journey if their battery level only matches the trip length, reflecting a fear of depleting the battery without sufficient charging opportunities. Conversely, they are more comfortable making trips when the battery level exceeds the trip length, even if the route is unfamiliar. Moreover, non-EV users seem less inclined to utilize public charging facilities. This behavior is likely influenced by their perception that public charging infrastructure is unreliable and may not always be available when needed, underscoring their lack of awareness and trust in the current charging network. Additional insight gained from the survey is that home charging remains a vital component for EV users, underscoring the need for accessible and reliable residential charging solutions. Moreover, the availability of multiple charging options—including home charging, Level 2, and Level 3 (DCFC)—is preferred by both EV users and non-EV users.

In the choice experiment, EV users ranked DCFC as their top preference, followed by DWPT and Level 2 charging. Home charging remains a vital component for EV users. Conversely, non-EV users preferred Level 2 charging first, with DCFC and DWPT last. Moreover, the availability of multiple charging options—including home charging, Level 2, and Level 3/DCFC—is preferred by both EV users and non-EV users since various options ensures convenience, addresses different charging needs, and enhances overall user confidence in the reliability and accessibility of charging facilities, thereby supporting the broader adoption of EVs.

WTP estimates also vary notably between these groups. EV users are willing to pay approximately $9.44 (median) and $2.93 (mean) per hour to reduce waiting times at Level 2 charging stations, whereas non-EV users indicated a much higher willingness-to-pay, around $86.97 (median) and $20.72 (mean) per hour. For reducing charging time at DCFC stations, EV users' WTP was estimated at $21.73 (median) and $6.73 (mean) per hour, while non-EV users were willing to pay $30.04 (median) and $7.16 (mean) per hour. Additionally, non-EV users expressed a WTP of an extra $4.10 (median) and $0.98 (mean) for amenities, such as restroom availability at DCFC stations, highlighting their preference for enhanced convenience and infrastructure.

7.1.3 EV Trip Detection and Demand Generation

EV trips can be detected from non-EV trips based on various trip features, such as trip speed and acceleration. A total of 1,340 users were identified as EV owners from an unlabeled cellular dataset, which is about 19% of the registered EV users in Indiana by the end of 2020 (6,990 EVs). Vehicle acceleration is the most important factor in distinguishing between EV and non-EV users, while the daily trip number is of the lowest importance. Meanwhile, by analyzing their driving behaviors, it was found that EV trips are concentrated in urban areas or along highways, and the trips are mainly for short-distance retailing and catering (more than 50%).

The synthetic dataset, covering users' social attributes and travel activities, was generated using the proposed framework and then validated against the Daily VMT dataset to affirm its accuracy and reliability. The synthetic data generated in this project closely aligns with the real-world data in terms of various key metrics, including trip duration, day-based trip numbers, number of locations visited, and home location distributions. These findings highlight the effectiveness of the synthetic data generation model, demonstrating its capability to produce data that closely mirrors real-world patterns.

Finally, future EV demand is predicted under a range of optimistic to pessimistic scenarios. In the most highly optimistic scenario, the number of EVs is projected to reach about 18 times the number in 2023. Conversely, under the most highly pessimistic scenario, the increase could be as modest as doubling the number of EVs.

7.2 Practical Implications and Recommendations to INDOT

This project enhanced the current understanding and perceptions of Indiana residents about EVs. The main barriers to EV adoption were analyzed to support policies related to EV usage in the state. Additionally, the findings about charging preferences can inform strategies for the deployment of charging stations, particularly during the implementation of the NEVI program. Furthermore, the EV demand prediction provides several scenarios of EV adoption in the state for the coming years, which can support INDOT, and other stakeholders prepare for the future.

In view of our analysis, the following recommendations for implementation are provided.

Better promotion of EV incentives among EV-users and non-EV users. The implementation of incentives proved to be important since almost half of the participants stated these incentives could influence them to adopt an EV. Even more interesting, the promotion of these incentives is also crucial because most non-EV users have never heard about any EV incentive. The incentives can directly affect the adoption, as can be observed by the survey results—most non-EV users are not aware of incentives to install home charging equipment. Additionally, these groups pointed out the absence of home charging as one of the main barriers to EV adoption. This example highlights not just the relevance of the implementation of the incentives but also the importance of their promotion.

Test drive/EV ride programs. The results of the survey suggest that EV adoption can be accelerated by the public experimentation of EVs. This is supported by the fact that one of the main barriers pointed out for EV adoption is the lack of familiarity with EV battery technology. On the other hand, EV users reported using their EVs for most of the different types of trips. Test drive/EV ride programs can address this barrier and improve public acceptance of EVs.

Workforce programs focused on EV maintenance. The number of used EVs will tend to rapidly increase in the future. It is recommended to prepare a specialized workforce to attend to the demand for maintenance and repairs that these vehicles naturally require. Since most potential users showed a preference for used EVs at an entry-level, it is expected that there will be a demand for such service. A good experience in this first contact can be crucial for future vehicle purchase decisions.

Investment in public charging infrastructure. Current and future EV users might benefit from public charging infrastructure deployment. Some EV users tend to avoid driving their EVs on long trips. Additionally, several difficulties in charging the EVs are pointed out as barriers by non-EV users to adopt these vehicles. Both EV users and non-EV users have expressed a WTP for reduced waiting times, indicating a clear demand for more accessible charging options. Investment in public charging infrastructure (new stations or additional charger ports in existing stations) can positively affect both groups. By expanding the network of charging stations, as the NEVI program is currently doing, EV users will have multiple locations to choose from, alleviating the congestion and queues that occur when relying on a single station. Furthermore, increasing the number of charging ports at each station will prevent bottlenecks, ensuring that users do not have to wait in long lines for a limited number of charging ports.

Availability of amenities at/close to public charging stations. Non-EV users are willing to pay more for amenities, such as restrooms at charging stations. Promoting these amenities can attract users and encourage EV adoption. One survey comment emphasized the need for playgrounds and entertainment at roadside charging stations. Enhancing charging stations with amenities makes them more appealing and convenient, especially for potential EV adopters. Additionally, NEVI program also recommend amenities beyond the minimum requirement including camera, canopy, emergency call system, free Wi-Fi, access to shopping or recreation center, availability of staff, and access to public transport.

Public awareness campaigns and signs for public charging technologies. To address the range anxiety experienced by non-EV users, which often stems from a low perception of public charging availability and reliability, it is crucial to improve public awareness and confidence in the availability of charging stations. Beyond increasing the number of charging stations, this can be achieved through enhanced signage and comprehensive awareness campaigns. Effective signage will make it easier for users to locate charging stations, while campaigns across traditional and social media platforms can educate the public on the reliability and convenience of public charging options. For non-EV users, comprehensive education on various charging technologies is essential due to a significant knowledge gap highlighted in Section 4.4.1.1. For EV users, advertising the advantages and disadvantages of DWPT, particularly with the absent of charging and waiting downtime, given the importance of time in charging decisions. Although new technologies, such as DWPT, may have higher initial service fees, competitive pricing is crucial due to cost considerations in charging decisions. When DWPT becomes available, encouraging early adoption is essential for its long-term success, as widespread use is necessary for achieving economic viability.

Public charging suitability analysis. Conducting suitability analyses for new charging stations, especially for business owners, involves considering socio-demographic factors such as income, education, and gender. This helps strategically place stations in areas with higher demand and usage patterns can enhance the effectiveness of charging station investments, supporting the growth and accessibility of EV infrastructure. Parallel investments in areas with low access to home charging are also recommended.

*New EV demand forecasts under different policies or incentives***.** The synthetic dataset helps to simulate the impact of various policy adjustments or incentives on EV adoption rates. By understanding how changes in policies (such as increased subsidies, tax incentives, or expanded charging infrastructure) influence user behavior, data-driven decisions can be made to optimize these interventions. Meanwhile, this allows for precise planning and allocation of resources, ensuring that infrastructure and services are scaled appropriately to meet future demand.

Enhanced infrastructure planning and investment. The accurate detection of EV trips and the generation of realistic synthetic data provide critical insights into EV usage patterns and behaviors. Therefore, charging stations can be strategically and efficiently placed to meet actual demand. This ensures that EV users have convenient, equitable access to charging facilities, reducing range anxiety and promoting EV adoption. Additionally, cost-effective infrastructure solutions can be implemented to focus on high-need locations, minimizing waste and maximizing the return on investment.

Long-term planning and scalability. The ability to predict future EV demand under various scenarios provides a robust foundation for long-term planning. This foresight ensures that infrastructure projects are scalable and adaptable, accommodating future growth in EV adoption and technological advancements. This predictive capability allows for the phased implementation of infrastructure projects, where initial investments can be expanded progressively to increasing demand. For example, charging stations can be designed with modular components that can be easily upgraded or expanded as more EVs come onto the roads.

Comprehensive data for research and innovation. The synthetic dataset offers a reliable proxy for real-world EV data, addressing data scarcity and privacy concerns. This comprehensive dataset can support ongoing and future research initiatives, fostering innovation in EV-related technologies and services. For example, vehicle charging patterns can be used to develop dynamic pricing models for charging services, optimizing both user costs and station profitability.

7.3 Limitations and Recommendations for Future Work

A limitation of this study is related to the fact that the survey was disseminated online. This approach excludes people who do not have access to the internet to participate. This exclusion may bias our results; this could be avoided in the future by disseminating the survey in person, via phone or via mail. Additionally, the hypothetical nature of the stated preference survey is a limitation of this work. Although the scenarios and situations replicate realistic situations, it is not possible to assure that the participants would act in real situations in the same way as they believe that they would act.

Furthermore, the analysis of EV adoption intentions may not capture the dynamic nature of these decisions. The lifestyle of the participants might evolve, potentially influencing their interest in EVs. For example, the responses about charging preferences of non-EV users might change after they adopt an EV and have more contact with the technologies and their specificities. Another relevant point is that many responses are linked to the current situation of charging stations. As the NEVI plan will accelerate the deployment of charging stations around Indiana, current perceptions may change. Future studies can employ a longitudinal approach with a panel structure. This approach would allow researchers to track the same group of participants over time, providing a more nuanced understanding of how changing circumstances impact EV adoption decisions.

Moreover, the datasets utilized for synthetic data generation may not fully capture the diversity of EV users and their behaviors. Although the synthetic data generation model closely mirrors real-world patterns, some nuances and rare usage scenarios might be underrepresented. Future studies should consider the impact of different mixes of users, such as commuters, delivery trucks, and commercial vehicles, on the EV infrastructure. This analysis will ensure that the needs of diverse user groups are addressed, supporting comprehensive and inclusive EV strategies.

Finally, current datasets can mimic existing users' travel patterns under established charging stations, but they cannot capture changes due to new stations, charging costs, or other factors. Future studies can address this by providing robust forecasts of EV travel patterns and guidance on optimal charging station locations. It predicts how and where EVs will travel, identifies high-usage corridors, and tracks evolving patterns.

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APPENDICES

Appendix A. Survey Questionnaire

Appendix B. Statistical Tests

Appendix C. Choice Experiment Model

APPENDIX A. SURVEY QUESTIONNAIRE

0.1 What is your age?
- O Under 18
- O 18–24
- O 25–34
- O 35–44
- O 45–54
- O 55–64
- O Over 65

0.2 Where do you currently live?

▼ Alabama ... I do not reside in the United States

End of Block: Section: Screening Questions

Start of Block: Section: EV knowledge/experience questions

Q51 To facilitate reading and answering the questions, from now on, "EV" will refer to the Electric Vehicles that are only powered with a battery pack

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1.1 Which statement best describes your situation:
- O I currently own an EV
- O I currently lease an EV
- O I owned an EV in the past and now I lease one
- O I leased an EV in the past and now I own one
- O I owned an EV in the past, but I do not have access to an EV anymore
- O I leased an EV in the past, but I do not have access to an EV anymore
- O I have never owned or leased an EV

Display This Question:
Which statement best describes your situation: I currently own an EV
Which statement best describes your situation: I currently lease an EV
Which statement best describes your situation: I owned an EV in the past and now I lease one
Which statement best describes your situation: I leased an EV in the past and now I own one

A1.2 On a typical day, how far do you use your EV?
- O 0–15.0 miles
- O 15.1–30.0 miles
- O 30.1–50.0 miles
- O 50.1–70.0 miles
- O more than 70.0 miles

Display This Question:
Which statement best describes your situation: I currently own an EV
Which statement best describes your situation: I currently lease an EV
Which statement best describes your situation: I owned an EV in the past and now I lease one
Which statement best describes your situation: I leased an EV in the past and now I own one

A1.3 What is the brand of the EV that you currently have the most access to?
- O Audi
- O BMW
- O Chevrolet
- O Hyundai
- O Kia
- O Nissan
- O Rivian
- O Tesla
- O Toyota
- O Volkswagen
- O Other ____

Display This Question:
Which statement best describes your situation: I currently own an EV
Which statement best describes your situation: I currently lease an EV
Which statement best describes your situation: I owned an EV in the past and now I lease one
Which statement best describes your situation: I leased an EV in the past and now I own one

A1.4 Currently, is the EV your most used vehicle in the household?
- O No
- O Yes

Display This Question:

Which statement best describes your situation: I currently own an EV

Which statement best describes your situation: I currently lease an EV

Which statement best describes your situation: I owned an EV in the past and now I lease one

Which statement best describes your situation: I leased an EV in the past and now I own one

A1.5 How is the overall experience with the EV?

O Very Negative
O Negative
O Neutral
O Positive
O Very Positive

Display This Question:

Which statement best describes your situation: I owned an EV in the past, but I do not have access to an EV anymore

Which statement best describes your situation: I leased an EV in the past, but I do not have access to an EV anymore

B1.2 How was the overall experience with the EV?

O Very Negative
O Negative
O Neutral
O Positive
O Very Positive

Display This Question:

Which statement best describes your situation: I have never owned or leased an EV

C1.2 Have you ever driven an EV?

O No
O Yes

Display This Question:

Have you ever driven an EV? Yes

C1.Y3 How was the driving experience?

O Very negative
O Negative
O Neutral
O Positive
O Very positive

Display This Question:
Have you ever driven an EV? No

C1.N3 Have you ever taken a ride in an EV?
- O No
- O Yes
- O I don't know / I am not sure

Display This Question:
Have you ever taken a ride in an EV? Yes

C1.Y4 How was the riding experience?
- O Very negative
- O Negative
- O Neutral
- O Positive
- O Very Positive

End of Block: Section: EV knowledge/experience questions

Start of Block: Section: Current Travel Patterns

Display This Question:
Which statement best describes your situation: I currently own an EV
Which statement best describes your situation: I currently lease an EV
Which statement best describes your situation: I owned an EV in the past and now I lease one
Which statement best describes your situation: I leased an EV in the past and now I own one

A2.0 How many EVs are in your household including the EV that you currently have the most access to?
- O 0
- O 1
- O 2
- O 3
- O 4 or more

2.1 How many non-EVs are in your household?
- O 0
- O 1
- O 2
- O 3
- O 4 or more

2.2 On average, how often do you travel for the activities listed below:

	Daily	Few times a week	Few times a month	Few times a year	Never
Work (or school for students and work-related business)	O	O	O	O	O
Shopping (running errands)	O	O	O	O	O
Personal (church, medical or family business)	O	O	O	O	O
Social (visiting friends/relatives)	O	O	O	O	O
Recreational (leisure, camping, fishing and similar)	O	O	O	O	O

Display This Question:

Which statement best describes your situation: I currently own an EV

Which statement best describes your situation: I currently lease an EV

Which statement best describes your situation: I owned an EV in the past and now I lease one

Which statement best describes your situation: I leased an EV in the past and now I own one

A2.3 Which of the following is your most frequently used mode of travel for each trip purpose? (Please select only one mode for each trip purpose)

	Walking	Personal Vehicle (Non-EV)	Personal Vehicle (EV)	Public Transit	Ride-hailing (Ex: Uber, Lyft…)	Personal Bike / scooter	N/A (I am not travelling for this purpose)	Other
Work (or school for students and work-related business)	O	O	O	O	O	O	O	O
Shopping (running errands)	O	O	O	O	O	O	O	O
Personal (church, medical or family business)	O	O	O	O	O	O	O	O
Social (visiting friends/relatives)	O	O	O	O	O	O	O	O
Recreational (leisure, camping, fishing and similar)	O	O	O	O	O	O	O	O

Display This Question:

Which statement best describes your situation: I owned an EV in the past, but I do not have access to an EV anymore

Which statement best describes your situation: I leased an EV in the past, but I do not have access to an EV anymore

Which statement best describes your situation: I have never owned or leased an EV

BC2.3 Which of the following is your most frequently used mode of travel for each trip purpose? (Please select only one mode for each trip purpose)

	Walking	Personal Vehicle (Non-EV)	Public Transit	Ride-hailing (Ex: Uber, Lyft…)	Personal Bike / scooter	N/A (I am not travelling for this purpose)	Other
Work (or school for students and work-related business)	O	O	O	O	O	O	O
Shopping (running errands)	O	O	O	O	O	O	O
Personal (church, medical or family business)	O	O	O	O	O	O	O
Social (visiting friends/relatives)	O	O	O	O	O	O	O
Recreational (leisure, camping, fishing and similar)	O	O	O	O	O	O	O

2.4 In an average week, how far do you travel for these specific purposes? (cumulative distance)

	Never/ 0 miles	0 to 10 miles	11 to 20 miles	21 to 30 miles	31 to 50 miles	51 to 70 miles	71 to 100 miles	101 to 150 miles	More than 150 miles
Work (or school for students and work-related business)	O	O	O	O	O	O	O	O	O
Shopping (running errands)	O	O	O	O	O	O	O	O	O
Personal (church, medical or family business)	O	O	O	O	O	O	O	O	O
Social (visiting friends/relatives)	O	O	O	O	O	O	O	O	O
Recreational (leisure, camping, fishing and similar)	O	O	O	O	O	O	O	O	O

End of Block: Section: Current Travel Patterns

Start of Block: Section: Public Perceptions about EV's questions

3.1 EVs and non-EVs have some differences in their characteristics. How much of an advantage (or disadvantage) are the following characteristics of EVs, compared to non-EVs?

	Major Disadvantage	Disadvantage	Neither	Advantage	Major Advantage	Don't know / not sure
EV purchase price:	O	O	O	O	O	O
EV maintenance cost:	O	O	O	O	O	O
EV fuel cost:	O	O	O	O	O	O
EV registration fees	O	O	O	O	O	O
EV life cycle cost:	O	O	O	O	O	O
EV depreciation:	O	O	O	O	O	O
EV refueling convenience	O	O	O	O	O	O
EV trip planning convenience:	O	O	O	O	O	O
EV noise:	O	O	O	O	O	O
EV driving comfort:	O	O	O	O	O	O
EV driving range	O	O	O	O	O	O
EV reliability:	O	O	O	O	O	O
EV safety:	O	O	O	O	O	O

3.2 Please rate your level of agreement with following statements:

	Strongly disagree	Disagree	Neither agree nor disagree	Agree	Strongly agree
Being environmentally responsible is an important part of who I am	O	O	O	O	O
I am the type of person to worry about being green	O	O	O	O	O
Reducing my car's environmental impact would make me feel good	O	O	O	O	O
Environmental issues are an important factor when deciding to purchase a vehicle	O	O	O	O	O

3.3 How likely are you to buy a new or used EV today or in the near future?

O I am more likely to buy new EV
O I am more likely to buy used EV

Display This Question:
How likely are you to buy a new or used EV today or in the near future? I am more likely to buy new EV

3.4.1 What are the **major** factors for your preference for a new EV? (multiple options can be selected)

O I prefer to buy new vehicles independently of the type.
O I think the purchase prices of new and old EVs are similar, so I prefer to buy a new one
O I don’t trust the reliability of used EVs
O New EVs have better financial incentives than the used ones
O The new EV would have better performance (acceleration, driving range…) than the used one
O Other: ____

Display This Question:

How likely are you to buy a new or used EV today or in the near future? I am more likely to buy used EV

3.4.2 What are the **major** factors for your preference for a used EV? (multiple options can be selected)

O I am just able to afford a used EV
O The cost-benefit of used EVs is much better than the new ones
O The depreciation price of the used vehicles is smaller than the new ones
O I am not aware of incentives/policies for purchasing new EV
O The EV would not be the most used vehicle in my household, so I would prefer to buy a cheaper one
O I am not sure if I will get used to an EV, so I prefer to not invest so much in one
O Other: ____

VER. Q1. Please, for this question select "1":

O 0
O 1
O 2
O 3
O 4

End of Block: Section: Public Perceptions about EV's questions

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Start of Block: Section: EV incentives/barriers questions

4.1 EV buyers may (or may not) be eligible for different incentives. Which of the following incentives for EV users are you familiar with? (multiple options can be selected)

O EV Federal Tax Credit
O Installing home charging rebates
O Special rates to home charging in off-peak hours
O Other ____
O I have never heard of any incentives related to EV users

Incentives Information: EV users are able to have different incentives, such as:
EV Federal Tax Credit: Buyers of new EVs may be eligible for a tax credit of up to $7,500.00 and buyers of used EVs may be qualified for up to $4,000.00 in tax breaks;
Installing home charging rebates: some utility companies offer rebates to customers who install specific types of charging stations at home;
Special rates for home charging in off-peak hours: some utilities offer special rates to customers who charge their EVs during off-peak hours;

4.2 Considering the provided information, please rate your level of agreement with the following statement:

"Knowing that EV users can be eligible for these incentives makes me willing to buy/lease an EV"

O Strongly disagree
O Disagree
O Neither agree nor disagree
O Agree
O Strongly agree

Display This Question:
Which statement best describes your situation: I owned an EV in the past, but I do not have access to an EV anymore
Which statement best describes your situation: I leased an EV in the past, but I do not have access to an EV anymore

B4.3 What are the main reasons why you do not own/lease an EV anymore? (multiple options can be selected)

O Inconvenience to plan long trips
O Inconvenience to charge
O I don't have access to home charging
O It's difficult to find reliable charging stations nearby
O The purchase price was too high
O The maintenance costs were too high
O The vehicle was unreliable
O I decided not to have any cars in general
O Other ____

Display This Question:
Which statement best describes your situation: I have never owned or leased an EV

C4.3 What are the main reasons why you have never owned/leased an EV? (multiple options can be selected)

O Inconvenience to plan long trips
O Inconvenience to charge
O I don't have access to home charging
O It's difficult to find reliable charging stations nearby
O The purchase price is too high
O The maintenance costs are too high
O The vehicle is unreliable
O I decided not to have any cars in general
O Other ____

End of Block: Section: EV incentives/barriers questions

Start of Block: Section: EV Adoption curves

5.1 If you were to buy or lease a vehicle today, which statement best describes your thoughts about an EV?

	Very Unlikely	Unlikely	Neutral	Likely	Very likely
I would buy an EV	O	O	O	O	O
I would lease an EV	O	O	O	O	O
I would seriously consider buying an EV	O	O	O	O	O
I would seriously consider leasing an EV	O	O	O	O	O
I might consider getting an electric-only vehicle in the future, but not If I were to buy or lease a vehicle today	O	O	O	O	O
I would definitely not consider getting an EV	O	O	O	O	O

5.2 How likely are you to purchase an EV within the next:

	Extremely unlikely	Somewhat unlikely	Neither likely nor unlikely	Somewhat likely	Extremely likely	I don't plan to purchase a vehicle in this period, independently of the type
1 year	O	O	O	O	O	O
2 years	O	O	O	O	O	O
3 years	O	O	O	O	O	O
5 years	O	O	O	O	O	O
8 years	O	O	O	O	O	O

5.3 How likely are you to lease an EV within the next:

	Extremely unlikely	Somewhat unlikely	Neither likely nor unlikely	Somewhat likely	Extremely likely	I don't plan to lease a vehicle in this period, independently of the type
1 year	O	O	O	O	O	O
2 years	O	O	O	O	O	O
3 years	O	O	O	O	O	O
5 years	O	O	O	O	O	O
8 years	O	O	O	O	O	O

End of Block: Section: EV Adoption curves

Start of Block: Section: Charging knowledge/experience questions

6.4 Which of the following charging technologies have you heard/read about? (multiple options can be selected)

O Alternating Current (AC): Level 1 - Slow charger
O Alternating Current (AC): Level 2 - Slow charger
O Direct Current Fast Charging (DCFC): Level 3 - Fast charger
O Dynamic Wireless Power Transfer: DWPT (i.e., EVs can recharge while driving on designated lanes)
O Battery swapping
O None of the above

Display This Question:

Which statement best describes your situation: I currently own an EV
Which statement best describes your situation: I currently lease an EV
Which statement best describes your situation: I owned an EV in the past and now I lease one
Which statement best describes your situation: I leased an EV in the past and now I own one

A6.0 Do you have a charging station at your home?

O No
O Yes

Display This Question:
Which statement best describes your situation: I currently own an EV
Which statement best describes your situation: I currently lease an EV
Which statement best describes your situation: I owned an EV in the past and now I lease one
Which statement best describes your situation: I leased an EV in the past and now I own one

A6.1 Where do you charge your EV? (multiple options can be selected)
- O Home charging stations (Level 1)
- O Public charging stations (Level 2)
- O Public charging stations (DCFC)

Display This Question:
Which statement best describes your situation: I owned an EV in the past, but I do not have access to an EV anymore
Which statement best describes your situation: I leased an EV in the past, but I do not have access to an EV anymore
Which statement best describes your situation: I have never owned or leased an EV

BC6.1
If you were an EV user, where would you charge your EV? (multiple options can be selected)
- O Home charging stations (Level 1)
- O Public charging stations (Level 2)
- O Public charging stations (DCFC)

6.2 What would be the maximum distance would you be willing to drive to charge your EV?
- O 0 miles (home charging)
- O 0.1–2 miles
- O 2.1–5 miles
- O 5.1–10 miles
- O more than 10 miles

6.3 If public charging is available at the following places, how much will you use them to charge your EV?

	Never	Rarely	Sometimes	Often	Always
Office	O	O	O	O	O
Retail	O	O	O	O	O
Public Administration (e.g.: town hall, court)	O	O	O	O	O
Medical	O	O	O	O	O
Educational	O	O	O	O	O
Leisure	O	O	O	O	O
Transit	O	O	O	O	O
Hotel	O	O	O	O	O
Restaurant	O	O	O	O	O

Display This Question:

Which statement best describes your situation: I currently own an EV

Which statement best describes your situation: I currently lease an EV

Which statement best describes your situation: I owned an EV in the past and now I lease one

Which statement best describes your situation: I leased an EV in the past and now I own one

A6.5 When you leave home with your EV for the first time in the day, what is your typical battery level?

O 0%–49.9%
O 50.0%–69.9%
O 70.0%–89.9%
O 90.0%–100.0%

Display This Question:

Which statement best describes your situation: I currently own an EV

Which statement best describes your situation: I currently lease an EV

Which statement best describes your situation: I owned an EV in the past and now I lease one

Which statement best describes your situation: I leased an EV in the past and now I own one

A6.6 At what battery level do you typically charge your EV?

O 0%–19.9%
O 20.0%–39.9%
O 40.0%–59.9%
O 60.0%–100.0%

Display This Question:
Which statement best describes your situation: I currently own an EV
Which statement best describes your situation: I currently lease an EV
Which statement best describes your situation: I owned an EV in the past and now I lease one
Which statement best describes your situation: I leased an EV in the past and now I own one

A6.7 At what time of the day do you usually charge your EV? (multiple options can be selected)

O From 7:01 AM to 9:00 AM
O From 9:01 AM to 12:00 PM
O From 12:01 PM to 5:00 PM
O From 5:00 PM to 9:00 PM
O From 9:01 PM to 7:00 AM

Display This Question:
Which statement best describes your situation: I currently own an EV
Which statement best describes your situation: I currently lease an EV
Which statement best describes your situation: I owned an EV in the past and now I lease one
Which statement best describes your situation: I leased an EV in the past and now I own one

A6.8 How long do you typically charge the EV in a day that you most have access to?

	0–14.9 minutes	15.0–29.9 minutes	30.0–59.9 minutes	1h–3 hours	More than 3 hours	I don't charge here	I don't know
Home charging stations	O	O	O	O	O	O	O
Public charging stations (Level 2)	O	O	O	O	O	O	O
Public charging stations (DCFC)	O	O	O	O	O	O	O

Display This Question:

Which statement best describes your situation: I currently own an EV
Which statement best describes your situation: I currently lease an EV
Which statement best describes your situation: I owned an EV in the past and now I lease one
Which statement best describes your situation: I leased an EV in the past and now I own one

A6.9 How long are you willing to walk from the nearby public charging stations/parking lots to your destination?

O 0–3 minutes
O 3–7 minutes
O 7–10 minutes
O More than 10 minutes

Display This Question:

Which statement best describes your situation: I currently own an EV
Which statement best describes your situation: I currently lease an EV
Which statement best describes your situation: I owned an EV in the past and now I lease one
Which statement best describes your situation: I leased an EV in the past and now I own one

A6.10 Rate your behavior in the following situation:
"If the EV's range is almost as same as the distance of my next trip, I will start the trip".

O Never
O Sometimes
O About half the time
O Most of the time
O Always

Display This Question:

Which statement best describes your situation: I currently own an EV
Which statement best describes your situation: I currently lease an EV
Which statement best describes your situation: I owned an EV in the past and now I lease one
Which statement best describes your situation: I leased an EV in the past and now I own one

A6.11 Rate your behavior in the following situation:
"If a trip is not familiar to me, I will keep the battery level higher than usual if possible before departing."

O Never
O Sometimes
O About half the time
O Most of the time
O Always

Display This Question:
Which statement best describes your situation: I owned an EV in the past, but I do not have access to an EV anymore
Which statement best describes your situation: I leased an EV in the past, but I do not have access to an EV anymore
Which statement best describes your situation: I have never owned or leased an EV

BC6.5 Answer this question by imagining that you are an EV-user: How long are you willing to walk from the nearby public charging stations/parking lots to your destination?

O 0–3 minutes
O 3–7 minutes
O 7–10 minutes
O More than 10 minutes

Display This Question:
Which statement best describes your situation: I owned an EV in the past, but I do not have access to an EV anymore
Which statement best describes your situation: I leased an EV in the past, but I do not have access to an EV anymore
Which statement best describes your situation: I have never owned or leased an EV

BC6.6 Rate your behavior by imagining that you are an EV user:
"If the EV's range is almost as same as the distance of my next trip, I will start the trip".

O Never
O Sometimes
O About half the time
O Most of the time
O Always

Display This Question:
Which statement best describes your situation: I owned an EV in the past, but I do not have access to an EV anymore
Which statement best describes your situation: I leased an EV in the past, but I do not have access to an EV anymore
Which statement best describes your situation: I have never owned or leased an EV

BC6.7 Rate your behavior by imagining that you are an EV user:
"If a trip is not familiar to me, I will keep the battery level higher than usual if possible before departing."

O Never
O Sometimes
O About half the time
O Most of the time
O Always

VER Q2. Please, for this question select "Disagree":

O Strongly agree
O Agree
O Neutral
O Disagree
O Strongly disagree

End of Block: Section: Charging knowledge/experience questions

Start of Block: Section: Charging Perceptions questions

Display This Question:
Which statement best describes your situation: I currently own an EV
Which statement best describes your situation: I currently lease an EV
Which statement best describes your situation: I owned an EV in the past and now I lease one
Which statement best describes your situation: I leased an EV in the past and now I own one

A7.1 Do you feel certain about being able to charge your vehicle when you need to?

O Never
O Sometimes
O About half of time
O Most of the time
O Always

Display This Question:
Which statement best describes your situation: I owned an EV in the past, but I do not have access to an EV anymore
Which statement best describes your situation: I leased an EV in the past, but I do not have access to an EV anymore
Which statement best describes your situation: I have never owned or leased an EV

BC7.1 If you were using an EV, would you feel certain about being able to charge your vehicle when you need to?

O Never
O Sometimes
O About half of time
O Most of the time
O Always

7.2 **Public charging stations will be built all over the state in the next few years.** What would be the minimum distance (in miles) between charging stations under which you would not be concerned about the driving range?

O 10 miles
O 30 miles
O 50 miles
O 100 miles
O More than 100 miles

7.3 Below are few statements about accessibility to EV charging. Please rate to what extent you agree or disagree with these statements:

	Strongly disagree	Disagree	Neither agree nor disagree	Agree	Strongly agree
Charging at public charging stations is cumbersome	O	O	O	O	O
I do not have the patience to wait for the car to charge	O	O	O	O	O
There are few charging stations near my home/workplace	O	O	O	O	O
Charging stations are hard to find	O	O	O	O	O
I expect that there will be more public charging facilities in the next five years	O	O	O	O	O
There are too many charging stations not working or with serious failures	O	O	O	O	O

VER. Q3. (Rel 2.1) Verification question: nowadays, how many non-EVs are in your household?

O 4 or more
O 3
O 2
O 1
O 0

Start of Block: Section G: Experimental Design - WTP questions

M1 If you are using mobile, please change your view to landscape to answer the next questions.

In the following section, you will be provided with 6 different scenarios for charging your EV during a long-distance trip.

For these questions (even if you own an electric vehicle), assume that you are driving an EV with a range of 200 miles and a battery capacity of 60 kWh. It means that this EV can travel 200 miles when the battery is at 100% charge. The destination is 100 miles from your house with a speed limit of 70 mi/hr.

Then, you can choose to use any chargers to reach your destination. Each charging station has varying travel time, travel cost, charging time, waiting time, and presence of other services such as restrooms or other amenities. There are no right or wrong answers, as we only want to learn about your preferences.

a. Travel time (without charging): The time required to travel 100 miles at the speed 70 mi/hour without charging
b. Charging time: Time required to charge the vehicle. For DCFC, assume that you are charging your EV to full
c. Access time: Time required to reach the charging station from your original route.
d. Waiting time (in the queue): Time spent waiting your turn in the queue
e. Total Travel Time: a+b+c+d
f. Cost per trip: Total cost of charging per trip (based on kWh)

Note that DWPT stands for Dynamic Wireless Power Transfer. Dynamic wireless power transfer (DWPT) technology enables Electric Vehicles (EVs) to be charged as they are driven at highway speeds.

From the options below, please choose a charging station where you would charge your EV.

This is an example of a question of the experimental design section:

Below are three charging stations you can use to charge your vehicle.
Each charging station has varying travel cost, charging time (time to charge your EV), access time (time to reach the charging station from highway), and waiting time (time waiting for your turn to charge your EV), as well as other amenities (restrooms and restaurant, retail and shopping).

Please choose the charging station where you would charge your EV.

	Level 2	DCFC	DWPT
Cost per trip ($)	15	27	35
Charging time (mins)	240	24	N/A
Access time (mins)	9	5	N/A
Waiting time (mins)	0	30	N/A
Total travel time (mins)	334 (5hr 34mins)	144 (2hr 24mins)	85 (1hr 25mins)
Restrooms	✓	✓	N/A
Restaurant, Retail and Shopping	✓	X	N/A

O Level 2
O DCFC
O DWPT

Start of Block: Section 9: Socio-demographic questions

9.1What gender do you identify with?
O Male
O Female
O Non-binary / third gender
O Other
O Prefer not to say

9.2 Which races do you identify with? (multiple options can be selected)
O White
O Black/African American
O Asian/Pacific Islander
O Native American/Alaskan Native
O Other
O Prefer not to say

9.3 Which ethnicity do you identify with?
O Hispanic
O Non-hispanic
O Prefer not to say

9.4 What is your highest level of education?
O Grade school or less
O Some high school
O High school graduate
O Technical training beyond high school
O Some college
O College graduate
O Graduate or professional school

9.5 What is your main occupation?
O Employed full-time
O Employed part-time
O Unemployed and looking for work
O Unemployed and not looking for work
O Retired
O Student
O Disabled

9.6 What is your approximate annual household income before taxes?
O Under $25,000
O $25,000–$49,999
O $50,000–$74,999
O $75,000–$99,999
O $100,000–$149,999
O $150,000 or more
O I prefer not to say

9.7 How many people are in your household (including you)?
O 0
O 1
O 2
O 3
O 4
O 5
O 6
O 7
O 8 or more

9.8 What kind of residence do you live in?
O Single family home
O Apartment complex
O Condo
O Duplex
O Townhome
O Other

9.9 Do you plan to move to a different type of residence in the next 3 years?
O Definitely not
O Probably not
O Might or might not
O Probably yes
O Definitely yes

9.10 What is your home ZIP code?

9.11 What is the ZIP code of your main activity outside the home (like work, study, health)?

9.12 For how many years have you lived in Indiana?

O 0 to 2 years
O 2 to 5 years
O 5 to 10 years
O more than 10 years

9.13 Generally speaking, do you usually think of yourself as a Democrat, a Republican, an independent, or a member of another party?

O Democrat
O Republican
O Independent
O Other

Display This Question:
Generally speaking, do you usually think of yourself as a Democrat, a Republican, an independent... Independent
Generally speaking, do you usually think of yourself as a Democrat, a Republican, an independent... Other

9.N14 Do you think of yourself as closer to the Democratic Party or to the Republican Party?

O Closer to Democrat
O Closer to Republican
O Neither

9.15 Politically, where would you place yourself on this scale?

O Extremely liberal
O Liberal
O Slightly liberal
O Moderate
O Slightly conservative
O Conservative
O Extremely conservative

End of Block: Section Z: Socio-Demographic Questions

Start of Block: Final Section

Final Question Please, use the space below to provide any other comments related to EVs that you think are relevant:

____

End of Block: Final Section

APPENDIX B. STATISTICAL TESTS

Table B.1 presents the Chi-squared and p-values for each of the 13 EV attributes analyzed in Section 4.3. The Chi-squared tests were performed to investigate if the responses of the EV users and non-EV users differ statistically.

Table B.1 Chi-squared and p-values for EV attributes

	Chi-squared	p-value
EV purchase price:	177.38	< 2.2e-16
EV maintenance cost:	387.15	< 2.2e-16
EV fuel cost:	125.85	< 2.2e-16
EV registration fees	183.85	< 2.2e-16
EV life cycle cost:	261.08	< 2.2e-16
EV depreciation:	154.06	< 2.2e-16
EV refueling convenience	161.70	< 2.2e-16
EV trip planning convenience:	149.39	< 2.2e-16
EV noise:	99.34	< 2.2e-16
EV driving comfort:	235.43	< 2.2e-16
EV driving range	144.36	< 2.2e-16
EV reliability:	269.93	< 2.2e-16
EV safety:	273.17	< 2.2e-16

APPENDIX C. CHOICE EXPERIMENT MODEL

We developed an Integrated Choice and Latent Variable (ICLV) model to understand public charging choices. This model incorporates both structural and measurement equations within a latent variable framework, along with a discrete choice model (Bhat & Dubey, 2014). The two-step process involves a measurement model that establishes the connection between latent variables and attitudinal variables. Latent variables are further structured with sociodemographic attributes through an ordered-logit model within this framework.

The utility function, latent variable structure, and latent variable measurement functions are defined as follows:

$$U_n(j) = \beta_j X_{jn} + \epsilon_j^n \qquad \text{(Eq. C.1)}$$

$$\alpha_c^n = \beta_c Z^n + \epsilon_c^n \qquad \text{(Eq. C.2)}$$

$$I_{s,c}^{n*} = \beta_{s,c}\alpha_c^n + \epsilon_{s,c}^n \qquad \text{(Eq. C.3)}$$

$$I_{s,c}^n = \begin{cases} \theta_{s,c}^1 \; if -\infty < I_{s,c}^{n*} < \tau_{s,c}^1 \\ \theta_{s,c}^2 \; if \; \tau_{s,c}^1 < I_{s,c}^{n*} < \tau_{s,c}^2 \\ \theta_{s,c}^3 \; if \; \tau_{s,c}^2 < I_{s,c}^{n*} < \tau_{s,c}^3 \\ \theta_{s,c}^4 \; if \; \tau_{s,c}^3 < I_{s,c}^{n*} < \tau_{s,c}^4 \\ \theta_{s,c}^5 \; if \; \tau_{s,c}^4 < I_{s,c}^{n*} < \infty \end{cases} \qquad \text{(Eq. C.4)}$$

Equation C.1: The utility function $U_n(j)$ represents the utility of respondent n choosing alternative j; β_j is the estimated coefficient expressed by the exogenous variable X_j^n (e.g., charging time, charging cost, latent variables) and an unobservable error term ϵ_j^n. It is assumed that the errors are independently and identically distributed with a Gumbel extreme value distribution.

Equation C.2: The latent variables structure is defined by α_c^n, denoting the latent variable c of respondent n. β_c is a vector of coefficients to be estimated, corresponding to the vector of exogenous variables Z^n (e.g., sociodemographic attributes). Additionally, the stochastic error term ϵ_c^n is assumed to be normally distributed as $\epsilon_c^n \sim N(0, \sigma_n^c)$.

Equations C.3 and C.4: These describe the latent variable measurement equations. $I_{s,c}^{n*}$ is associated with the s^{th} attitudinal statement of respondent n and uses the unobservable variable c as an explanatory factor. $I_{s,c}^n$ represents the final estimated value ($\theta_{s,c}^1 - \theta_{s,c}^5$) for the attitudinal statement s. $\beta_{s,c}$ are the coefficients to be estimated for the attitudinal statement s, with the random disturbance $\epsilon_{s,c}^n$ assumed to be normally distributed.

Table C.2 ICLV estimation results for EV users

	Variables	Level 2 Coeff. (t-value)	Level 3 /DCFC Coeff. (t-value)	DWPT Coeff. (t-value)
Alternative Specific Variable	Constant	–	0.770 (1.272)	0.478 (0.582)
	State of Charging (SoC $\geq$ 80%)	0.776** (2.494)	–	–
	Charging time proportion over total trip time – mean (mu) [a]	1.602** (2.166)	–	–
	Charging time proportion over total trip time – standard deviation (sigma) [a]	-2.545** (-3.695)	–	–
	Charging time	–	-0.036** (-2.491)	–
Common Variable	Charging cost – mean (mu) [a]	-2.298** (-6.189)		
	Charging cost – standard deviation (sigma) [a]	1.531*** (6.355)		
	Waiting time	-0.016** (-2.339)		
Latent Variables	Environmentalist	–	-0.270** (-2.249)	–
	Positive attitude toward EV features and convenience	–	–	-0.789*** (-4.547)
Social-demographic variables	Occupation (Retired) – mean (mu) [b]	–	3.977** (2.192)	–
	Occupation (Retired) – standard deviation (sigma) [b]	–	3.794** (2.131)	–

Note: *** p-value < 0, ** p-value < 0.001, * p-value < 0.05, p-value < 0.1

[a] Negative log-normal distribution

[b] Normal distribution

Table C.3 ICLV estimation results for non-EV users

	Variables	Level 2 Coeff. (t-value)	Level 3/DCFC Coeff. (t-value)	DWPT Coeff. (t-value)
Alternative Specific Variable	Constant	–	-0.483** (-2.434)	-0.642** (-2.906)
	Restroom (1: available/0: unavailable)	–	0.188** (2.742)	–
	Charging time proportion over total trip time	-2.728*** (-8.022)	–	–
	Charging time	–	-0.023*** (-4.132)	–
	Waiting time	-0.066*** (-4.428)	–	–
Common Variable	Charging cost – mean (mu) [a]	-3.083*** (-15.964)		
	Charging cost – standard deviation (sigma) [a]	1.694*** (11.513)		
Social-demographic variables	Income (≥ $100,000)	-0.607*** (-4.404)	–	–
	Education (1: college graduate or higher/0: otherwise)	-0.463*** (-4.821)	–	–
	Female (1: yes/ 0: no) - mean (mu)	–	–	-0.534*** (-4.528)
	Female (1: yes/ 0: no) - deviation (sigma)	–	–	-1.547*** (-12.361)

Note: *** p-value < 0, ** p-value < 0.001, * p-value < 0.05, p-value < 0.1

[a] Negative log-normal distribution

[b] Normal distribution

Table C.4 EV users structural and measurement model components

	Variables	LV1: Environmentalist				LV2: Positive attitude toward EV feature and convenience			
		AV1: Environ mental Responsi bility	**AV2: Environ mental Concern**	**AV3: Reducing car usage**	**AV4: Environment factor to buying car**	**AV5: EV purchase price**	**AV6: EV refueling convenience**	**AV7: EV trip planning convenience**	**AV8: EV driving range**
Measurem ent model	Coefficient for attitudinal indicator	2.696 (9.748)	3.432 (7.144)	2.400 (9.057)	3.570 (10.073)	1.316 (7.059)	1.582 (7.067)	2.137 (8.291)	1.789 (7.978)
	1st threshold	-7.548 (-9.545)				-3.643 (-14.354)			
	2nd threshold	-5.115 (-7.668)				-0.857 (-4.943)			
	3rd threshold	-2.670 (-4.631)				0.509 (3.024)			
	4th threshold	0.817 (1.544)				1.977 (10.575)			
Structural Model	College graduate or higher (1: yes/0: no)	-0.836 (-6.655)							
	Income < $25,000 (1: yes/0: no)	-1.123 (-4.630)				1.445 (3.600)			
	Income < $100,000 - $149,999 (1: yes/0: no)	-0.502 (-3.981)							

About the Joint Transportation Research Program (JTRP)

On March 11, 1937, the Indiana Legislature passed an act which authorized the Indiana State Highway Commission to cooperate with and assist Purdue University in developing the best methods of improving and maintaining the highways of the state and the respective counties thereof. That collaborative effort was called the Joint Highway Research Project (JHRP). In 1997 the collaborative venture was renamed as the Joint Transportation Research Program (JTRP) to reflect the state and national efforts to integrate the management and operation of various transportation modes.

The first studies of JHRP were concerned with Test Road No. 1—evaluation of the weathering characteristics of stabilized materials. After World War II, the JHRP program grew substantially and was regularly producing technical reports. Over 1,600 technical reports are now available, published as part of the JHRP and subsequently JTRP collaborative venture between Purdue University and what is now the Indiana Department of Transportation.

Free online access to all reports is provided through a unique collaboration between JTRP and Purdue Libraries. These are available at http://docs.lib.purdue.edu/jtrp.

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